

# **Emerging & data technologies applied to public sector: An AI-copiloted systematic literature review<sup>1 2</sup>**

**Maurício Vasconcellos Leão Lyrio**

Universidade Federal de Santa Catarina - UFSC, Brasil

**Rogério João Lunkes**

Universidade Federal de Santa Catarina - UFSC, Brasil

**Miklos Vasarhelyi**

Rutgers Business School - RBS, Estados Unidos

## **Tecnologías emergentes y de datos aplicadas al sector público: Una revisión sistemática de la literatura copilotada por IA**

Este estudio tiene como objetivo explorar el uso de tecnologías emergentes y de datos (Rotolo et al., 2015) en el sector público, investigando sus aplicaciones, desafíos y beneficios mediante las perspectivas analíticas propuestas por Criado et al. (2024). Para ampliar la capacidad analítica, minimizar el tiempo de procesamiento de datos y analizar estudios relevantes sobre el tema en revistas de alto impacto, el estudio adopta un proceso de revisión sistemática de la literatura, inspirado en los estudios de inteligencia artificial (IA) copilotada en auditoría de H. Gu et al. (2024) y fundamentado en métodos de revisión de literatura previos (Lyrio et al., 2018; Page et al.,

<sup>1</sup> This article received financial support from the National Council for Scientific and Technological Development (CNPq, Brasil).

<sup>2</sup> During the preparation of this work, the authors used ChatGPT and OpenAI API to retrieve information and process data (see methodological section). After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.



2021; Ruijer et al., 2023; Straub et al., 2023). A partir de las perspectivas de Criado et al. (2024), los resultados mostraron que, a nivel macro, la IA y el big data destacan en la formulación de políticas públicas. A nivel meso, los casos de uso demostraron el potencial de esas tecnologías para optimizar procesos y mejorar la eficiencia organizacional. A nivel micro, los estudios destacaron la personalización de los servicios públicos y las mejoras en la interacción con la ciudadanía, aunque también advirtieron sobre riesgos como la exclusión digital y la pérdida de confianza en los gobiernos. El estudio concluye que la investigación sobre el tema aún se encuentra en una fase de evolución, y ha priorizado las cuestiones éticas y regulatorias para equilibrar la eficiencia, la innovación y los valores democráticos del sector público.

**Palabras clave:** tecnologías emergentes, inteligencia artificial, sector público, revisión sistemática de la literatura

### **Emerging & data technologies applied to public sector: An AI-copiloted systematic literature review**

This study aimed to explore the use of emerging and data technologies (Rotolo et al., 2015) in the public sector, investigating their applications, challenges, and benefits through the analytical perspectives proposed by Criado et al. (2024). To amplify the analytical capacity, minimize data processing time and analyze relevant studies on the topic in high-impact journals, the study adopts a systematic literature review process, inspired by H. Gu's et al. (2024) co-piloted artificial intelligence (AI) in audit studies and informed by prior literature review methods (Lyrio et al., 2018; Page et al., 2021; Ruijer et al., 2023; Straub et al., 2023). Based on Criado's et al. (2024) perspectives, the results showed that, at a macro level, AI and big data stand out in the formulation of public policies. At a meso level, use cases demonstrated the potential of these technologies to optimize processes and improve organizational efficiency. At a micro level, the studies highlighted the personalization of public services and improvements in interaction with citizens, although they also warned of risks such as digital exclusion and loss of trust in governments. The study concludes that research on the topic is still in an evolving phase and has prioritized ethical and regulatory issues to balance efficiency, innovation, and the democratic values of the public sector.

**Keywords:** emerging technologies, artificial intelligence, public sector, systematic literature review

### **Tecnologias emergentes e de dados aplicadas ao setor público: Uma revisão sistemática da literatura copilotada por IA**

Este estudo teve como objetivo explorar o uso de tecnologias emergentes e de dados (Rotolo et al., 2015) no setor público, investigando suas aplicações, desafios e benefícios, por meio das perspectivas analíticas propostas por Criado et al. (2024). Para ampliar a capacidade analítica, minimizar o tempo de processamento de dados e analisar estudos relevantes sobre o tema em periódicos de alto impacto, o estudo adota um processo de revisão sistemática da literatura, inspirado no estudo de H. Gu et al. (2024) sobre inteligência artificial (IA) copilotada em auditoria e fundamentado em métodos de revisão de literatura anteriores

(Lyrio et al., 2018; Page et al., 2021; Ruijer et al., 2023; Straub et al., 2023). Com base nas perspectivas de Criado et al. (2024), os resultados mostraram que, em nível macro, IA e big data se destacam na formulação de políticas públicas. Em nível meso, casos de uso demonstraram o potencial dessas tecnologias para otimizar processos e melhorar a eficiência organizacional. Em nível micro, os estudos destacaram a personalização dos serviços públicos e melhorias na interação com os cidadãos, embora também tenham alertado para riscos como exclusão digital e perda de confiança nos governos. O estudo conclui que a pesquisa sobre o tema ainda está em fase de evolução e tem priorizado questões éticas e regulatórias para equilibrar eficiência, inovação e os valores democráticos do setor público.

**Palavras-chave:** tecnologias emergentes, inteligência artificial, setor público, revisão sistemática da literatura

## 1. Introduction

Emerging technologies such as artificial intelligence (AI), Internet of Things (IoT), block-chain, machine learning, deep learning, big data, real-time analytics, among others, have played a growing role in several sectors, including the public sector. (Bodó & Janssen, 2022; Desouza & Jacob, 2017; Duan et al., 2020, 2023; Fertier et al., 2020; Hashim, 2024; Neumann et al., 2024; Uras et al., 2020; Zekić-Sušac, Mitrović, et al., 2021). These technologies have been applied in the private sector to optimize operations, improve customer experience, and foster innovation (Cheong et al., 2022; H. Gu et al., 2024; Moffitt et al., 2018). In the public sector, these technologies promise to transform service delivery, increase administrative efficiency, and promote greater transparency. However, the integration of these technologies is not without challenges and controversies, there is growing concern about ethical issues, privacy and the potential for abuse when these technologies are used by governments and corporations (Aoki, 2020; Keppeler, 2024; Zuiderwijk et al., 2021).

This debate has gained increasing academic and practical relevance due to their growing societal impact. Rotolo et al. (2015) defines emerging technologies as radical novelties that expand rapidly and have the potential to transform socio-economic domains through interactions among actors, institutions, and production processes. Their key attributes include: (i) radical novelty, representing fundamentally new or recontextualized applications; (ii) rapid expansion, reflected in the accelerated growth of research and involved actors; (iii) coherence, marked by shared terminology and convergent development paths; (iv) impact, indicating their transformative potential across sectors; and (v) uncertainty, stemming from ambiguous outcomes and multiple development trajectories.

According to Gil-Garcia et al. (2014), the use of information technologies in the public sector dates back to the 1960s, with the 1990s and the advent of the Internet marking a turning point in how governments operate and interact with citizens. Contemporary technologies such as big data, social networks, cloud computing, and mobile applications have redefined public management, enabling more transparent, participatory, and efficient governance. In this sense, emerging technologies function as enablers of smarter governance in complex and dynamic public environments, challenging traditional administrative models while expanding opportunities for innovation and citizen engagement.

This article explores these issues by examining how research has been conducted on the use of AI and other emerging technologies in public sector. Adopting the concept of co-piloting proposed by H. Gu et. al. (2024), a collaborative approach between human researchers and AI models to capitalize on the potential of both in delivering a literature review on the topic has been conducted. Thus, the study presents as contributions (i) a co-piloted approach to systematic literature review, (ii) a mapping of research on the topic in high-impact journals, and (iii) a set of recommendations for future research that can guide the advancement of discussion in this field of knowledge.

The study is organized as follows: section 2 presents the literature review approach adopted in the study. The research results are presented in section 3, while section 4 is dedicated to discussing these results. Finally, section 5 presents the conclusions and suggestions for future research.

## 2. Methodology

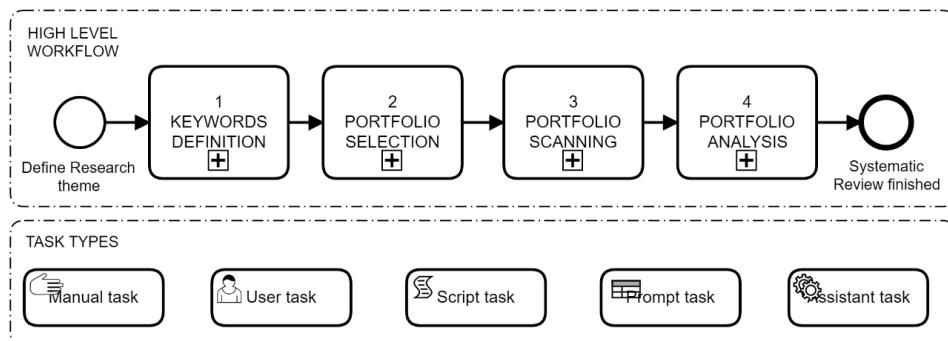
Literature reviews are fundamental for identifying knowledge gaps, synthesizing accumulated knowledge, and providing theoretical foundations for research (Lyrio et al., 2018; Short, 2009). They contextualize theories and findings, delineate conceptual frameworks, and establish the state of the art in a given field, guiding scholarly advancement. According to Short (2009), an effective review combines scientific rigor and interpretive synthesis, integrating theoretical and practical progress to build frameworks for future studies. Lyrio et al. (2018) highlight that, in the public sector, literature reviews are crucial for understanding complex phenomena and identifying research opportunities. Building on this perspective, the present study adopts a systematic literature review process co-piloted by AI, inspired by H. Gu et al. (2024) and informed by prior methodological contributions (Lyrio et al., 2018; Page et al., 2021;

Ruijer et al., 2023; Straub et al., 2023), establishing an organized and replicable analytical flow for knowledge generation<sup>3</sup>.

The proposed approach comprises four phases designed to identify, classify, and analyze a portfolio of studies, revealing research profiles and opportunities for future investigation. Figure 1 summarizes the high-level workflow, outlining the main phases, tasks, and responsibilities within the process.

Tasks are defined according to research needs and supporting tools: (i) manual tasks, conducted in reference managers or analytical environments; (ii) user tasks, performed by researchers in journal databases; (iii) scripts, automated through Python for data processing or searches; (iv) prompts, instructions used to query AI models; and (v) assistant tasks, delegated to AI agents for operations such as filtering or article categorization.

**Figure 1.** Artificial intelligence copiloted systematic literature review (AI-Cop SLR) – High level workflow



## 2.1. Keywords definition

The literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology (Page et al., 2021) and best practices for systematic reviews, beginning with a set of seed articles (Straub et al., 2023) provided by experts from the Rutgers Accounting Research Center (RARC), within the Emerging Technologies & Data in Accounting and Auditing discipline. These articles, exported in .xml format from the reference manager, served as the basis for extracting initial keywords. To refine and align the keyword set with the research scope, prompt engi-

<sup>3</sup> The source code, details of methodological procedures, prompts and data related to the research are in the main author's Github repository, to be made publicly available with the publication of the article.

neering based on the chain-of-thought (CoT) approach (H. Gu et al., 2024) was applied using OpenAI GPT-4o model. The resulting query string — “big data” OR “cybersecurity” OR “blockchain” OR “machine learning” OR “artificial intelligence” — was used to re-search the Web of Science. The 50 most cited articles retrieved were imported into a reference manager, and their keywords were re-extracted and filtered through the same CoT prompt-engineering process, yielding the final validated keyword set used to search the articles, as shown below.

## 2.2. Portfolio selection

The identification task was done by searching Web of Science and Scopus databases using the selected keywords, refining the results, and importing them to the reference manager. The table 1 and table 2 present the identification and refinement process.

**Table 1. Identification / Refinement in Web of Science**

Stage	Criteria	Parameter	Result
Initial search	Keyword string	(“artificial intelligence” OR “big data” OR “data science” OR “data mining” OR “data democratization” OR “data visualization” OR “feature learning” OR “representation learning” OR “online learning” OR “transfer learning” OR “machine learning” OR “neural networks” OR “deep learning” OR “anomaly detection” OR “predictive modeling” OR “evolutionary computation”) AND (“public sector” OR “public administration”)	-
	Search fields	“title” OR “abstract” OR “author keywords”	834 articles
Refinement 1	Document type	Article	539 articles
	Languages	English	479 articles
Refinement 2 (Pareto 85%)	Categories (87,68%)	“public administration”, “information science library science”, “management”, “computer science information systems”, “political science”, “law”, “social sciences interdisciplinary”, “environmental studies”, “environmental sciences”, “computer science interdisciplinary applications”, “multidisciplinary sciences”	341 articles
	Publication years (87,47%)	“2019”, “2020”, “2021”, “2022”, “2023”, “2024”	298 articles

**Table 2. Identification / Refinement in Scopus**

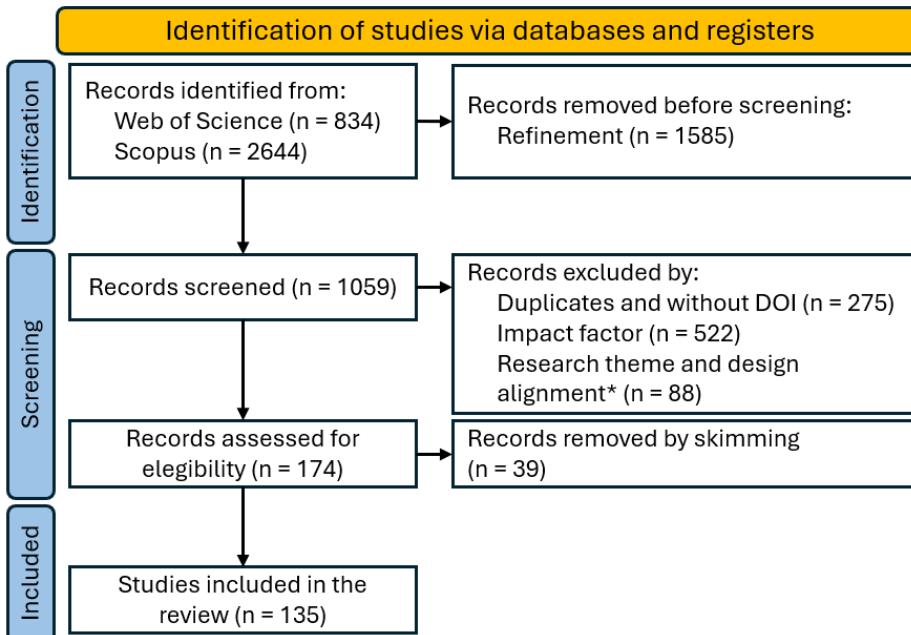
Stage	Criteria	Parameter	Result
<b>Initial search</b>	Keyword string	(“artificial intelligence” OR “big data” OR “data science” OR “data mining” OR “data democratization” OR “data visualization” OR “feature learning” OR “representation learning” OR “online learning” OR “transfer learning” OR “machine learning” OR “neural networks” OR “deep learning” OR “anomaly detection” OR “predictive modeling” OR “evolutionary computation”) AND (“public sector” OR “public administration”)	-
	Search fields	article title, abstract, Keywords	2644 articles
	Document type	Article	1156 articles
	Languages	English	1028 articles
<b>Refinement 1</b>	Publication stage	End	977 articles
	Source type	Journal	945 articles
<b>Refinement 2 (Pareto 85%)</b>	Subject areas (84.81%)	“social sciences”, “computer science”, “business, management and accounting”, “engineering”, “environmental science”, “decision sciences”, “mathematics”, “economics, econometrics and finance”, “medicine”	889 articles
	Publication years (85.60%)	“2017”, “2018”, “2019”, “2020”, “2021”, “2022”, “2023”, “2024”	761 articles

Lyrio et al. (2018) define “screening” as selecting relevant articles using clear criteria—specific keywords, journal impact factors (JIF), and alignment with the research theme and design. This process may combine multiple reviewers and automation tools to remove duplicates and reduce errors (Page et al., 2021). The subsequent skimming stage involves rapidly reading selected texts to grasp their main ideas and confirm relevance through key excerpts, figures, and other elements (Lyrio et al., 2018; Page et al., 2021). Table 3 summarizes the screening and selection process.

**Table 3. Screening / Eligibility results**

Stage	Criteria	Parameter	Result
Screening 1	Duplicates and DOI	Exclusion of duplicate articles and articles without DOI	784 articles
Screening 2	JIF	Articles found in JCR Quartile 01	262 articles
Screening 3	Research theme and design alignment	Reading the titles and abstracts in order to exclude articles that do not specifically fit the research topic. <b>Activity conducted out with the support of an intelligent agent tool call</b> (function: exclude by full reading the title and abstract)	174 articles
Eligibility	Remove by skimming	Exclusion of literature reviews, articles for which there was no access to the full document and by manual review of themes and research design	135 articles

The portfolio selection process was conducted using an AI-driven approach, using tasks performed by researchers and tool calls made to the OpenAI API using the GPT-3.5-turbo model. The results of the portfolio selection phase are shown in figure 2 below, according to the PRISMA model.

**Figure 2. Result of portfolio selection**

(\*) Removed by Intelligent Agent Tool Call

### 2.3. Portfolio scanning

The *scanning* process involves locating specific information in documents, serving as a complementary technique to detailed reading for identifying key elements of interest (Nation, 2009). In this study, scanning was conducted through article coding using a parameter document or codebook (Ruijer et al., 2023), structured around methodological and contextual categories (Lyrio et al., 2018) and the macro, meso, and micro perspectives proposed by Criado et al. (2024).

The coding parameters were defined in a JSON dictionary and applied via prompt engineering with OpenAI's GPT-4o model. Each of the 135 articles was processed individually, and the large language model (LLM) generated coded outputs based on predefined guidelines. The co-piloted coding was refined through iterative prompt fine-tuning (H. Gu et al., 2024): researchers reviewed model feedback, approved correct outputs, and corrected errors, when necessary, progressively enhancing the model's accuracy. Final feedback files were consolidated and verified using Python scripts to remove inconsistencies, resulting in a validated portfolio of coded articles.

### 2.4. Portfolio analysis

The portfolio analysis stage was based on the coded database, enriched by collecting the number of citations for each article. The analysis was divided into two phases, namely: (i) corpus analysis – in which we sought to describe the general characteristics of the studies in terms of analysis of journals, authors and keywords, and (ii) content analysis – in which we sought to analyze the articles from a methodological perspective and from the context in which the studies were carried out.

To organize and present the results, an application was developed that presents the results in graphical and tabular form and incorporates a specialized research assistant – an intelligent agent – enriched with the research database, which supports the researchers in discussing the studies. After analysis all source code, files, and databases were made available on GitHub repository.

## 3. RESULTS

### 3.1. Corpus analysis

Figure 4 presents a histogram and boxplot showing the distribution of JIF, illustrating the centrality and dispersion of this index. In the JIF-Q1 2023 cut-off, most studies appear in moderate-impact journals, with JIFs ranging from 2,5 to 7,5 and a median around 4,5. The histogram indicates right-skewed asymmetry, with few journals excee-

ding a JIF of 10, while the boxplot reveals outliers above 12. The *International Journal of Information Management* leads with a JIF of 20.1, followed by *Technological Forecasting and Social Change* (JIF 12.9), both addressing technology's role in societal and organizational transformation.

**Figure 4. Frequency distribution of JIF**

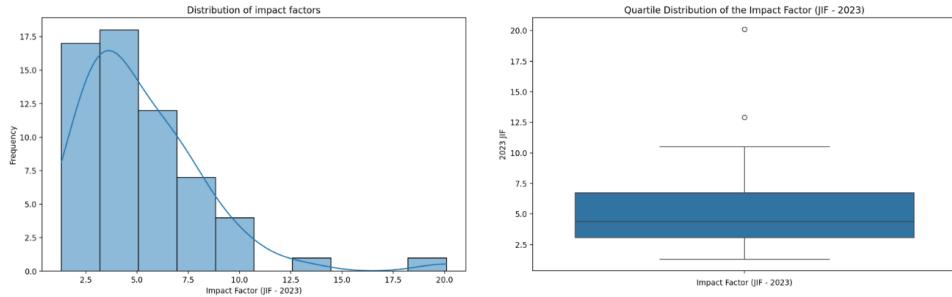


Figure 5 shows that journals with the highest impact are not necessarily those with the most citations. *Scientific Reports* leads with 734.562 citations, followed by the *Journal of Cleaner Production* (317.153) and *Energy* (171.282). Excluding outliers, the average is 5.670 citations per journal. The scatter plot reveals an upward curve linking citation volume and impact factor, with bubble sizes representing impact. Journals such as *Technological Forecasting and Social Change*, *International Journal of Information Management*, *Journal of Cleaner Production*, *Energy*, and *Journal of Business Research* combine high impact and citation levels, standing out as key outlets for research dissemination.

**Figure 5. Journal distribution by impact and citations**

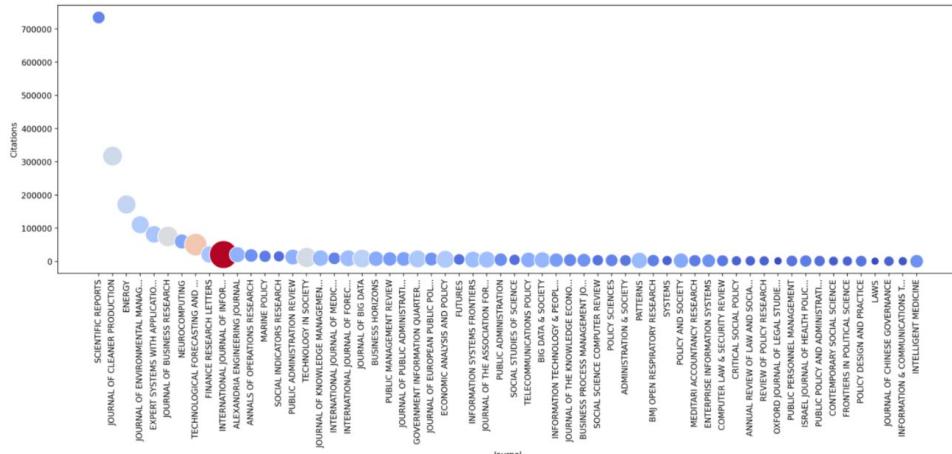


Figure 6 shows that 12 journals—20% of the sample—published more than two articles on the topic, totaling 65 papers (48% of all publications). Six of these focus directly on the public sector, accounting for 45 articles, or over 30% of publications, underscoring their importance in advancing the debate on emerging technologies. *Government Information Quarterly*, *Public Policy and Administration*, and *Public Management Review* stand out, with *Government Information Quarterly* alone responsible for nearly 20% of the publications. Its impact factor (7,8) and 7,190 citations highlight its prominence at the intersection of public policy, information technology, and governance.

**Figure 6. Journal with more than 2 publications**

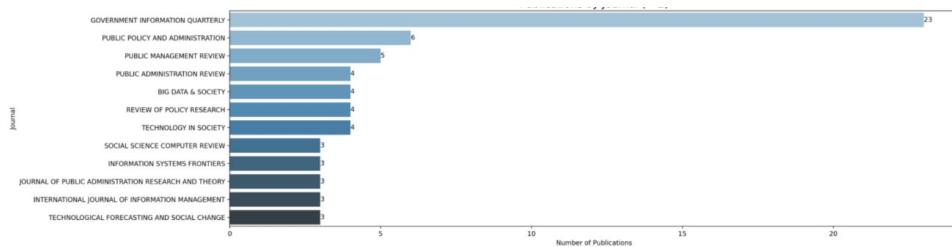


Figure 7 shows the evolution of publications, with sharp growth from 2019 and a peak in 2022, confirming the rising academic interest and the consolidation of the topic in public sector research. AI plays a central role among the analyzed technologies, aligning with the launch of ChatGPT by OpenAI in November 2022 (OpenAI, 2022). The emergence of generative AI, part of the so-called third wave of AI (Y. Gu et al., 2024), marked a theoretical and practical turning point, driving new discussions and reinforcing AI's growing relevance in contemporary public sector literature.

**Figure 7. Publication evolution overtime**

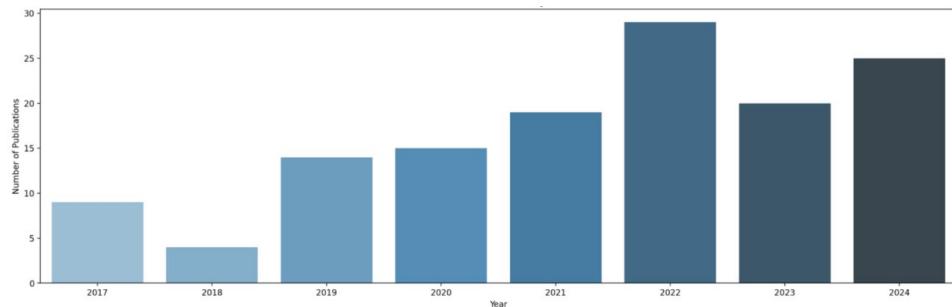


Figure 8 presents the 25 most cited articles in the Web of Science database, whose relevance is reinforced by citations in Scopus and Google Scholar. The prominence of themes such as AI, big data, and machine learning highlights the growing academic

and governmental interest in their application to public administration. The most cited article, Sun and Medaglia (2019), examines challenges in adopting AI in China's public health sector, emphasizing economic, social, regulatory, and ethical issues from multiple stakeholder perspectives. Androutsopoulou et al. (2019) follow, proposing AI-guided chatbots to improve communication between citizens and governments, enhancing service efficiency and addressing ethical concerns. Busuioc (2021), Klievink et al. (2017), and Kuziemski and Misuraca (2020), complete the top five, collectively discussing the ethical, regulatory, and operational implications of integrating emerging technologies in governance, highlighting tensions between innovation, accountability, and trust in public sector digital transformation.

**Figure 8. Citations per article (Top 25 Web of Science)**

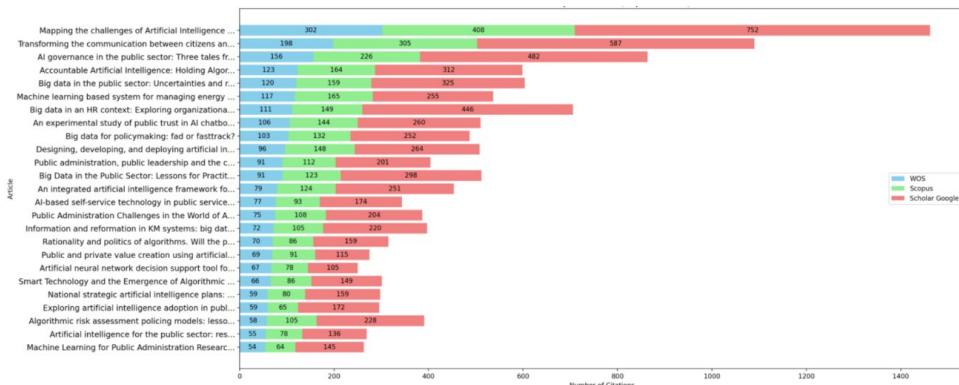


Figure 9's keyword cloud highlights "artificial intelligence," "big data," and "machine learning" as central to academic debate, confirming their leading role in research on emerging technologies. Terms such as "decision making," "governance," "public sector," and "public policy" emphasize their link to policymaking and governance, while "management," "public administration," and "public service" reflect efforts to enhance efficiency and transparency. Altogether, these keywords reveal a comprehensive perspective connecting emerging technologies to governance, management, innovation, and responsiveness in public service delivery.

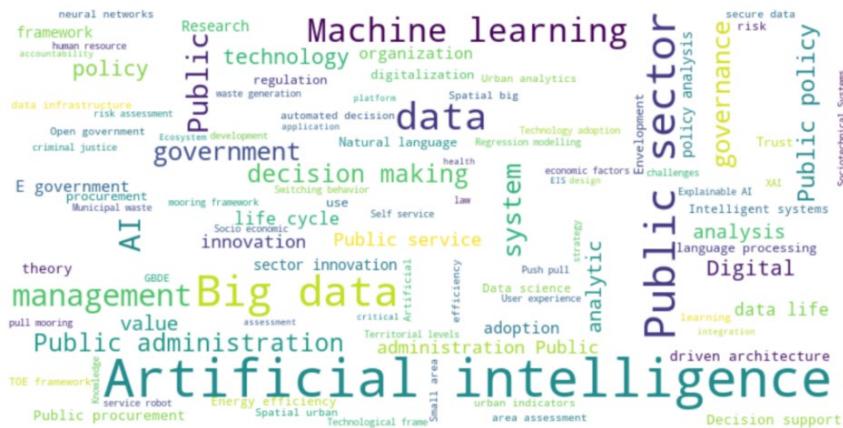
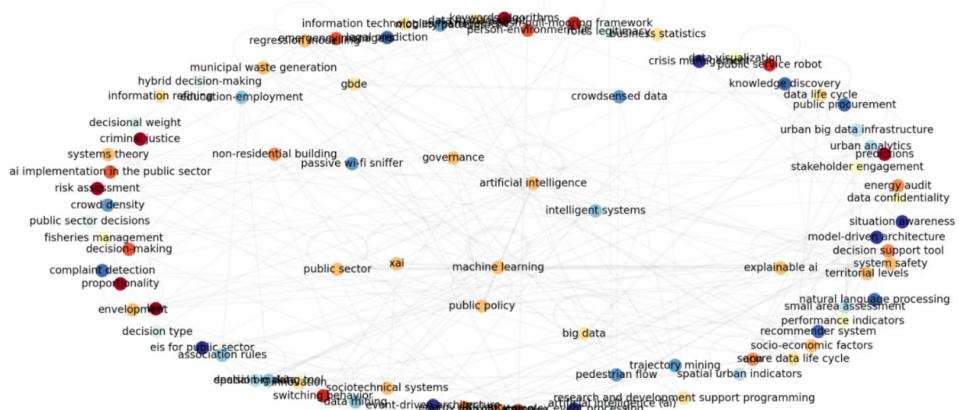
**Figure 9. Word Cloud (top 100)**

Figure 10 illustrates the keyword co-occurrence network, showing strong centrality for “artificial intelligence,” “machine learning,” and “big data,” which form the core of interconnected themes. Additional nodes such as “governance,” “public sector,” and “public policy” highlight the relationship between emerging technologies, decision-making, and governance. Thematic clusters are color-coded: orange tones represent AI and machine learning applications; blue relates to analytics, crisis management, and smart cities; brown addresses ethics, privacy, and data security; and yellow focuses on governance, management, and the data lifecycle. Together, these clusters reveal the multidimensional and integrative nature of current research in the field.

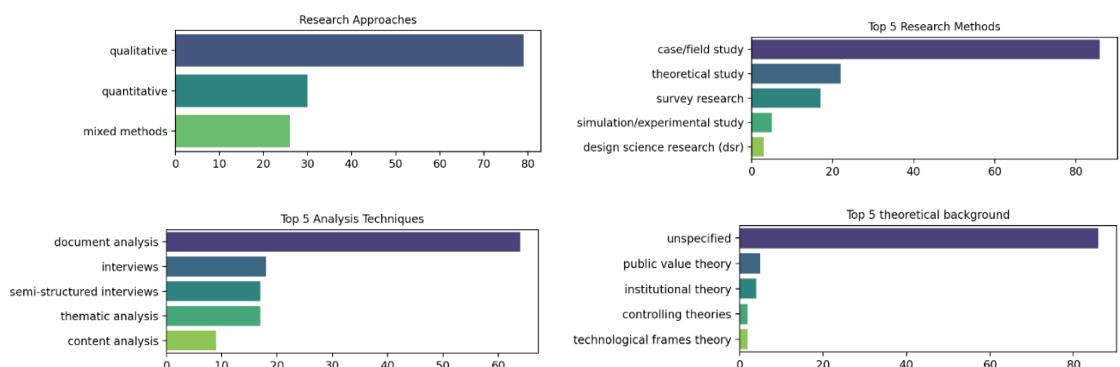
**Figure 10. Most relevant keywords co-occurrence network**

### 3.2. Content analysis

Content analysis involves, on the one hand, the discussion of research in methodological terms and, on the other, the discussion of the research in terms of the thematic context in which the studies were conducted. Initially, the methodological profile is presented in figure 11. The figure indicates that research on the topic has been developed using a qualitative approach, with case studies as the main method. The main analysis technique used is documentary analysis, aligned with qualitative case studies.

Examples of this type of methodological approach can be seen in Andrews (2019), who investigates how public leaders address ethical and governance issues associated with using algorithms and, through documentary analysis, identifies risks and proposes an approach to address these issues. van der Voort et al. (2019), who explores the impact of big data on public decision-making in studies in the Netherlands and Italy; and Kuziemski and Misuraca (2020) who use documentary analysis and semi-structured interviews to discuss the benefits and risks of automated decision systems, highlighting the increase in power asymmetries and the need for a robust regulatory framework to ensure accountability and fairness in areas such as immigration control and employment services.

**Figure 11. Research methodological profile**



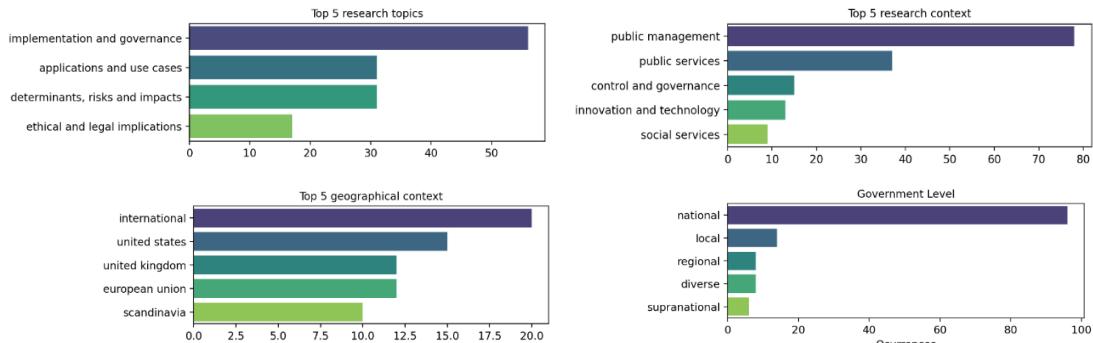
Still regarding the research methods, the volume of theoretical studies found in the sample is noteworthy. In the text “skimming phase”, literature reviews were excluded; however, theoretical studies that use documentary and literature analysis to propose theories and analysis frameworks, as well as theoretical studies that discuss the topic and associated concepts, were maintained. Among these, the theoretical framework for integrating big data into knowledge management systems proposed by Intezari and Gressel (2017); the framework for implementing AI initiatives by Wirtz and Müller (2019)

that addresses the potential and risks of this technology for the public sector, and the study by Busuioc (2021), which explores the challenges of accountability and transparency in the use of AI in the public sector, especially in complex deep-learning models. These theoretical studies contribute greatly to advancing discussion in the field and by offering theoretical bases for future empirical validations of these models.

Most authors did not formally specify the theoretical background of their studies, which is in line with the findings of Straub et al. (2023). These authors argue that although studies on AI in government are evolving, the field remains fragmented, with a clear lack of crossover between different literatures and theoretical foundations. In terms of formally accepted theories in the field of applied social sciences, theories, such as Public Value Theory (Andrews, 2019; Henriksen & Blond, 2023; Hjaltalin & Sigurdarson, 2024; Li et al., 2023; Wang et al., 2021), Institutional Theory (Berman et al., 2024; Giest & Klievink, 2024; Hashim, 2024; Madan & Ashok, 2024), Controlling Theories (Ingrams, 2019; Schmid, 2017) and Technological Frames Theory (Criado & de Zarate-Alcarazo, 2022; Madsen, 2018), are highlighted.

Regarding the thematic profile, figure 12 presents the main topics covered, the sectors of activity, geographic regions in which the studies were developed and the level of government investigated. As evidenced, in general, the research has been developing addressing topics related to the implementation and governance of these technologies, having been carried out in contexts of activities linked to management, in cases that cover more than one country, and discussing the topic at a national level.

Among the research topics, the highlight goes to “implementation and governance”, in which the authors address implementation challenges such as data fragmentation and silos, ethical issues, and infrastructure limitations (Desouza et al., 2020; Desouza & Jacob, 2017; Selten & Klievink, 2024). Other authors emphasize the need for institutional capacity for effective implementation of initiatives, as well as address issues related to organizational readiness and maturity in relation to data use (Giest, 2017). Data governance emerges as a central theme in implementation processes, in discussions on the use of big data in control and decision-making (Cerrillo-Martínez & Casadesús-de-Mingo, 2021; Intezari & Gressel, 2017), as well as in discussions on the importance of clear structures for effective and transparent data management (Berman et al., 2024; Botta et al., 2024).

**Figure 12. Research thematic profile**

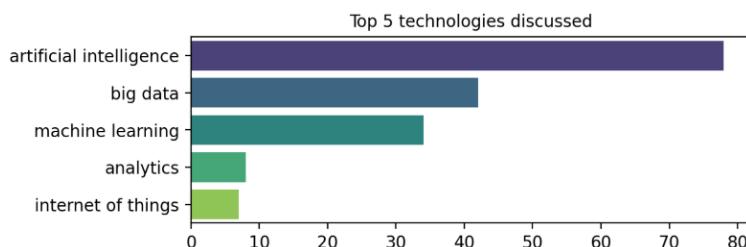
The research was mainly carried out within the scope of activities linked to management (Neumann et al., 2024), followed by the provision of public services (Gesk & Leyer, 2022) and activities linked to control and governance (Mökander & Schroeder, 2024). By associating the contexts of management with control and governance, the focus of the research on support activities to the detriment of the State's final activities becomes evident. However, it is worth highlighting the cases in which the focus was on managerial activities related to the final activities of the entities investigated, such as, for example, fishing (Schug et al., 2020), urban management (Anejionu et al., 2019; Malomo & Sena, 2017; Uras et al., 2020) and technology and innovation (Lee, 2019; Wang, 2020).

Regarding the geographical context, the results showed that research has mainly occurred at an international level, that is, research has simultaneously addressed more than one country. In terms of countries, the trend of research in developed countries is noteworthy, emphasizing the USA and the United Kingdom.

Finally, regarding the levels of government investigated, the research focuses on the national level, with few studies taking place at the regional and local levels. This focus of the discussion at the national level has already been verified by Lyrio et al. (2018) in an article that reviews the literature on transparency and corruption in the public sector, leaving a gap for investigations at the regional and local levels.

### 3.3. Technologies discussed

As seen previously, research on emerging technologies applied to the public sector has been on the rise in recent years (figure 7). These technologies have not only been providing analytical tools but also promoting a paradigmatic change in the way public organizations operate and make decisions. Figure 13 presents the 5 technologies that were most discussed in the studies in the sample.

**Figure 13. Top 5 technologies discussed by the authors**

AI stands out as one of the most influential technologies in research. Studies such as Becali et al.'s (2017) who discuss the use of AI for energy auditing in public buildings in Southern Italy and Desouza et al. (2020) who discuss lessons learned in the design, development and deployment of AI systems in the public sector demonstrate the importance of this technology in analyzing large volumes of data and well-informed decision-making.

Big data, in turn, has been discussed in studies that explore its implementation in public organizations. The research emphasizes the need for adequate structures for the effectiveness of initiatives involving this technology in the sector, as well as the role of leaders in governance and the generation of public value through big data (Andrews, 2019; Huang & Wey, 2019; Klievink et al., 2017).

Machine learning, as a sub-area of AI, has also received special interest in literature. Once again, the discussion about governance, job losses and ethical issues of using machine learning in the public sector stands out (Agarwal, 2018; Bignami, 2022; Oswald et al., 2018).

Analytics emerges as an essential practice for integrating big data and AI initiatives in the sense of building advanced analysis tools and reforming knowledge management systems. Studies on analytics in general, appear associated with big data, showing the importance of discussing big data analysis and addressing issues related to the implementation and success factors of these initiatives (Choi et al., 2018; Intezari & Gressel, 2017; Merhi, 2021)

Finally, the IoT has been mentioned in studies that relate physical devices and massive data collection, enabling real-time analysis in different contexts. Issues related to implementation also stand out in relation to the IoT (Hashim, 2024; Madsen, 2018), as well as use cases. Studies such as that by Wang (2020), which explores the use of IoT in the analysis of intellectual property data in China, and Zekić-Sušac, Mitrović

et al. (2021), which addresses the use of machine learning and IoT for energy efficiency management in public buildings, are examples of studies using this approach.

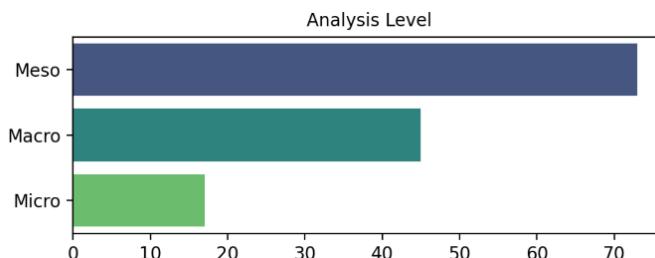
The studies clearly show that these technologies, taken together, not only allow for new perspectives for analysis in the academic field, but also pose challenges for professional practice. As the practice of use evolves, academic research can contribute to the understanding of how they can be applied effectively to solve complex problems and promote innovation in the public sector.

#### 4. Discussion

Emerging technologies are characterized by their radical novelty profile with accelerated growth, coherence of terminology, prominent impact, and uncertainty (Rotolo et al., 2015). These characteristics, when dealing with the public sector, require appropriate frameworks for analysis, in order to encapsulate the complexity of the discussion (Kuziemski & Misuraca, 2020). To this end, Criado et al. (2024) proposed an analysis model for understanding the phenomenon of AI in the public sector from 3 perspectives: (i) macro, dealing with issues about institutional and governance structures; (ii) meso, exploring sectoral and organizational impacts; and, (iii) micro, which focuses on individual interactions between civil servants and citizens, also used here as a way of grouping studies on the subject.

As shown in figure 15, the studies primarily focused on the phenomenon at the meso level, that is, at the organizational level, leaving the institutional and individual levels of analysis in the background. Below we will address what was discussed at each of these levels.

**Figure 15. Articles by Criado et al. (2024) analysis levels**



*Note.* Adapted from "Artificial intelligence and public administration: Understanding actors, governance, and policy from micro, meso, and macro perspectives", by J.I. Criado, R. Sandoval-Almazán, and J.R. Gil-García, 2024, *Public Policy and Administration*, 40(2), pp. 178-179 (<https://doi.org/10.1177/09520767241272921>).

#### **4.1. At the macro level: governance and institutional challenges**

The macro level of analysis, that is, the institutional level of analysis, was the one in which most theoretical studies were grouped. It is natural for theoretical discussions in a given field of knowledge to occur at a broader and more institutional level, seeking to develop concepts and level their understanding to advance research. In this case, the focus of these discussions addressed the proposal of analysis and implementation frameworks, such as the studies by Busuioc (2021), and Intezari and Gressel (2017), as well as theoretical discussions on the impact of big data and AI on the formulation of public policies and on the institutional capacity of States to use these technologies (Agarwal, 2018; Desouza et al., 2020; Giest, 2017), highlighting the need for governments to adapt to ensure the effectiveness of decision-making processes based on these technologies.

Macro-level studies also shed light on ethical, legal, and social issues. Studies such as that of Busuioc (2021) raise questions related to transparency and equity in contexts in which decisions based on algorithmic models directly impact citizens, such as the distribution of public benefits and the monitoring of regulations. Kuziemski and Misuraca (2020) also addresses this issue of algorithmic regulation and governance, when discussing the challenges and benefits of using automated systems for decision-making and the risks associated with generating power asymmetries in field studies carried out in Canada, Finland and Poland.

This macro level of analysis shows a growing concern among researchers regarding the use of algorithm-based decision-making models and the risk of compromising democratic principles. These discussions highlight tensions between technological efficiency and social values and the need to balance technological innovation with democratic principles, ensuring that these technologies reinforce, rather than undermine, the fundamental values that guide the public sector.

#### **4.2. At the meso level: Use cases and sectoral and organizational impacts**

The analysis at the organizational level reveals the discussion on how emerging technologies have been implemented in public organizations and the consequent improvement in administrative efficiency associated with their use.

Most of the studies that are configured as use cases were found at this level. Cases about refugees in the European Union (Baur, 2017), use of text mining to analyze the reputation of public organizations (Anastasopoulos & Whitford, 2019), analysis of citizen feedback regarding public services in the United Kingdom (Kowalski et al., 2020),

analysis of citizen reactions on social media about plans and actions related to environmental disclosure in Italy, among others, reveal the use of analytics and exogenous data to organizations in the development of cases in the public sector.

Cases applied in specific sectors, such as public health services, also stand out, using AI to detect critical areas of tuberculosis spread (Zaidi et al., 2024), transportation (Botta et al., 2024), energy efficiency (Zekić-Sušac, Has, et al., 2021), and social services (Conejero et al., 2021). These studies converge on issues related to the challenges of integrating data from multiple sources, scalability, cost, and ethical implications of AI-based applications. In addition, they highlight the consistent use of machine learning, big data, and analytics techniques to optimize organizational efficiency and inform public policy proposals in different contexts.

#### **4.3. At the micro level: individual and behavioral interactions**

At the micro level, the studies analyzed highlight the transformation in relationships between governments, public sector workers, and citizens driven by emerging technologies. Shah et al. (2017) explore the impact of big data in the context of human resources, showing how data analysis can provide critical insights into job satisfaction, organizational loyalty and readiness for change. The study concludes that job satisfaction mediates the relationship between salary, promotions and organizational readiness for change, highlighting the potential for using big data in strategic people management.

Chen et al. (2021), in turn, investigate the user experience with AI-based self-service technologies in public services. The research reveals that factors such as personalization, aesthetics, and trust in government are determinants of a positive experience, while the perceived time to perform tasks negatively affects satisfaction. These results suggest optimizing usability and trust in public interfaces to maximize their adoption and impact.

Still in this perspective, Wang et al. (2021) analyze the creation of public and private value through AI-based voice robots in the Chinese public sector. The study highlights that the effective use of these systems increases perceived usefulness, enjoyment, procedural fairness, and trust in government, improving the value of public services for citizens. In addition, the research emphasizes the importance of understanding demographic differences in value perception, suggesting that service design should consider user diversity.

These studies have in common how they demonstrate how technologies such as AI and big data can improve public services' efficiency and user experience and point out challenges related to trust, usability, and equity. These results provide a path for research related to citizen satisfaction and the impact of these technologies on the interaction between governments and society.

## 5. Conclusion

This study aimed to explore the use of emerging technologies in the public sector, examining their applications, challenges, and potential impact through a systematic literature review co-piloted by AI. The analysis revealed a significant evolution in the adoption of these technologies, with an emphasis on promoting administrative efficiency, personalizing services and providing informational support for the development of public policies. However, it also revealed concerns on the part of researchers regarding ethical, social, and operational challenges that require continued attention.

The discussion of the results sought to frame the research regarding macro, meso, and microanalysis perspectives. At the macro level, the discussions on regulatory frameworks to balance technological efficiency and democratic principles are noteworthy. From the meso perspective, the cases illustrate how AI and big data have been used to optimize operations and provide public services, and at the micro level, discussions on improvements in the interaction between governments and citizens and the need to strengthen equity and public trust in governments came to the fore.

Despite advances in the field, gaps remain in literature that researchers could explore in future studies. From a social perspective, future studies could address issues related to digital exclusion, the impact of technologies on specific and/or marginalized communities/organizations, and implementation methods that integrate new technologies without compromising the values and principles of the public sector. From the perspective of government levels, the regional and local levels lack studies exploring these technologies' applications. From a methodological point of view, applied quantitative studies based on methodologies such as Design Science Research and simulations/experiments emerge as paths yet to be explored in greater depth.

Regarding the proposed literature review approach, it proved to be effective in combining the analytical capabilities of AI models and human expertise. The use of the co-piloted approach not only increased the capacity for analysis and synthesis but also reduced the time for data processing and preparation. The authors of this study adhere to a line of thought in which they believe that, in an increasingly competitive and complex research environment, "keeping up with technology" is a matter of

survival. AI, far from being an existential threat, should be seen as a tool for research and the advancement of its use in academic environments is, above all, an opportunity for evolution and productivity gains that should be explored.

Finally, regarding its limitations, the research was based on articles only in English, and studies that cover other languages may provide other important insights. Limitations related to the approach, especially dependence on the quality of the databases and risk of bias and errors in automated article curation decisions, may have occurred, although this type of error can also occur in manual procedures performed by humans. Future studies may increase the database analyzed as well as improve the functionalities of the review process in terms of interactions with the AI models used, as well as explore the potential of other language models available on the market.

#### **Author contributions:**

**Lyrio, M. V. L.:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing, review, and editing, Visualization.

**Lunkes, R. J.:** Conceptualization, Validation, Investigation, Writing, review, and editing, Project administration, Funding acquisition. **Vasarhelyi, M.:** Conceptualization, Validation, Investigation, Writing, review, and editing.

Maurício Vasconcellos Leão Lyrio (Lyrio, M. V. L.)

Rogério João Lunkes (Lunkes, R. J.)

Miklos Vasarhelyi (Vasarhelyi, M.)

#### **Conflict of interest statement**

Authors declare that, throughout the research process, there has not been any sort of personal, professional, or economic interest that may have influenced the researchers' judgement and/or actions during the elaboration and publication of this article.

#### **References**

Agarwal, P. K. (2018). Public administration challenges in the world of AI and bots. *Public Administration Review*, 78(6), 917–921. <https://doi.org/10.1111/puar.12979>

Anastasiadou, M., Santos, V., & Montargil, F. (2021). Which technology to which challenge in democratic governance? An approach using design science research. *Transforming Government: People, Process and Policy*, 15(4), 512–531. <https://doi.org/10.1108/TG-03-2020-0045>

Anastasopoulos, L. J., & Whitford, A. B. (2019). Machine learning for public administration research, with application to organizational reputation. *Journal of Public Administration Research and Theory*, 29(3), 491–510. <https://doi.org/10.1093/jopart/muy060>

Andrews, L. (2019). Public administration, public leadership and the construction of public value in the age of the algorithm and 'big data.' *Public Administration*, 97(2), 296–310. <https://doi.org/10.1111/padm.12534>

Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. *Government Information Quarterly*, 36(2), 358–367. <https://doi.org/10.1016/j.giq.2018.10.001>

Anejionu, O. C. D., Thakuriah, P. (Vonu), McHugh, A., Sun, Y., McArthur, D., Mason, P., & Walpole, R. (2019). Spatial urban data system: A cloud-enabled big data infrastructure for social and economic urban analytics. *Future Generation Computer Systems*, 98, 456–473. <https://doi.org/10.1016/j.future.2019.03.052>

Aoki, N. (2020). An experimental study of public trust in AI chatbots in the public sector. *Government Information Quarterly*, 37(4), 1-10. <https://doi.org/10.1016/j.giq.2020.101490>

Baur, A. W. (2017). Harnessing the social web to enhance insights into people's opinions in business, government and public administration. *Information Systems Frontiers*, 19(2), 231–251. <https://doi.org/10.1007/s10796-016-9681-7>

Beccali, M., Ciulla, G., Lo Brano, V., Galatioto, A., & Bonomolo, M. (2017). Artificial neural network decision support tool for assessment of the energy performance and the refurbishment actions for the non-residential building stock in Southern Italy. *Energy*, 137, 1201–1218. <https://doi.org/10.1016/j.energy.2017.05.200>

Berman, A., de Fine Licht, K., & Carlsson, V. (2024). Trustworthy AI in the public sector: An empirical analysis of a Swedish labor market decision-support system. *Technology in Society*, 76, 1-15. <https://doi.org/10.1016/j.techsoc.2024.102471>

Bignami, F. (2022). Artificial intelligence accountability of public administration. *The American Journal of Comparative Law*, 70(Supplement\_1), i312–i346. <https://doi.org/10.1093/ajcl/avac012>

Bodó, B., & Janssen, H. (2022). Maintaining trust in a technologized public sector. *Policy and Society*, 41(3), 414–429. <https://doi.org/10.1093/polsoc/puac019>

Botta, F., Lovelace, R., Gilbert, L., & Turrell, A. (2024). Packaging code and data for reproducible research: A case study of journey time statistics. *Environment and Planning B: Urban Analytics and City Science*, 52(4), 1002-1013 <https://doi.org/10.1177/23998083241267331>

Busuioc, M. (2021). Accountable artificial intelligence: Holding algorithms to account. *Public Administration Review*, 81(5), 825–836. <https://doi.org/10.1111/puar.13293>

Cerrillo-Martínez, A., & Casadesús-de-Mingo, A. (2021). Data governance for public transparency. *El Profesional de La Información*, 30(4), 1-13. <https://doi.org/10.3145/epi.2021.jul.02>

Chen, T., Guo, W., Gao, X., & Liang, Z. (2021). AI-based self-service technology in public service delivery: User experience and influencing factors. *Government Information Quarterly*, 38(4), 1-11. <https://doi.org/10.1016/j.giq.2020.101520>

Cheong, A., Duan, H. K., Huang, Q., Vasarhelyi, M. A., & Zhang, C. A. (2022). The rise of accounting: making accounting information relevant again with exogenous data. *Journal of Emerging Technologies in Accounting*, 19(1), 1–20. <https://doi.org/10.2308/jeta-10812>

Choi, Y., Lee, H., & Irani, Z. (2018). Big data-driven fuzzy cognitive map for prioritising IT service procurement in the public sector. *Annals of Operations Research*, 270(1–2), 75–104. <https://doi.org/10.1007/s10479-016-2281-6>

Conejero, J. M., Preciado, J. C., Fernández-García, A. J., Prieto, A. E., & Rodríguez-Echeverría, R. (2021). Towards the use of Data Engineering, Advanced Visualization techniques and Association Rules to support knowledge discovery for public policies. *Expert Systems with Applications*, 170, 1-22. <https://doi.org/10.1016/j.eswa.2020.114509>

Criado, J. I., & O. de Zarate-Alcarazo, L. (2022). Technological frames, CIOs, and Artificial Intelligence in public administration: A socio-cognitive exploratory study in Spanish local governments. *Government Information Quarterly*, 39(3), 1-13. <https://doi.org/10.1016/j.giq.2022.101688>

Criado, J. I., Sandoval-Almazán, R., & Gil-Garcia, J. R. (2024). Artificial intelligence and public administration: Understanding actors, governance, and policy from micro, meso, and macro perspectives. *Public Policy and Administration*, 40(2), 173–184. <https://doi.org/10.1177/09520767241272921>

Desouza, K. C., Dawson, G. S., & Chenok, D. (2020). Designing, developing, and deploying artificial intelligence systems: Lessons from and for the public sector. *Business Horizons*, 63(2), 205–213. <https://doi.org/10.1016/j.bushor.2019.11.004>

Desouza, K. C., & Jacob, B. (2017). Big data in the public sector: Lessons for practitioners and scholars. *Administration & Society*, 49(7), 1043–1064. <https://doi.org/10.1177/0095399714555751>

Duan, H. K., Hu, H., Vasarhelyi, M. A., Rosa, F. S., & Lyrio, M. V. L. (2020). Open government data (OGD) driven decision aid: A predictive model to monitor COVID-19 and support

decisions in a Brazilian state. *Revista Do Serviço Público*, 71, 140–164. <https://doi.org/10.21874/rsp.v7i0.5009>

Duan, H. K., Vasarhelyi, M. A., Codesso, M., & Alzamil, Z. (2023). Enhancing the government accounting information systems using social media information: An application of text mining and machine learning. *International Journal of Accounting Information Systems*, 48, 1-19. <https://doi.org/10.1016/j.accinf.2022.100600>

Edelson, D. C. (2002). Design research: What we learn when we engage in design. *Journal of the Learning Sciences*, 11(1), 105–121. [https://doi.org/10.1207/S15327809JLS1101\\_4](https://doi.org/10.1207/S15327809JLS1101_4)

Fertier, A., Montarnal, A., Barthe-Delanoë, A.-M., Truptil, S., & Bénaben, F. (2020). Real-time data exploitation supported by model- and event-driven architecture to enhance situation awareness, application to crisis management. *Enterprise Information Systems*, 14(6), 769–796. <https://doi.org/10.1080/17517575.2019.1691268>

Gesk, T. S., & Leyer, M. (2022). Artificial intelligence in public services: When and why citizens accept its usage. *Government Information Quarterly*, 39(3), 1-12. <https://doi.org/10.1016/j.giq.2022.101704>

Giest, S. (2017). Big data for policymaking: Fad or fasttrack? *Policy Sciences*, 50(3), 367–382. <https://doi.org/10.1007/s11077-017-9293-1>

Giest, S. N., & Klievink, B. (2024). More than a digital system: how AI is changing the role of bureaucrats in different organizational contexts. *Public Management Review*, 26(2), 379–398. <https://doi.org/10.1080/14719037.2022.2095001>

Gil-Garcia, J. R., Helbig, N., & Ojo, A. (2014). Being smart: Emerging technologies and innovation in the public sector. *Government Information Quarterly*, 31(Supplement 1), I1–I8. <https://doi.org/10.1016/j.giq.2014.09.001>

Gu, H., Schreyer, M., Moffitt, K., & Vasarhelyi, M. A. (2024). Artificial intelligence co-piloted auditing. *International Journal of Accounting Information Systems*, 54(July), 1-30. <https://doi.org/10.1016/j.accinf.2024.100698>

Gu, Y., Huang, Q., & Vasarhelyi, M. A. (2024). It's not intelligence; It's Functionality! *Journal of Emerging Technologies in Accounting*, 21(2), 9–18. <https://doi.org/10.2308/JETA-2024-025>

Hashim, H. (2024). E-government impact on developing smart cities initiative in Saudi Arabia: Opportunities & challenges. *Alexandria Engineering Journal*, 96, 124–131. <https://doi.org/10.1016/j.aej.2024.04.008>

Henriksen, A., & Blond, L. (2023). Executive-centered AI? Designing predictive systems for the public sector. *Social Studies of Science*, 53(5), 738–760. <https://doi.org/10.1177/03063127231163756>

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 28(1), 75–105. <https://doi.org/10.2307/25148625>

Hjaltalin, I. T., & Sigurdarson, H. T. (2024). The strategic use of AI in the public sector: A public values analysis of national AI strategies. *Government Information Quarterly*, 41(1), 1-16. <https://doi.org/10.1016/j.giq.2024.101914>

Huang, J.-Y., & Wey, W.-M. (2019). Application of big data and analytic network process for the adaptive reuse strategies of school land. *Social Indicators Research*, 142(3), 1075–1102. <https://doi.org/10.1007/s11205-018-1951-y>

Ingrams, A. (2019). Big data and Dahl's challenge of democratic governance. *Review of Policy Research*, 36(3), 357–377. <https://doi.org/10.1111/ropr.12331>

Intezari, A., & Gressel, S. (2017). Information and reformation in KM systems: Big data and strategic decision-making. *Journal of Knowledge Management*, 21(1), 71–91. <https://doi.org/10.1108/JKM-07-2015-0293>

Keppeler, F. (2024). No thanks, dear AI! Understanding the effects of disclosure and deployment of artificial intelligence in public sector recruitment. *Journal of Public Administration Research and Theory*, 34(1), 39–52. <https://doi.org/10.1093/jopart/muad009>

Klievink, B., Romijn, B.-J., Cunningham, S., & de Bruijn, H. (2017). Big data in the public sector: Uncertainties and readiness. *Information Systems Frontiers*, 19(2), 267–283. <https://doi.org/10.1007/s10796-016-9686-2>

Kowalski, R., Esteve, M., & Jankin Mikhaylov, S. (2020). Improving public services by mining citizen feedback: An application of natural language processing. *Public Administration*, 98(4), 1011–1026. <https://doi.org/10.1111/padm.12656>

Kuziemski, M., & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, 44(6), 1-13. <https://doi.org/10.1016/j.telpol.2020.101976>

Lee, G. (2019). What roles should the government play in fostering the advancement of the Internet of Things? *Telecommunications Policy*, 43(5), 434–444. <https://doi.org/10.1016/j.telpol.2018.12.002>

Li, Y., Fan, Y., & Nie, L. (2023). Making governance agile: Exploring the role of artificial intelligence in China's local governance. *Public Policy and Administration*, 40(2), 276–301 <https://doi.org/10.1177/09520767231188229>

Lyrio, M. V. L., Lunkes, R. J., & Castello-Taliani, E. T. (2018). Thirty years of studies on transparency, accountability, and corruption in the public sector: The state of the art and opportunities for future research. *Public Integrity*, 20(5), 512–533. <https://doi.org/10.1080/10999922.2017.1416537>

Madan, R., & Ashok, M. (2024). Making sense of AI benefits: A mixed-method study in Canadian public administration. *Information Systems Frontiers*, 27, 889-923. <https://doi.org/10.1007/s10796-024-10475-0>

Madsen, A. K. (2018). Data in the smart city: How incongruent frames challenge the transition from ideal to practice. *Big Data & Society*, 5(2), 1-13. <https://doi.org/10.1177/2053951718802321>

Malomo, F., & Sena, V. (2017). Data intelligence for local government? Assessing the benefits and barriers to use of big data in the public sector. *Policy & Internet*, 9(1), 7-27. <https://doi.org/10.1002/poi3.141>

March, S. T., & Smith, G. F. (1995). Design and natural science research on information technology Salvatore. *Decision Support Systems*, 15, 251-266. [https://doi.org/10.1016/0167-9236\(94\)00041-2](https://doi.org/10.1016/0167-9236(94)00041-2)

Merhi, M. I. (2021). Evaluating the critical success factors of data intelligence implementation in the public sector using analytical hierarchy process. *Technological Forecasting and Social Change*, 173, 121180. <https://doi.org/10.1016/j.techfore.2021.121180>

Moffitt, K. C., Rozario, A. M., & Vasarhelyi, M. A. (2018). Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting*, 15(1), 1-10. <https://doi.org/10.2308/jeta-10589>

Mökander, J., & Schroeder, R. (2024). Artificial intelligence, rationalization, and the limits of control in the public sector: The case of tax policy optimization. *Social Science Computer Review*, 42(6), 1359-1378. <https://doi.org/10.1177/08944393241235175>

Nation, P. (2009). Reading faster. *International Journal of English Studies*, 9(2), 133-144. <https://doi.org/10.58837/CHULA.PASAA.36.1.1>

Neumann, O., Guirguis, K., & Steiner, R. (2024). Exploring artificial intelligence adoption in public organizations: A comparative case study. *Public Management Review*, 26(1), 114-141. <https://doi.org/10.1080/14719037.2022.2048685>

OpenAI. (2022, November 30). *Introducing ChatGPT*. OpenAI. <https://openai.com/blog/chatgpt>

Oswald, M., Grace, J., Urwin, S., & Barnes, G. C. (2018). Algorithmic risk assessment policing models: Lessons from the Durham HART model and 'experimental' proportionality. *Information & Communications Technology Law*, 27(2), 223-250. <https://doi.org/10.1080/13600834.2018.1458455>

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Mckenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance

and exemplars for reporting systematic reviews. *The BMJ*, 372, 1-36. <https://doi.org/10.1136/bmj.n160>

Rotolo, D., Hicks, D., & Martin, B. R. (2015). What is an emerging technology? *Research Policy*, 44(10), 1827–1843. <https://doi.org/10.1016/j.respol.2015.06.006>

Ruijer, E., Porumbescu, G., Porter, R., & Piotrowski, S. (2023). Social equity in the data era: A systematic literature review of data-driven public service research. *Public Administration Review*, 83(2), 316–332. <https://doi.org/10.1111/puar.13585>

Schmid, A. (2017). Big data-public Controlling fundamental changes in public management. *Public Policy and Administration*, 16(2), 325–334. <https://doi.org/10.13165/VPA-17-16-2-11>

Schug, D. M., Taylor, P. H., Iudicello, S., & Swasey, J. H. (2020). Using online data visualization and analysis to facilitate public involvement in management of catch share programs. *Marine Policy*, 122, 1-7. <https://doi.org/10.1016/j.marpol.2020.104272>

Seckler, C., Mauer, R., & vom Brocke, J. (2021). Design science in entrepreneurship: Conceptual foundations and guiding principles. *Journal of Business Venturing Design*, 1(1-2), 1-12. <https://doi.org/10.1016/j.jbvd.2022.100004>

Selten, F., & Klievink, B. (2024). Organizing public sector AI adoption: Navigating between separation and integration. *Government Information Quarterly*, 41(1), 1-14. <https://doi.org/10.1016/j.giq.2023.101885>

Shah, N., Irani, Z., & Sharif, A. M. (2017). Big data in an HR context: Exploring organizational change readiness, employee attitudes and behaviors. *Journal of Business Research*, 70, 366–378. <https://doi.org/10.1016/j.jbusres.2016.08.010>

Short, J. (2009). The art of writing a review article. *Journal of Management*, 35(6), 1312–1317. <https://doi.org/10.1177/0149206309337489>

Straub, V. J., Morgan, D., Bright, J., & Margetts, H. (2023). Artificial intelligence in government: Concepts, standards, and a unified framework. *Government Information Quarterly*, 40(4), 1-16. <https://doi.org/10.1016/j.giq.2023.101881>

Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, 36(2), 368–383. <https://doi.org/10.1016/j.giq.2018.09.008>

Uras, M., Cossu, R., Ferrara, E., Liotta, A., & Atzori, L. (2020). PMa: A real-world system for people mobility monitoring and analysis based on Wi-Fi probes. *Journal of Cleaner Production*, 270, 1-14. <https://doi.org/10.1016/j.jclepro.2020.122084>

van der Voort, H. G., Klievink, A. J., Arnaboldi, M., & Meijer, A. J. (2019). Rationality and politics of algorithms. Will the promise of big data survive the dynamics of

public decision making? *Government Information Quarterly*, 36(1), 27–38. <https://doi.org/10.1016/j.giq.2018.10.011>

Wang, W. (2020). Data analysis of intellectual property policy system based on Internet of Things. *Enterprise Information Systems*, 14(9–10), 1475–1493. <https://doi.org/10.1080/17517575.2020.1712744>

Wang, C., Teo, T. S. H., & Janssen, M. (2021). Public and private value creation using artificial intelligence: An empirical study of AI voice robot users in Chinese public sector. *International Journal of Information Management*, 61, 1–15. <https://doi.org/10.1016/j.ijinfomgt.2021.102401>

Wirtz, B. W., & Müller, W. M. (2019). An integrated artificial intelligence framework for public management. *Public Management Review*, 21(7), 1076–1100. <https://doi.org/10.1080/14719037.2018.1549268>

Zaidi, S. M. A., Mahfooz, A., Latif, A., Nawaz, N., Fatima, R., Rehman, F. U., Reza, T. E., & Emmanuel, F. (2024). Geographical targeting of active case finding for tuberculosis in Pakistan using hotspots identified by artificial intelligence software (SPOT-TB): Study protocol for a pragmatic stepped wedge cluster randomised control trial. *BMJ Open Respiratory Research*, 11(1), 1–10. <https://doi.org/10.1136/bmjresp-2023-002079>

Zekić-Sušac, M., Has, A., & Knežević, M. (2021). Predicting energy cost of public buildings by artificial neural networks, CART, and random forest. *Neurocomputing*, 439, 223–233. <https://doi.org/10.1016/j.neucom.2020.01.124>

Zekić-Sušac, M., Mitrović, S., & Has, A. (2021). Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities. *International Journal of Information Management*, 58, 1–12. <https://doi.org/10.1016/j.ijinfomgt.2020.102074>

Zuiderwijk, A., Chen, Y.-C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly*, 38(3), 1–19. <https://doi.org/10.1016/j.giq.2021.101577>

Reception date: 28/10/2025

Review date: 28/10/2025

Acceptance date: 30/10/2025

Contact: mauricio.lyrio@sea.sc.gov.br