AI-Driven Innovation and Collaboration in Public Services: A Review and Taxonomy

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Abstract. Recently, governments and organizations have expanded their interest and efforts toward acquiring Artificial Intelligence-powered systems to support the delivery of public services. However, there is insufficient information in the literature to help us understand how different types of public services are supported by AI, particularly regarding aspects such as collaboration support and the innovation achieved within organizations. To address these literature gaps, we conducted a rapid review to identify types of AI applications, problem solved, government functions supported, their impacts on innovation in public organizations, and the collaborative arrangements they have fostered among various stakeholders. Furthermore, in this same scope, we also designed a taxonomy as an analytical framework to answer the literature review questions. The review found that AI in the public sector is mainly used for prediction, data visualization, predictive analysis, and automating repetitive processes, particularly in economic affairs, health, and public order. Governments develop AI solutions primarily for administrative and repetitive tasks. In this sense, there is potential growth for new AI adoption forms and public management innovations, benefiting public service delivery and society. These contributions aim to help researchers, public managers, and tech companies better understand and analyze the complex domain of AI in public services, enabling them to develop and responsibly implement new AI solutions in the future.

Keywords. Artificial Intelligence, Public Services, Taxonomy, Digital Government, Human-AI interaction, Collaboration
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1. Introduction

Recently, governments and organizations responsible for providing public services have increased their interest in acquiring Artificial Intelligence (AI) technologies to support public services (Sousa et al., 2019). Potential benefits are pointed out in several sectors related to the public sector, such as public health, climate change, disaster prevention and response, and government-citizen interaction, among others (Luusua et al.,2023), (Valle-Cruz et al., 2019). Such AI-powered services can be incorporated into the urban environment (Luusua et al.,2023), be made available in digital services such as citizen inquiries and information (Mehr, 2017), or be directly linked to the bureaucratic functioning of public entities or directly related to the decision-making process. of decision-making by public managers (Kuziemski and Misuraca, 2020).

In this context, many researchers have been investigating the topic of AI in the public sector. For example, Wirtz et al. (2019) present a conceptual approach to and analysis of AI applications and challenges. They identify ten AI application areas and discuss their value creation and functioning, as well as specific public use cases. Similarly, Sousa et al. (2019) discuss insights from AI projects in government and present a classification framework for AI applications in the public sector. Their framework aims to facilitate the deployment of AI in the public sector by providing a lens to different deployment-related questions.

Nevertheless, Desouza et al. (2020) and Zuiderwijk et al (2021) highlight governments and public organizations' increasing interest in and adoption of AI systems. More specifically, the first offers a systematic review of existing literature on the implications of AI in public governance, and the latter reviews a sample of 250 cases across the European Union and finds that AI is primarily used to support improving public service delivery, followed by enhancing internal management. They both also discuss the complexities and risks of implementing those systems. Also, through a systematic review, Valle-Cruz et al. (2019) collected 78 publications and applied a public policy framework to identify future areas of implementation. In addition to these, Straub et al. (2023) also conducted a literature review and developed a typology addressing concepts such as operational fitness, epistemic alignment, and normative divergence.

Despite the advancements in the field and the efforts from academia to understand this phenomenon, some aspects related to the impact of AI adoption on innovation and collaboration in the public sector remain open. Besides, it is noted that there is a need to create more robust classification structures that allow organizing knowledge about AI applications in public services.

In this sense, this work has two complementary objectives: (i) to conduct a literature review aimed at mapping how AI applications have been used, their impacts on innovation in the public sector, and the collaborative arrangements they have fostered among various stakeholders; (ii) to design a taxonomy that allows for the classification of AI applications in the public sector, including aspects related to innovation and collaboration. Furthermore, we validated the taxonomy as an analytical framework to answer the literature review questions. Finally, we expect that these contributions can support researchers, public managers, and tech companies in understanding and analyzing the complex domain of AI in public services to create and responsibly adopt new AI solutions.

2. Theoretical background

2.1 Public Services and Government Functions Definitions

As presented by Denhardt and Denhardt (2000), although the execution of services conducted by complex and organized governments is ancient, public administration as a field of practice and reflection dates back to the late 19th century. The traditional public management practice, primarily centered on hierarchy and efficiency, and the perception of the public interest has evolved. The two main contemporary streams of thought regarding models of public service revolve around the clash of market-based models focusing on efficiency versus models based on democratic values and the effectiveness of government work.

The concept of Public Services in this work is associated with the idea of Services of General Interest (SGIs), which are services provided by government and private organizations operating under some form of state regulation or public contract. The term SGI was coined within the context of the European Union and reasonably avoids the semantic ambiguities that the term' public services' may carry due to the philosophical perspective one holds on the subject. The term primarily refers to tasks and functions assumed as essential services for the quality of life of citizens, their well-being, and the functioning of society (Bjørnsen et al., 2015).

Given the differing perceptions of what constitutes public services, this work will utilize the Classification of the Functions of Government (COFOG) developed by the Organisation for Economic Cooperation and Development (OECD), as presented in Table 1, to reference the context or function of public services that AI tools support. COFOG consists of 10 first-level groups of government functions divided into 69 second-level subgroups.

Tab. 1 - Classification of the Functions of Government (COFOG).

First-level	Second-level
General public services	Executive and legislative organs, financial and fiscal affairs, external affairs
	Foreign economic aid
	General services
	Basic research
	R&D general public services
	General public services n.e.c.
	Public debt transactions
	Transfers of a general character between different levels of government
Defense	Military defense
	Civil defence

	Foreign military aid
	R&D defense
	Defense n.e.c.
Public order and safety	Police services
	Fire-protection services
	Law courts
	Prisons
	R&D public order and safety
	Public order and safety n.e.c.
Economic affairs	General economic, commercial and labor affairs
	Agriculture, forestry, fishing and hunting
	Fuel and energy
	Mining, manufacturing and construction
	Transport
	Communication
	Other industries
	R&D economic affairs
	Economic affairs n.e.c.
Environmental protection	Waste management
	Waste water management
	Pollution abatement
	Protection of biodiversity and landscape
	R&D environmental protection
	Environmental protection n.e.c.
Housing and community amenities	Housing development
	Community development
	Water supply
	Street lighting
	R&D housing and community amenities
	Housing and community amenities n.e.c.
Health	Medical products, appliances and equipment
	Outpatient services
	Hospital services
	Public health services
	R&D health
	Health n.e.c.
Recreation, culture and religion	Recreational and sporting services
	Cultural services
	Broadcasting and publishing services
	Religious and other community services
	R&D recreation, culture and religion

	Recreation, culture and religion n.e.c.
Education	Pre-primary and primary education Secondary education Post-secondary non-tertiary education Tertiary education Education not definable by level Subsidiary services to education R&D education Education n.e.c.
Social protection	Sickness and disability Old age Survivors Family and children Unemployment Housing Social exclusion n.e.c. R&D social protection Social protection n.e.c.

2.2 Types of problems and AI applications in Public Services

Wirtz et al. (2019) discussed types of AI applications, describing various categories of AI-based systems, their functional propositions, and public sector use cases. The systems addressed in this research are AI-Based Knowledge Management (KM) Software, AI Process Automation Systems, Virtual Agents, Predictive Analytics & Data Visualization, Identity Analytics, Cognitive Robotics & Autonomous Systems, Recommendation Systems, Intelligent Digital Assistants (IDA), Speech Analytics, Cognitive Security Analytics & Threat Intelligence. Wirtz et al. applied an AI value creation and functional proposition within each of them, as well as its use cases in the public sector.

• AI-Based Knowledge Management Software: Generation and systematization of knowledge – gathering, sorting, transforming, recording, and sharing knowledge. Distribution, sharing, and analysis of knowledge with neural networks, with its usage in the public sector on clinical documentation powered by AI.

• AI Process Automation Systems: Automation of standard tasks; performing formal logical tasks with unpredictable conditions, complex human action processes, and robotic process automation, with its usage in the public sector on Faster and higher quality request processing for immigration applications, automated image diagnoses, human-computer interaction for repetitive tasks.

• Virtual Agents: Computer-based systems that interact with users through speech analysis, computer vision, and written data input. For example, it is used in the public sector in virtual nursing assistance and chatbots to help refugees seeking asylum.

• Predictive Analysis & Data Visualization: Analytics based on quantitative and statistical data analysis. Processing of Big data for reporting, prescriptive and predictive analysis. Its usage in the public sector is in control, performance, and monitoring of public areas for police departments to determine terror threats and crime hotspots for preventive action.

• Identity Analytics: Software combined with big data, advanced analytics and identity access management to control access to IT systems with deep and machine learning. Facial recognition software is used in the public sector to verify and identify criminals in public spaces.

• Cognitive Robotics & Autonomous Systems: Higher-level cognitive function systems involving knowledge representation that can learn and respond. Its usage in the public sector in electric-powered autonomous vehicles for public transportation.

• Recommendation Systems: An information filtering system. Its usage in the public sector in E-service for government offices to provide personalized information for employees.

• Intelligent Digital Assistants (IDA): Software based on speech analytics, providing an intuitive interface between user and system. Its public sector usage connects federal programs to IDAs to make public service information available to customers.

• Speech Analytics: Software for intelligent recognition and processing of language, translation from spoken to written language, or from one to another natural language. Its usage in the public sector in Real-time universal translation to translate speech and text in face-to-face communications in public service settings.

• Cognitive Security Analytics & Threat Intelligence: Additional application for cognitive technologies to analyze security information through natural language processing and machine learning. Its usage in the public sector in Applications like Watson for cybersecurity to support human security analysis.

Mehr et al. (2017) also acknowledge the potential benefits of AI in the public sector, such as improving government efficiency, enhancing citizen engagement, and modernizing service delivery. However, they also highlight several significant concerns, difficulties, and obstacles that must be addressed.

• Resource Allocation: Require administrative support to speed up task completion. Its Inquire response times are long due to insufficient support.

• Large Datasets: The dataset is too extensive for employees to work efficiently. Internal and external can be combined to enhance outputs and insights.

• Predictable Scenario: The situation is predictable based on historical data. Prediction will help with time-sensitive responses.

• Procedural: The task is repetitive by its nature. Its inputs and outputs have a binary answer.

• Diverse Data: It includes visual/spatial and auditory/linguistic information. Quantitative and qualitative data need to be summarized regularly.

2.3 A typology of Public Service innovation

Processing of Big data for reporting, prescriptive and predictive analysis. Its usage in the public sector is in control, performance, and monitoring of public areas for police departments to determine terror threats and crime hotspots for preventive action.

Chen et al. (2020) introduced a comprehensive typology to elucidate and classify innovative endeavors within public service organizations. This typology is characterized by two pivotal dimensions: 'innovation focus,' which encompasses three distinct public value creation processes, namely strategy, capacity, and operations, and 'innovation locus,' which discerns between internal and external innovation sources. The confluence of these dimensions yields an intricate taxonomy comprising six distinct categories of innovation, each delineated as follows:

• Mission Innovation: This classification introduces a novel worldview, mission, or overarching purpose that transcends the entirety of the organization, encapsulating a holistic transformation in its fundamental ethos.

• Policy Innovation: Within this purview, the emphasis lies in introducing new paradigms of benefits and obligations to stakeholders, aiming to address and alleviate societal issues. Policy innovation extends beyond traditional frameworks to encompass a broader societal perspective.

• Management Innovation: This facet pertains to the infusion of innovative management practices, processes, structures, or techniques, with the express objective of enhancing the organization's capacity for advancement and effectiveness.

• Partner Innovation: This category is characterized by establishing innovative partnerships to augment the organization's prowess in achieving its strategic goals and objectives. Partner innovation underscores the value of external collaborations in catalyzing organizational progress.

• Service Innovation: Under this rubric, the focus is on the inception and provision of innovative services meticulously designed to align with and fulfill the organization's overarching goals and mission.

• Citizen Innovation: This genre encompasses the creation of novel platforms and avenues geared explicitly towards facilitating citizen engagement and collaboration in pursuing organizational objectives. Citizen innovation heralds a shift towards inclusive governance models.

This typology will help identify the focus and locus of AI solutions and their contribution to innovation in public services.

2.4 Collaboration between Agents and Human-Machine Networks

Artificial intelligence can significantly enhance collaboration among diverse agents, thus facilitating innovation in public services. Hartley et al. (2013) explain that theories of collaborative innovation in the public sector emphasize the importance of network governance and inter-organizational learning. These theories highlight how collaborative networks can solve complex problems and drive significant changes through interaction. Another widely recognized theory addressing how innovation is a product of interaction among multiple agents is presented by Leydesdorff & Etzkowitz (1998). Through the concept of the triple helix of innovation and entrepreneurship, the authors argue that the key agents responsible for innovation are universities, industry, and government through their interactions. Therefore, this collaboration is essential for knowledge-based economic growth, as it allows the public sector to benefit from the knowledge and expertise of academia and industry. The innovations resulting from this process can potentially transform the delivery of public services, making them more efficient, accessible, and tailored to societal needs.

Furthermore, Linders (2012) highlights citizens as another important agent by emphasizing the growing significance of "citizen co-production" in public service provision. Instead of being passive clients, citizens play an active role as partners in service delivery. This approach helps mitigate budgetary challenges in the public sector and leverages new technological tools that enable mass collaboration. As technology advances, the relationship between government and citizens evolves, with "citizen co-production" becoming more relevant and feasible. This phenomenon means that citizens can actively contribute to innovation in the delivery of public services by participating in policy definition and service improvement.

Kattel et al. (2020) focus on the increasing adoption of technology and automation in the public sector, presenting intelligent machines as yet another agent. As intelligent machines play a greater role in delivering public services, collaboration includes machine-machine and human-machine interactions. These interactions are shaping the space for innovation as new technologies and approaches are developed to enhance the efficiency and quality of public services. Automation and artificial intelligence can play a fundamental role in process optimization, data collection and analysis, and personalization of services to meet individual citizens' needs. Furthermore, Tsvetkova et al. (2017) demonstrated that we can represent the collaboration between human agents and intelligent machines through graphical schemes illustrating human-machine networks and their fundamental interactions. In this research context, hybrid arrangements produce synergistic effects in the provision of public services.

3. Methodology

In broad terms, the research design developed to conduct this study integrates, in a complementary manner, the methodological procedures of the Rapid Review method (Tricco et al., 2015) and a method for developing taxonomies in the Information Systems (Nickerson et al., 2013). A Rapid Review is a simplified approach to Systematic Review, where some steps, such as information search and synthesis, can be omitted (Tricco et al., 2015). On the other hand, Nickerson et al. (2013) proposed a method for developing taxonomies that incorporates the Design Science Research (DSR) (Iivari, 2007) approach to generate new knowledge about AI applications in government while designing the artifact, in this case, the taxonomy.

Figure 1 illustrates the methodological procedures carried out in parallel for the rapid review and taxonomy development. After defining the research questions, conducting the search process, and selecting the studies, the extracted data was utilized to develop the taxonomy. This section provides an overview of the review process as well as the systematic approach to creating a comprehensive taxonomy. It details each phase, from establishing the initial meta-characteristics and ending conditions to the iterative refinement cycles, transitioning between conceptual-to-empirical and empirical-to-conceptual stages.

In the first iteration, following a Conceptual-Deductive approach, 60 AI use cases from the selected publications in the review are examined based on the conceptualized characteristics and dimensions. Subsequently, during the second iteration, employing an empirical-inductive approach, all the 103 AI use cases in the selected publications in the review are utilized to identify common characteristics and perform object groupings. After grouping the characteristics into dimensions, we refined the taxonomy. Once finalized, we validated the taxonomy using an analytical framework for data analysis and synthesis of the 103 AI use cases described in the publications.

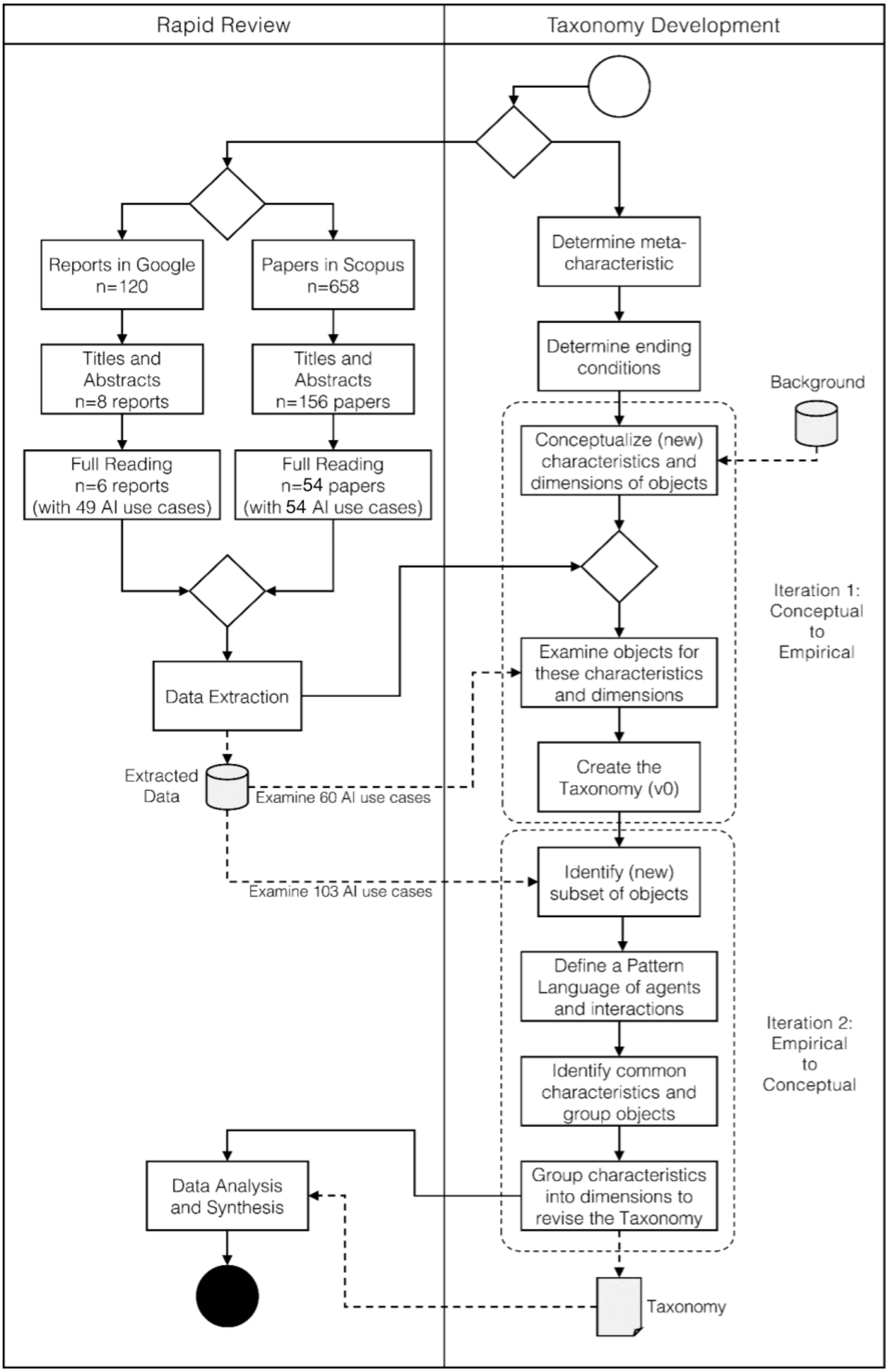


Fig. 1. Diagram of the Research Process.

3.1 Research Questions and Search Process

The planning of this review enables the identification of objectives and the construction of a protocol that presents the research methodology used. Table 2 shows three research questions (RQs) developed to characterize how AI applications have been used, their impacts on innovation in the public sector, and the collaborative arrangements they have fostered among various stakeholders.

Tab. 2 - Research Questions.

ID	Research Question
RQ1	What are the types of AI solutions developed to support public services? And what problems do they solve?
RQ2	Which government functions are using artificial intelligence? And what is the extent of these government functions covered by AI?
RQ3	In what ways do AI solutions support collaboration in the public sector? And, what types of innovation are achieved by implementing AI in public service organizations?

We formulated a search string to answer the research questions by combining terms related to the topic. Tab. 3 shows the search terms. We tested several string combinations of the terms to assess the potential of the returned results. The searches were conducted in the Scopus database for dates after 2018.

Tab. 3 - Search String for Scopus database.

SUBJAREA (comp) TITLE-ABS-KEY (“Artificial Intelligence” OR “Machine Learning” OR “AI”) AND TITLE-ABS-KEY (“public services” OR “public sector” OR “government” OR “city”) AND TITLE-ABS-KEY (“collaborat*” OR “cooperat*”) AND PUBYEAR > 2018

We also formulated another string to collect public reports directly in the Google search engine, as shown in 4. It was necessary because many AI solutions adopted by the public sector are described only in the gray literature.

Tab. 4 - Search String for Google search.

(“Artificial Intelligence” OR “AI” OR “machine learning”) AND (“public services” OR ‘government“ OR “public sector” OR “city”) AND (“collaborate” OR “cooperate”)

3.2 Selection of Studies and Quality Assessment

Table 5 presents the exclusion criteria applied across the search engines throughout the search process. In the Scopus database, the first step involved using the search strings, which returned 658 publications. Then, duplicate publications were excluded, and all selected publications had their titles and abstracts analyzed according to the exclusion criteria, resulting in 156 publications. In the full reading step, we applied the exclusion criteria again and selected 54 publications, each with one AI use case. In Google, the first step involved using the search strings that yielded 33.800.000 results. Then, we went through the first 120 results on the list, evaluating titles and abstracts according to the exclusion criteria. This process resulted in 8 reports with a collection of AI use cases in the public sector. In the full reading step, we again applied the exclusion criteria and selected six reports with 49 AI use cases.

Tab. 5 - Exclusion Criteria.

Criterion	Scopus	Google
The study does NOT answer at least one research question from the RQs	✓	✓
The study does NOT present at least one developed application	✓	✓
The study is a literature review	✓	✓
The study is NOT a report with a collection of AI cases in the public sector		✓

3.3 Meta-characteristic and Ending Conditions

We started by defining a clear meta-characteristic as the base for all classifications. This meta-characteristic ensures that every category logically follows from it, avoiding arbitrary groupings and addressing the needs of scholars, practitioners, and public managers. These users are interested in high-level features that allow them to understand AI's various concepts and applications in public services and how the agents involved collaborate or do not collaborate with these systems. In this sense, these users are not interested in technical aspects of AIs, such as the algorithms used, the model training technique, or the strategies applied for data processing. By anchoring our taxonomy in this high-level meta-characteristic, we ensure each category is relevant and aligned to clarify AI's essential properties and practical uses in the public sector. This method provides the taxonomy remains coherent and purposeful throughout its development.

Our taxonomy development process follows objective and subjective ending conditions as Nickerson et al. (2013) outlined. The objective conditions are met when the taxonomy is mutually exclusive and collectively exhaustive, meaning each element of AI in public services fits into one unique category without overlap, and all possible elements are covered. The subjective conditions require the taxonomy to be concise, robust, comprehensive, extensible, and explanatory. These conditions imply that the taxonomy should have a manageable number of well-differentiated categories, cover all relevant aspects of AI in public services, allow for future additions, and provide clear, valuable explanations. The development process concludes when these conditions are fully satisfied, ensuring the taxonomy is valid and useful for its intended users.

3.4 First Iteration: Conceptual-to-Empirical

In this iteration, we decided to use a conceptual-to-empirical approach because we already had a theoretical background that provided relevant conceptualizations for this study. From this background, we conceptualized the following dimensions: AI application (Wirtz et al., 2019), Problem-solving (Mehr, 2017), Innovation (Chen et al., 2020), and Government Function (COFOG) (OECD,2023).

Then, we randomly selected 60 of the 103 use cases collected in the literature review and examined them according to the conceptualized characteristics. We noticed that almost all the characteristics identified in the four dimensions corresponded in at least one of the observed cases. The only exception was the Government Function dimension, which had several unmatched characteristics across use cases. Despite this, we still decided to maintain these characteristics because, even if there are no AI applications for certain government functions, soon, this could be different.

Although we inserted four dimensions in this iteration, making it concise, extendable, and explanatory, we realized it could become more robust if we included one more dimension related to supporting collaboration. Because of this, we decided to carry out a second iteration.

3.5 Second Iteration: Empirical-to-Conceptual

In this iteration, we used an empirical-to-conceptual approach to include a new dimension related to collaboration support and discover its characteristics. To do this, we selected all 103 cases from the literature review so that common characteristics could be analyzed and identified.

However, before starting this analysis, defining the types of agents and their relevant interactions was necessary to characterize collaboration. To do this, we were inspired by the work used by Tsvetkova et al. (2017) and used a Human-Machine Networks approach to conduct this research stage. More specifically, we define a pattern language (Van Welie and Van der Veer, 2003) based on an arrangement of agents and interactions, as presented in Fig. **2**.

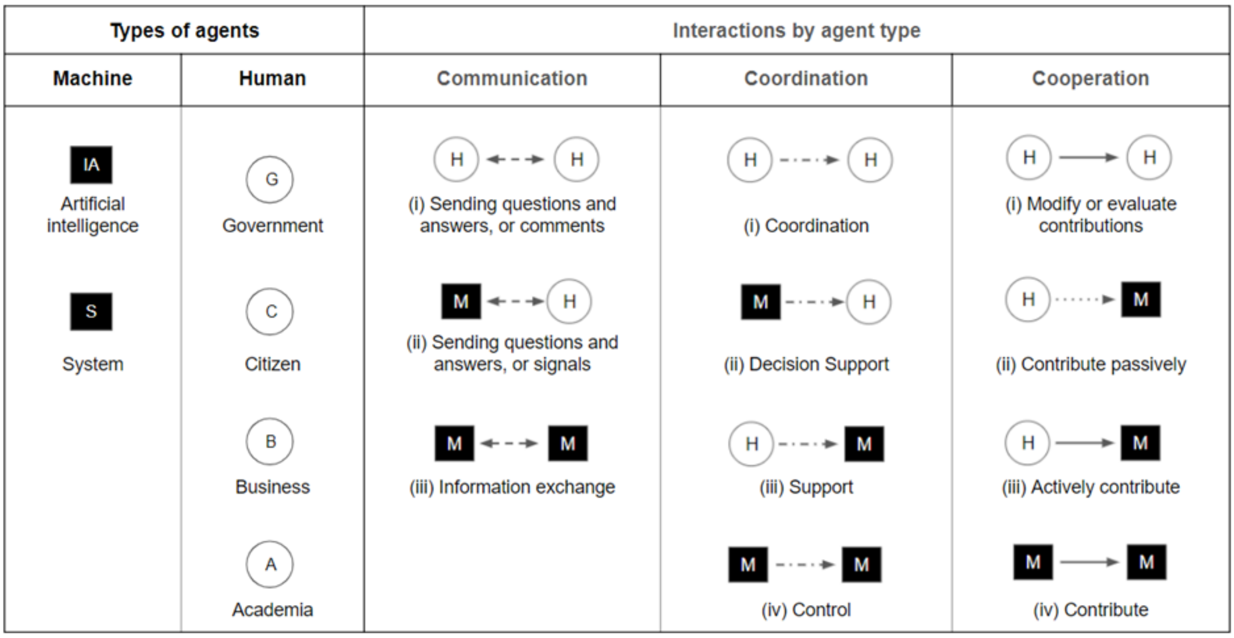


Fig. 2 - Pattern Language of Agents and Interaction in AI in the Public Sector.

In this arrangement, first, we define the types of agents, which can be machines or humans. The machines were identified as Systems or Artificial Intelligence. System refers to public or private systems that already exist and are in use, which can be traditional information systems or systems that include physical devices such as sensors, actuators, and signals (such as traffic systems and their traffic lights, for example). Artificial Intelligence refers to the AIs presented in the respective selected studies and is a new element within the specific government context in which it is applied. As for human agents, we identified from the theoretical background that Government, Citizens, Business (this term includes industry), and Academia are the main interested parties capable of interacting and collaborating.

Next, we define the types of interactions related to communication, coordination, and cooperation (Fuks et al., 2008). Communication involves exchanging questions, answers, comments, or signals between humans, between humans and machines, and between machines themselves. Coordination occurs when humans organize and manage others, machines support human decision-making, organizations or individuals maintain system functionality through resources and technical upkeep, and machines have command and control relationships with others. Cooperation involves humans modifying or evaluating the contributions of others, passive contributions from humans to machines usually collected automatically, active and voluntary contributions between humans and machines, and machines building upon the contributions of other machines.

We analyzed the 103 use cases identified in the literature from the constructed pattern language. The HMN arrangements represent how they incorporated AI in that government context. Therefore, it was possible to identify common characteristics and group objects according to the agents involved. Fig. **3** presents the primary arrangements already grouped according to the agents involved, which are the characteristics of this new dimension called collaboration support.

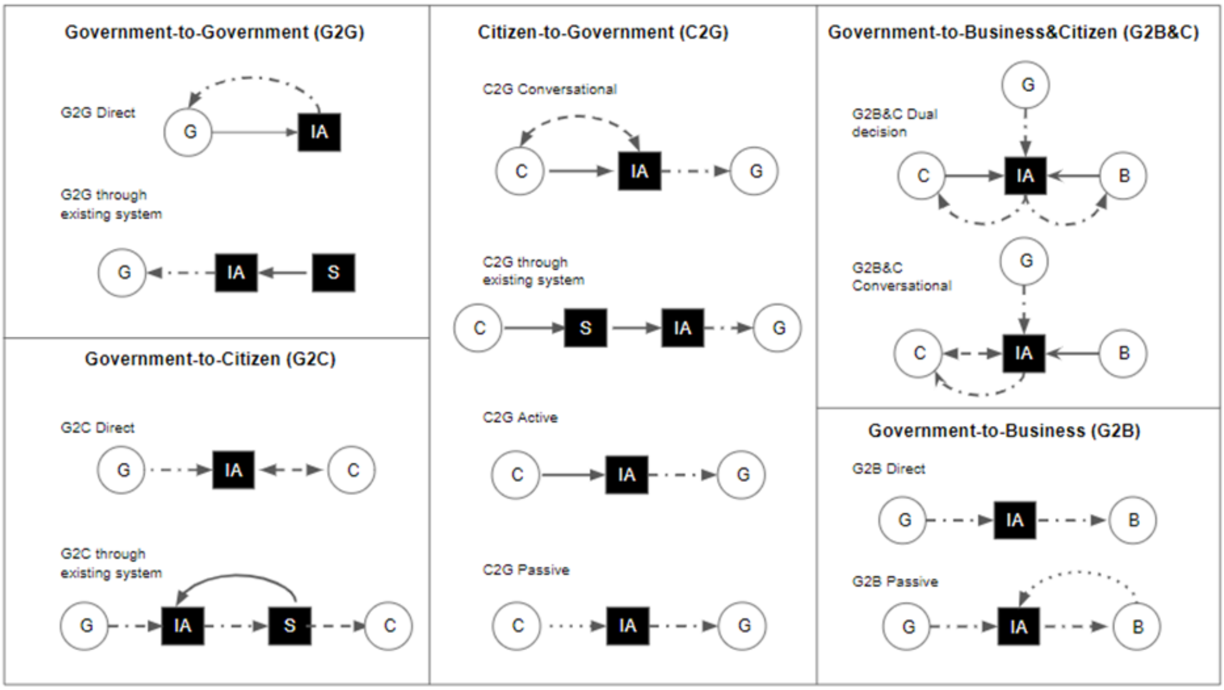


Fig. 3 - Collaboration Support grouped by the Agents involved.

Below, we summarize these main characteristics and sub-characteristics found and described in Fig. **3**:

Government-to-Government (G2G): The government uses AI to solve its own problem. It could be an internal approach for a particular agency or an inter-agency solution.

- Direct G2G: The government actively contributes to AI, providing the necessary data, and AI supports some decision-making directly.

- G2G through the existing system: There is another existing system, private or from the public sector itself, that provides data for the AI and supports some government decision-making.

Government-to-Citizen (G2C): The Government provides an AI capable of supporting citizens in some task type.

- G2C through the existing system: The government supports an AI that receives active contributions from another system and simultaneously controls it, with this system being responsible for sending signals to citizens.

- Direct G2C: The government supports an AI that exchanges questions and answers or sends signals to citizens.

Citizen to Government (C2G): The government supports an AI that directly or indirectly interacts with citizens, obtains information, and supports government decision-making.

- Conversational C2G: Citizens advancing AI while exchanging questions and answers. The data obtained in this process supports government decisions.

- C2G through existing system: Citizens active with an existing system, who in turn actively contribute AI to support government decisions.

- Active C2G: Citizens advanced with AI, and the data obtained in this process supports government decisions.

- Passive C2G: Citizens invest passively with AI, and the data obtained from this process supports government decisions.

Government-to-Business&Citizen (G2B&C): The government leverages AI to support collaboration between citizens and businesses.

- G2B&C Dual Decision: The government supports an AI that receives active contributions from citizens and businesses while supporting the decision-making of these same agents.

- Conversational G2B&C: The government sustains an AI that receives active input from businesses, exchanges questions and answers with citizens, and supports the latter's decision-making.

Government-to-business (G2B): The government supports AI to support businesses.

- Direct G2B: The Government supports AI that supports companies' decision-making.

- Passive G2B: The Government supports an AI that supports companies' decision-making based on passive contributions from the last.

4. Results

4.1 Taxonomy for AI applications for public services

As presented previously, throughout the first iteration with a Conceptual-to-empirical approach, it was possible to conceptualize the taxonomy with the following dimensions: AI application, Problem Solved, Innovation, and Government Function (COFOG), which were already described. In the second iteration, we conceptualized a new dimension called collaboration support and its characteristics with an empirical-to-conceptual approach.

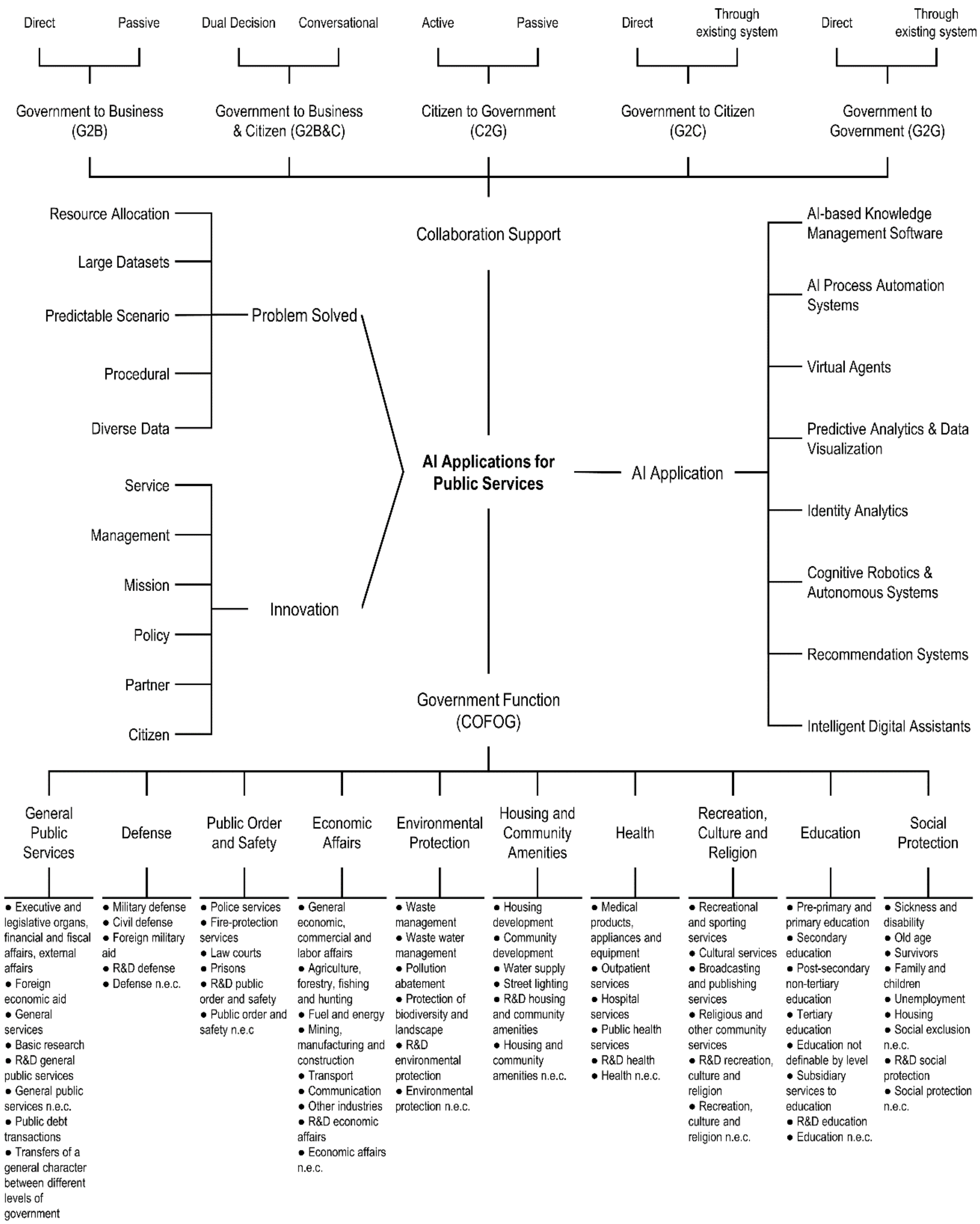


Fig. 4 - Taxonomy of AI applications in the Public Sector.

4.2 Answering the Research Questions

Once we conceptualized the taxonomy, we analyzed the documents identified during the review to demonstrate the usefulness and generalizability of the proposed taxonomy. In this way, we applied the taxonomy as an analytical framework to make it possible to answer the following questions below.

RQ 1: What are the types of AI solutions developed to support public services? And what problems do they solve?

The primary type of AI solution identified, as seen in Fig. **5**, was Predictive Analysis & Data Visualization, followed by AI Process Automation Systems in 41.75% and 22.33% of cases, respectively. All other types were below 10% of occurrence each, with a greater emphasis on Intelligent Digital Assistants (IDA) and AI-Based Knowledge Management (KM) Software, identified in 9.71% and 6.80% of cases, respectively.

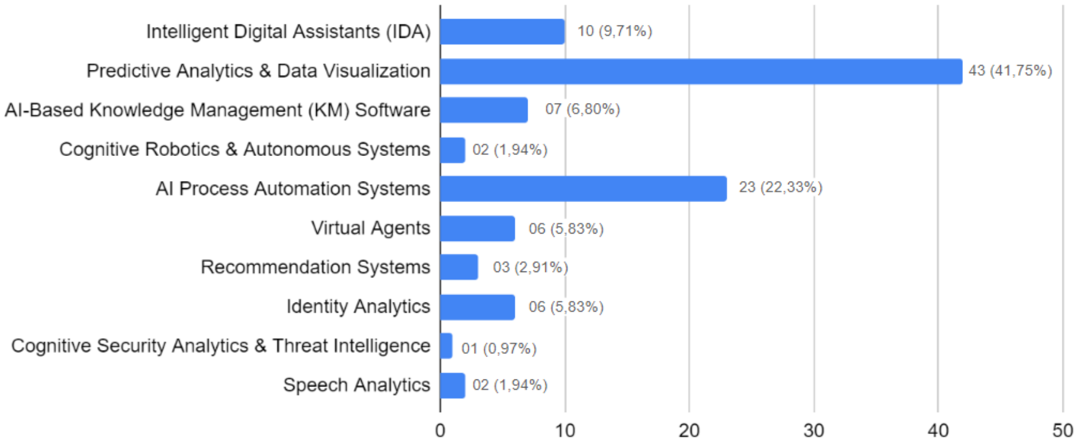


Fig. 5 - Distribution of types of AI applications in the publications analyzed.

As for the types of problems solved through AI, it is clear that the main problems addressed are the Diverse Data and Predictable Scenario problems, identified in 41.75% and 27.18% of cases, respectively. All other types were below 13% of occurrence each, with a greater emphasis on Resource Allocation, identified in 12.62% of cases, as seen in Fig. **6**.

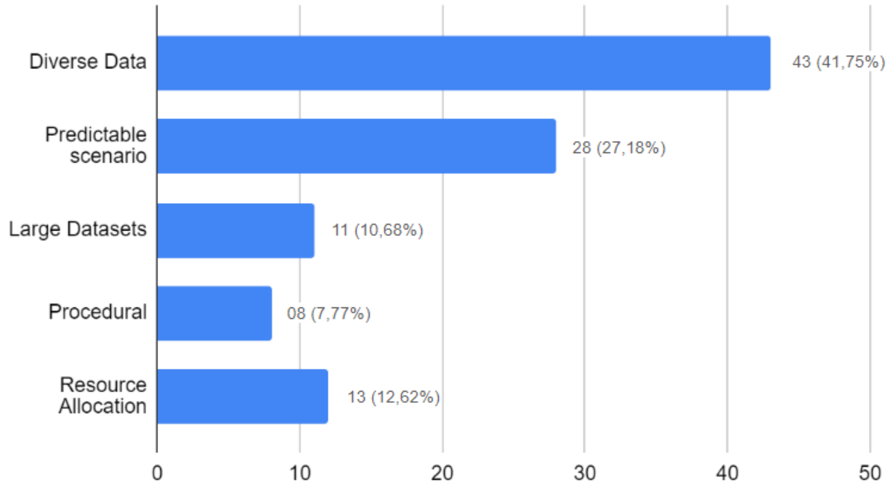


Fig. 6 - Distribution of types of problems in the publications analyzed.

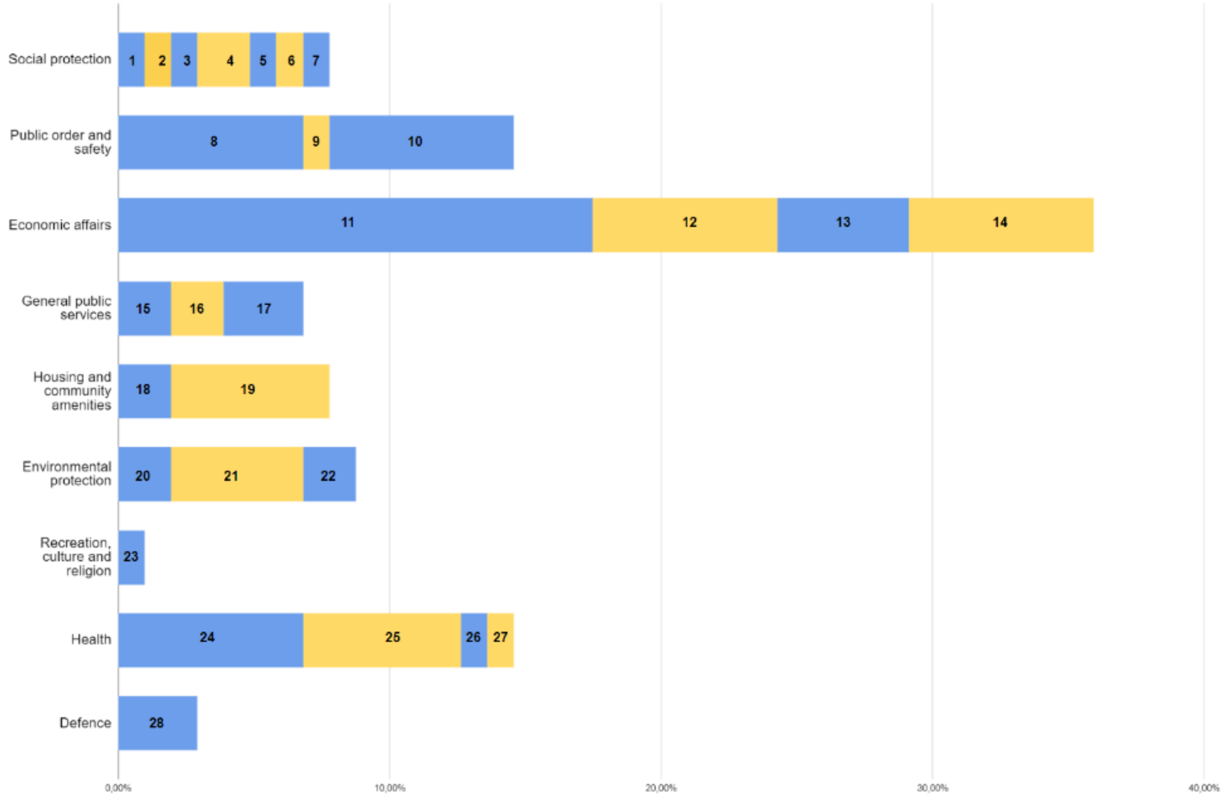
Fig. **7** presents the correlation between the problems identified and the AI solutions employed. The same solution can be used to solve different problems, as in the case of Predictive Analysis & Data Visualization, which addresses four of the five types of problems encountered. The same problem can be solved through different solutions, as in the case of Diverse Data, which is addressed by nine of the ten types of solutions. Furthermore, somewhat obviously, the relationship between Predictive Analysis & Data Visualization solutions and Predictable Scenario problems stands out, with an occurrence of 24%. Next, the Predictive Analysis & Data Visualization solution stands out again, but now with the relationship with Diverse Data problems with an occurrence of 10.68%. Next, the relationships between the AI Process Automation Systems Solution and the Diverse and Procedural problems stand out, with 9.71% and 7.77% of the cases found.

	Resource Allocation	Large Datasets	Predictable scenario	Procedural	Diverse Data
AI-Based Knowledge Management (KM) Software	0,00%	2,91%	0,00%	0,00%	3,88%
AI Process Automation Systems	2,91%	1,94%	0,00%	7,77%	9,71%
Virtual Agents	1,94%	0,00%	0,00%	0,00%	3,88%
Predictive Analytics & Data Visualization	2,91%	3,88%	24,27%	0,00%	10,68%
Identity Analytics	0,97%	0,97%	0,00%	0,00%	3,88%
Cognitive Robotics & Autonomous Systems	0,00%	0,00%	1,94%	0,00%	0,00%
Recommendation Systems	0,97%	0,00%	0,97%	0,00%	0,97%
Intelligent Digital Assistants (IDA)	1,94%	0,97%	0,00%	0,00%	6,80%
Speech Analytics	0,97%	0,00%	0,00%	0,00%	0,97%
Cognitive Security Analytics & Threat Intelligence	0,00%	0,00%	0,00%	0,00%	0,97%

Fig. 7 - Correlation heat map for problems and AI applications.

RQ 2: Which government functions are using artificial intelligence? And what is the extent of these government functions covered by AI?

The central government function category that stands out is Economic Affairs, followed by Public Order and Safety, and Health, with 35.92%, 14.56%, and 14.56%, respectively, as can be seen in Fig. **8**. All other government function categories individually do not reach 9% of occurrences; if totaled, they reach 34.96%. As for the most prominent government function subcategories, we have Transport (#11) within the Economic Affairs category with 17.48% and then tied with 6.80%. We have the subcategories of Law Courts (#10), Agriculture, Forestry, fishing and hunting (#12), General, economic, commercial and labor affairs (#14), and Hospital services (#24) from the categories of Public Order and Safety, Economic Affairs, Economic Affairs, and Health respectively. Of all 28 subcategories, 16 (57.14%) present up to 1.94% of occurrences and a total of 21.34% of occurrences.



Social protection 7,77%		
1	Survivors	0,97%
2	Housing	0,97%
3	Family and children	0,97%
4	Social protection n.e.c	1,94%
5	Unemployment	0,97%
6	Old age	0,97%
7	R&D social protection	0,97%

Public order and safety 14,56%		
8	Police services	6,80%
9	Fire-protection services	0,97%
10	Law courts	6,80%

Economic affairs 35,92%		
11	Transport	17,48%
12	Agriculture, forestry, fishing and hunting	6,80%
13	Fuel and energy	4,85%
14	General economic, commercial and labour affairs	6,80%

General public services 6,80%		
15	Executive and legislative organs, financial and fiscal affairs, external affairs	1,94%
16	R&D general public services	1,94%
17	General public services	2,91%

Housing and community amenities 7,77%		
18	Housing development	1,94%
19	Community development	5,83%

Environmental protection 8,74%		
20	R&D environmental protection	1,94%
21	Pollution abatement	4,85%
22	Environmental protection n.e.c.	1,94%

Recreation, culture and religion 0,97%		
23	Cultural services	0,97%

Health 14,56 %		
24	Hospital services	6,80%
25	Public health services	5,83%
26	Medical products, appliances and equipment	0,97%
27	Outpatient services	0,97%

Defence 2,91%		
28	Civil defence	2,91%

Fig. 8 - Distribution of Government Functions in the publications analyzed.

On the other hand, as can be seen in Fig. **9**, it is worth mentioning that the fact that some categories, such as Education and Defense, still seem to be poorly supported by AI, which may be a reflection of a limitation of this research related to the search protocol used. More specifically, in the case of Defense, for example, it may be that AI research is being published in other forums that were not reached with the strings used in the database consulted (Scopus). The same goes for the Education category, which, despite having many new features related to well-publicized AI applications, was not mentioned in this work, probably because the published AI applications for educational purposes are developed with a focus on the private sector that sees AI as a solution capable of bringing competitive advantage. Regardless of the limitations of this research, it is possible to note that seven of the ten government function categories have at least 50% of subcategories not supported by AI.

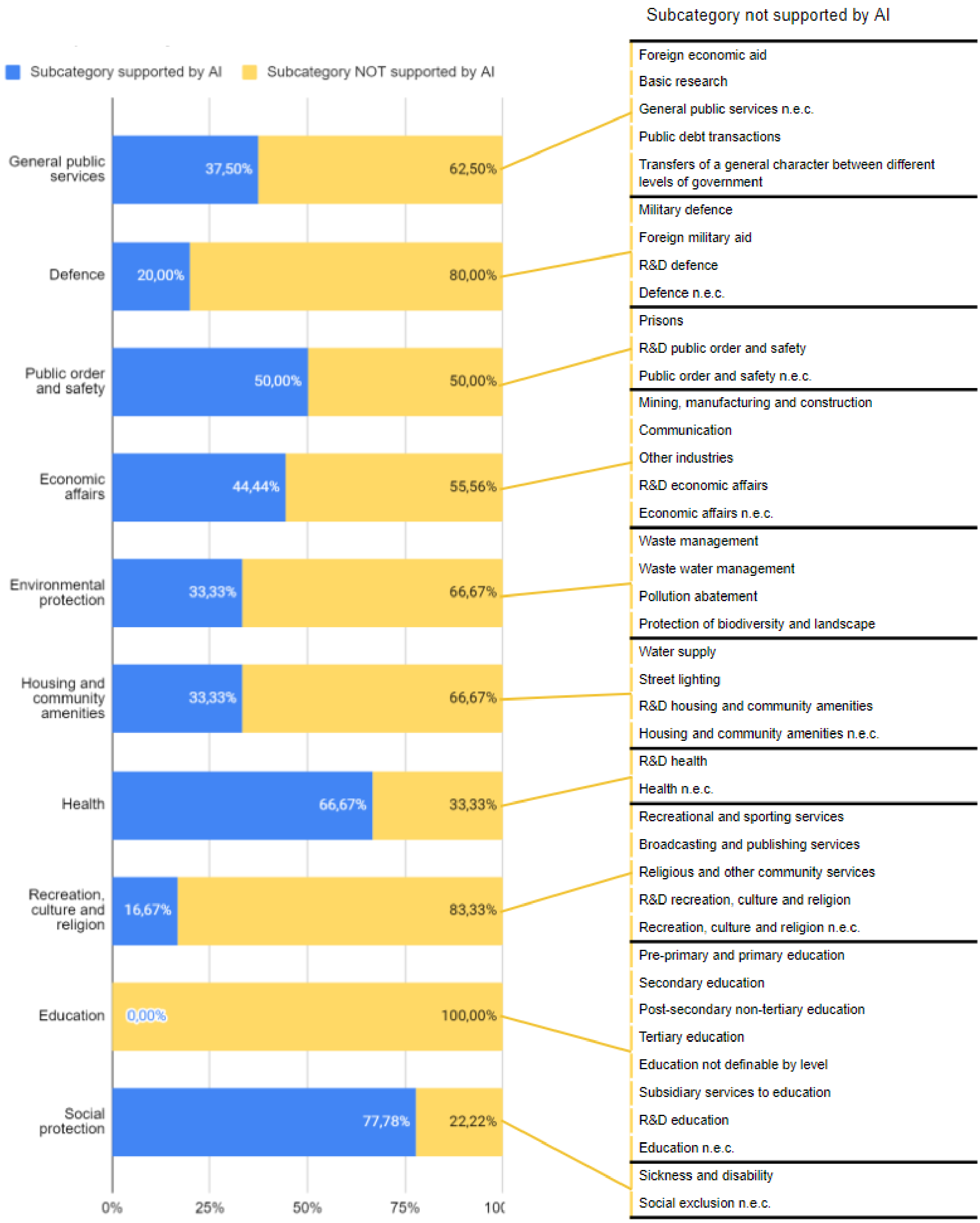


Fig. 9 - Distribution of the AI support in different Government Functions in the publications analyzed.

RQ 3: In what ways do AI solutions support collaboration in the public sector? And, what types of innovation are achieved through the implementation of AI in public service organizations?

The main collaboration category identified is Government-to-Government (G2G), followed by Citizen-to-Government (C2G), with 67.9% and 16.5% of occurrences, respectively, as seen in Fig. **10**. When we analyze the collaboration subcategories, we find that the G2G Direct subcategory is identified in 65% of cases, followed by C2g Active. All subcategories were identified individually, with a maximum of up to 4.9% of occurrences each.

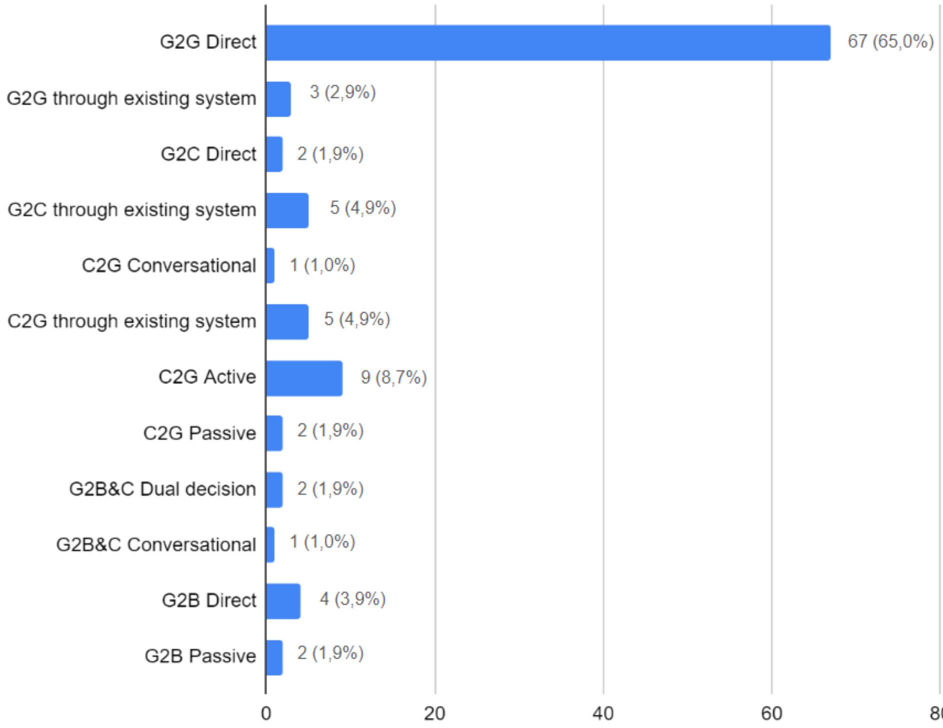


Fig. 10 - Distribution of types of Collaboration support in the publications analyzed.

As shown in Fig. **11**, regarding the type of innovation in organizations providing public services, innovations at the Management, Citizen, and Policy levels stand out mainly with 55.3%, 16.5%, and 11.6% of occurrences, respectively. The other types of innovation do not exceed 6.8% of occurrences each. It is also important to highlight that there is no direct relationship between the classification made regarding collaboration and the classification made regarding innovation. For example, the fact that collaboration involves citizens in some way does not imply that that innovation will necessarily be characterized as an innovation at the citizen level.

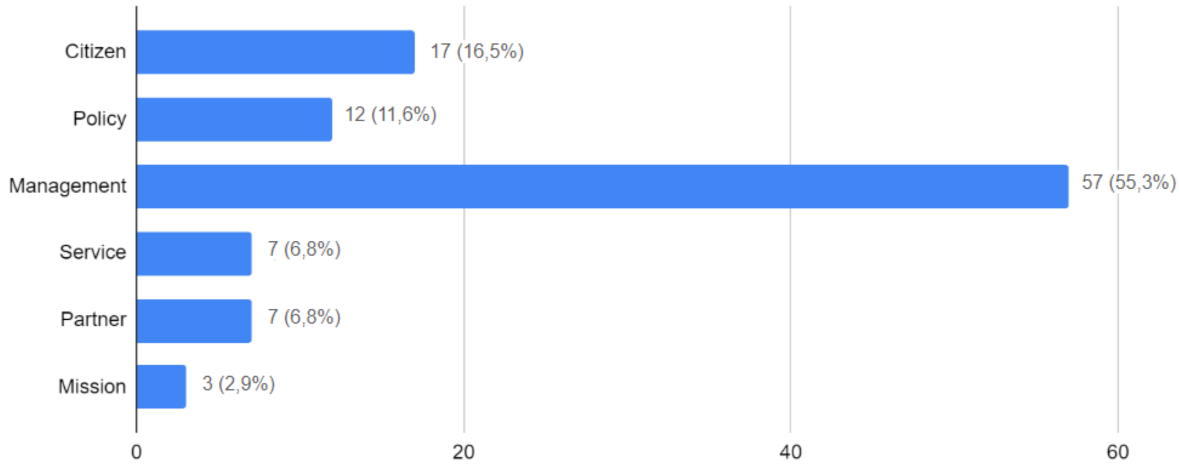


Fig. 11 - Distribution of types of Innovation in the organization in the publications analyzed.

5. Discussion

5.1 AI support beyond government administrative tasks

Based on the results of this research, AI in the public sector is primarily oriented towards addressing prediction problems and diverse datasets. Hence, the solutions often involve data visualization and predictive analysis, as well as the automation of repetitive processes. Furthermore, AI is predominantly applied in government functions such as Economic Affairs, Health, and Public Order. The reasons for the predominance of AI adoption in these areas are uncertain. One possible driver for acquiring these technologies may be the budget, as Economic affairs and Health are among the 4 COFOGs with the highest expenditure (Eurostat., 2024). However, this factor does not explain the high adoption of AI in the Public Order government function. The willingness to adopt AI technologies in government depends on how officials perceive their positive and negative impacts on society in the long run and their familiarity with these technologies (Ahn and Chen, 2022). In this way, some of the impacts of AI have already been part of the collective social imagination for a long time, such as health and transport (inserted in economic affairs) as hopeful visions or the threat of surveillance, which denotes its power to be applied in the context of public order (Fast and Horvitz, 2017).

In terms of collaboration, it is evident that most of the collaboration achieved is within the government itself. The government tends to create technological solutions that it will utilize internally. When citizens are involved, they typically interact with AI systems to facilitate the production of information, knowledge, or decision support that the government needs. The government mainly develops AI solutions to its administrative and repetitive problems. These problems are often characterized by having extremely diverse, poorly structured, and fragmented datasets that require automation and predictive capabilities, particularly in sectors with large budgets.

While this focus on administrative efficiency is somewhat expected and natural, there is also a range of applications, problems, government functions, and innovative and collaborative efforts that, although currently in the minority, show significant potential for growth. For instance, government initiatives using AI applications can operate as platforms (O'Reilly, 2011) that impact citizens and businesses in crucial areas to enhance life quality and contribute to sustainable development goals (Singh et al., 2024). The concept of public services in this research is associated with Services of General Interest (SGIs), which are tasks and functions deemed essential for the quality of life of citizens, their well-being, and the overall functioning of society.

In this light, the diversity found in AI applications within the public sector offers alternative and innovative pathways for public services. These pathways differ from the traditional models we have seen and hold the potential for disruptive innovation, leading to new collaborative governance models. Such models could transcend the current dichotomy between market-based approaches focused on efficiency and those grounded in democratic values and the effectiveness of government work. This research underscores AI's potential to streamline administrative tasks and drive meaningful improvements in public service delivery, ultimately benefiting society.

5.2 How do Language Models and this Taxonomy connect?

When this research began, we had not yet experienced the boom of generative AI and the use of LLMs on a large scale. The rapid adoption of LLMs, which are machines with conversational and textual synthesis capabilities previously unfamiliar to much of the public, combined with extensive marketing from AI companies often backed by big tech, presents a vision of the future where LLMs are seen as a near step to Artificial General Intelligence (AGI). This AI hype already presents us with costs and threats that go opposite to what governments should pursue (Markelius et al., 2024). Furthermore, overestimating the ability to use LLMs in the public sector can generate a series of problems, and the risks of its use must be mitigated well (Analysis and Research Team, 2023).

In other words, AI lacks genuine understanding despite its ability to mimic human communication (Bishop, 2021). LLM does not indicate a direct pathway to AGI and its generalized problem-solving capabilities, but we can consider Biological and Quantum approaches to AGI (Mohammad et al., 2023). Therefore, we use Narrow AI (Berryhill et al., 2019), which refers to a machine with specific capabilities. In this context, the taxonomy presented in this work is especially valuable as it offers an analytical framework for classifying AI applications and types of problems, reminding us that LLM is not a panacea for the public sector challenges.

So, a question that might arise for those using the taxonomy is: how do LLMs fit into the dimension of AI application? First, it's important to understand how the specific LLM is primarily used to answer this question. Second, it's important to consider that a particular LLM could be part of a more robust architecture capable of presenting various capabilities. However, this is not unique to LLMs. Some solutions investigated in the review also pointed to certain multi-capabilities. Nonetheless, this is entirely different from claiming that LLMs, simply because they are LLMs, can perform all the diverse capabilities of various types of AI applications.

6. Conclusion

In this work, we investigated the support of AI-powered technologies in public services. Despite advancements in the field and academic efforts to understand the phenomenon, certain aspects related to the impact of AI adoption on innovation and collaboration in the public sector remain unresolved. A recognized need is also to create more robust classification structures for organizing knowledge about AI applications in public services. To address these gaps, we conducted a rapid review to identify how AI applications have been used, their impacts on innovation in the public sector, and the collaborative arrangements they have fostered among various stakeholders. Furthermore, we designed a taxonomy to classify AI applications in the public sector that was used as an analytical framework to answer the research questions.

The review results indicated that AI in the public sector is mainly used for prediction problems with diverse datasets, involving data visualization, predictive analysis, and automating repetitive processes. These applications are primarily found in economic affairs, health, and public order. These are government functions with substantial budgets and where potential AI applications have been part of the collective imagination for a long time. Generally, governments develop AI solutions to their administrative and repetitive problems. However, fewer applications and collaborative arrangements were identified, suggesting potential growth for new AI adoption forms and possible public management disruptions, ultimately benefiting public service delivery and society.

Regarding the development of the taxonomy, two iterative cycles led to a result encompassing five dimensions along with a new conceptualization of collaborative arrangements based on a language of patterns of agents and interactions. Ultimately, these contributions are expected to support researchers, public managers, and tech companies in understanding and analyzing the complex domain of AI in public services to create and responsibly adopt new AI solutions in the future.

The main limitation of this study lies in the search protocol. Our search strings did not include broader terms such as "algorithm", nor did they draw from curated repositories like the OECD AI Observatory. Consequently, we may have overlooked relevant cases, especially AI applications in health, education, and defence that, although developed in predominantly private settings, are already being adopted by public organisations. Moreover, our collaboration framework (G2G, G2C, C2G, G2B..) aggregates interactions at a macro level and therefore does not adequately reflect public-private partnerships, citizen co-creation initiatives, or decentralised governance arrangements. Finally, ethical risks and challenges, algorithmic bias, transparency, accountability, and citizen trust, receive only limited attention.

Future work will address these gaps by (i) expanding the search strategy with additional descriptors and specialised databases to capture a more diverse set of cases; (ii) developing an extended version of this article that includes detailed case studies, demonstrating the taxonomy's applicability and refining it to accommodate intergovernmental and multi-stakeholder collaborations; and (iii) deepening the discussion on ethics and AI governance in the public sector by integrating systematic risk assessments and models of organisational, social, and environmental impact. These efforts aim to guide both the development of more responsible, explainable AI solutions and the formulation of evidence-based public policies.

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