Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Policy Capacities & Policy Normatives: Analyzing Artificial Intelligence Adoption in the Health and Justice Sectors in Latin America

Oliver David Meza Canales

oliver.meza@tec.mx

Tecnologico de Monterrey

Irma Guerra

Universidad Veracruzana

Elizabeth Perez-Chiquez

University of New Mexico

Miguel Guajardo

El Colegio Mexiquense

Research Article

Keywords:

Posted Date: November 27th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11681404/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Policy Capacities & Policy Normatives: Analyzing Artificial Intelligence Adoption in the Health and Justice Sectors in Latin America

Abstract

Building on the Policy Capacity Framework (PCF) we propose a normative dimension to evaluate the public value toward which those capacities are directed. This article examines the relationship between AI adoption and policy capacities in the health and justice sectors across five major Latin American countries. Artificial intelligence (AI) is rapidly entering into public administration, and while increasing efforts are made to adopt the technology over the promises of efficiency gains, little attention has been devoted to the capacities required to govern it, ergo, implementing it effectively, ethically, and sustainably. Using a comparative, theory-informed research design, we formulate nine ideal guiding PCF propositions to assess the two portfolios of capacities -technical and governance- that should accompany the public sector's AI adoption efforts. We then analyze 40 national-level AI applications in Argentina, Brazil, Chile, Colombia, and Mexico to understand what is happening on the ground. Thanks to our augmented version of the PCF analytical tool, we found that current efforts primarily concentrate on developing the technical portfolio of capacities required to deploy AI systems, while the governance portfolio remains underdeveloped. The results suggest that technical capacities can surge at individual and organizational levels autonomously, but governance-related normative capacities are only observed in the cases where systemic political capacities have enabled them. We also attest the power of political systemic capacities to influence both sets of portfolios -technical and normative- in improving analytical and operative capacities in the other two levels. The article contributes by integrating normative considerations into policy capacity theory and by identifying institutional conditions necessary for responsible AI governance in public organizations.

Introduction

A recent commentary in the journal *Nature* has raised support of the following proposition: perhaps it is not a lack of effectiveness of policies that has caused a global democratic backlash in recent years, but a lack of trustworthiness of public institutions (Foa & Mounk, 2016; Bartels, 2023; Cella, Cinar, Stokes & Uribe 2026). Trustworthiness instead of effectiveness is an axiological change associated with recent calls to bring democracy into policy and science (Tyler et al. 2026). To take matters into our hands, as policy scientists we should recalibrate our own theoretical frameworks for assessing this deficit; *"to collectively move the elephant -democracy- to the center of the room"*(Ingram, DeLeon & Schneider 2016). In this article we contribute to the latter effort by using the case of AI adoption in the public sector as an example of what our analytical frameworks could do. Using an augmented version of the Policy Capacity Framework, we created a series of propositions that function as a theoretical counterfactual to define the policy capacities that should be considered in the public sector for it to adopt AI with public values in mind. We then compare, and realize about the current deficit, in the health and judicial sectors in five major Latin American countries.

This article proposes a normative dimension to the existing Policy Capacity Framework (PCF). While an assumption of value neutrality has often accompanied the use of this analytical framework it may have inadvertently claimed that greater policy capacity is necessarily associated with better government. Nonetheless, there is continued debate concerning the purposes toward which public capacities are directed (Wellstead & Howlett, 2026). We examine not only whether governments possess policy capacities, but also how and toward what ends those capacities are to be exercised (Ball, 2025). Building on these contributions, we argue that a Policy Normative orientation could occupy a more central place in the PCF. Public policies are not merely technical instruments of state action, but an intervention designed to address collective problems within institutional arrangements structured by laws, rules, and democratic norms. As such, policy processes in democratic contexts are expected to uphold the rule of law, respect human rights, ensure transparency, enable public scrutiny, and hold powerful actors accountable for their decisions. This conception of public policy contains an explicit normative orientation regarding both the purposes and the procedures of state action, as envisioned by Laswell more than 70 years ago (DeLeon, 1995; Dryzek, 1989; Easton, 1950). Although normative dimensions constitute longstanding concerns in policy studies, these remain insufficiently incorporated into policy capacity research, not say policy analysis.

This article examines the implementation of Artificial Intelligence (AI) in the public sector as a critical case that reveals the need to incorporate a normative dimension into the PCF (Cho et al., 2026). Artificial intelligence promises transformative benefits compared to earlier technological breakthroughs that reshaped human societies (i.e the printing press, the steam engine, electrification, industrialization, and the digital revolution). Its adoption is already generating global economic, social, and political transformations. Yet institutional frameworks capable of anticipating, governing, and mitigating its adverse effects remain underdeveloped (Taeihagh, 2025). This challenge is especially significant in the public sector. Whereas private-sector success is typically measured through profitability, productivity, or market performance, the success of AI adoption in government should ultimately be assessed in terms of the public value it creates, the rights it protects, and the legitimacy of the processes through which it is designed and implemented (Howlett et al., 2025; Wellstead & Howlett, 2026). From this perspective, strengthening policy capacity is insufficient unless those capacities are normatively oriented toward publicly valuable objectives.

Across the globe, public organizations are incorporating AI-based applications (AIA) to improve decision-making processes, optimize resource allocation, automate administrative tasks, and expand access to essential public services. Yet, while AI promises significant gains in effectiveness and productivity, its incorporation into public administration raises important concerns regarding issues such as algorithmic bias, explainability, accountability, automation of administrative functions, and the transformation of bureaucratic work (Yuan & Chen, 2025).

Our main argument is that given the research that has soundly established both positive and risky aspects of AI incorporation into the public sector, the policy capacities involved have favoured portfolios related to technical empowerment of individuals and organizations within the policy systems in the use of AI. Less has been done to incorporate a portfolio of capacities geared to govern, mitigate and manage the risk involved with the use of AI. To explore this proposition we ask: *what are the policy capacities involved in the process of adoption and implementation of AI in the public sector?*

Empirically, we focus on two key sectors in Latin America (LA); health and justice, and how these two sectors have incorporated AIA into their work. These sectors represent areas where AI adoption is expanding rapidly and where the consequences of technological decisions have direct implications for fundamental rights and public trust. Our analysis examines national or federal-level AIA implemented in Argentina, Brazil, Chile, Colombia, and Mexico.

Methodologically, the article adopts an exploratory and theory-informed comparative design. Using the AI Systems in the public sector of Latin America and the Caribbean (AISPLAC) data set (Gutiérrez et al., 2026), we identify AIAs functioning in the health and justice sectors in the selected countries. These AIAs are then analyzed through an augmented-version of the PCF supported by a *Human-Validated AI-*

assisted Document Scrapping (see Appendix 1). The objective is to identify recurring patterns and develop theoretically-grounded propositions regarding the relationship between AI adoption and policy capacities in the public sectors.

We contribute in two relevant ways. First, we support the perspective that policy scientists should incorporate questions regarding democratic implications when approaching policy studies (Ingram, DeLeon and Schneider 2016). By incorporating a normative dimension into the PCF, we respond to recent calls made by other policy scholars (see Howlett et al., 2025; Legrand & Moon, 2025; Wellstead & Howlett, 2026). Beyond governmental capacity, we should also ask: capacity for what, for whom, and under which normative constraints?

Secondly, the inclusion of a normative dimension within the PCF is relevant in any context as the work on 'bad policies' (Howlett et al., 2025) or 'dark-side of policy-making' (Legrand & Moon, 2025; McConnell, 2018), clearly demonstrates.This literature highlights policy processes that deliberately diverge from the public good (Legrand & Moon, 2025). We focus on Latin American countries, where governments face rampant and unconstrained elites, uneven state capacities, and significant social inequalities. In these contexts, AI may contribute to expanding access to rights and improving service delivery, or it may reproduce and deepen existing inequalities and violations to human rights at an even more accelerated pace.

Our findings suggest that current efforts primarily concentrate on developing the technical portfolio of capacities required to deploy AI systems, while the normative and governance-related portfolio remains comparatively underdeveloped. Findings also suggest that organizational and individual level capacities to adopt AI could rise autonomously by the push of public officials seeking greater efficiency, but that normative portfolios need the political systemic capacity to enable them. Furthermore, the political systemic capacities may influence both sets of portfolios in improving analytical and operative capacities at the organizational and individual levels. We argue that this asymmetry is consequential. Technical capacities may rise to develop rapidly and autonomously while the corresponding development of normative capacities is needed to provide a democratic compass for AI adoption.

The remainder of the article proceeds as follows. We present our main argument, followed by a set of nine propositions that should be seen in the implementation of AI in the public sector as our theoretical counterfactual. We then present our case study, research methods and findings. The two final sections discuss the theoretical and practical implications of the findings and conclude by outlining a research agenda on policy capacities and AI governance in the public sector.

A Policy Normative Dimension for Policy Capacity

Recent scholarship has questioned the assumption that policy capacity is inherently beneficial, arguing that the Policy Capacity Framework (PCF) pays insufficient attention to the purposes for which governments develop and use their capacities (Howlett et al., 2025; Wellstead & Howlett, 2026). This critique builds on two traditions in public administration and policy studies.

The first tradition, the public value literature, assesses government performance in terms of efficiency, effectiveness, and the public values it advances (Bozeman et al., 2018; Jørgensen & Bozeman, 2007; Moore, 1995; Riccucci, 2001). Moore (1995) emphasizes the responsibility of public managers to create public value as circumstances and understandings of that value change. Jørgensen and Bozeman (2007, p. 355) contend that "there is no more important topic in public administration and policy than public values." Riccucci (2001) likewise treats public values as the criterion for judging whether management practices borrowed from the private sector are appropriate for democratic governance.

The second tradition shows that policy processes involve political choices and expose governments and citizens to policy risks (Cairney, 2023). Research on policy instruments (Capano & Howlett, 2020), malignity in policy design (Legrand & Moon, 2025), administrative burdens (Herd & Moynihan, 2018),

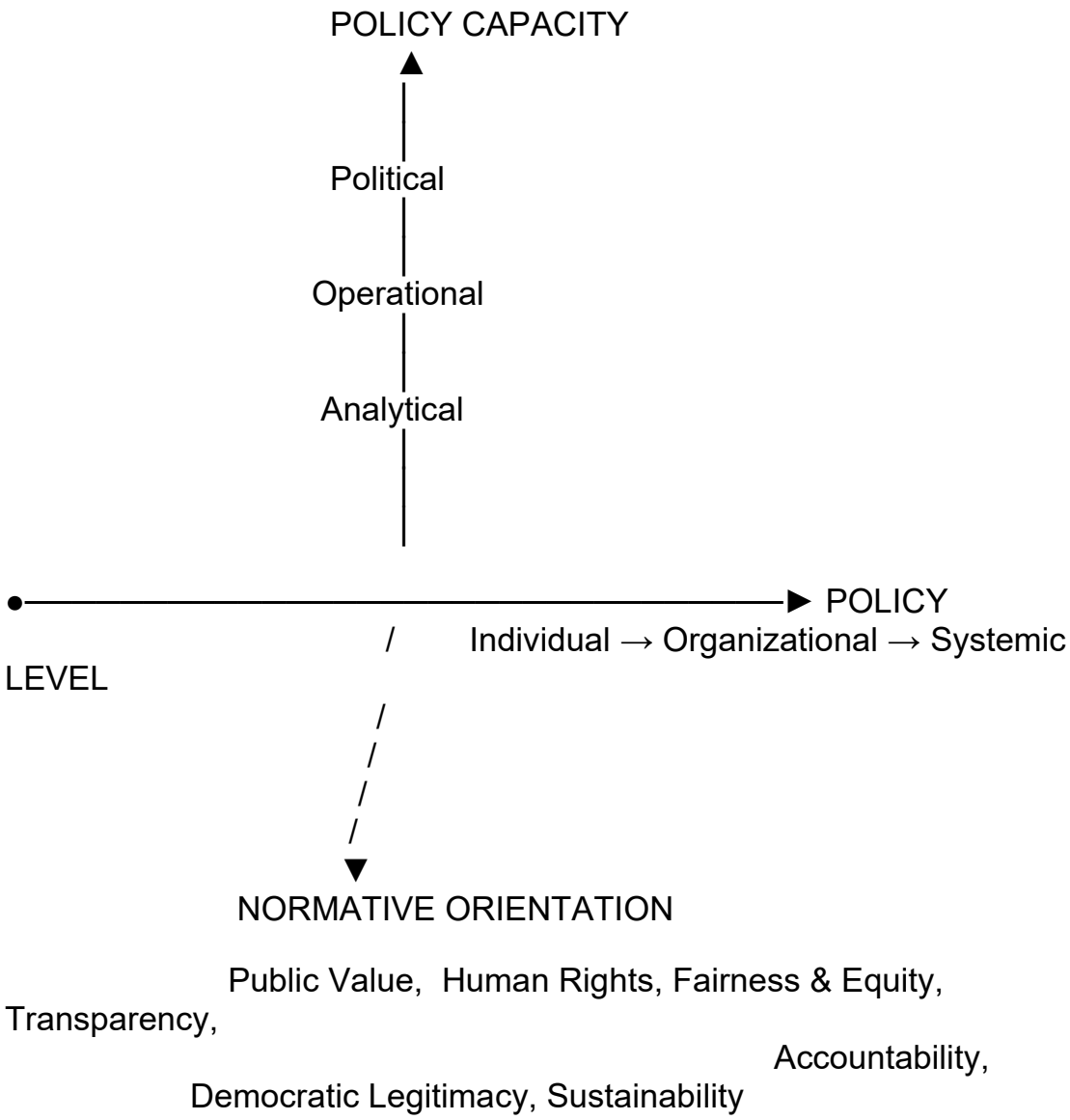
and performance management and evaluation (Bovens et al., 2008) illustrates how seemingly neutral administrative devices embody normative assumptions (Halpern, 2021). These devices allocate authority, distribute benefits and burdens, and privilege some values over others (Schneider & Ingram, 1993). The inclusion of deontological reasoning and human-centered competencies in policy capacity training similarly reflects the ethical and practical judgments expected of public servants (Munoz-del-Campo, 2026).

Whose values do policy capacities serve, and to what ends? The question gains urgency when populist governments reorganize state capacities in pursuit of objectives that can erode democratic governance. Wellstead and Howlett (2026), for example, argue that the deployment of capacities through the U.S. Department of Government Efficiency (DOGE) diminished public value. The case illustrates how even highly developed capacities can undermine public value when mobilized for purposes at odds with democratic commitments. A government may strengthen its ability to carry out its own agenda while weakening the institutions that hold it to account.

Scholarship from the Global South also calls attention to the institutional assumptions that underpin dominant policy theories. Many of these theories were developed in settings with relatively stable democratic governance, mature bureaucracies, and pluralistic participation. Their assumptions may travel poorly to settings where state capacity is uneven and where accountability, exclusion, and democratic backsliding pose recurring challenges (Peeters et al., 2024). For comparative research across the Global North and South, institutional differences matter because similar capabilities may be put to different uses. The purposes for which governments mobilize their capacities must therefore be examined in their institutional context.

We propose *Policy Normative Orientation* as a distinct dimension of the PCF (see Figure 1). Public policy is a form of collective action governed by institutional and constitutional arrangements that define the legitimate purposes and limits of state intervention. These arrangements call on public institutions to uphold democratic principles, respect the rule of law and human rights, promote transparency, facilitate public scrutiny, and hold those exercising public authority to account. Although these commitments are central to theories of public policy, prevailing approaches to policy capacity give them limited attention. The proposed dimension brings these commitments into the assessment of policy capacity. It complements the analysis of what governments can do with their analytical, operational, and political capacities by examining the purposes those capacities serve and the principles that govern their use.

Figure 1. Normative Orientation Dimension extending Policy Capacity Framework



AI and Policy Capacity

High expectations, as well as concerns, surround the incursion of AI into the public policy process (see Gomes de Sousa et al., 2019; Margalit & Raviv, 2026; Valle-Cruz et al. 2020; Young et al., 2019). Some of the concerns regard having "automated" agents having discretion and making political decisions (Salah & Alnoor, 2026; Wuttke et al., 2026). We review existing literature to understand what policy capacities should be invoked in AIA implementation in the public sector beyond a technocratic portfolio, and specifically regarding a policy normative portfolio. We organize the insights using the PCF-- which encompasses capacities across multiple actors within the entire policy process (Wu et al., 2015)-- as our departing point. The PCF considers nine different sets of capacities originally shaped from two dimensions. The first dimension is marked by the level of resources, and the second dimension by the type of "skills" (Wu et al., 2015). Table 1 frames nine capacities depending on the intersection of these two dimensions.

Capacity/Level	Analytical	Operational	Political
Individual	IAC	IOC	IPC
Organizational	OAC	OOC	OPC
Systemic	SAC	SOC	SPC

Table 1. Schematic view of the Policy Capacity Framework

We then elaborate nine policy capacity propositions that include the two sets of capacity portfolios: (1) technical capacities, or the dominant set of capacities associated with the technical success of policies, and (2) a policy normative dimension in each proposition based on the literature regarding AI involvement in the public sector.

Analytical Capacity in AI implementation

Analytical capacity encompasses the individual, organizational, and systemic abilities required to generate, interpret, and apply knowledge for the effective implementation of AI in the public sector. At the individual level, public servants must possess the technical expertise to understand how AI systems are trained, how outputs are produced, and how these outputs should be critically interpreted rather than accepted uncritically (Carney et al., 2020; Mergel et al., 2024; Wu et al., 2015). Experts must be capable of identifying algorithmic bias, coding errors, and other deficiencies that citizens are unlikely to detect (Busuioc, 2021). At the organizational level, analytical capacity requires specialized personnel, permanent monitoring protocols, and mechanisms for ensuring data quality, traceability, and the detection of legal and ethical risks throughout the AI lifecycle (Bracci, 2023; Brand et al., 2022; Busuioc, 2021; Franzke et al., 2021; Henman, 2020; Jørgensen & Nissen, 2022; Kuziemski & Misuraca, 2020; Liu et al., 2019; Mergel et al., 2024; Plantinga et al., 2024; Yusuf et al., 2024). At the systemic level, governments depend on broader scientific and technological ecosystems to generate evidence capable of addressing uncertainty surrounding disruptive technologies and informing AI governance (Radu, 2021; Taeihagh et al., 2021).

Proposition	Policy technical dimensions	Policy normative dimension
P1. Individual Analytical Capacity for AIA includes professional expertise and experience…	…to understand how AI applications are trained, and what outcomes are produced,...	…and to critically appraise those outcomes that deviate from democratic and public values.
P2. Organizational Analytical Capacity for AIA includes organizational…	…capacity to provide human, physical, and financial resources for analytical tasks together with...	… institutionalized mechanisms to manage data quality, algorithmic outcomes, and legal or ethical risks.
P3. System Analytical Capacity for AIA includes…	…access to scientific and technical environments capable of supporting technological advances…	…while generating critical, risk-oriented evidence on AI adoption.

Operational Capacity in AI implementation

Operational capacity refers to the ability to organize people, resources, and institutions for AI to be embedded into everyday policy implementation. Individually, officials must integrate AI into their daily routines while retaining the expertise and discretion necessary to contextualize and correct automated recommendations (Alon-Barkat & Busuioc, 2023; Broecke, 2023; Gupta, 2023; Höddinghaus et al., 2021; Oder & Béland, 2025; Taeihagh, 2025; Yilmaz & Yilmaz, 2023; Yuan & Chen, 2025; Wu et al., 2015). Organizationally, AI adoption requires governance structures that coordinate resources, redefine responsibilities, ensure transparency, and establish accountability, supported by sufficient organizational resources and learning capacities (Bracci, 2023; Burrell, 2016; Cobbe & Singh, 2020; Erman & Furendal, 2024; Fink, 2018; Fountain, 2001; Giest & Klievink, 2024). Moreover, the changing role of bureaucrats in organizational contexts should be assessed (Contini, 2024; Giest & Grimmelikhuijsen, 2020; Meijer & Bekkers, 2015; Mannes, 2020; Mergel et al., 2019; Neumann et al., 2024; Rakova et al., 2021; Robinson, 2020; Selten & Meijer, 2021). At system level, operational capacity requires coordination across governmental and non-governmental actors to manage collective risks, oversight, and accountability (Bignami, 2022; Bracci, 2023; Redden et al., 2020; Sætra, 2020; Taeihagh, 2025; Yuan & Chen, 2025).

Proposition	Policy technical dimensions	Policy normative dimension
P4. Individual Operative Capacity for AIA includes…	…the capacity to accommodate AI in daily policy or administrative routines...	…while being able to respond to its operational consequences derived from AI failure.
P5. Organizational Operative Capacity for AIA includes…	…coordinating resources, processes, and actors to support AI-related activities,...	…and establishing specialized mechanisms to troubleshoot AI systems in case of democratic or public value failures.
P6. System Operative Capacity for AIA involves…	…coordinating internal and external organizations and resources to support policy implementation and objectives…	…while also addressing collective challenges arising from the widespread use of AI.

Political Capacity in AI implementation

Political capacity captures the ability to generate legitimacy, trust, and governance arrangements around AI adoption. Individually, officials must navigate technological change, communicate the rationale for AI use, and rebuild public trust when failures occur (Cobbe & Singh, 2020; Mergel et al., 2024; Neumann et al., 2024; Wu et al., 2015). Organizationally, AI implementation requires alliances, citizen engagement, accountability mechanisms, and external ethical oversight to sustain legitimacy (Bignami, 2022; Bracci, 2023; Busuioc, 2021; Pande et al., 2025; Weiss et al., 2018). At the system level, political capacity depends on regulatory frameworks, inter-institutional coordination, and governance arrangements capable of balancing innovation with transparency, accountability, and democratic legitimacy, particularly where AI is developed by private actors (Brynjolfsson & Ng, 2023; Cao, 2022; Liu et al., 2024; Montes & Goertzel, 2019; Sætra, 2020; Taeihagh et al., 2021; Tallberg et al., 2023).

Proposition	Policy technical dimensions	Policy normative dimension
P7. Individual Political Capacity for AIA involves…	…the capacity to navigate AI-enabled work, maintaining or restoring trust among citizens,...	…and address distrust or lack of confidence from users following AI failures.
P8. Organizational Political Capacity for AIA involves…	…coordinating with allied organizations to build legitimacy towards policy objectives,...	…while addressing public concerns, and responding effectively to AI failures...
P9. System Political Capacity involves…	…establishing sector-wide regulatory and governance frameworks that steer AI implementation…	…while mitigating associated risks.

Case Studies in Latin America: Country-Sector

We used the case of AIA as a critical case study (Thomas, 2011; Yin, 2009) given the high expectations and risks accompanying this disruptive technology in the public sector. Our main unit of observation is country-sector level. Our analytical anchor is composed of five countries: Argentina, Brazil, Chile, Colombia and Mexico. These countries have an important relative weight in the region and differences that are theoretically relevant: they account for 85% of the region's GDP and 74% of the population (Our World in Data, 2026). Additionally, the group includes three federalist countries -Mexico, Argentina, Brazil-, two unitary countries -Chile and Colombia-, and currently a mixture of left and right-wing governments.

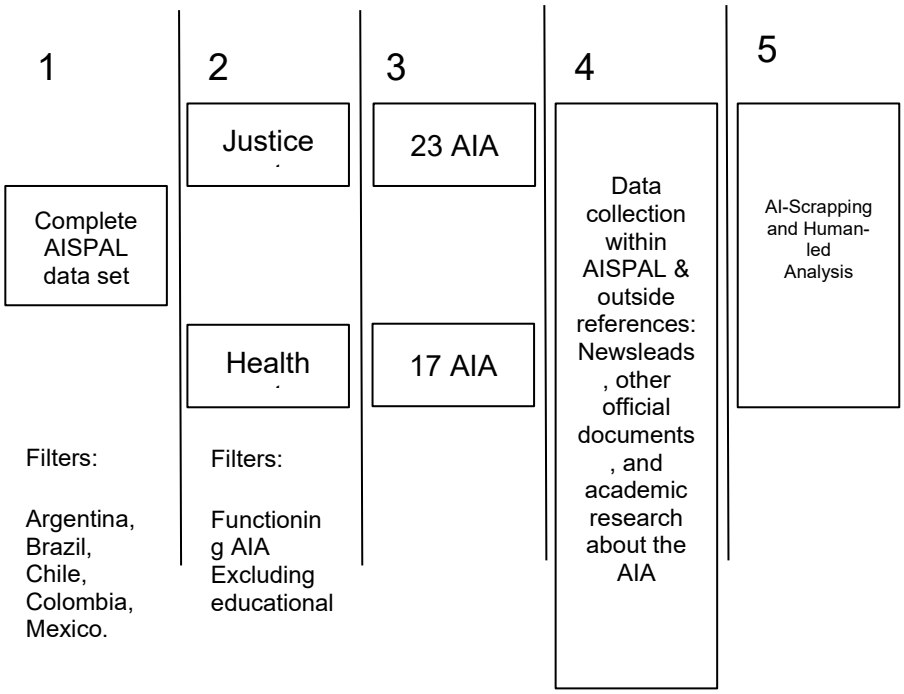
We focus on the health and justice sectors, which employ highly specialized and professionalized personnel with ample discretion in their decision-making processes, and stand to be highly affected by AI adoption. Finally, the country-sector level allows us to understand the systemic context of a country, including its policy decisions, practices, and reasoning regarding the incorporation of AIAs in the public sector. It also offers a clear and homogeneous level for international comparison.

Research Design

What capacities are invoked in the adoption of AI in the public sector in Latin America? Examining AI applications in health and justice, this article contributes to policy capacity theory by distinguishing between two complementary portfolios of capacities: a) technical capacities that enable AI implementation and b) normative capacities that ensure its alignment with democratic principles, public values, and responsible governance.

The level of knowledge in this subject calls for an exploratory research that is theoretically guided with an inductive approach (see Figure 2). We use the policy capacities framework to guide the search for data within a universe of AIAs circumscribed to the public health and justice sector in five Latin American countries.

Figure 2. Research Design and Analytical Process



Data collection

Our research has a sequential and multi-methodological design. We identify the universe of applications provided in the work of Gutiérrez et al. (2026) with the AISPAL database. From this base, we selected a set of cases with analytical utility for the health sector (N=17) and for the justice sector (N=23). Table 2 shows the number of AIAs in each *country-sector*: including only those at the national or federal levels, regardless of whether they were being piloted or in the process of being scaled up (see Appendix 4.1 and 4.2 for table of AIAs by country and sector as well as details).

Country	Justice AIA sector	Health AIA sector
Argentina	2	2
Brazil	12	6
Chile	1	6
Colombia	4	2
Mexico	4	1
Total	23	17

Table 2. Artificial Intelligence Applicatives by unit of observation

Source: Own elaboration using the AISPAL data set

Data analysis

The PCF guided the analysis of data; we used the nine propositions reported in the previous section that included two portfolios of capacities; technical and normative types. A summary sheet was made for each AIA using information available in the AISPAL dataset. Two human research assistants webscrapped to explore three additional sources of information for each AIA: a) official sources on the AIA, b) sources from think-tanks or academics specialized in the AIA, c) and journalistic sources on the AIA. We downloaded all references and produced a PDF package for each *country-sector* as our main empirical data platform. Using a large-language AI model application we scrapped information from the PDF package for each *country-sector* to produce a matrix of relevant information sorted according to the PCF. Our scrapping effort was based on a purposefully designed prompt (see Appendix 2). The prompt indicated to scrap information regarding the nine propositions; it included safeguards to control for hallucinations; it asked to reveal the exact source, and to qualify assertiveness of the task performed. We piloted the analysis using three models: Claude, Deepseek and ChatGPT. Pilot outputs of the three were similar and consistent, however the analysis portrayed in the next section is from ChatGPT for convenience purposes. Although automated document classification and information extraction are not entirely novel (see Wellstead et al., 2024), similar analyses in the past have generally required specialized programming, custom machine learning pipelines, or extensive model training. After the document-scraping, a review was made by two researchers in our team to verify the work done by the LLM. The analysis of the information was carried out by two human-researchers in the corresponding unit of analysis, in this case *country-sector.* Complete outputs are organized and available in Appendix 3.

Nguyen-Trun & Friese (2026) recognized methodological risks associated with LLM-assisted analysis. In attention to them we developed several safeguards in our process. We included detailed prompt engineering to minimize interpretative ambiguity, structured analytical protocols explicitly defining coding categories and valid evidence, iterative testing across multiple prompt versions, and replication using different commercial LLMs. Although human validation remains indispensable, these findings suggest that commercially available LLMs can substantially reduce the costs and time associated with large-scale qualitative document analysis while maintaining sufficient analytical consistency for theory-driven research.

General Findings

Using the nine hypotheses in the previous sections, the analysis shows a clear tendency favouring technical policy capacities being invoked in the AIA adoption processes. This runs unfavorably against the portfolio of policy capacities designed to normatively govern the AI which is associated with

mitigating its risks, monitoring its performance and evaluating its ultimate impact regarding policy normative precepts within the policy-making process. This general findings cuts across both the Health and Justice sector. We devote this section to explain details of the most relevant findings with respect to policy capacities in the two sectors.

In both the health and justice sectors, the strongest evidence gathered relates to the organizational level across the three types of capabilities: Analytical, Operational, and Political. While the implementation of AI is relatively recent, this situation could explain the noticeable imbalances in capabilities across different levels. We theorize that the organizational level could have developed an initial set of capacities which would eventually spillover into other levels depending on its evolution and need. However we further theorize this organizational push could only apply well to technical capacities but not necessarily to the normative portfolio of capacities. Our findings suggest that these other normative capacities are more a product of system level capacities.

Analytical Capacity

The available evidence on analytical capacity indicates that its technical dimension is generally present across both sectors at all three levels: individual, organizational, and systemic. For the governance dimension, however, evidence at the individual and organizational levels was found only for applications in Argentina, across both sectors. At the systemic level, findings were concentrated in justice-sector applications in Colombia, Mexico, and Brazil. Brazil stands out because its National Council of Justice issued a resolution establishing formal regulation to prevent risks associated with the use of AI.

P1. Individual Analytical Capacity for AIA includes professional expertise and experience to understand how AI applications are trained, and what outcomes are produced, and to critically appraise those outcomes that deviate from democratic and public values.

At the individual level, technical analytical capacity was found to be substantially present in the systems developed across both sectors and all five countries. Although evidence could not be identified in some cases, the implementation of these applications implies the availability of personnel with sufficient technical skills and knowledge to develop different programming models, as well as personnel with specialized knowledge of justice and health.

In Colombia, for example, PretorIA involved assistant justices, legal scholars, engineers, and data scientists in defining legal criteria, preparing datasets, and training and auditing the system. In Argentina, the design of Chat Crecer drew on specialized teams in health, epidemiology, user experience, and digital government.

With regard to governance analytical capacity at the individual level, only two systems in Argentina examined potential risks associated with AI implementation, including bias. The design of the judiciary's AI-powered Virtual Assistant took into account potential biases arising from its training data. Its tasks therefore focus on text summarization rather than complex reasoning or evaluative judgments, with human oversight maintained throughout and final validation performed by the responsible officeholders. In the health sector, the ARPHAI project considered the need for individuals handling data to hold certification in Good Clinical Practice.

P2. Organizational Analytical Capacity for AIA includes organizational capacity to provide human, physical, and financial resources for analytical tasks together with institutionalized mechanisms to manage data quality, algorithmic outcomes, and legal or ethical risks.

At the organizational level, evidence of the deployment of institutional resources to launch the projects was found in all cases examined, particularly those in which AI applications had been formally implemented. Both sectors provided examples of specialized teams responsible for implementing and maintaining the systems. These included the Transparency Virtual Assistant of Mexico's Supreme Court of Justice of the Nation, supported by a General Directorate of Information Technologies, and the AI-powered Virtual Assistant of Argentina's national judiciary, which incorporates an ongoing process of database curation and updating.

As with governance capacity at the individual level, only the two Argentine cases discussed above—the AI-powered Virtual Assistant of the national judiciary and the ARPHAI project—address risks associated with AI use and establish mechanisms to prevent them. In the first case, a governance model assigns responsibility for oversight, requires periodic reports to a council, and sets out procedures to follow in the event of security incidents. In the second case, the ARPHAI project explicitly includes bias audits.

P3. System Analytical Capacity for AIA includes access to scientific and technical environments capable of supporting technological advances while generating critical, risk-oriented evidence on AI adoption.

Of the three levels, the systemic level yielded the most evidence of analytical capacity, in both its technical and governance dimensions. In the technical dimension, several projects emerged from formal collaboration between the responsible agencies and different levels of government, as well as external actors such as universities, civil society organizations, and domestic and international companies. Examples in the justice sector included the judiciary's Case Law Search Engine in Chile, PretorIA and Relati 3.0 in Colombia, VICTOR in Brazil, and ARPHAI in Argentina. Examples in the health sector included ARPHAI and Chat Crecer in Argentina, Mírame a los Ojos in Mexico, and Helô and Robô Laura in Brazil.

In the governance dimension, Colombia and Mexico documented the work undertaken by civil society organizations to identify risks associated with AI use: in Colombia, specifically in relation to PretorIA, and in Mexico, in relation to applications developed in the justice sector. In Brazil, CNJ Resolution 615/2025 was issued, covering Information and Communication Technology; the Operation of Judicial Bodies; Information and Judicial Caseload Management; and Judicial Management and Organization. The resolution establishes explicit measures to prevent and correct bias and to manage AI-related risks.

Operative Capacity

Across both sectors, the available evidence of operative capacity is concentrated in the technical dimension, particularly at the organizational level. Brazil and Chile show comparatively substantial evidence across levels, while the other countries display greater variation. Governance-related operative capacities are much less documented, with limited evidence. These findings suggest an imbalance between the arrangements supporting AI integration into administrative work and those addressing its operational consequences.

P4. Individual Operative Capacity for AIA includes the capacity to accommodate AI in daily policy or administrative routines while being able to appropriately respond to its operational consequences.

Evidence of individual technical operative capacity varies across countries and sectors. Substantial evidence appears in Brazil's health and justice sectors and Chile's health sector, whereas the reviewed materials provide little information on this capacity in Mexico's justice sector. In Argentina's justice sector, *Justicia Inteligente* provides partial evidence of individual operative capacity. Tribunal members, law clerks, and their teams integrate automated drafts into preparatory work while retaining responsibility for final review and validation. Its search tool also allows legal professionals to use semantic searches and automated summaries when researching precedents. However, the documentation does not specify individual-level procedures for addressing omissions, hallucinations, or technical failures, limiting the evidence of officials' capacity to respond to these operational consequences.

Some evidence relevant to individual-level normative operative capacity appears in Colombia's justice sector. In PretorIA, assistant magistrates use AI to support the search, classification, and analysis of *"tutela"* claims while retaining final decision-making authority. This retention of human authority suggests a safeguard within the workflow, although it does not by itself establish officials' capacity to identify and address AI failures. Intuitive interfaces and the involvement of an internal team provide further evidence of adaptation of legal work to the system.

P5. Organizational Operative Capacity for AIA includes coordinating resources, processes, and actors to support AI-related activities and establishing specialized mechanisms to troubleshoot AI systems.

Organizational technical operative capacity is comparatively well documented. In Chile's justice sector, the Judicial Branch Case Law Database illustrates coordination among specialized actors. Its implementation took approximately two and a half years under the direction of a technical committee, with participation from the Directorates of Libraries and the Documentation Center, Studies, law clerks, chamber attorneys, the Judiciary Administrative Corporation, and a specialized external company. The Documentation Center assumed responsibility for implementation. The publicly accessible application brings together databases from different courts and offers continuous access, search functions, alerts, annotations, and personalized features through *Clave Única*. However, the documentation provides no evidence of governance-related normative operative capacity: it does not specify budgetary arrangements, contracts, permanent maintenance structures, or contingency procedures.

Examples of governance-related evidence for normative capacities appear in Argentina's health sector and Brazil's justice sector. In Argentina's health sector, both AIAs show evidence of processes and teams that calibrate results to address biases and errors in AI assessments, as well as teams responsible for these activities. They also indicate detailed processes for the use of personal data and processes for review or consultation with end users. These arrangements suggest organizational efforts to address operational consequences, although their effectiveness cannot be established from the documentation alone.

P6. System Operative Capacity for AIA involves coordinating internal and external organizations and resources to support policy implementation and objectives while also addressing collective challenges arising from the widespread use of AI.

There is a notable absence of regulations, standards, and global policy frameworks addressing the use and risks of AI in the public sector. National initiatives, including the Brazilian Artificial Intelligence Plan 2024–2028 and Chile's 2021 National AI Policy, provide broader frameworks within which

implementation may occur. Their existence, however, does not by itself establish how coordination, oversight, or responses to operative problems function in practice.

In Brazil's health sector, the applications examined show coordination across federal agencies, hospitals, universities, technology companies, civil society organizations, and municipal governments. Examples include the MCTIC–HFA–RNP–Instituto Laura agreement, cooperation between INSS and Dataprev, the PROADI-SUS partnership with Hospital Israelita Albert Einstein, and plans to integrate federal procurement and teleconsultation systems. In several cases, however, geographic expansion remains planned rather than fully implemented.

Overall, the examined materials provide clearer accounts of coordination supporting AI deployment than of arrangements addressing its collective operative risks.

Political Capacity

Across both health and justice sectors, systemic political capacity emerges as one of the weakest dimensions of AI adoption. In health, this weakness may reflect the rapid and relatively recent introduction of AI technologies, which has outpaced the development of broader governance arrangements. This finding is particularly relevant given that Wu et al. (2015) identify systemic political capacity as fundamental to supporting and steering other policy capacities. Brazil stands as a notable exception, having established a sector-specific regulatory framework through National Council of Justice (CNJ) Resolution No. 332/2020. Together, these findings suggest that AI adoption is advancing faster than the institutional normative capacities needed to ensure its effective, sustainable, and accountable implementation.

P7. Individual Political Capacity for AIA involves the capacity to navigate AI-enabled work, maintaining or restoring trust among citizens, and address distrust or lack of confidence from users following AI failures.

Political capacity at individual level represented a challenge to identify using the data collected. However, these capacities were invoked in a few cases. Argentina's *Chat Crecer AIA* involved the deployment of 10 university students enrolled as digital literacy instructors aimed to resolve initial questions, addressing objections and difficulties during the AIA's design. While this action could have enabled the maintenance of citizen's trust in the AIA, no further evidence was collected on how health officials would have handled any disputes or distrust following AIA's possible failures.

The TFN's (*Tribunal Fiscal de la Nacion - National Tribunal*) AIA works with administrative acts, appeals, and responses to grievances, and adapts to the style of each individual chamber -*Vocalía*-. Officials' work flows cross several safeguards. First, the AIA's is limited to make summaries of the facts, the arguments of the parties, the cited case law and regulations; reasoning features are disabled. The AIA's outcomes are in editable format along with a watermark "AI production - revision required", which then needs human intervention to finalize the document.

PretorIA in Colombia is an AIA implemented by the Constitutional Court of Colombia to support the process of selecting and reviewing actions (*tutelas*). The selection process works under a supervised machine learning model using previously -selected by a judge- criteria to both training and executing to select actions. This gives judges more time to study cases by diminishing the time devoted to select them.

While these are good accounts of how public servants navigate an IA-enabled workflow along certain safeguards, there is still a lack of precision around how to identify, reverse, mitigate or address possible AI failures.

P8. Organizational Political Capacity for AIA involves coordinating with allied organizations to build legitimacy towards policy objectives while addressing public concerns and responding effectively to AI failures.

Technical examples of organizational political capacity are seen in Brazil with the Supreme Federal Court who allied with the Secretariat for Information Technology (STI) and the Court's Precedent Management (SPR) to form an Artificial Intelligence Advisory unit to unveil the AIA named VitorIA. This AIA was designed to amplify the capacity to process legal cases, eliminate duplication and offer more transparency around the judicial process.

Also in Brazil's health sector, the AIA Laura, designed to provide early alerts of clinical deterioration of patients originated from a signed agreement between the Laura Fressatto Institute, the Armed Forces Hospital (HFA), the Ministry of Science, Technology, Innovations and Communications (MCTIC), and the National Education and Research Network. The agreement forms part of an initiative aimed for the future implementation of these technologies in public, university, and philanthropic hospitals across Brazil, with the goal of improving patient care in Intensive Care Units (ICUs).

Political capacity at organizational level was seen too in Argentina´s health sector where a joint initiative between the Undersecretariat for Digital Government and the National Directorate for Maternity and Childhood of the Ministry of Health gave birth to the Chat-Crecer. An AIA designed to accompany the maternity processes of women in Argentina.

A normative dimension within the Political capacity at organizational level should address concerns of the public effectively. In this sense, in Chile's Justice sector, the AIA Telesalud reports conducting satisfaction surveys reaching feedback from 2.5 thousands users along with accounts of undergoing preparatory phases of algorithmic accountability and risk prevention, however there is no evidence of any specialized team or audit involved for further monitoring along the service network.

Perhaps one of the best examples is the ARPHAI AIA in Argentina which illustrates the normative dimension of organizational political capacity by explicitly prioritizing equity, particularly gender equity, through bias mitigation, responsible data management, and diverse working teams along a healthcare network of units in Buenos Aires and the Rioja province. The AIA development also involved intergovernmental coordination, institutional safeguards for health data protection, and an independent ethical oversight.

P9. System Political Capacity involves establishing sector-wide regulatory and governance frameworks that steer AI implementation while mitigating associated risks.

The Justice sector in Colombia has increased its political capacity at the system level by endorsing a set of regulations coming from international organization's recommendations. Furthermore, the regulatory framework offered by CONPES 3975 established guidelines on ethical frameworks, inclusion, cybersecurity, testing environments, and data governance. Evidence seen across the studied AIA in Colombia does not suggest these frameworks to apply systematically.

On the other hand, several AIA in Brazil's Justice sector provides a more robust example of the normative political capacity at the system level. Evidence note that several AIA such as Gemini, Amon, Victor, VictorIA were founded under the frame of the CNJ (National Justice Council) resolution No. 332/2020 which among many other things regulates the use of artificial intelligence in the Brazilian Judiciary system, also framed under the National Artificial Intelligence Strategy (EBIA) of the federal government. The 332/2020 resolution covers general aspects of AIA such as respect for fundamental rights, non-discrimination, openness and transparency, governance and quality, security, user control, research, development, and implementation of artificial intelligence services, and accountability. It

promotes ethics, transparency, and governance in the production and use of artificial intelligence within the Judiciary, and establishes other measures. The resolution follows the same recommendation path founded in a previous white-paper regulatory exercise performed previously in the year 2020 in the Europe Commission.

Discussion

We examined which policy capacities public organizations mobilize to implement artificial intelligence applications (AIA) in Latin America. AI offers benefits for public services while introducing risks to public value. The two-dimensional Policy Capacity Framework (PCF) provides limited scope for distinguishing capacities that support technical deployment from those that safeguard public value. We propose a third dimension, *Policy Normative Orientation*, to make this distinction explicit and contribute to efforts to give democratic governance greater attention in policy studies. The distinction allows us to assess whether the capacities that enable adoption also equip institutions to protect the public values at stake.

Our findings indicate that public organizations prioritize technical capacities for experimentation, pilot projects, and systems integration. The normative portfolio remains less developed, particularly in algorithmic oversight, risk management, monitoring, bias detection, accountability, and performance evaluation. This pattern contrasts with the Council of Europe's approach to AI governance in judicial systems, which brings together regulatory instruments, assessment tools, guidelines, monitoring, and a Cyberjustice Taskforce (EC 2024). In the Latin American cases examined here, experimentation and technical integration generally preceded investment in more developed governance arrangements.

The evidence suggests that organizational and individual capacities for AI adoption can emerge from the bottom up as public officials seek greater efficiency. Building a normative portfolio appears to depend more heavily on political direction and coordination from the top. From an organizational learning perspective, this sequencing creates a governance gap. As public organizations learn to deploy AI, they may expose themselves and the people they serve to avoidable institutional and ethical risks if they develop safeguards only after implementation matures. Normative capacities therefore belong in the initial stages of adoption.

Systemic political capacity appears particularly important in shaping the normative portfolio. In health, national strategies and policy frameworks promoting AI in Brazil and Chile appear to have influenced the capacities developed within their respective health systems. These soft-law instruments illustrate how systemic political capacity can give organizations a basis for developing their own governance arrangements. In justice, Brazil's Resolution No. 332/2020 addresses authorization, risk assessment, bias mitigation, transparency, and mandatory human oversight. Colombia's CONPES 3975 provides strategic guidance on ethics, data governance, cybersecurity, inclusion, and institutional coordination. Across the two justice cases, these system-level frameworks are associated with stronger documentary evidence of organizational analytical capacities and a more developed normative portfolio.

Improving data and algorithms can address some AI risks, but many arise from how public officials interact with these systems in practice. As public services adopt hybrid human–machine arrangements, decisions increasingly emerge from interactions between officials and algorithms. Automation bias, undue reliance on algorithmic recommendations, unclear accountability, and coordination problems therefore call for governance capacities that help officials scrutinize recommendations, clarify responsibilities, and coordinate responses when problems arise.

We found comparatively limited evidence of individual analytical, operational, and political capacities. This may reflect an early stage of implementation, when organizations are still identifying the competencies officials need to work with AI. It may also reflect the documentary sources, which primarily capture institutional initiatives and organizational arrangements. Investments in individual capabilities through university programs, professional certifications, specialized training, or national AI

education strategies therefore remain largely outside the scope of the analysis. Future research should use complementary sources to examine how public servants acquire and exercise these capabilities as AI becomes part of routine public service.

Conclusion

Democracy is the elephant in the room. It belongs at the center of policy studies. This article extends the Policy Capacity Framework by proposing *Policy Normative Orientation* as a distinct analytical dimension. Drawing on scholarship on public value and policy design, we argue that the consequences of policy capacity depend on the purposes it serves and the principles that govern its use. Governments can mobilize well-developed analytical, operational, and political capacities to advance or erode public value. Evaluating capacity therefore requires asking what governments can do, whose interests they serve, and how democratic principles, the rule of law, and human rights constrain their actions. These questions matter across institutional settings with different administrative resources, opportunities for public scrutiny, and safeguards against abuses of authority.

In health and justice, an agency may deploy artificial intelligence (AI) reliably and process cases more efficiently while having limited capacity to detect unequal effects, explain decisions, or provide meaningful avenues for review. The proposed dimension provides a basis for assessing whether institutions govern AI in ways that protect equitable access to health and justice, enable public scrutiny, and preserve accountability for decisions affecting people's rights. This assessment considers the governance of AI alongside the effectiveness with which public institutions deploy it.

Our analysis of AI adoption in the health and justice sectors across five Latin American countries finds that implementation creates demands for analytical, operational, and political capacities. The adoption of AI offers an opportunity to observe how public organizations build these capacities as a new technology enters routine policymaking. Across both sectors, public organizations tended to develop technical capacities for deployment, while capacities for mitigating risks, monitoring performance, and evaluating impacts against public values remained less developed. Although the mix of capacities varied across cases, AI adoption frequently required new forms of coordination, specialized expertise, organizational adaptation, and mechanisms for securing legitimacy and trust.

These findings underscore that institutional readiness for effective, ethical, and sustainable AI adoption includes the ability to govern its use as systems become embedded in public organizations. Future research should use detailed sectoral studies and longitudinal analyses to examine how AI adoption and policy capacities evolve together over time and how the balance between technical and normative capacities changes.

Acknowledgements

Authors would like to thank our team of research assistants.

Conflict of interest statement

We declare to have no conflict of interest.

References

Alon-Barkat, S., & Busuioc, M. (2023). Human–AI interactions in public sector decision making: "automation bias" and "selective adherence" to algorithmic advice. *Journal of Public Administration Research and Theory*, *33*(1), 153-169.

Ball, S. (2025). Doing the right thing, not just doing the thing right: The importance of explicitly ethical policy advice. *Australian Journal of Political Science*, *60*(2), 163-176.

Bartels, L. M. (2023). Democracy erodes from the top: Leaders, citizens, and the challenge of populism in Europe. Princeton University Press.

Bignami, F. (2022). Artificial intelligence accountability of public administration. *The American Journal of Comparative Law*, *70*(Supplement_1), i312-i346.

Bovens, M., t' Hart, P., & Kuipers, S. (2008). The Politics of Policy Evaluation. In R. Goodin, M. Moran, and M. Rein (Eds.), *The Oxford Handbook of Public Policy* (pp. 319-335). Oxford University Press.

Bozeman, B., Molina Jr, A. L., & Kaufmann, W. (2018). Angling for sharks, not pilot fish: Deep corruption, venal corruption, and public values failure. *Perspectives on Public Management and Governance*, *1*(1), 5-27.

Bracci, E. (2023). The loopholes of algorithmic public services: An "intelligent" accountability research agenda. *Accounting, Auditing & Accountability Journal*, *36*(2), 739-763.

Brand, D. (2022). Responsible artificial intelligence in government: Development of a legal framework for South Africa. *JeDEM: eJournal of eDemocracy and Open Government, 14*(1), 130–150. https://doi.org/10.29379/jedem.v14i1.678

Broecke, S. (2023). Artificial intelligence and the labour market: Introduction. *OECD Employment Outlook*, 93-101.

Brynjolfsson, E., & Ng, A. (2023). Big AI can centralize decision-making and power, and that's a problem. In B. Prud'homme, C. Régis and G. Farnadi (Eds), *Missing links in AI Governance* (pp. 66-87). UNESCO.

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, *3*(1), 2053951715622512

Busuioc, M. (2021). Accountable artificial intelligence: Holding algorithms to account. *Public Administration Review*, *81*(5), 825-836.

Cairney, P (2023) The politics of policy analysis: theoretical insights on real world problems, Journal of European Public Policy, 30:9, 1820-1838

Cao, L. (2022). Decentralized ai: Edge intelligence and smart blockchain, metaverse, web3, and desci. *IEEE Intelligent Systems*, *37*(3), 6-19.

Capano, G., & Howlett, M. (2020). The knowns and unknowns of policy instrument analysis: Policy tools and the current research agenda on policy mixes. *Sage Open*, *10*(1), 2158244019900568.

Carney, M., Webster, B., Alvarado, I., Phillips, K., Howell, N., Griffith, J., Jongejan, J., Pitaru, A., & Chen, A. (2020). Teachable machine: Approachable web-based tool for exploring machine learning

classification. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–8).

Cella, L., Çınar, I., Stokes, S., & Uribe, A. (2026). Building Tolerance for Backsliding by Trash-Talking Democracy: Theory and Evidence From Mexico. *Comparative Political Studies*, 59(6), 1226-1253.

Cho, W., Fan, Z., & Zheng, Y. (2026). Artificial intelligence across the public administration system: Public values, institutions, and bureaucrats in the algorithmic age *Global Public Policy and Governance*, *6*, 103-123.

Cobbe, J., & Singh, J. (2020). Reviewable automated decision-making. *Computer Law & Security Review*, *39*, j.clsr.2020.105475.

Contini, F. (2020). Artificial intelligence and the transformation of humans, law and technology interactions in judicial proceedings. *Law, Technology and Humans, 2*(1), 4–18. https://doi.org/10.5204/lthj.v2i1.1478

Council of Europe (2024). Council of Europe opens first ever global treaty on AI for signature. Newsroom September 2024 retrieved in 9th November 2026: https://www.coe.int/en/web/portal/-/council-of-europe-opens-first-ever-global-treaty-on-ai-for-signature

DeLeon, P. (1995). Democratic values and the policy sciences. *American Journal of Political Science*, *39*(4), 886-905.

de Sousa, W. G., de Melo, E. R. P., Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. *Government Information Quarterly*, *36*(4), 101392.

Dryzek, J. S. (1989). Policy sciences of democracy. *Polity*, *22*(1), 97-118.

Easton, D. (1950). Harold Lasswell: Policy scientist for a democratic society. *The Journal of Politics*, *12*(3), 450-477.

Erman, E., & Furendal, M. (2024). Artificial intelligence and the political legitimacy of global governance. *Political Studies*, *72*(2), 421-441.

Fink, K. A. (2018). Opening the government's black boxes: Freedom of information and algorithmic accountability. *Information, Communication & Society, 21*(10), 1453–1471.

Foa, R.S., & Mounk, Y. (2016). The Danger of Deconsolidation: The Democratic Disconnect. *Journal of Democracy* 27(3), 5-17.

Fountain, J. E. (2001). The virtual state: Transforming American government? *Nat'l Civic Rev., 90*, 241-251.

Franzke, A. S., Muis, I., & Schäfer, M. T. (2021). Data Ethics Decision Aid (DEDA): A dialogical framework for ethical inquiry of AI and data projects in the Netherlands. *Ethics and Information Technology*, *23*(3), 551-567.

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.

Giest, S., & Grimmelikhuijsen, S. (2020). Introduction to special issue algorithmic transparency in government: Towards a multi-level perspective. *Information Polity*, *25*(4), 409-417.

Gupta, R., Goldstone, L., Eisen, S., Ramachandram, D., Cassata, A., Fraser, R. D., ... & Allport, J. (2023). Towards an AI-based objective prognostic model for quantifying wound healing. *IEEE Journal of Biomedical and Health Informatics*, *28*(2), 666-677.

Gutiérrez, J. D., Castellanos-Sánchez, M., Muñoz-Cadena, S. y Peralta, D. S. (2026). "Sistemas de inteligencia artificial en el sector público de América Latina y el Caribe (*Versión V3.1*)" [Data set]. Universidad de los Andes. https://algoritmos.uniandes.edu.co/sistemas-de-ia-en-america-latina

Halpern, C. (2021). Policy Solution Ownership: Road-Space Re-Allocation as a New Approach to Urban Mobility. En P. Zittoun, F. Fischer, & N. Zahariadis (Eds.), The Political Formulation of Policy Solutions (1a ed., pp. 173–190). Bristol University Press.

Herd, P., & Moynihan, D. P. (2018). *Administrative burden: Policymaking by other means*. Russell Sage Foundation.

Henman, P. (2020). Improving public services using artificial intelligence: Possibilities, pitfalls, governance. *Asia Pacific Journal of Public Administration*, *42*(4), 209-221.

Höddinghaus, M., Sondern, D., & Hertel, G. (2021). The automation of leadership functions: Would people trust decision algorithms? *Computers in Human Behavior*, 116, 106635.

Howlett, M., & Leong, C. (2022). The "inherent vices" of policy design: Uncertainty, maliciousness, and noncompliance. *Risk Analysis*, 42(5), 920-930.

Howlett, M., Leong, C., & Legrand, T. (2025). *Bad public policy: Malignity, volatility and the inherent vices of policymaking*. Cambridge University Press.

Ingram, H., deLeon, P., & Schneider, A. L. (2016). Conclusion: Public policy theory and democracy: The elephant in the corner. En B. G. Peters & P. Zittoun (Eds.), *Contemporary approaches to public policy: Theories, controversies and perspectives* (pp. 175–200). Palgrave Macmillan. https://doi.org/10.1057/978-1-137-50494-4

Jørgensen, T. B., & Bozeman, B. (2007). Public values: An inventory. *Administration & Society*, *39*(3), 354-381.

Jørgensen, A. M., & Nissen, M. A. (2022). Making sense of decision support systems: Rationales, translations and potentials for critical reflections on the reality of child protection. *Big Data & Society*, *9*(2), 20539517221125163.

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), 101976.

Legrand, T., & Moon, M. J. (2025). Malignity in policy sciences: A theory and framework. *Policy and Society*, *44*(2), 129-135.

Liu, X., He, P., Chen, W., & Gao, J. (2019). Improving multi-task deep neural networks via knowledge distillation for natural language understanding. arXiv preprint arXiv:1904.09482.

Liu, Y., Lu, Q., Zhu, L., & Paik, H. Y. (2024). Decentralised governance for foundation model based AI systems: exploring the role of blockchain in responsible AI. *IEEE Software*, *41*(5), 34-42.

Mannes, A. (2020). Governance, risk, and artificial intelligence. *Ai Magazine*, *41*(1), 61-69.

Margalit, Y., & Raviv, S. (2026). The politics of using AI in policy implementation: Evidence from a field experiment. *British Journal of Political Science*, *56*, e13.

McConnell, A. (2018). Hidden agendas: Shining a light on the dark side of public policy. *Journal of European Public Policy*, *25*(12), 1739-1758.

Meijer, A., & Bekkers, V. (2015). A metatheory of e-government: Creating some order in a fragmented research field. *Government Information Quarterly*, *32*(3), 237-245.

Mergel, I., Dickinson, H., Stenvall, J., & Gasco, M. (2024). Implementing AI in the public sector. *Public Management Review*, 1–14.

Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, *36*(4), 101385.

Montes, G. A., & Goertzel, B. (2019). Distributed, decentralized, and democratized artificial intelligence. *Technological Forecasting and Social Change*, *141*, 354-358.

Moore, M.H. (1995) *Creating public value: Strategic management in government.* Harvard University Press.

Munoz-del-Campo, N. (2026). Rethinking policy capacity: integrating deontological and human dimensions. Policy Sci. https://doi.org/10.1007/s11077-026-09626-8

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.

Nguyen-Trung, K., & Friese, S. (2026). Towards a methodologically congruent framework for GenAI use in nonpositivist qualitative research. *International Journal of Social Research Methodology*, 1–22.

Oder, N. & Béland, D. (2025). Artificial intelligence, emotional labor, and the quest for good work in the public sector. *Policy and Society*, *44*(1), 116–132.

Pande, D., Khanal, S., & Taeihagh, A. (2025). Conceptualising public trust in high-risk AI policymaking: A comparative analysis of Seoul, Singapore and Tokyo. *Journal of Comparative Policy Analysis: Research and Practice, 27*(5-6), 578-602.

Peeters, R., G. Lotta y F. Nieto Morales (Eds.). (2024). *Street-level bureaucracy in weak state institutions.* Policy Press.

Plantinga, P., Shilongo, K., Mudongo, O., Umubyeyi, A., Gastrow, M., & Razzano, G. (2024). Responsible artificial intelligence in Africa: Towards policy learning. *Data & Policy, 6*, e72.

Radu, R. (2021). Steering the governance of artificial intelligence: National strategies in perspective. *Policy and Society*, *40*(2), 178-193.

Rakova, B., Yang, J., Cramer, H., & Chowdhury, R. (2021). Where responsible AI meets reality: Practitioner perspectives on enablers for shifting organizational practices. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW1), 1-23.

Riccucci, N. M. (2001). The" old" public management versus the" new" public management: Where does public administration fit in? *Public Administration Review*, *61*, 172.

Redden, J., Dencik, L., & Warne, H. (2020). Datafied child welfare services: Unpacking politics, economics and power. *Policy Studies*, *41*(5), 507-526.

Robinson, S. C. (2020). Trust, transparency, and openness: How inclusion of cultural values shapes Nordic national public policy strategies for artificial intelligence (AI). *Technology in Society, 63*, 101421.

Sætra, H. S. (2020). A shallow defence of a technocracy of artificial intelligence: Examining the political harms of algorithmic governance in the domain of government. *Technology in Society*, *62*, 101283.

Salah, M., & Alnoor, A. M. (2026). Agentic AI, Street-Level Bureaucracy, and the Recomposition of Discretion in Public Administration: From Human Judgment to human–Machine Co-Discretion. *International Journal of Public Administration*, 1–5.

Selten, F., & Meijer, A. (2021). Managing algorithms for public value. *International Journal of Public Administration in the Digital Age, 8*(1), 1-16.

Schneider, A., & Ingram, H. (1993). Social construction of target populations: Implications for politics and policy. *American Political Science Review*, *87*(2), 334-347.

Taeihagh, A. (2025). Governance of generative AI. *Policy and Society*, *44*(1), 1-22.

Taeihagh, A., Ramesh, M., & Howlett, M. (2021). Assessing the regulatory challenges of emerging disruptive technologies. *Regulation & Governance*, *15*(4), 1009–1019.

Tallberg, J., Erman, E., Furendal, M., Geith, J., Klamberg, M., & Lundgren, M. (2023). The global governance of artificial intelligence: Next steps for empirical and normative research. *International Studies Review*, *25*(3), viad040.

Thomas, G. (2011). A typology for the case study in social science following a review of definition, discourse, and structure. *Qualitative inquiry*, *17*(6), 511-521.

Tyler, C., Akerlof, K. L., al-Gharbi, M., Bedsted, B., Boeira, L., Brown, T., Christopherson, E., Scheufele, D. A., Farooque, M., Head, B. W., Piquado, T., & Pedersen, D. B. (2026). Six ways to put the public at the heart of science and policy. *Nature*, 655(8121), 34–37.

Weiss, D., Rydland, H. T., Øversveen, E., Jensen, M. R., Solhaug, S., & Krokstad, S. (2018). Innovative technologies and social inequalities in health: A scoping review of the literature. *PLOS ONE, 13*(4), Article e0195447.

Wellstead, A. & Howlett, M. (2026). Capacity for what? Elon Musk's DOGE, public value destruction and the darkside of policy capacity. *Public Administration and Policy*, *29*(1), 8-21.

Wellstead, A. M., Mechling, S. M., Carter, A., & Gofen, A. (2024). Artificial intelligence possibilities to improve analytical policy capacity: The case of environmental policy innovation labs and sustainable development goals. *Policy Design and Practice*, *7*(4), 456–467.

Woo, J. J., Ramesh, M., & Howlett, M. (2015). Legitimation capacity: System-level resources and political skills in public policy. *Policy and Society*, *34*(3-4), 271-283.

Wu, X., Ramesh & Howlett. (2015). Policy capacity: A conceptual framework for understanding policy competences and capacities. *Policy and Society*, *34*(3-4),165–171.

Wuttke, A., Jungherr, A., & Rauchfleisch, A. (2026). Artificial intelligence in government: Why people feel they lose control. *Journal of European Public Policy*, 1–25.

Yilmaz, R., & Yilmaz, F. G. K. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. *Computers and Education: Artificial Intelligence*, *4*, 100147.

Yin, R. K. (2009). *Case study research: Design and methods* (4th ed.). SAGE Publications.

Yuan, Q., & Chen, T. (2025). Holding AI-based systems accountable in the public sector: A systematic review. *Public Performance & Management Review*, *48*(6), 1389-1422.

Yusuf, A., Bello, S., Pervin, N., & Tukur, A. K. (2024). Implementing a proposed framework for enhancing critical thinking skills in synthesizing AI-generated texts. *Thinking Skills and Creativity*, *53*, 101619.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix1.HumanValidatedAIassisteddocumentscrapping.pdf
- Appendix4.1HealthSectorAIA.pdf
- Appendix4.2JusticiaSectorAIA.pdf
- Appendix2.PromptEnglishandSpanishoriginalversion.pdf
- Appendix3.AIOutputenglish.pdf
- Appendix3.IAoriginalespanol.pdf