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Human and Institutional Capacity in Public Sector AI Adoption: Evidence from OPSI Cases and TACT

Kamu Sektöründe Yapay Zekâ Benimsenmesinde Beşerî ve Kurumsal Kapasite: OPSI Vakaları ve TACT Çerçevesinde bir Bir İnceleme

ABSTRACT

This study examines how institutional capacity and human capacities shape the realization of artificial intelligence (AI) affordances and constraints in public sector organizations. Drawing on 143 AI-related case studies from the OECD Observatory of Public Sector Innovation (OPSI), the research adopts a three-stage inductive analytical approach combining descriptive mapping, qualitative coding, and theory-informed interpretation. The analysis is grounded in Technology Affordances and Constraints Theory (TACT), which conceptualizes technological effects as relational and context-dependent. The findings reveal that AI initiatives in the public sector primarily enable process automation, predictive analytics, and decision support, while implementation is frequently constrained by data limitations, skills shortages, legal uncertainty, and organizational fragmentation. Based on the findngs, these affordances and constraints are shown to emerge through socio-technical interactions shaped by governance arrangements, organizational routines, and professional competencies. Rather than functioning as static prerequisites, institutional and human capacities evolve through iterative processes of learning and adaptation. By providing large-scale comparative evidence, this study advances a relational understanding of capacity in public sector AI adoption and demonstrates the analytical value of curated innovation case repositories. The findings offer theoretical insights for research on digital governance and practical guidance for policymakers seeking to design sustainable and capacity-sensitive AI strategies.
Keywords: Artificial Intelligence, Public Sector Innovation, Institutional Capacity, Human Capacity, Technology Affordances and Constraints Theory (TACT), OECD OPSI.

ÖZ

Bu çalışma, kamu kurumlarında yapay zekâ uygulamalarının sunduğu imkânlar ve karşılaşılan sınırlılıkların kurumsal kapasite ve insan kapasitesi tarafından nasıl şekillendirildiğini incelemektedir. Araştırma, OECD Kamu Sektörü İnovasyon Gözlemevi (OPSI) tarafından derlenen 143 yapay zekâ odaklı vaka çalışmasına dayanmaktadır. Çalışmada betimleyici analiz, nitel kodlama ve teori temelli yorumlamayı birleştiren üç aşamalı tümevarımsal bir yöntem benimsenmiştir. Analiz, Teknoloji İmkânları ve Sınırlılıkları Teorisi (TACT) çerçevesinde yürütülmüştür. Bulgular, kamu sektöründeki yapay zekâ projelerinin ağırlıklı olarak süreç otomasyonu, öngörü analitiği ve karar destek mekanizmalarını güçlendirdiğini, ancak veri altyapısı eksiklikleri, beceri yetersizlikleri, hukuki belirsizlikler ve örgütsel parçalanma gibi faktörlerin projelerin başarısını sınırlandığını göstermektedir. Çalışmada bu imkânların ve sınırlılıkların, yönetişim yapıları, kurumsal rutinler ve mesleki yetkinlikler tarafından şekillenen sosyo-teknik etkileşimler sonucunda ortaya çıktığı saptanmıştır. Çalışma, kamu sektöründe yapay zekâ benimsemesinde kapasitenin ilişkisel ve dinamik bir unsur olduğunu ortaya koymakta ve politika yapıcılar için sürdürülebilir yapay zekâ stratejilerine yönelik önemli çıkarımlar sunmaktadır.
Anahtar Kelimeler: Yapay Zeka, Kamu Sektörü İnovasyonu, Kurumsal Kapasite, İnsan Kapasitesi, Teknoloji Olanakları ve Kısıtlamaları Teorisi (TACT), OECD OPSI.

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Introduction

In recent years, artificial intelligence (AI) has become an increasingly prominent component of public sector reform agendas, driven by expectations of improved efficiency, enhanced decision-making, and more responsive public services. Governments across the world are experimenting with AI-based systems in areas ranging from service delivery and regulatory enforcement to risk prediction and policy design (Berryhill et al., 2019; Selten & Klievink, 2024). At the same time, international organizations and policy networks have developed normative and regulatory frameworks to promote responsible and trustworthy AI in government, emphasizing transparency, accountability, and human-centred governance (OECD, 2019; UNESCO, 2022).

Despite growing political commitment and technological investment, empirical evidence suggests that AI adoption remains uneven and fragile within governmental departments[1][2][3] (Min, 2026; Aldane, 2025; Larson et al., 2024). Many initiatives fail to scale, encounter institutional resistance, or struggle to deliver sustainable public value (Nikiforova et al., 2025; Maragno et al., 2023). Existing research increasingly recognizes that these challenges cannot be explained solely by technical limitations. Instead, they are closely linked to the institutional environments, governance arrangements, and professional capacities within which AI systems are developed and implemented (Kaur et al., 2022; Anomah, 2025).

Accordingly, recent scholarship has emphasized the importance of institutional and human capacity as central determinants of AI adoption outcomes in the public sector. In this sense, "institutional capacity" encompasses regulatory frameworks, coordination mechanisms, data infrastructures, and organizational routines that enable public organizations to govern and integrate AI technologies (Anomah, 2025; Madan and Ashok, 2022). "Human capacity" also refers to the skills, expertise, and professional competencies required to design, manage, interpret, and oversee AI systems (OECD, 2026). However, while these concepts are widely acknowledged, empirical research has rarely examined how such capacities emerge, interact, and shape AI implementation in practice across diverse organizational contexts.

Moreover, much of the existing literature relies on predefined readiness indicators or survey-based assessments, which risk overlooking informal practices, contextual adaptations, and ongoing learning processes that characterize real-world implementation; consistent with this concern, recent taxonomies of responsible AI adoption challenges highlight that organizational and environmental dimensions often fall outside the scope of traditional readiness models (Nikiforova et al., 2025).

Against this background, this study examines how institutional and human capacities shape the realization of AI-related affordances and constraints in public sector organizations. Drawing on 143 AI-related case studies from the OECD Observatory of Public Sector Innovation (OPSI) Case Study Library, the research adopts an inductive, qualitative research design grounded in systematic document analysis. The analysis is theoretically informed by Technology Affordances and Constraints Theory (TACT), which conceptualizes technological effects as relational and context-dependent outcomes of socio-technical interaction (Majchrzak & Markus, 2013; Leonardi, 2011).

The study pursues three main objectives. First, it maps the structural characteristics of documented public sector AI initiatives in terms of geography, timing, governance level, and technological orientation. Second, it identifies recurring patterns of AI-enabled actions and implementation constraints through inductive qualitative coding of case narratives. Third, it

[1] Despite progress in AI adoption, the UK public sector remains inconsistent; while 37% of staff have received training, many still lack the necessary infrastructure and approved tools to use it effectively.

[2] According to the Public Accounts Committee, a lack of uniform expertise has caused fragmented AI adoption across the UK public sector. Use cases range significantly between departments, from dozens in Business and Trade to only a handful in the Treasury and Housing departments.

[3] While the U.S. Department of Defense usually handles a minority of federal IT spending, it currently commands the vast majority (70–90%) of AI contracts, according to the report from Brookings.

interprets these patterns through the lens of TACT to explain how institutional and human capacities mediate the emergence of affordances and constraints.

By integrating large-scale descriptive mapping with theory-informed qualitative analysis, this study contributes to the literature in three ways. Empirically, it provides one of the most comprehensive cross-case examinations of public sector AI initiatives to date. Conceptually, it advances a relational understanding of capacity as a constitutive element of AI implementation processes. Methodologically, it demonstrates the value of inductive analysis of curated innovation case repositories for studying emerging governance challenges. In doing so, the study offers evidence-based insights for scholars and policymakers seeking to design more sustainable and capacity-sensitive approaches to AI adoption in the public sector.

The remainder of this article is structured as follows. The next section outlines the conceptual background, focusing on institutional and human capacity, as well as the theoretical foundations of TACT. This is followed by a detailed description of the research design, data sources, and analytical procedures. The subsequent section presents the empirical findings, including descriptive patterns and inductively derived thematic categories. These findings are then interpreted through a theory-informed discussion that highlights their implications for public sector AI governance and capacity development. The article concludes by summarizing the main contributions, acknowledging limitations, and outlining directions for future research.

1. Institutional and Human Capacity for AI Adoption in the Public Sector

The adoption of artificial intelligence in the public sector extends beyond technological acquisition and requires substantial institutional and human capacities to ensure effective, legitimate, and sustainable implementation. Existing research emphasizes that public sector AI initiatives are embedded within complex organizational, legal, and socio-political environments that shape how technological systems are adopted (Selten and Klievink, 2024: 12).

The conceptual framework for institutional capacity employed here is rooted in the literature of political science, sociology, and economics regarding “state capacity.” Specifically, it draws on Mann’s (1984) conceptualization of infrastructural power, which describes a state’s logistical ability to execute political decisions across its entire territory and the influence of government agencies. What Mann’s argument makes the most applicable for the conceptualization is that these logistical techniques are not specific to state. They are part of the growth of any social unit aiming to increase “capacities for collective social mobilization of resources” (Mann, 1984:193). In terms of AI adoption in the public sector, institutional capacity refers to the formal and informal structures, regulatory frameworks, coordination mechanisms, technical readiness, organizational routines and strategic leadership structures that enable public organizations to govern and integrate AI systems into administrative processes (Anomah, 2025: 2-3). Strong institutional capacity is expected to facilitate alignment between technological innovation and public sector dynamics such as strategic priority setting, regulatory coherence, data governance arrangements, and inter-organizational coordination, thereby enabling public organizations to integrate and sustain innovation effectively within their core missions (Kaur et al., 2022, 23-26).

In parallel, human capacity encompasses the skills, expertise, and professional competencies required to develop, manage, and evaluate AI systems. This includes not only technical capabilities in data science and machine learning, but also interdisciplinary competencies related to ethics, law, public management, and policy analysis (OECD, 2026: 4). In public sector contexts, human capacity is particularly important due to the need to balance innovation with regulatory compliance and societal expectations

Recent studies highlight that deficiencies in either institutional or human capacity can significantly constrain AI adoption, regardless of technological sophistication (Misra et al., 2023; Campion et al., 2022; Alshahrani et al., 2022). Limited data infrastructure, fragmented governance arrangements, and weak inter-agency coordination often undermine implementation efforts; these systemic challenges are identified as barriers in responsible AI adoption taxonomies that highlight data-related obstacles, governance weaknesses, and organizational misalignments in public sector settings (Nikiforova et al., 2025: 1). Similarly, attaining the potential benefits of AI in the public sector is challenged by the complexity of the field and its steep learning curve, indicating that governments often encounter capacity limitations in workforce readiness and organizational adaptation when translating AI capabilities into operational practice (Berryhill et al., 2019: 3).

Importantly, institutional and human capacities are interdependent and co-evolving. Organizational routines and governance structures influence how skills are developed and deployed, while professional competencies shape institutional adaptation and reform trajectories — a relational dynamic observed in socio-technical studies of organizational change, where technological configurations and institutional infrastructures mutually shape each other (Leonardi, 2011; Straub et al., 2023; Larsen, 2021). Rather than functioning as static preconditions, capacities evolve through iterative processes of experimentation, learning, and institutionalization.

Within the public sector, capacity development is further shaped by political accountability, public trust, and legal constraints. Governments are expected to ensure that AI systems comply with principles such as fairness and human-centred values, transparency and explainability, and accountability and oversight, which places additional demands on both institutional governance and professional judgment (UNESCO, 2022). Consequently, AI adoption in government settings involves not only technical implementation but also continuous capacity-building to sustain legitimacy and social acceptance.

Taken together, the literature suggests that successful public sector AI adoption depends on the alignment between technological capabilities, institutional arrangements, and human expertise. Understanding how these capacities interact is therefore essential for explaining variations in AI implementation outcomes across organizational and national contexts.

2. Theoretical Framework: Technology Affordances and Constraints Theory (TACT)

The analysis is theoretically informed by Technology Affordances and Constraints Theory (TACT), as articulated by Majchrzak and Markus (2013). The concept of "affordances" was originally introduced within the field of ecological psychology by Gibson (1986: 134) to refer action possibilities provided to the actor by the environment. This concept was adapted to the information systems context by Majchrzak and Markus (2013) through their formulation of TACT, which argues that understanding the uses and consequences of technologies requires examining the dynamic interplay between individuals, organizations, and the technological artifact itself. In this framework, a "technology affordance" denotes a possible action that a person or organization is enabled to undertake through a particular technology, whereas a "technology constraint" refers to the ways in which the same actor may be restricted from achieving certain objectives when using that technology. The authors caution against conflating affordances with "technological features" (i.e., the functionalities embedded in the system), or constraints with "human and organizational attributes", such as tasks, capabilities, or needs.

From this perspective, technologies do not produce fixed or universal effects; instead, they generate affordances, defined as action potentials, and constraints, defined as limitations on action, which emerge through the interaction between technological features, organizational structures, and human actors. Consistent with Leonardi's (2011) concept of socio-technical interaction, these affordances and constraints are understood as relational and context-dependent phenomena that arise through the ongoing alignment of technological systems with organizational routines and human practices (Majchrzak and Markus, 2013: 833).

Within this framework, the effects of AI systems in public sector organizations are not treated as inherent technological properties but as outcomes of situated enactment processes shaped by institutional arrangements and professional competencies. Recent research applying TACT in public sector AI contexts further demonstrates that the realization of AI's potential depends fundamentally on socio-technical configurations and organizational readiness rather than on technical sophistication alone (Maragno et al., 2023). These observations provide the theoretical grounding for interpreting capacity not as an external variable, but as a constitutive element of how AI affordances and constraints are produced in practice.

In line with TACT, institutional and human capacities should be acknowledged as relational mediators rather than static attributes. This study conceptualizes institutional capacity as the dynamic ability of public organizations to structure, coordinate, and regulate the socio-technical conditions under which AI affordances and constraints emerge. Rather than constituting a fixed organizational resource, institutional capacity shapes how AI systems are selected, governed, monitored, and integrated into administrative processes. It encompasses the alignment of regulatory frameworks, accountability mechanisms, data governance arrangements, and inter-organizational coordination structures that condition how AI systems are enacted in practice.

Human capacity similarly refers to the professional competencies, interpretive judgment, and adaptive learning abilities that enable public officials to meaningfully engage with AI systems in decision-making, oversight, and implementation processes. However, consistent with a relational and socio-technical understanding, human capacity is not reducible to technical AI literacy alone. Its governance significance lies in how expertise is embedded within institutional routines, ethical standards, collaborative practices, and discretionary authority structures.

Accordingly, the institutional and human capacities defined above provide the analytical lens through which such misalignments can be understood, as they condition whether AI affordances are effectively enacted or instead materialize as constraints within specific organizational and governance settings.

3. Research Design and Methodological Approach

The main purpose of the study is to identify how institutional and human capacity features emerge empirically from documented public sector AI initiatives, rather than imposing predefined capacity categories derived from prior conceptual and theoretical analysis. In this respect, the research adopts a qualitative, inductive research design grounded in systematic document analysis. Inductive methods are particularly effective for exploratory research in emerging and still interesting fields where a scientific knowledge database has yet to be established (Bijker et al., 2024: 2). An inductive approach is, therefore, appropriate given the diversity and popularity of institutional contexts represented in public sector AI applications.

Instead of testing existing capacity frameworks, the study seeks to derive capacity-related dimensions from empirical descriptions, allowing patterns to emerge from the data itself. The empirical basis of the research consists of 143 case studies drawn from the OECD Observatory of Public Sector Innovation (OPSI) Case Study Library, all of which are explicitly tagged under the “Artificial Intelligence” innovation category.

The research intends to move beyond the technocentric reductionism found in common AI adoption narratives by focusing on how AI technologies are enacted within specific organizational and institutional contexts. Rather than measuring predefined capacity indicators, the study seeks to reveal how capacity-related dimensions are articulated and operationalized within real-world public sector AI initiatives as documented in the case narratives.

3.1. Data Source and Case Selection

The OPSI Case Study Library provides systematically documented descriptions of public sector innovation initiatives to disseminate and replicate good ideas. The case studies include contextual information on objectives and innovativeness, implementation processes, actors involved, beneficiaries, results and impacts, challenges encountered, conditions for success and lessons learned. The library contained 1,024 public sector innovation case studies as of January 27, 2026. The dataset used in this study comprises all AI-tagged innovations available at the time of data collection (N = 143) on November 22, 2025[4], thereby constituting a comprehensive and non-sampled corpus rather than a selective subset.[5]

The OPSI case study library as a primary data source fits in with the nature of this study not only by the richness of the case narratives, but also by the institutional credibility of the OECD as a producer of comparative policy knowledge. The cases are explicitly designed to capture organizational, institutional, and implementation-related aspects of innovation, rather than merely technical system features. This makes the data source particularly suitable for analysing how AI-related action possibilities and limitations emerge in practice.

3.2. Systematic Analytical Strategy

The analysis followed a three-stage inductive research strategy, designed to combine descriptive mapping of OECD OPSI AI Case Dataset (N = 143) followed by in-depth qualitative interpretation and theory-based abstraction. This sequential approach enables both an overview of structural patterns across cases and a detailed examination of how AI-related affordances and constraints are represented in practice. Figure 1 provides an overview of this sequential process and the role of each analytical stage.

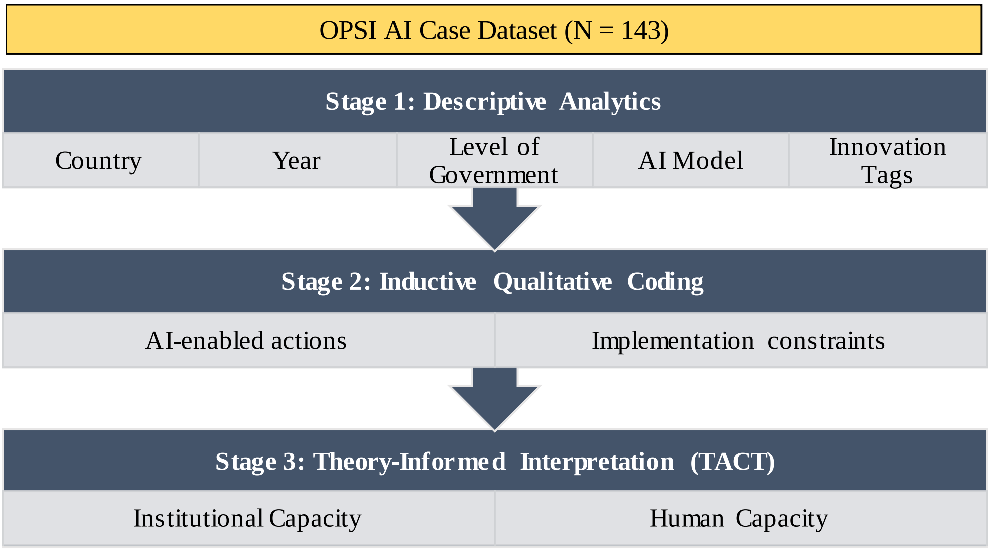

Figure 1. Three-Stage Analytical Strategy

3.2.1. Descriptive Mapping of Dataset

The first stage includes descriptive analytics conducted to systematically map the characteristics of the OPSI AI case corpus. This stage contextualized frequency of structural patterns without making analytical or causal claims. Specifically, descriptive statistics examined the distribution of cases by country, year of implementation, level of government (e.g. national, regional, local), type of AI model or technique used (where specified), and innovation tags associated with each case.

This mapping serves two methodological purposes. First, it unveils empirical scope and diversity of the dataset. Second, it provides a contextual grounding, ensuring that the inductive findings are interpreted in relation to the overall distribution and characteristics of AI initiatives in the OPSI database.

[4] A follow-up verification on January 27, 2026, confirmed that the number of AI-tagged cases remained unchanged at 143.

[5] The dataset can be retrieved for free from https://oecd-opsi.org/case_type/opsi/?_innovation_tags=artificial-intelligence-ai

3.2.2. Inductive Qualitative Coding of Case Narratives

The second stage was designed for a qualitative interpretation of the case narratives to identify textual references to AI-related action possibilities and limitations. Rather than applying predefined capacity indicators, the analysis focused on how AI use was described in relation to organizational practices and implementation experiences.

This approach reflects both the heterogeneous nature of the OPSI cases and the context-dependent character of capacity in public sector AI initiatives. Predefined indicators risk neglecting informal and practice-based forms of capacity that are central to understanding how AI-related affordances and constraints materialize in real-world settings. The qualitative coding targeted empirical expressions of: (i) actions enabled by AI applications, such as enhanced decision-making, automation of tasks, prediction, or personalization of services; and (ii) constraints encountered during implementation, including regulatory uncertainty, data governance challenges, skills shortages, or organizational resistance.

This inductive coding process allowed patterns to emerge directly from the case narratives, capturing how AI-based public sector innovations were described as shaping organizational and institutional conditions in practice.

3.2.3. Theoretical Interpretation Through the Lens of TACT

In the third stage, inductively identified patterns were interpreted by using TACT. This stage analytically grouped recurring themes to understand how institutional and human capacities mediated the realization or restriction of AI affordances across cases.

Institutional capacity was analyzed by regarding governance frameworks, coordination mechanisms, data infrastructures, and regulatory arrangements, while human capacity was examined through references to skills, expertise, professional roles, and interdisciplinary collaboration. This stage represents an abductive analytical move, linking empirically grounded observations to a socio-technical theoretical framework without imposing predefined assumptions about AI impacts.

Consistent with TACT's essential premise, understanding the uses and consequences of information systems requires attention to the dynamic interactions between people and organizations and the technologies they use (Majchrzak and Markus, 2012: 1). From this perspective, AI systems do not produce fixed or universal effects; rather, they give rise to affordances and constraints that emerge through these ongoing socio-technical interactions.

Given the narrative and secondary nature of the OPSI case material, the analysis does not capture the full dynamic unfolding of TACT processes but instead relies on inferential assessment based on how such interactions are narrated and reflected in the case descriptions. Employing TACT as an analytical lens still provides a suitable framework for examining OPSI cases, since case descriptions typically recount the problem context, the technological intervention, implementation processes, challenges encountered, and observed outcomes. Such narrative accounts do not merely document technical features; rather, they reveal how technologies are enacted within specific organizational settings, how public officials interpret and operationalize AI tools, and how institutional arrangements shape realized results. Instead of treating AI systems as possessing inherent effects, the TACT lens enables a relational examination of how technological potentials are activated, limited, or transformed within particular governance contexts. TACT allows for a structured interpretation of socio-technical alignment, institutional mediation, and the contingent realization of AI-driven innovation in the public sector.

3.3. Methodological Limitations

To provide a transparent guidance for future research in the field, the methodological limitations should be acknowledged. First, the analysis relies on secondary case descriptions produced by OPSI, which may vary in depth and emphasis across cases. As a result, some capacity-related dimensions may be underreported or unevenly documented. Second, the study focuses on descriptive and interpretive analysis rather than causal inference, and therefore does not claim to establish direct causal relationships between capacity factors and AI outcomes.

Despite these limitations, the comprehensive coverage of AI-related public sector cases and the application of a theoretically grounded, inductive analytical framework provide a robust basis for identifying shared capacity-related patterns across diverse institutional contexts. Moreover, as the OPSI cases are curated through OECD-led processes emphasizing transparency and comparability, the risk of systematic distortion in the reported experiences is limited, supporting cautious confidence in the dataset.

4. Findings: Descriptive Patterns and Capacity-Mediated Affordances and Constraints in Public Sector AI Initiatives

This section presents the empirical findings derived from the three-stage inductive analysis of the OPSI case narratives. It first reports descriptive patterns across the dataset and then examines the recurrent AI-enabled actions and implementation constraints identified through qualitative coding. The findings highlight how institutional and human capacities mediate the realization of technological affordances and shape implementation outcomes across diverse public sector contexts.

4.1. Stage 1: Descriptive Mapping of Public Sector AI Initiatives

The first stage of the analysis provides a descriptive overview of the OECD OPSI AI case dataset (N = 143) in order to contextualize subsequent qualitative interpretation.

4.1.1. Distribution of AI Case Narratives by Country

The cases are geographically diverse and cover a wide range of national contexts. However, a concentration is observed in a limited number of countries. The United Kingdom (UK) (11 cases) and Australia (10 cases) represent the most frequently documented contexts, followed by Korea (9), Colombia (8), Canada (8), Brazil (7), and the United States (USA) (7). Several Middle Eastern and Eastern European countries, including Saudi Arabia (6), the United Arab Emirates (UAE) (6), and Serbia (5), are also prominently represented.

Figure 2 presents the geographical distribution of AI-related public sector initiatives, highlighting the concentration of documented cases in a limited number of countries. This distribution suggests that documented public sector AI initiatives are concentrated in countries with relatively advanced digital government infrastructures and established innovation ecosystems, while still reflecting considerable cross-national variation.

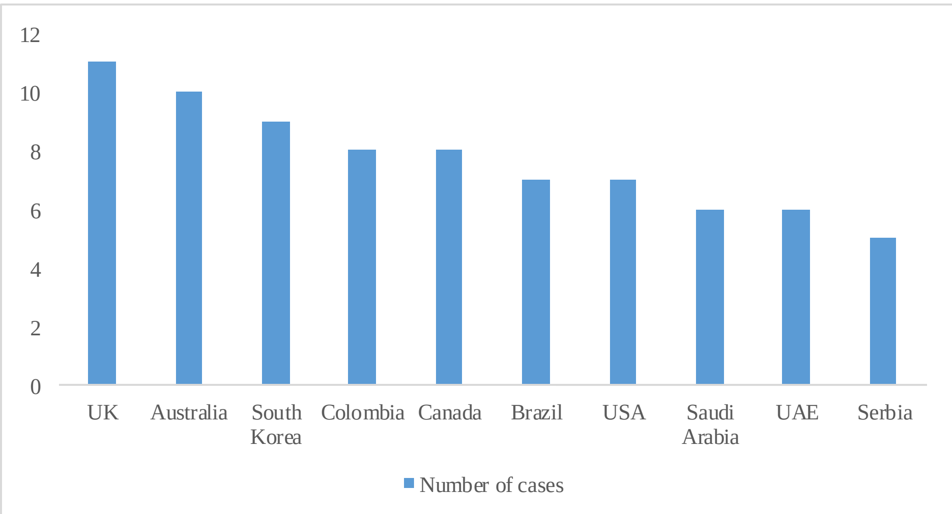

Figure 2. Top 10 Countries by Number of AI Cases

4.1.2. Time-Based Distribution of AI Cases

To capture temporal patterns in public sector AI adoption, Figure 3 presents the annual distribution of documented cases. The time-based distribution of cases indicates a marked increase in AI-related public sector initiatives after 2016. Only sporadic cases are observed before this period, whereas a rapid expansion occurs from 2017 onwards. A slight decline is observed after 2022, reflecting the partial lag in documenting more recent initiatives.

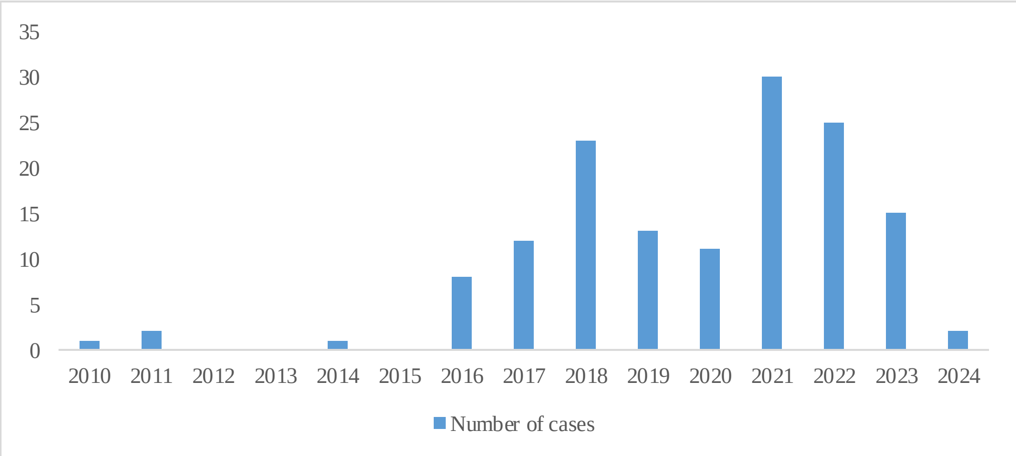

Figure 3. Distribution of AI Cases by Year

The highest concentration of cases appears between 2018 and 2022, with a peak in 2021 (30 cases) and sustained activity in 2022 (25 cases). This period is not surprising that the respective years coincide with a series of major global developments in artificial intelligence, reflecting intensified investment, governance commitments, indices and policy frameworks at the international level.

One of the most significant milestones was the emergence and institutionalization of multilateral AI governance initiatives. The Global Partnership on Artificial Intelligence (GPAI) was proposed at the G7 Summits in 2018 and 2019, and formally launched in June 2020 with the support of governments including Australia, Canada, France, India, Japan, the Republic of Korea, the United Kingdom, and the United States (Innovation, Science and Economic Development Canada, 2020). Hosted by the OECD, the GPAI now aims to promote the responsible development and use of artificial intelligence (AI) with its 44 member countries[6].

At the same time, OECD countries adopted the Recommendation on Artificial Intelligence, the *OECD AI Principles*[7], in May 2019. This was the first intergovernmental standard on AI and provided the basis for the G20 AI Principles endorsed by Leaders in June 2019. In the same period, the adoption of the *UNESCO Recommendation on the Ethics of Artificial Intelligence* in 2021 marked a major global milestone in establishing shared normative principles for responsible AI development and use as the first global standard-setting instrument on AI ethics (UNESCO, 2023). The OECD Artificial Intelligence Policy Observatory (OECD.AI)[8], launched in 2020, itself became a central global resource during this period, providing access to 900+ national AI policies and initiatives, helping countries track and benchmark AI adoption and governance approaches.

Alongside policy frameworks, global indices tracking government AI readiness and governance performance gained prominence. The Government AI Readiness Index, first introduced in 2017, continued to evolve through the early 2020s, offering comprehensive comparative metrics for

[6] More information about GPAI can be obtained from the link, https://oecd.ai/en/about/about-gpai.
[7] Values-based principles and recommendations for policymakers are available at https://oecd.ai/en/ai-principles.
[8] More about the mission, content and resources of OECD.AI is available at https://oecd.ai/en/about/about-oecd-ai.

how governments can harness AI for public benefit and informing national strategies worldwide. By 2025 the Index covered nearly 200 governments, reflecting the rapid mainstreaming of AI governance considerations across diverse national contexts (Oxford Insights, 2025).

These global developments — formation of international partnerships, the proliferation of benchmarking indices and rapid legislative engagement — correspond chronologically with the increase in public sector AI cases in the OPSI dataset between 2018 and 2022. They suggest a broader ecosystem of political, economic, and governance activity that has likely influenced how governments approach AI adoption and institutionalization, reinforcing the descriptive patterns observed in the OPSI case data.

4.1.3. Distribution of AI Cases by Level of Government

The dataset is strongly dominated by initiatives implemented at the national or federal level. A total of 89 cases (nearly 62%) are classified as national or federal government projects, accounting for more than half of the dataset. Local government initiatives (20 cases) and regional or state-level initiatives (18 cases) constitute smaller shares, while 16 cases fall into the "Other" category. Figure 4 illustrates the distribution of initiatives across different governance levels.

This pattern suggests that the adoption of AI in the public sector is primarily driven by central government institutions, which are typically expected to possess greater financial, technical, and regulatory capacities (Jonathan et al., 2025: 12). Subnational adoption appears more limited and fragmented, potentially reflecting capacity constraints and governance challenges at lower administrative levels.

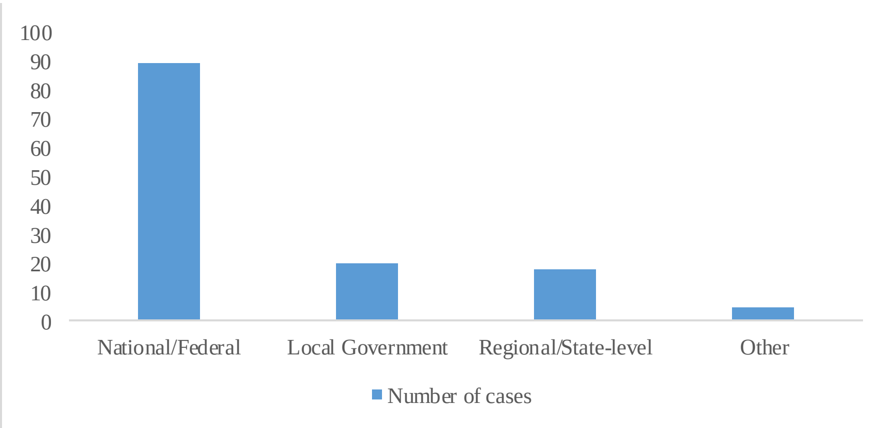

Figure 4. Distribution of AI Cases by Level of Government

4.1.4. Type of AI Model / Technique Used in AI Cases

With regard to the type of AI model or technique used, the majority of OPSI cases do not provide detailed technical specifications. Where such information is available, projects primarily rely on machine learning–based classification and prediction models, natural language processing techniques for text simplification and translation, and, more recently, generative AI systems.

Given the limited technical transparency in many case descriptions, the objective of this stage of analysis is not to produce a mutually exclusive or frequency-based distribution of AI types. Instead, cases were classified based on the underlying decision logic and technical architecture described in the narratives rather than surface-level terminology such as "AI-powered" or "smart system". The references to AI techniques were inductively grouped into descriptive analytical categories derived from explicit technical mentions and indicative keywords within the narratives. Case narratives were scanned for explicit technical descriptions (e.g., "machine learning," "computer vision," "predictive model") as well as indicative keywords suggesting particular methodological approaches (e.g., "forecasting," "text analysis," "image recognition," "chatbot").

The categories—Machine Learning, Predictive Analytics, Computer Vision, Natural Language Processing, Generative AI, Rule-based / Expert Systems, and Unspecified—should therefore be interpreted as contextual descriptors of technological orientation, not as definitive classifications of system architecture (Table 1). The distinction between Natural Language Processing and Generative AI was made on functional grounds. NLP refers to systems that process, classify, or transform existing textual data, whereas Generative AI denotes systems capable of producing novel content, such as dynamically generated responses or original text outputs. Although generative models are technically rooted in NLP research, they were analytically separated due to their distinct functional logic and governance implications.

Table 1: AI Techniques Identified in OPSI Cases

Text Segment	**Initial Code**
Machine Learning	Classification, clustering, pattern recognition
Predictive Analytics	Forecasting, risk scoring, demand estimation
Computer Vision	Image recognition, object detection
Natural Language Processing	Text simplification, translation, document analysis
Generative AI	Chatbots, automated content generation
Rule-based / Expert Systems	Deterministic decision rules, logic-based automation
Unspecified	AI referenced without technical detail

For example, the OPSI case "U-Ask" (UAE) explicitly states that the system "harnesses the power of generative AI, specifically ChatGPT," and that it underwent "a substantial upgrade in 2023, incorporating generative AI capabilities." This description clearly situates the innovation within the generative AI category, as the system is designed to produce context-aware and dynamically generated responses rather than relying on predefined rules.

By contrast, the case "Neyim Var?" (Türkiye) is described as "an expert system application that evaluates the patient's complaints and past medical records and presents possible diagnoses." The narrative further notes that "medical guidelines were used while creating complaint-diagnosis and diagnosis-outpatient referral algorithms," indicating a logic-driven and rule-structured decision architecture characteristic of expert systems.

Because case descriptions often employ generic terminology and do not consistently distinguish between hybrid or evolving technical configurations, the categories are presented as heuristic groupings intended to capture broad patterns of AI usage in public sector innovation. Accordingly, this section aims to map the descriptive technological landscape rather than to determine technical dominance or comparative prevalence across cases.

4.1.5. Distribution of Innovation Tags in the OPSI Dataset

A word cloud was generated from the innovation tags to provide an exploratory overview of the dominant thematic orientations within the dataset. This visual technique enables the identification of recurrent concepts and policy framings by highlighting the relative prominence of frequently used terms.

By mapping the discursive emphasis of the cases, the word cloud helps situate subsequent qualitative analysis within the broader narrative context of public sector AI initiatives and supports the identification of dominant technological, organizational, and governance-related themes. Figure 4 presents a word cloud generated from the innovation tags associated with the OPSI AI cases.

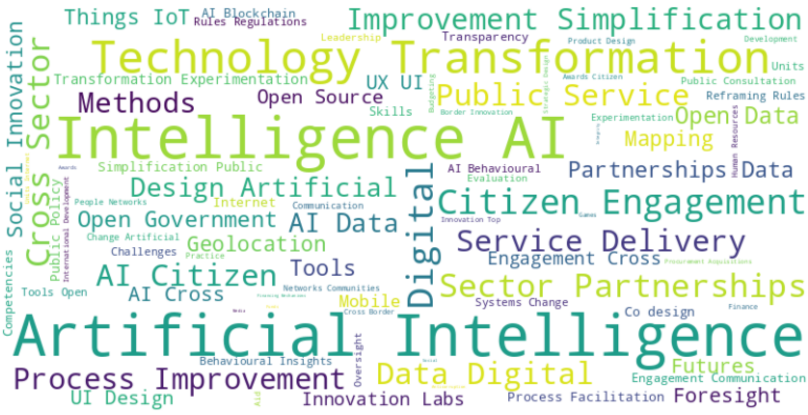

Figure 4. Distribution of Innovation Tags in the OPSI Dataset

The word cloud analysis of innovation tags reveals a strong concentration around terms such as "Digital," "Data," and "Technology Transformation," indicating that most AI initiatives are embedded within broader digital reform agendas. Prominent references to "Public Service," "Service Delivery," and "Citizen Engagement" further suggest that AI adoption is predominantly framed in relation to service improvement and citizen-oriented governance. In addition, the presence of terms such as "Process Improvement," "Simplification," and "Partnerships" highlights the organizational and collaborative dimensions of public sector AI initiatives.

Taken together, the descriptive analysis reveals some key structural characteristics of the dataset. First, the dataset reveals geographical concentration, with a limited number of countries accounting for a substantial share of documented initiatives. The research also highlights temporal acceleration, particularly after 2017, reflecting the institutionalization of AI use in public administration in parallel with the global significance of the issue. Centralized implementation of AI projects is the second output of the first stage of the methodology with national governments playing a dominant role in the dataset. Thirdly, integration with broader innovation agendas is displayed in the co-occurrence of AI and digital transformation tags. Lastly, a substantial proportion of cases do not specify technical architectures in detail, suggesting that public sector AI initiatives are commonly framed in functional and organizational terms rather than through explicit technical descriptions of AI models or technique used. These patterns provide an empirical baseline for the subsequent inductive analysis by situating individual case narratives within the broader landscape of public sector AI initiatives documented by the OECD OPSI.

4.2. Stage 2: Inductive Qualitative Coding

Based on the descriptive mapping in Stage 1, Stage 2 shifts the analytical focus from aggregate distributions to the core elements of implementation narratives. Rather than applying predefined capacity indicators, the analysis inductively coded how AI adoption was described in relation to organizational practices and implementation experiences across the OPSI cases. As a result of the analysis, two overarching code families emerged: (A) AI-enabled actions (affordances) and (B) implementation constraints.

Each case narrative was read and segmented into meaning units describing what the AI system enabled in practice and what limited or complicated its implementation. Initial codes were developed using terms drawn directly from the case narratives (e.g., "automating permit process," "early-warning prediction," "data quality issues," "training needs"). First-order codes were then clustered into recurrent themes that appeared across sectors and span of authority.

To clarify how the recurring themes were obtained, the methodological steps are illustrated through direct examples drawn from the dataset. In the first step of the inductive coding process, each case narrative was systematically segmented into meaningful textual units. Each segment was examined to identify explicit references to what the AI system enabled in practice and what challenges were encountered during implementation. For example, when a case description stated that "*all HR processes have been consolidated into a single digital system*" and that "*the* *preparation of annual reports now takes 15 minutes instead of a full week*," these segments were interpreted as indicating administrative streamlining. Accordingly, they were assigned initial descriptive codes such as "*HR processes consolidated*" and "*annual reports reduced to 15 minutes*."

Similarly, when a narrative reported that the system allowed inspection teams to "*act preventively*" and to "*mitigate the risks of blackouts*," these segments were coded as "*act preventively*" and "*mitigate risks*," capturing anticipatory intervention enabled by AI. At this stage, coding focused exclusively on capturing the explicit meaning of the text, without introducing theoretical interpretation. Codes functioned as brief analytical notes that summarized what each segment conveyed using language closely derived from the case narratives. This initial coding phase aimed to remain as close as possible to the original language of the cases, ensuring that subsequent analytical stages were grounded in empirical material rather than in predefined conceptual categories.

In the second step, the initial descriptive codes generated in the first coding cycle were systematically reviewed and compared in order to identify conceptual similarities and recurring patterns. As the coding progressed, multiple short analytical notes accumulated across cases. For instance, codes such as "*HR processes consolidated*," "*digital HR analytics*," and "*annual reports reduced to 15 minutes*" were found to refer to similar operational transformations and were therefore clustered under the broader analytical theme "Process Automation & Workflow Optimization." Likewise, codes such as "*act preventively*," "*mitigate the risks of blackouts*," and "*monitoring tool*" were grouped under the theme "Predictive & Early-Warning Capacity," as they all described anticipatory and risk-oriented functions enabled by AI systems.

Rather than treating each code in isolation, the study examined their relational meanings and organized them into higher-order categories reflecting shared enactment patterns. In practical terms, Step 2 involved asking whether different initial codes reflected the same underlying organizational transformation and, where appropriate, integrating them into a common analytical category. This process enabled the transition from fragmented descriptive observations to a structured thematic framework that supports cross-case comparison while remaining empirically grounded. The resulting themes are reported in Table 2 below, with illustrative examples. The table summarizes the main thematic patterns emerging from the inductive coding process. The themes reflect repeatedly occurring forms of AI-enabled actions and implementation constraints observed across the OPSI case narratives and illustrate how technological functionalities are mediated by institutional and human capacities.

Across the dataset, AI is consistently framed as enabling the digitization and acceleration of administrative workflows, anticipatory risk mitigation, data-driven decision support, expanded citizen accessibility, personalized service delivery, cross-sectoral data integration, and enhanced transparency and monitoring. Rather than being described primarily in technical terms, AI is narrated as reshaping organizational routines, service interfaces, and coordination mechanisms. At the same time, implementation narratives reveal recurring constraints related to data availability and quality, skills and training needs, legal and ethical compliance requirements, institutional fragmentation, resource limitations, and challenges of user adoption and trust. Importantly, the cases suggest that AI-enabled enactments—such as preventive monitoring or personalized service delivery—often evolve more rapidly than the institutional arrangements and professional competencies required to sustain them. This misalignment may generate persistent difficulties for scaling, institutionalization, and long-term governance stability.

Table 2. AI-Enabled Actions (Affordances)

Affordance Category	**Core Enactment in Practice**	**Sample First-order Codes**	**Analytical Theme**	**Illustrative Examples (Case – Country)**
Process Automation & Workflow Optimization	Administrative routines are digitized and accelerated	"HR processes consolidated"; "annual reports reduced to 15 minutes"; "digital HR analytics"	AI restructures bureaucratic workflows by automating and streamlining procedures.	*e-Qyzmet – Integrated HRM Information System* – Kazakhstan
Predictive & Early-Warning Capacity	Risks are identified before escalation	"act preventively"; "mitigate risks"; "monitoring tool"	AI enables anticipatory governance through preventive intervention mechanisms.	*AI and geospatial data to protect against wildfires (GGT System)* – Brazil
Enhanced Decision Support	Data-driven insights inform professional judgment	"AI-assisted platform"; "make informed decisions"; "diagnostic recommendations"	AI augments administrative discretion through analytical support.	*Neyim Var? (What do I have)* – Türkiye
Improved Citizen Interaction & Accessibility	Services become accessible in real time and across barriers	"real-time translation"; "online recruitment"; "accessible to all"	AI transforms citizen-state interaction by lowering administrative barriers.	*SIMTOMI: AI-Powered Multilingual Medical Support* – Korea; *e-Qyzmet* – Kazakhstan
Personalization of Public Services	Outputs adapt to user characteristics and needs	"tailored for Italian administrative texts"; "align with user needs"; "user evaluation"	AI enables user-centered and context-sensitive service delivery.	*Text Simplification for Citizens with GenAI* – Italy
Data Integration & Cross-Sector Coordination	Fragmented knowledge and actors are connected	"shared holistic picture"; "in one database"; "cross-sectoral"	AI facilitates horizontal coordination across institutional silos.	*U-Ask* – United Arab Emirates; *Digital Twin (Patras)* – Greece
Transparency & Monitoring Enhancement	Institutional processes become traceable and auditable	"recorded and traceable"; "monitoring tool"; "chain-tracked criminal voices"	AI strengthens oversight and institutional accountability infrastructures.	*e-Qyzmet* – Kazakhstan; *Voice Phishing Detection Model* – Republic of Korea

Source: Author's own elaboration.

Table 3. Implementation Constraints

Constraint Category	Core Implementation Constraint	Sample First-order Codes	Analytical Theme	Illustrative Examples (Case – Country)
Data Quality & Availability Limitations	AI performance constrained by incomplete, inconsistent, or domain-specific data	“little information about artificial intelligence”; “risk of mistranslation”; “data variations”; “medical guidelines were used”	Data integrity, domain specificity, and interoperability gaps limit AI reliability.	*AI to support translational research in patient care* – Colombia
Skills & Professional Capacity Gaps	Implementation complicated by limited AI literacy or professional adaptation	“professional skepticism”; “lack of resources [requires]… partnering with young employees”; “lack of IT skills”	Human capacity and interpretive judgment shape effective AI enactment.	*CrowdBots* – USA; *Establishment of an AI Competence Centre for the City of Munich* – Germany
Legal & Ethical Compliance Requirements	Regulatory and ethical safeguards condition AI deployment	“ensuring data privacy”; “compliance with regulatory standards”; “essential to … [incorporate] mechanism for checks and balances”	Governance and compliance requirements mediate AI adoption and scaling.	*Machine Learning Model for Type 2 Diabetes Mellitus Incidence Prediction for the People Medically treated with EDUS* – Costa Rica; *Disruptive technology for Preventive Geriatric care* – Israel
Organizational Fragmentation & Coordination Barriers	Cross-agency and cross-disciplinary coordination complicates implementation	“different actors”; “across organizational boundaries”; “shared holistic picture”	Institutional silos and coordination challenges affect integration of AI systems.	*Knowledge-based platform for children and families* – Finland
Resource & Infrastructure Constraints	Technical limitations and structural readiness affect scalability	“initial limitations”; “structural challenges”; “complex implementation”; “quality analysis”	Infrastructure readiness and organizational maturity shape sustainability.	*InteliPipes* – Canada
Adoption & Trust Barriers	Professional skepticism and user behavior affect uptake	“physicians gave feedback”; “generalizations could give wrong results”; “preference for Google searches”	Legitimacy, trust, and behavioral adaptation influence sustained use.	*Neyim Var?* – Türkiye; *U-Ask* – UAE; *Text Simplification for Citizens with GenAI* – Italy

Source: Author’s own elaboration.

To identify implementation constraints, the same inductive procedure applied to affordances was followed that the analysis examined how difficulties, limitations, and implementation tensions were explicitly described in the narratives rather than imposing predefined categories. In the first step of the coding process, each case was segmented into meaning units that referred to challenges encountered during deployment or scaling. For example, when a case noted that there was "*little information about artificial intelligence*," this segment was interpreted as reflecting limited institutional preparedness and coded as "*limited AI knowledge.*" Similarly, when a narrative stated that "*medical guidelines were used while creating complaint-diagnosis algorithms*," this was coded as "*dependence on medical guidelines*," indicating domain-specific data and knowledge constraints. In another case, references to the "*risk of mistranslation*" were coded as "*translation risk*," capturing concerns about output reliability.

This stage kept first-order codes short and as close as possible to the wording of the case narratives. They functioned as descriptive labels summarizing the explicit implementation difficulty without theoretical abstraction. For instance, segments such as "*physicians gave feedback that generalizations could give wrong results*" were coded as "*professional skepticism*," while references to "*initial limitations in the 2018 rule-based chatbot*" were coded as "*initial system limitations*."

In the second step, these first-order codes were systematically reviewed across cases to identify conceptual similarities. Codes such as "*translation risk*," "*data variations*," and "*little information about artificial intelligence*" were grouped under the broader analytical theme "Data Quality & Availability Limitations," as they all pointed to constraints arising from insufficient, domain-sensitive, or fragmented data environments. Likewise, codes including "*professional skepticism*," "*lack of resources [requires]… partnering with young employees*," and "*lack of IT skills*" were clustered under "Skills & Professional Capacity Gaps," since they reflected challenges related to human interpretation and expertise.

Other recurring clusters included "Legal & Ethical Compliance Requirements" (derived from references to some codes like ethical use and implementation of AI and responsibility concerns), "Organizational Fragmentation & Coordination Barriers" (based on segments describing different actors and coordination across organizational boundaries), "Resource & Infrastructure Constraints" (linked to structural challenges and implementation complexity), and "Adoption & Trust Barriers" (stemming from user preferences and professional reservations). Table 3 summarized the constraints obtained from the dataset.

4.3. Stage 3: Theory-Informed Interpretation Using Technology Affordances and Constraints Theory (TACT)

In the third step, the thematic patterns identified through inductive coding were interpreted through the lens of Technology Affordances and Constraints Theory (TACT). This stage aimed to move beyond descriptive pattern identification and to develop an explanatory understanding of how AI-related capabilities and limitations emerge in public sector contexts.

Building on TACT's core premise that the uses and consequences of information systems are shaped through dynamic interactions between technological features, organizational arrangements, and human actors (Maragno et al., 2023: 3), the analysis examined how institutional and human capacities mediated the realization of identified affordances and constraints.

At this stage, the analysis systematically assessed how each thematic cluster was connected to specific organizational practices and capacity conditions. For instance, in the "AI and geospatial data to protect against wildfires" case,[9] predictive analytics capabilities were closely linked to inter-agency data-sharing arrangements and the technical expertise of regulatory staff, illustrating how forecasting affordances depended on both data governance structures and human capacity.

[9] The case was narrated to explain the AI initiative launched in Brazil in 2017.

Similarly, the “BRISE Vienna” initiative[10] demonstrates how process automation in building permit approvals relied on the integration of fragmented municipal databases and the availability of digitally skilled personnel.

In contrast, several cases illustrate how constraints emerged from institutional misalignments. In the “Skrinja” data analytics platform from Slovenia (dated 2017), limitations in data quality and interoperability restricted the practical use of analytical tools, despite advanced technical infrastructure. Likewise, the “Algorithmic Bias Bounties” initiative (from the United States, 2021) highlights how legal and ethical requirements related to transparency and accountability constrained algorithmic deployment, necessitating extensive oversight mechanisms and specialized expertise.

Rather than treating affordances and constraints as inherent properties of AI systems, this analytical step conceptualized them as relational and context-dependent phenomena. In practice, this involved examining how similar technological functionalities —such as real-time translation, automated monitoring, or AI-assisted recommendations— produced different outcomes across cases depending on variations in governance arrangements, coordination mechanisms, and professional competencies.

Through this interpretive process, institutional capacity was understood in terms of regulatory frameworks, coordination structures, and organizational routines, while human capacity was analyzed in relation to skills development, interdisciplinary collaboration, and experiential learning. These capacity dimensions were then linked to observed variations in the realization, limitation, or transformation of AI affordances.

Constraints observed in the cases—such as legal ambiguity, organizational inertia, or limited technical expertise—are therefore interpreted not as failures of AI technology itself, but as outcomes of misalignment between technological possibilities and existing institutional or human conditions. This interpretation aligns with empirical research emphasizing the centrality of organizational and governance factors in AI implementation in public sector contexts, where socio-technical, structural, and managerial challenges shape realized outcomes (Maragno et al., 2023).

An important observation emerging from the analysis concerns cases in which no clear first-order codes could be identified for either affordances or constraints. In these instances, the absence of codable material does not necessarily indicate the absence of socio-technical dynamics. Rather, it reflects variability in narrative depth and reporting practices within the dataset. Public innovation reporting often emphasizes intended successes while underreporting implementation tensions and outcomes (de Vries, Bekkers and Tummers, 2016: 159). As a result, certain organizational frictions, data limitations, or professional resistance dynamics may remain implicit or insufficiently articulated.

This asymmetry is consistent with broader findings in public administration and innovation studies suggesting that official case narratives frequently privilege solution framing over problem exposition. A researcher might, in principle, try to identify or construct accounts of clearly unsuccessful innovations, provided that practitioners are willing to participate in such an effort—though securing that cooperation would be far from guaranteed (Borins, 2010: 8). From a TACT perspective, such narrative silence does not imply the absence of constraints, but rather indicates that the socio-technical interactions through which affordances and limitations emerge are not always made visible in formal reporting formats. Accordingly, the absence of explicit coding in some cases should be interpreted as a feature of narrative construction rather than as evidence of frictionless AI implementation. This highlights a structural limitation of secondary case-based datasets and underscores the importance of interpretive caution when analyzing curated innovation repositories.

[10] The BRISE Vienna case refers to “Building Regulations Information for Submission Envolvement”, initiated in Austria in 2022.

Finally, this theory-informed interpretation enabled the integration of empirical findings into a coherent analytical framework, explaining not only what types of AI-enabled actions and constraints were observed, but also why they emerged and how they were shaped by socio-technical configurations. In this way, Step 3 provided the conceptual foundation for the study's broader contributions to research on public sector AI governance and capacity development.

Conclusion

This study examined how institutional and human capacities shape the realization of artificial intelligence affordances and constraints in public sector organizations. Drawing on 143 AI-related case studies from the OECD OPSI Case Study Library, the research adopted a three-stage inductive analytical strategy combining descriptive mapping, qualitative coding, and theory-informed interpretation based on Technology Affordances and Constraints Theory.

The descriptive analysis revealed that public sector AI initiatives areconcentrated in specific geographic regions , temporally clustered after 2017, and predominantly implemented at the national level. Most projects are embedded within broader digital transformation agendas and are framed in functional and organizational terms rather than through detailed technical specifications. These patterns indicate that AI adoption in government is closely linked to institutional reform processes and centralized governance structures.

The inductive qualitative analysis identified two overarching thematic domains: AI-enabled actions and implementation constraints. Across cases, AI is consistently framed as enabling automation, predictive capacity, service personalization, decision support, and inter-organizational coordination. At the same time, implementation is constrained by data limitations, skills shortages, legal and ethical uncertainty, organizational fragmentation, resource constraints, and trust-related challenges. These findings demonstrate that technological possibilities frequently outpace the institutional and human capacities required for stabilization and scaling.

The theory-informed interpretation showed that affordances and constraints do not arise from technological features alone, but are produced through socio-technical interactions shaped by governance arrangements, organizational routines, and professional competencies. Institutional capacity conditions the structural environments within which AI systems canbe embedded, while human capacity influences how actors perceive, interpret, and enact technological possibilities. Constraints emerge primarily from misalignments between technological potential and existing institutional or human conditions rather than from intrinsic technological deficiencies.

Taken together, the findings support a relational and process-oriented understanding of capacity in public sector AI adoption. Rather than functioning as static prerequisites, institutional and human capacities evolve through iterative processes of experimentation, learning, and institutionalization. Successful implementation depends not only on acquiring advanced technologies but also on sustaining governance infrastructures, developing interdisciplinary skills, and fostering organizational learning mechanisms.

This study makes several contributions to research and practice. First, it provides large-scale empirical evidence on how capacity-related dynamics shape AI implementation across diverse national and organizational contexts. Second, it advances the application of TACT to public sector AI governance, demonstrating its usefulness for analyzing socio-technical transformation processes. Third, it highlights the limitations of technocentric adoption strategies and underscores the need for integrated capacity-building policies.

From a policy perspective, the findings suggest that governments should complement technological investments with sustained efforts to strengthen regulatory coherence, data governance, inter-agency coordination, and professional development. Capacity-building initiatives should be designed as long-term institutional projects rather than short-term technical interventions. In particular, greater attention should be paid to developing interdisciplinary expertise that combines technical, legal, ethical, and managerial competencies.

Several limitations should be acknowledged. The analysis relies on secondary case narratives, which may vary in depth and emphasis, and cannot capture the full dynamics of implementation processes. In addition, the study focuses on interpretive rather than causal analysis and does not establish direct causal relationships between capacity factors and outcomes. Future research could complement this approach with longitudinal field studies, interviews, and comparative institutional analysis.

Despite these limitations, this study demonstrates that institutional and human capacities constitute central mediating mechanisms through which AI technologies acquire meaning, functionality, and legitimacy in public sector contexts. Understanding these relational dynamics is essential for designing governance frameworks that enable AI to contribute to public value in sustainable, accountable, and socially legitimate ways.

Future research could build on this study in several directions. First, longitudinal and process-oriented studies are needed to examine how institutional and human capacities evolve over time and how affordances and constraints shift across different stages of AI institutionalization. Such research would provide deeper insights into learning dynamics, path dependencies, and capacity accumulation processes. Second, mixed-methods designs combining large-scale case analysis with interviews, surveys, and ethnographic observations could enhance understanding of how practitioners interpret and negotiate AI-related challenges in everyday administrative settings. Third, comparative studies across governance systems and administrative traditions would enable systematic assessment of how national institutional configurations influence the realization of AI affordances. Finally, future work should explore the implications of emerging generative AI systems for public sector capacity development, particularly with regard to regulatory adaptation, professional competencies, and organizational accountability. Developing integrated analytical frameworks that connect technological evolution with institutional learning and human capability formation remains a promising avenue for advancing research on public sector AI governance.

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