People, Processes, and Innovation Progress: Understanding Organizational Drivers of AI Adoption in the Public Sector

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Abstract

This paper explores organizational factors such as culture, structure, and personal behaviors that influence the successful adoption of artificial intelligence (AI) in public sector organizations in the EU. While AI offers the potential for enhanced efficiency and service quality, its adoption remains constrained by barriers like employee resistance, rigid bureaucratic structures, and cultural inertia. Using the Technology-Organization-Environment (TOE) framework, the research identifies AI adoption challenges and enablers. The research reveals that people-centricity is the primary facilitator in adopting AI. This can be achieved by building trust, multidisciplinary teams, and sustainable implementation strategies.

Keywords

Artificial Intelligence, Public Sector, Digital Transformation, Innovation Teams

1. Adopting AI in the Public Sector: Introduction

Recognizing the impact and opportunities of artificial intelligence (AI) within the public sector, several nations have emphasized enhancing administrative efficiency and the quality of self-service through AI implementation [9, 18, 21], and facilitation of AI research. It is widely assumed that the digital transformation of public service activities can contribute to larger and more efficient information processing, improved service quality, and mitigating societal challenges, prompting governments to experiment with several technologies [12, 13]. This AI transformation, unlike others, has influenced decision-making processes by supporting public professionals in making informed decisions. Several use cases of AI as citizen-centric solutions in government already exist: The Energy Vulnerability Project uses AI to process and integrate information from heterogeneous systems to enable better information exchange [3], Robot Tengai, used in the Swedish municipality of Upplands-Bro, makes recruitment processes less biased, and The Early Help Profiling System (EHPS) in the United Kingdom identifies children and families as vulnerable or at risk of child abuse [19].

Although artificial intelligence is associated with improved governance systems, its integration into public sector operations remains limited. The adoption of AI faces significant challenges [14, 16] including a lack of skills and employees' resistance to change, both indicating a need for capacity building. In Slovakia, when municipalities transitioning to AI relied heavily on EU funding to shift their focus from ICT to adopting new information systems, resistance to these changes emerged not only from within - both management and employees - but also from outside, particularly in engaging citizens in the design and implementation of these services [20]. Similarly, in the case of Flanders Investment and Trade (FIT), AI support was considered insufficient for widespread adoption due to a lack of trust and inclination toward AI. Efforts to seamlessly integrate AI into workflows faced hurdles, which builds a case for understanding the stakeholders involved in the process [17].

These technological innovations can create conflicts or disharmony in the system, depending on how they interact with the existing setup and culture of public organizations. Public sector entities

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often operate with rigid structures and formal procedures characterized by lengthy mechanisms and hierarchical control. Contrariwise, technological advancements like AI require flexibility and often introduce disruption and uncertainty [18]. This dynamic influences implementation at procedural, cultural, and individual levels, with the extent of impact varying based on the size and structure of the organization [8]. Despite numerous studies addressing the ethical and technical aspects of these challenges, a compelling area of exploration remains in the form of understanding AI adoption within the organizational context of public sector entities. Analyzing how organizational factors either facilitate or inhibit such adoption across different levels can offer recommendations for effectively integrating dynamic innovations, particularly within the rigid bureaucratic systems prevalent in the public sector [18]. Therefore, this study bases its foundation on the following Primary Research Question:

"What cultural, structural, and individual factors within public sector organizations shape the successful adoption of artificial intelligence?"

To further understand the impact of an innovative transformational environment and then to construct a theoretical lens to concretize the theoretical framework model, this article explores the most recent and relevant niche (2020-2024) literature in this field to identify the abovementioned factors. This paper is structured as follows: Building on findings from the literature (Section 2), the study integrates the Technology-Organization-Environment (TOE) framework with a newly developed CSI (Culture-Structure-Individual) model for a more granular understanding of organizations. Methodologically (Section 3), the paper uses qualitative interviews with public sector experts to assess these factors in practice. The findings are then analyzed thematically in the results section (Section 4), leading to a discussion (Section 5) on the implications for sustainable AI adoption and a conclusion (Section 6) with key insights, limitations, and future research directions.

2. Organizational Influencers: Literature Review

Understanding organizational readiness through cultural adaptation and structural barriers is crucial in the public sector, where rigid structures and cultural inertia prevail. With this literature review, we synthesize existing studies to identify key organizational drivers and hindrances to AI integration in public organizations.

2.1. Cultural Barriers and Change Management in AI Adoption

An organization's AI readiness depends on the right culture (innovation, risk-taking, and experimentation), context (e-government initiatives and strategic tech alignment), and institutional orientation (New Public Management). Cross-agency collaboration, transformational leadership, and institutionalized learning also significantly impact adoption efforts [10]. For both incremental and transformational changes, the presence of an innovative and open culture is a crucial determinant [8].

Contrariwise, cultural challenges such as a lack of innovation spirit, insufficient skills, aversion to risk-taking, and difficulties with AI procurement can become significant obstacles if not mitigated [18]. The integration of AI into organizations often leads to unintended cultural and structural consequences. For example, in a Dutch case of fraud detection, automated processes replaced human intervention, resulting in 1/3rd of staff being laid off and a shift from traditional bureaucratic roles to system-monitoring functions. This transition limited professionals' discretionary freedom, reducing their ability to provide feedback on the AI system's broader implications.

The failure to align AI adoption with strategic cultural changes affected trust, adaptability, and the effective evolution of bureaucratic roles adversely [7]. Consequently, risk-averse behavior, often prevalent in publicly funded organizations, poses another greater barrier to AI adoption due to the novel and uncertain nature of AI projects, which associates them with such perceived risks. Implementing AI, like other disruptive technologies, requires change management strategies and skills training to mitigate these risks and reconfigure organizational structures effectively [10, 16].

An innovation culture that tolerates some failure and employs agile project management methods tends to support AI adoption. Despite efforts to build trust in AI systems, particularly for business-critical decisions, researchers emphasize that while AI is effective for repetitive tasks, it lacks the understanding and knowledge inherent in human interactions. Public Managers consistently stress that the *"human touch"* remains indispensable in workplaces, particularly in roles that involve managing people. And therefore, culturally, balancing technological advancements with human-centric approaches becomes paramount [2, 16].

Employee resistance to change is inevitable but relatively manageable. Resistance can be mitigated through better communication and collaboration among employees, education, and engagement strategies. Transparent communication is essential to address concerns about shifts in power dynamics and to convey the potential benefits of transformation for individuals and groups within the organization [1, 6]. Senior management or Decision-makers not only encourage technological adoption and digital transformation but also drive cultural change by recruiting younger generations to balance and shift the mindset of current employees. Leadership and financial support combined with a data-driven culture bring a successful transition [6]. Investing in social ties between departments and building cross-functional expertise helps build responsiveness and adaptability that makes the organization change-ready. Change management programs that address employee's legitimate concerns and promote continuous learning tend to evolve the cultural mindset within the institution. By integrating AI systems into daily tasks and providing platforms for data storage and sharing, organizations can ensure a smoother transition while maintaining trust and collaboration across all levels [6, 18]. This culture is materialized and reinforced through structures and processes followed within the system, and therefore, structural barriers become prominent factors of influence.

2.2. Structural and Procedural Barriers to AI Adoption

Despite a few successful AI adoptions in government, changes in organizational structures and administrative processes remain unclear. Effective AI innovation requires clear transformation to create value [15]. AI adoption is context-specific and embedded in structures, processes, and routines. Case studies show AI's technical complexity demands alignment with existing systems and complementary, signature structures [18]. Structural barriers require changes in development, operations, support, and legal frameworks. Employee concerns, though mitigated by communication and upskilling, persist [1]. Rigid structures, formal processes, and control needs pose unique public sector challenges. The tension between these and flexibility limits adoption. Balancing experimentation and identity is essential [18].

A structured environment that enables employees to collaborate with machines through clear task divisions rather than replacing humans or forcing them to adapt to machine directives helps overcome these barriers to an extent [11]. For instance, in the Netherlands, AI was initially treated as a technical analytics upgrade rather than a strategic transformation. Human oversight was later mandated to ensure ethical and accurate decision-making. This exhibits the need for an organizational approach that integrates technical and strategic considerations [7], which also sheds light on ethical and normative considerations. These considerations are more salient for AI innovations than for traditional IT implementations. Successful adoption demands the integration of technical, operational, managerial, ethical, and legal expertise into new organizational structures and processes [18].

Investments in intangible organizational capital are equally critical. Beyond training in digital skills, organizations need to redesign their processes, including hiring, performance evaluations, and reward systems, as well as broader initiatives such as business process reengineering and organizational redesign [17]. An organization's culture and structure build a foundation for its people to innovate, even though resistance to change might emerge.

2.3. Individual Barriers: Employee Resistance in AI Adoption

Employees' attitudes and mindsets are significant challenges in adopting AI. Felemban et al (2024) showed behavior and attitudes determine organizational readiness. Resistance is fueled by lack of understanding, cognitive misperceptions, and preference for the status quo. Skepticism about AI's reliability and fairness affects trust [1]. Employee skills are critical for digitally-induced change. Digital and cross-functional skills enable integration of new technologies, especially for incremental changes [8]. In the public sector, lack of AI expertise is a barrier; targeted training is needed to design and implement AI solutions [12]. More so, Job security concerns are a major source of resistance. Employees fear that AI might lead to job losses, diminished managerial authority, and the downgrading of roles. This anxiety reflects a strong bias toward maintaining familiar work (status quo inertia) environments [1].

Resistance also stems from routine disruption, lack of explainability, and unclear task prioritization [16]. Perceived usefulness and task routineness influence acceptance. Adoption requires rethinking task divisions between technology and workers and between junior and senior employees [17]. Organizational resistance is influenced by inadequate communication between management and employees. In Slovakia, lack of participation and insufficient incentives hindered adoption. Effective communication and engagement are critical for frontline employees, management, and end-users [16, 20].

The behavioral implications of digitally-induced changes, like AI transformation, are complex. Adjustments to new digital environments introduce new norms and values in the workplace where employees take on new tasks. Public managers are critical in managing transformation and addressing workforce changes [8]. These changes require examining automation's long-term effects on jobs and legislative implications [21]. Public sector organizations would need to address concerns like job losses, discrimination, and loss of trust by creating opportunities and building a new generation of AI specialists [12].

2.4. Key Facilitators of Sustainable AI Adoption

The long-term success of AI adoption hinges on building in-house technical competencies through hiring and training individuals skilled in AI use and management. Case studies highlight the need for permanent teams dedicated to collaborating with AI systems and adapting to non-deterministic workflows [11]. Training programs and workshops via knowledge-sharing platforms can enhance technology literacy to position AI as a tool to assist in decision-making and service delivery, as exhibited by the UK, where local councils equipped employees with necessary skills through targeted training programs [20]. "*AI trainers*" in another case study demonstrated how dedicated interaction with AI systems requires organizational knowledge and adaptability. Cross-cutting issues such as digital literacy and resistance to task changes were observed across multiple domains [4, 11]. Governments can catalyze AI talent pools by using tailored approaches to address sector-specific challenges. A supportive culture of learning and continuous skill development reduces resistance to change and enhances the chances of organizational success [2, 6].

AI adoption requires understanding the tradeoff between efficiency and effectiveness while addressing challenges such as limited resources and aging populations. Scholars identify two key approaches: structural separation, which isolates innovative initiatives from routine operations, and contextual integration, which embeds innovation within existing frameworks. Managing the tension between exploration and exploitation is critical to adapting to technological changes effectively [18]. In Europe, despite governments being pioneers in leveraging AI to enhance service delivery, strategies often lack specificity in achieving ambitious goals [9]. To build AI-related capacity, many public organizations are establishing AI or innovation labs. These labs provide experimentation spaces to test emerging AI technologies and align them with existing practices and routines. This creates a safe environment for experimentation where organizations address knowledge gaps and refine their understanding of AI technologies and their broader implications [12, 13]. Creating sustainable AI innovation ecosystems requires governments to work on their legislative and judicial capacities. Balancing reward and punishment systems to favor innovators can help address the public sector's lack of innovation spirit. Strategic initiatives, such as AI labs and experimentation spaces, also support human-centric AI integration while being aligned with organizational goals [12, 14].

Organizations with intermediate AI experience require management support to allocate resources effectively and transition from exploration to implementation. For state-owned enterprises and experienced organizations, internal development of AI solutions often leads to greater complexity and the need for customer-centric approaches. However, increased intra-organizational diffusion of AI can amplify resistance, which might be reduced through change management strategies [16].

2.5. The Evergreen Need for Human Oversight

A critical concern is the tendency to over-rely on AI-driven decisions, assuming that they are inherently superior to human judgment. However, this is almost never the case, particularly when AI decisions are based on poor-quality or biased data. Increasing the use of AI in staff allocation may lead to feedback loops where biased data accumulates, reinforcing existing disparities and errors. Widespread AI applications aimed at tackling fraud may conflict with other fundamental public values, such as privacy and the right to a fair trial [19, 21]. Significant investments in AI labs focused on automating decision-making and supporting human decision preparation have been made [13]. In this context, Stakeholders involved realize that human oversight in AI-driven decision-making is crucial. Human review mechanisms are usually advised to be in place, especially for decisions with serious implications, such as those affecting individuals' lives and liberties [14].

In the subsequent section, the theoretical lens of this article will be introduced, along with the data and methods employed in the study.

3. Methodology

3.1. Theoretical Frameworks

The existing research in this domain employs various theoretical models to understand different dimensions within an organization, such as the POPIT Model (People, Organization, Processes, and IT) [12], the Public AI Canvas (PAIC) for public value creation [5], Technology - Organization - Environment (TOE) framework [6, 11], Status Quo Bias Theory [1], while others use custom models [2, 7, 14, 21] for their studies and some PRISMA based systematic literature reviews were also conducted.

To categorize the organizational factors affecting AI adoption, identified with the help of the literature, this study adopts the Technology-Organization-Environment (TOE) framework as the primary analytical lens. The TOE framework provides a flexible, multidimensional approach to assess AI adoption when compared to other existing frameworks. The Technology-Organization-Environment (TOE) framework assesses technology adoption in a structured way by categorizing interdependent influencing factors that collectively shape the integration and institutionalization of emerging technologies within organizations into three domains: technological, referring to the attributes and maturity of the technology itself; organizational, referring to internal structures, resources, strategy, and readiness; and environmental, referring to external pressures such as regulatory frameworks, and industry standards. [6, 11]

More so, this study expands on the "*Organizational*" component of the framework by introducing three new sub-levels within the organization, namely "*Culture (C), Structure (S), and Individual (I)*". CSI builds on the TOE framework by offering a more detailed view of organizations. Instead of seeing them as a single unit, it breaks them down into culture, structure, and individuals. CSI adds depth and clarity, making it easier to understand how these factors interact. Factors such as innovation spirit, open culture, failure tolerance, discretionary freedom, risk-avoiding behavior, agility, and responsiveness of the organization are a part of the cultural component. Factors including defining strategy, supporting guidelines, policies laws and regulations, current structures, processes and routines, defined roles and tasks are part of the structure component. While knowledge, cross-functional skills, and competence. Status quo inertia, trust in reliability, trust in usefulness and job security are factors categorized as individual components. Together, this CSI framework integrates and becomes a part of the TOE framework.

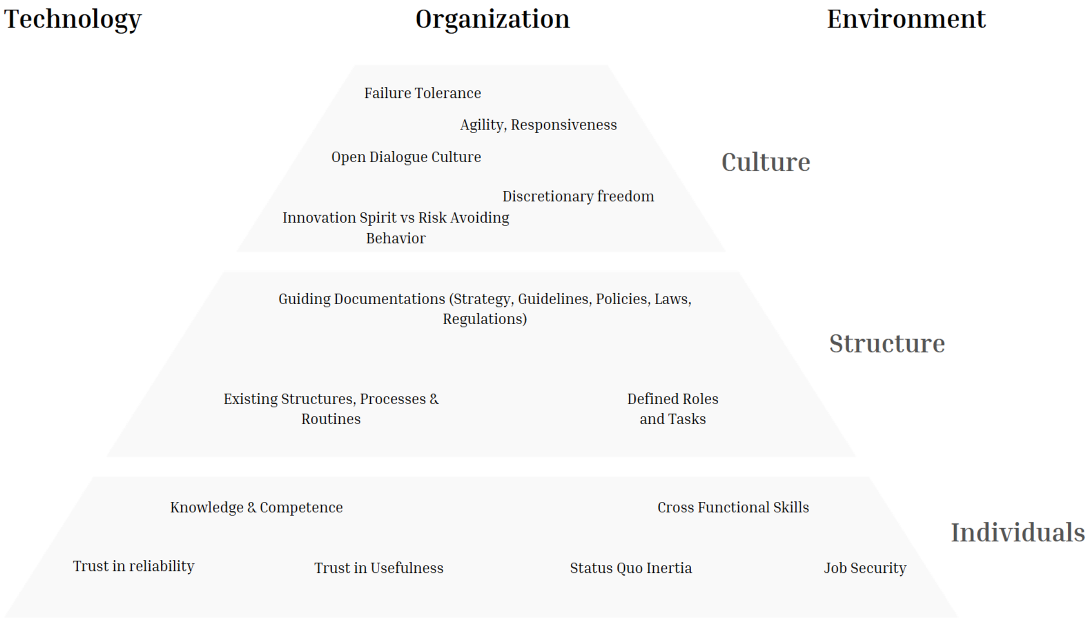

Figure 1: TOE Framework-based CSI Theoretical Model (Author's Elaboration).

Table 1
Attributes (Experience, Role & Expertise) of Experts Interviewed.

Respondent [R]	Experience (Years)	Current Role	Area of Expertise
A	8	Audit Research	AI Algorithm and Public Innovation
B	12	Consultancy	Digital Transformation
C	6	Civil Services	Capacity Building and Training

3.2. Data Collection

To understand the impact of the above-mentioned CSI factors, this exploratory research takes a qualitative approach through the TOE framework. The research aims to identify the most impactful factors or barriers to artificial intelligence adoption in public sector organizations. To address the research question, this paper employs a semi-structured interview approach conducted with experts from public and government services, consultancies, civil servants, researchers, and auditors.

Purposive and snowball sampling ensured participants met eligibility criteria, defined as professionals with substantial experience in AI adoption, digital transformation, or governance within the public sector. Eligibility was based on direct involvement in policy-making, implementation, consultancy, research, or auditing of AI. Experts were identified via professional networks and institutional affiliations. Ten were approached, five responded, and three participated. Participants required direct or indirect experience in researching, designing, implementing, or governing AI solutions in the public sector, with a focus on the EU. As detailed in Table 1, the final group brought diverse perspectives from within, outside, and in support roles to public organizations. (see Table 1).

Data collection occurred in November-December 2024. The flexible, semi-structured format supported in-depth qualitative insights. Ethical guidelines ensured participant confidentiality, with verbal consent obtained and anonymity maintained through coded identifiers. Recordings and transcripts, stored via Microsoft Teams' secure protocols, were accessed only during the study period.

3.3. Data Analysis

The data collected from semi-structured interviews was analyzed using a thematic analysis approach. Interview transcripts were systematically reviewed to identify key phrases, patterns, and recurring concepts, with a focus on listing contributing factors mentioned by participants. These concepts were then organized into broader themes that emerged from the data. The final themes “organizational, cultural, and individual factors” are presented in the Results section, and form the basis of the CSI model used to categorize influences on AI adoption in public sector organizationsTo ensure a structured categorization process that accurately reflects the perspectives of the interviewees, theme selection, categorization, and interpretation were conducted manually.

3.4. Methodology Limitation

The small sample size and potential self-selection bias limit generalizability, possibly excluding voices less experienced or more resistant to AI. The qualitative approach, while offering depth, does not provide statistical representativeness, limiting external validity. Additionally, data collected in late 2024 may not fully capture ongoing developments in government AI adoption. Social desirability bias remains a concern, as participants may have portrayed efforts more positively. Nonetheless, these limitations do not diminish the study’s value, but highlight the need for ongoing research and cross-context validation.

The next section discusses the analyzed data, exploring emerging themes related to the organization’s approach to innovation (4.1), individuals (4.2), and the roles of culture and structure (4.3).

4. Results

4.1. Organizational Outlook

To understand the current state of AI adoption in government entities and their outlook, a recurring theme emerged: outsourcing. While outsourcing knowledge, infrastructure, and projects is a common solution, it often creates a void in the organization’s internal capabilities to independently pursue similar projects in the future, raising concerns about over-reliance. As stated by [A] “*They get it from external sources, which works for a while, but then the external leaves. They do not translate into institutional capabilities. And if there are no institutional capabilities, then you really do not know how to do it, how to manage it*”. This lack of internal expertise means that organizations often lack in-house expertise and thus rely on intermediaries with technical backgrounds, “*there’s usually a liaison or individual with a technical background to whom we can translate the requirements*” [B].

Outsourcing is often chosen due to insufficient internal competencies and the absence of cross-functional skills. Although considered cost-effective, it can backfire: “*They often end up stuck in an impossible situation: they lack infrastructure, can’t use external infrastructure, and then what, pufff, progress stops*” [B].

While outsourcing can be efficient due to external expertise and resources, it also raises concerns about excessive dependence on third parties. The questions remain regarding whether governments should rely so heavily on third parties [B]. Furthermore, while outsourcing can be efficient because external companies have the expertise, technology, and infrastructure, “*it also makes governments overly reliant on others*” [C].

A lack of strategic vision in these organizations is evident. Many organizations approach AI implementation in an ad hoc manner, with no clear long-term strategy: “*The first is that there’s no strategic action, no vision, no view. It’s very ad hoc. Most organizations take this approach when they want to scale AI*” [A].Others fall into “mindless experimenting” or complete inaction, both problematic. Resistance to change, outdated systems, and legacy infrastructure impede integration “*if they’re too old, such as legacy systems, then you probably wouldn’t be able to connect those two dots*”, [B]. While some say, it’s time that may be the impeding factor, prompting administrations to frequently opt for shortcuts instead, the key challenge with these innovation teams is the lack of time [C]. Rather than investing in long-term structures that could better fit the project, “*administrations and governments often look for shortcuts*” [C].

4.2. Importance of People (Individuals) in AI Implementation

People within these institutions play a crucial role in the implementation process, making them a vital factor. However, resistance often arises due to fear and uncertainty. As per [B], the primary concerns within this sector itself are the trust issue, as "*accountability becomes an issue*" and both internal and external stakeholders require assurance that AI technologies serve as assistants rather than decision-makers. People from within and outside require assurance that these technologies are not necessarily acting as decision-makers but as assistants to the decision-maker: "*whoever that might be, which will always be a human*" [B], even more so, when dealing with decision-making dilemmas.

While AI-recommended decisions may sometimes feel mandated, similar risks exist when a manager dictates actions without question [A]. Moreover, there may be hints of AI-recommended decisions being mandated, but the same risk exists if managers act in a more imperative way: "*It's not the system itself that's the problem; it's how leadership interacts with it, and that can be far more dangerous...*" [A].

To mitigate this resistance, collaboration between domain experts and technology builders is essential. Despite this, within the same group, there are multidisciplinary experts with both technical and non-technical skills who can drive successful implementation. Thus, while the challenge lies with people, the solution also stems from them. The process is people-centric, with solutions emerging organically from within, rather than being imposed externally. There is an importance of having internal expertise, and individuals who can identify opportunities and experiment with technology, while also recognizing that AI adoption requires more than just technical knowledge [A]. Furthermore, people inside the institutions with the operational know-how and the talent for opportunities-spotting and experimenting are key [A]. Having such experiments in-house is thus instrumental: "*Understanding technology requires more than techies. An organization needs a multidisciplinary team, people who understand both technology and organizational strategy*" [A]. Similarly, when people themselves propose AI use cases rather than having solutions imposed on them, engagement and interest naturally increase: "*We are not imposing any solutions on them, but they themselves are coming up with the use cases of these technologies*" [B]. Then, they become more interested because they are the ones who proposed it [B]. People lie at the core of this: "*Tools and technology are merely components of a larger process aimed at meeting people's needs, not the entirety of the process*" [C].

4.3. Cultural (C) and Structural (S) Shifts

The interviews highlighted that cultural resistance and bureaucratic inertia often hinder innovation and its adoption in public sector organizations, rooted in the inherent traits of bureaucracy. Public sector employees frequently follow repetitive routines, making them reluctant to embrace change. Their skepticism can be a barrier, which is why it is essential to engage them in activities that create a cultural shift: "*Now the system more or less becomes your assistant in the decision-making process rather than dictating what to do*" [C]. If people are required to follow the system, this will likely be followed by resistance and to avoid it, it's essential to have good collaboration with domain experts and builders [C].

A mindset shift is necessary given the fact that many public sector organizations are resistant to change [B]. Moreover, as respondents mentioned, most projects are undertaken for political reasons or as publicity stunts, rather than as part of a cohesive strategy: "*Governments often fall into a pseudo sense of digitization, implementing small, isolated AI projects without integrating them*" [B].

Therefore, a need for a cultural or mindset shift gains prominence, which itself varies significantly based on organizational size as smaller organizations find it easier to onboard everyone due to fewer hierarchical barriers, depending on the organizational culture: "*If the organization has very short lines or hierarchy, [...] then you can have all the people on board*" [A]. The issue of organizing a collaborative effort is further exacerbated with the growth of the group's size [A]. A delicate balance between experimentation and implementation being a tedious task is further highlighted: "*It's a fine line*" [B]. Thus, this diffusion of innovation, particularly people's acceptance of it, "*is a very difficult task*" [B].

4.4. Sustainable Implementation Strategies

Innovation, being highly context-specific, requires careful adaptation. Interviewees emphasized the importance of engaging innovators and early adopters within the organization to serve as anchors and catalysts for change. Establishing a team of enthusiastic individuals who are eager to be part of the innovation process can be a crucial first step. Once people see tangible results, they are more likely to support and adopt new initiatives: "*Probably they'd jump on the wagon and be more on-board. But yeah, that's it, that's really it*" [B].

While [A] believes that truly innovative, exciting applications are often unique to an organization. They come to light when experts identify opportunities and decide to act on them, decide to do something about it. "*Figure out what they need. You're trying to assist with a specific business process or task they perform daily*" [A]. Though it might seem straightforward, issues often arise: "*Even so, most people want their jobs to be easier*" [A].

A key takeaway for successfully implementing sustainable strategies is, to begin with small pilot projects as proof of concept. This approach allows for combining experimentation with feasibility and sustainability assessments. The focus can be on identifying and addressing use cases aligned with the specific organizational needs and context of the local government.

5. Discussion

The findings of this study provide a perspective on the systematic challenges in adopting artificial intelligence within government entities. Broadly, it reveals the relationship between technology and governance through the lens of human interactions. Outsourcing, while addressing immediate skill gaps, creates dependency. Therefore, it should not be a transactional fix but a strategic move for capacity-building through knowledge transfer agreements and upskilling programs. These provisions should be embedded in procurement contracts.

Trust emerges as both a psychological and structural barrier, influenced by accountability and transparency frameworks. Participatory decision-making and feedback loops during implementation can build this trust and enhance societal value. Establishing interdepartmental steering groups or advisory boards can lend legitimacy. Bureaucratic inertia, often seen as an innovation barrier, can be repurposed for sustainable change. Its predictability and scalability offer potential for systematic, equitable AI adoption. Public sector leaders should be trained not just in AI, but also in change management and digital-era leadership. People remain both the greatest barrier and solution, translating technical potential into human-centric outcomes is key. Cultural architects in leadership roles can reshape mindsets.

Change begins with small steps. Pilot projects and iterative learning can formalize innovation hubs within organizations. Institutional "innovation sandboxes" should be considered to test and scale new ideas. This study shows the need for systemic thinking in AI adoption. Isolated interventions are insufficient. AI should be integrated as part of an interdependent system of people, technology, policy, and society. Addressing root causes and anticipating ripple effects are essential for sustainable public sector AI initiatives. The study cautions against fragmented efforts and supports a whole-of-government approach.

There is room for expansion. Limited to three interviews, the study's findings may lack generalizability. A larger qualitative study, especially as an organizational case study within the EU, could deepen context-specific understanding [13]. Including multiple organizations and contexts outside the EU could enhance global relevance and allow exploration of long-term effects and cross-departmental dynamics [17]. Future research should also explore ethical AI use, innovation legislation, and cultural influences on adoption. Communication, trust, and transparency are critical long-term enablers that offer substantial opportunities for further study [2, 14, 15].

6. Conclusion

The successful AI adoption in the public sector is shaped by cultural, structural, and individual factors. Organizationally, lack of in-house expertise and reliance on outsourcing hinder sustained adoption. Structurally, outdated systems and absent strategic vision lead to fragmented efforts. Culturally, resistance and skepticism toward AI decision-making highlight the need for participatory models and trust-building mechanisms. Multidisciplinary teams and engaged leaders are central to overcoming these barriers. A people-centric approach bridges technical potential with practical outcomes. Small-scale pilots, iterative learning, and institutionalized innovation hubs support enduring adoption.

The study reaffirms that AI adoption is not just a technical challenge but an organizational one. These challenges, however, are surmountable. People-centric strategies, leadership, and trust-building will determine whether adoption succeeds or stagnates. Outsourcing, while helpful short term, does not build long-term capabilities. The focus needs to shift to internal capacity-building, cross-functional collaboration, and structured change management. AI in government should move beyond experimentation toward sustainable integration. A culture of innovation, institutional learning, and participatory governance is crucial. AI's effectiveness depends on its alignment with governance structures and public service values. As digital transformation accelerates, the need for strategic vision, leadership support, and workforce adaptability grows. Future research should explore long-term impacts, intergovernmental comparisons, and the role of human oversight in AI decision-making.

Successful AI adoption demands more than readiness. It requires innovation aligned with human and procedural systems. Public leaders can build trust and transparency while investing in skilled, cross-functional teams and small-scale pilots to build momentum. Outsourcing should serve long-term capacity development. Ultimately, sustainable technological progress relies on people-centricity. A resilient public sector ecosystem is built through iterative learning, mindful experimentation, and participatory decision-making.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

1. Almatrodi, I., Li, F., Alojail, M.: Organizational Resistance to Automation Success: How Status Quo Bias Influences Organizational Resistance to an Automated Workflow System in a Public Organization. Systems 11(4) (2023). https://doi.org/10.3390/systems11040191
2. Bartolotta, S. J., Gritt, E.: Artificial Intelligence: Threat or "Colleague"? Exploring Managers' Perceptions of AI in Organisations. In: UKAIS 2021. (2021). https://aisel.aisnet.org/ukais2021
3. Bosch, M. J., Müller, R.: Artificial Intelligence for Interoperability in the European Public Sector: An Exploratory Study. (2023). https://doi.org/10.2760/633646
4. Butt, J. S.: A Comparative Study About the Use of Artificial Intelligence (AI) in Public Administration of Nordic States with Other European Economic Sectors. (2024)
5. Fatima, S., Desouza, K. C., Buck, C., Fielt, E.: Public AI Canvas for AI-enabled Public Value: A Design Science Approach. Government Information Quarterly 39(4) (2022). https://doi.org/10.1016/j.giq.2022.101722
6. Felemban, H., Sohail, M., Ruikar, K.: Exploring the Readiness of Organisations to Adopt Artificial Intelligence. Buildings 14(8) (2024). https://doi.org/10.3390/buildings14082460
7. Giest, S. N., Klievink, B.: More than a Digital System: How AI is Changing the Role of Bureaucrats in Different Organizational Contexts. Public Management Review 26(2), 379–398 (2024). https://doi.org/10.1080/14719037.2022.2095001

8. Haug, N., Dan, S., Mergel, I.: Digitally-Induced Change in the Public Sector: A Systematic Review and Research Agenda. Public Management Review 26(7), 1963–1987 (2024). https://doi.org/10.1080/14719037.2023.2234917
9. Hjaltalin, I. T., Sigurdarson, H. T.: The Strategic Use of AI in the Public Sector: A Public Values Analysis of National AI Strategies. Government Information Quarterly 41(1) (2024). https://doi.org/10.1016/j.giq.2024.101914
10. Madan, R., Ashok, M.: AI Adoption and Diffusion in Public Administration: A Systematic Literature Review and Future Research Agenda. In: Government Information Quarterly 40(1). Elsevier (2023). https://doi.org/10.1016/j.giq.2022.101774
11. Maragno, G., Tangi, L., Gastaldi, L., Benedetti, M.: Exploring the Factors, Affordances and Constraints Outlining the Implementation of Artificial Intelligence in Public Sector Organizations. International Journal of Information Management 73 (2023). https://doi.org/10.1016/j.ijinfomgt.2023.102686
12. Marzouki, A., Chouikh, A., Mellouli, S., Haddad, R.: Barriers and Actions for the Adoption and Use of Artificial Intelligence in the Public Sector. ACM International Conference Proceeding Series, 94–100 (2023). https://doi.org/10.1145/3614321.3614334
13. Mergel, I., Dickinson, H., Stenvall, J., Gasco, M.: Implementing AI in the Public Sector. Public Management Review (2023). https://doi.org/10.1080/14719037.2023.2231950
14. Misra, S. K., Sharma, S. K., Gupta, S., Das, S.: A Framework to Overcome Challenges to the Adoption of Artificial Intelligence in Indian Government Organizations. Technological Forecasting and Social Change 194 (2023). https://doi.org/10.1016/j.techfore.2023.122721
15. Misuraca, G., van Noordt, C.: Overview of the Use and Impact of AI in Public Services in the EU. EUR 30255 EN, (2020). https://doi.org/10.2760/039619
16. Neumann, O., Guirguis, K., Steiner, R.: Exploring Artificial Intelligence Adoption in Public Organizations: A Comparative Case Study. Public Management Review 26(1), 114–141 (2024). https://doi.org/10.1080/14719037.2022.2048685
17. Nurski, L.: AI Adoption in the Public Sector: A Case Study. Bruegel Working Paper No. 03/2023, (2023). https://hdl.handle.net/10419/274209
18. Selten, F., Klievink, B.: Organizing Public Sector AI Adoption: Navigating Between Separation and Integration. Government Information Quarterly 41(1) (2024). https://doi.org/10.1016/j.giq.2023.101885
19. Van Noordt, C., Misuraca, G.: Artificial Intelligence for the Public Sector: Results of Landscaping the Use of AI in Government Across the European Union. Government Information Quarterly 39(3) (2022). https://doi.org/10.1016/j.giq.2022.101714
20. Weerakkody, V., El-Haddadeh, R., Sabol, T., Ghoneim, A., Dzupka, P.: E-Government Implementation Strategies in Developed and Transition Economies: A Comparative Study. International Journal of Information Management 32(1), 66–74 (2012). https://doi.org/10.1016/j.ijinfomgt.2011.10.005
21. Wirtz, B. W., Weyerer, J. C., Sturm, B. J.: The Dark Sides of Artificial Intelligence: An Integrated AI Governance Framework for Public Administration. International Journal of Public Administration 43(9), 818–829 (2020). https://doi.org/10.1080/01900692.2020.1749851