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An Iterative Framework for AI Adoption in the Public Sector: Insights from a Swiss Case Study

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Abstract: In the step from prototype to the productive, the sustainable use of Artificial Intelligence (AI) applications remains a significant challenge. This creates a demand for frameworks that guide organisations and help to bridge this gap in specific domains. This study validates the Adoption Framework for AI in the Public Sector (AFAIPS) by examining its application in a Swiss AI chatbot project for healthcare cost verification, addressing how an iterative framework can be used to navigate public sector constraints. Using a detailed single case study within an Elaborated Action Design Research (EADR) setting, this research recorded a 34-week AI chatbot implementation over eleven iterations, drawing evidence from project documentation and user interviews. The findings show that AFAIPS effectively guided the project through its adoption phases, enabling user-driven development and flexible adjustments. Iterative prototyping and continuous feedback were essential for handling public sector limitations and technical uncertainties. Key results included organisational learning, such as the development of "AI-ready" documentation, and strategic changes like planning for external Machine Learning Operations (MLOps) support to address internal capability gaps. This study provides empirical validation of AFAIPS in public healthcare administration, offering new insights into how an integrated framework — combining the Diffusion of Innovations theory (DOI) with Design Thinking (DT), Lean Startup (LS), and MLOps connects theory with the practicalities of government AI implementation, to improve public value. For public managers and policymakers, this research offers a validated roadmap and practical strategies for stakeholder engagement, iterative development, and agile management to guide digital transformation and AI governance.

Keywords: Artificial Intelligence (AI), Public Sector, AI Adoption, Digital Transformation

Statement on the use of AI: During the preparation of this work, the author(s) used Claude Opus 4.6 - 4.8 and Grammarly in order to check spelling, correct grammar, and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

1. Introduction

The introduction of Artificial Intelligence (AI) into the public sector presents a significant opportunity to enhance administrative efficiency, augment service delivery, and reshape citizen interactions, particularly within complex domains like public healthcare administration (Charalabidis and Medaglia 2024). Global investments in public sector AI are growing (European Commission. Joint Research Centre. 2022), driven by this transformative potential. The Swiss healthcare sector has a long history of adopting private management practices to address rising costs, and AI integration represents the latest evolution in this ongoing effort to balance cost efficiency with service quality. However, public organizations face distinct hurdles rooted in their unique operational and institutional characteristics. These include inherent risk aversion tied to accountability (Buurman et al. 2012; Chang 2024), complex regulatory and governance frameworks, shortages in specialized technical expertise, and the critical imperative to balance efficiency gains with core public values, such as equity and transparency (Madan and Ashok 2023; Vogl et al. 2019). Such challenges can contribute to what has been termed algorithmic bureaucracy (Vogl et al. 2019).

The successful adoption of AI in the public sector requires strong, context-sensitive strategies. Research has identified key barriers and success factors (Pechtor and Basl 2022), but a significant gap still exists in practical, evidence-based frameworks tailored for government that can also keep up with emerging AI technologies (Lichtenthaler 2020; Madan and Ashok 2023). Many current models are either too theoretical or do not connect basic adoption theories with modern, flexible methods (Pechtor and Basl 2022). While technical frameworks like MAISTRO (Petrin, Néto, and Mariano 2025) guide the execution of AI projects, the Adoption Framework for AI in the Public Sector (AFAIPS) offers a wider organizational view. Its unique contribution comes in the early phases—Agenda-Setting and Matching—where it uses DT and LS principles to discover and validate the appropriate problem and solution, answering the "what" and "why." This emphasis on achieving a solid problem-solution fit before moving into development ensures that organizations are ready and aligned with public value, which is essential for responsible AI deployment in resource-limited, risk-averse government settings.

The main goal of this research is to fill this gap by creating and testing the iterative framework, AFAIPS. This framework aims to offer practical advice for AI adoption efforts in public sector organizations. We accomplish this through a case study of how the framework was applied in developing and launching an AI chatbot for healthcare cost verification in a Swiss public healthcare department, here referred to as, 'The Office'. The study looks at how well AFAIPS works and notes necessary changes for this specific, yet typical, public sector setting.

Consequently, this research addresses two research questions:

RQ1. How does an iterative framework guide the adoption of an AI solution within a public healthcare administration context?

RQ2. What key organizational and technical adaptations are required when applying an iterative AI adoption framework in the public sector?

To address this research question, a single case study methodology (Yin 2018) was employed, chronicling a 34-week AI implementation project. Data collection involved analyzing extensive project documentation across eleven iterations from mid-2024 to February 2025 and conducting post-implementation user interviews to ensure triangulation and gather practical insights. It provides empirical validation of AFAIPS, specifically within public healthcare administration, responding to calls for tailored approaches.

2. Literature Review

AI is set to change public administration in major ways. This potential is clear from the growing research interest and substantial investment by institutions since 2018 (European Commission 2025; Pini et al. 2025). Governments are already using AI in important areas, including policy-making, internal workflows, and direct service delivery through chatbots and predictive analytics (Van Noordt and Misuraca 2022; Wirtz, Weyerer, and Geyer 2019). However, turning this potential into lasting and measurable public benefit is still an area of research (Madan and Ashok 2023).

As well as in the public sector, AI promises to deliver significant potential to improve many public health functions (Fisher and Rosella 2022). Much of its use has focused in the past on monitoring population health. This includes predictive modeling to forecast the spread of infectious diseases (Malik et al. 2021; Martin-Moreno et al. 2022) and real-time health surveillance (Șerban et al. 2019). It also helps predict environmental risks (Sadilek et al. 2018). These systems identify patterns in various data sources, including electronic health records (Knevel and Liao 2023) and free-text documents (Ward et al. 2019). They support everything from targeting health campaigns (Chu et al. 2019) to improving interventions (Yi et al. 2022). Beyond these functions in epidemiology and population health, AI has begun to be used to simplify important health administration tasks that support these services. In this context, a key application—and the focus of this study—is the use of conversational AI agents (Wah 2025). These tools serve as intelligent knowledge management systems. They provide staff with immediate and accurate answers to complex policy or cost-coverage questions. This helps reduce administrative workloads and improve the consistency of service delivery.

Implementing AI in the public sector has several barriers. These include institutional and cultural challenges, such as risk aversion and rigid bureaucracy (Pechtor 2023; Selten and Klievink 2024), as well as operational issues like data silos, skill shortages, and poor data quality (Gong and Janssen 2021; Kučević, Grünewald, and Schanz 2024). Additionally, the technical complexity of AI systems demands ongoing adjustments that go beyond the requirements of typical IT projects (Ndlovu 2025). To address this complexity, the Diffusion of Innovations (DOI) theory byRogers (2003) offers a useful framework. It outlines a process for organizations to adopt innovations, starting from initial agenda-setting and matching an innovation to a need, then moving to redefining, clarifying, and finally integrating it into daily operations (Rogers 2003).

However, while the DOI theory offers a valuable process model for understanding how innovations move from initial consideration to routine use, scholars have noted its limits when applied to fast-changing technologies like AI (Madan and Ashok 2023). Misuraca and Viscusi (2020) argue that AI in the public sector is not just an innovation to adopt; it is a transformative force that constantly reshapes organizational practices and governance models. Their distinction between sustaining and disruptive AI applications shows that implementation is not a one-time event but an ongoing process of change (European Commission. Joint Research Centre. 2020; Van Noordt and Misuraca 2022). This transformation perspective is backed by evidence indicating that most government AI initiatives remain stuck in pilot phases. Systemic barriers, such as skills gaps, organizational inertia, and risk aversion prevent full implementation (OECD 2025; Selten and Klievink 2024). This paper argues that these perspectives are complementary, not contradictory. DOI provides a useful process structure for managing implementation stages, while Misuracaís transformation lens reminds us that each stage must support continuous learning and organizational change. The AFAIPS framework, proposed here, seeks to merge these views by incorporating iterative, adaptive methods like DT, LS, and MLOps within DOI's stage-based structure. This creates a framework that is both practical and responsive to AI's transformative nature.

Recent research has highlighted the real challenges that hinder AI projects in government. The 2025 OECD (Organisation for Economic Co-operation and Development) report found that most public sector AI projects are still in pilot or experimental phases (OECD 2025). There are few examples of successful scaling across government. Key issues include a significant skills gap, which is often mentioned as the main barrier to AI adoption, as well as outdated IT systems, fragmented data management, and a cautious culture that discourages experimentation. In response, governments are investing in programs to build skills. These range from basic AI training for all staff to specialized programs for leaders and technical workers. They are also making strategic hiring efforts to attract limited digital talent. However, even with the right skills, changing organizations is still very challenging. Selten and Klievink point out a major conflict between the rigid, hierarchical structures common in public administration and the flexible, experimental culture needed for AI innovation. Their research shows that agencies have trouble finding the right organizational model. Some may create separate AI units that risk becoming isolated from core operations, while others may integrate AI teams into existing departments where they might be limited by bureaucratic rules. These findings highlight that successful AI implementation needs, not only technical skills, but also a strong focus on developing the workforce and managing organizational change.

Despite these developments, a significant research gap remains. There are few existing AI adoption frameworks for the public sector, and they often lack practical guidance for practitioners (Pechtor and Basl 2022). Many frameworks describe adoption through theories like DOI or the Technology-Organization-Environment (TOE) framework (Tornatzky, Fleischer, and Chakrabarti 1990) but do not effectively connect these ideas with current iterative practices such as DT or LS. They also do not adequately cover the important post-deployment phase, which includes sustainable operations and governance using methods like MLOps (De Silva and Alahakoon 2021; Levy, Chasalow, and Riley 2021; Pechtor and Basl 2022). This paper addresses these gaps by proposing AFAIPS, a framework that incorporates iterative, adaptive methods into DOI's stage-based structure. The framework combines DT, LS, and MLOps to tackle the implementation challenges highlighted in recent literature. DTs focus on prototyping helps reduce risk aversion. Lean Startup's Minimum Viable Product (MVP) approach offers a clear path from pilot to production. MLOps ensures ongoing adaptation in line with Misuraca et als perspective on transformation.

Design Thinking (DT) is a human-centered, step-by-step method that is helpful for guiding AI adoption in the public sector. Its main principle is to concentrate on real user needs before settling on a technical solution. This approach balances what users want with what is technically possible and what the organization can support (Brenner and Uebernickel 2016). By including users from the start, it lowers the chance of developing AI systems that people will ultimately reject (Brenner, Van Giffen, and Koehler 2021; Brown and others 2008). The process of creating prototypes and embracing early failures fits well with the uncertainties of AI projects. It helps manage what stakeholders expect and builds trust by making the technology easier to understand and open to feedback (Staub et al. 2023; Westenberger, Schuler, and Schlegel 2022). Although its flexible and exploratory nature might clash with the cautious culture of public administration, DT's power to tackle complex problems makes it a valuable tool for ensuring AI solutions provide meaningful public value (Mergel and Ney 2022).

Following a comparable philosophy, the experimental approaches of the Lean Startup methodology provide a practical way to deal with the uncertainty of implementing AI. While DT focuses on idea generation and evaluation, this method focuses on the build-measure-learn feedback loop, which is a continuous cycle where an MVP is implemented to gather essential insights about user needs with minimal effort (Palacios et al. 2024; Ries and Ries 2023). This iterative strategy enables public organizations to test assumptions, reduce waste, and demonstrate value by implementing practical solutions. This is particularly important due to budget limits and the risk-averse nature of the sector (Venson, Da Costa Figueiredo, and Canedo 2024; Vogl et al. 2019). This enables a gradual adoption of AI while building internal skills and stakeholder support (Mergel, Ganapati, and Whitford 2021; Serban and Visser 2022).

When using AI solutions in a production setting, the standard methodology is to apply Machine Learning Operations (MLOps). It is an agile framework that manages the entire lifecycle of AI systems, from development to production and continuous monitoring (Sorvisto 2023). Its main goal is to tackle the drop in AI model performance that happens because of real-world changes in data, known as "data drift" (Ansell, Sørensen, and Torfing 2021). MLOps encourages teamwork among different groups, including data scientists, engineers, and subject matter experts. It also automates tasks like model retraining, testing, and deployment to minimize manual mistakes (Koenders et al. 2022; Treveil 2021). A vital part of MLOps is the ongoing monitoring of live AI models to spot performance issues and in the best case, trigger automatic fixes. This ongoing process, with its built-in feedback loops, is essential for the public sector. It helps keep high standards for transparency, traceability, and accountability by providing a fully documented and auditable machine learning lifecycle (Ruf et al. 2021).

In light of these significant implementation, capacity, and organizational challenges, a notable research gap exists. While traditional frameworks like DOI explain the reasons for adoption, they often do not offer practical guidance for handling these real-world situations (Pechtor and Basl 2022). This paper aims to fill that gap by introducing AFAIPS, a framework that incorporates iterative methods into the DOI structure. By including DT Lean Startup, and MLOps, AFAIPS is specifically designed to tackle the issues of risk aversion, the gap from pilot to production, and the need for ongoing organizational change.

3. The Adoption Framework for AI in the Public Sector (AFAIPS)

AFAIPS offers a modern, organized way to innovate by modifying Rogers (2003) DOI theory for the uncertain and evolving nature of AI development. It breaks down Rogers' five stages into a clear yet adaptable path for public sector organizations: Agenda-Setting, Matching, Redefining/Restructuring, Clarifying, and Routinizing. To relate these stages to AI, the framework includes three important methods. It employs DT to ensure that solutions focus on users and meet actual public needs, especially during the early problem exploration (Brenner and Uebernickel 2016). To address the public sector's tendency to avoid risks, it uses Lean Startup principles, relying on iterative build-measure-learn cycles and MVPs to test ideas early on (Ries and Ries 2023). Finally, AFAIPS brings in MLOps to manage the specific operational lifecycle of AI systems, ensuring their long-term viability, trustworthiness, and maintainability while working within the limits of public resources (Ruf et al. 2021). Each of these methods was chosen to address the main obstacles to implementation identified in the literature. These include risk aversion, skills gaps, and the pilot-to-production gap.

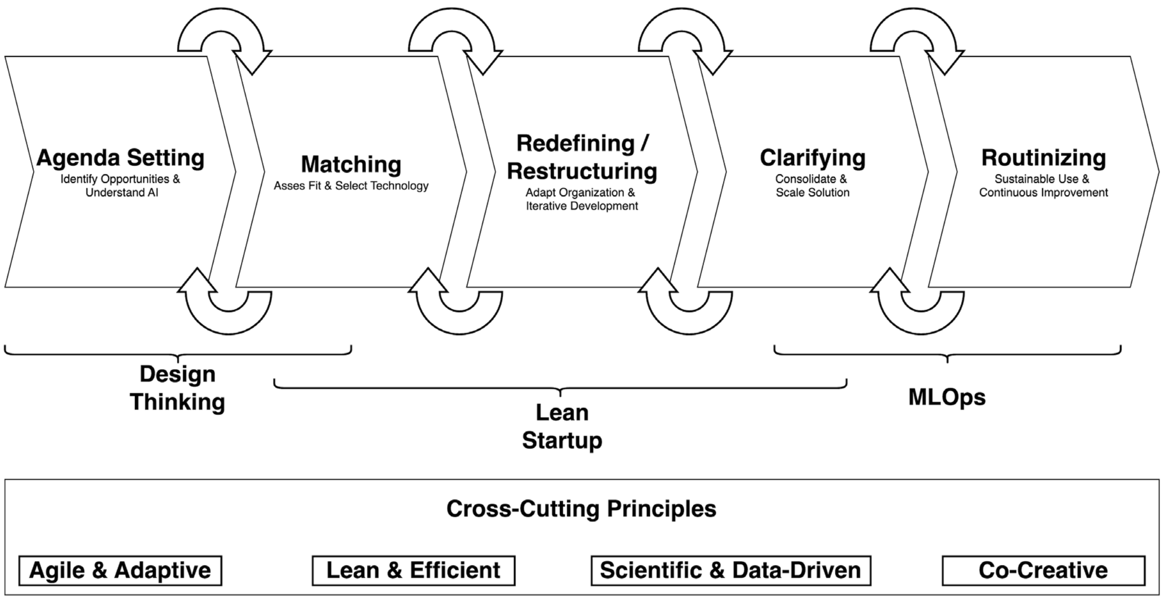

Figure 1- The Adoption Framework for AI in the Public Sector (AFAIPS) (Source: author)

The framework starts with Agenda-Setting, a key exploratory stage where DT helps identify major AI opportunities rooted in real organizational needs. This stage involves working with various stakeholders to find performance gaps and collaboratively create basic concepts, building foundational AI knowledge, and a shared understanding of the issue. A crucial part of this stage is learning about the realistic capabilities of AI based on comparable cases from real-world applications. From this base, the process progresses to the Matching phase, focused on establishing a strong connection between the problem and the solution. Here, the framework combines DT and LS principles to evaluate AI's fit, set clear success metrics, and confirm the solution's main value with an MVP-ready prototype, before investing significant resources. It is important to note that a possible outcome is to find out that AI maybe isn't necessary to solve a particular problem. The next phase; Redefining/Restructuring, is especially dynamic. It involves developing the AI solution alongside the organization itself. Using LS and Agile methods, an MVP is created and tested in a limited, real-world setting. The data and insights gathered from its performance help refine both the technology and the related organizational structures, skills, and processes. Short cycles, intensive collaboration, and communication are typical for this phase. To address realistic challenges, the use of real-world data is recommended. As the solution demonstrates its worth, the Clarifying phase helps transition from a limited experiment to a scalable service. This stage introduces essential MLOps practices, such as automated testing and deployment pipelines, to solidify the AI solution, ensure reliable scaling, and establish solid operational governance. It is important to note that the introduction of MLOps can happen gradually, starting with simpler principles first and then increasing the level of automation. Lastly, the Routinizing phase secures long-term impact by fully embedding the AI solution into the organization's standard processes. At this stage, MLOps practices become crucial for the regular monitoring, maintenance, and ongoing improvement of the system, reinforcing its lasting public value and turning it into a vital part of service delivery. A key principle of AFAIPS is its multi-faceted approach to evaluation, which goes beyond basic technical outputs (Cordella and Bonina 2012). The framework requires measuring Technical Metrics, such as model accuracy, Organizational Metrics such as user adoption, and importantly, Public Value Metrics that include improvements in service quality, citizen satisfaction, fairness, and transparency. For the framework to work well, it needs strong change management, including clear communication and training to promote an AI-ready culture (Mergel et al. 2021). Additionally, solid governance structures are necessary to ensure accountability and manage risks, while ongoing skill development is vital for long-term sustainability and navigating the complexities that the framework's iterative nature aims to address.

Table 1 - Connection between implementation challenges and AFAIPS. Source: author

Implementation Challenge (from Literature)	How AFAIPS Addresses It
Risk Aversion & High Failure Rates	DT encourages low-cost prototyping and Lean Startups MVP approach tests assumptions early, making failure a learning opportunity rather than a costly mistake.
Pilot-to-Production Gap	The build-measure-learn loop of LS provides a structured path from pilot to scaled service, while MLOps provides the technical backbone for stable, sustainable production deployment.
Capacity & Skills Gaps	The iterative nature of the framework allows for gradual capability building. Teams learn by doing, and the framework helps identify specific skill gaps (like MLOps expertise) early in the process.
Organizational Rigidity vs. Need for Transformation	DT fosters a user-centric, collaborative culture, while the phased DOI structure provides a familiar process that is more palatable to traditional organizations. MLOps ensures the solution adapts over time, supporting continuous transformation.

While this case study focuses on a generative AI system, AFAIPS is built to work with any technology. The challenges it tackles, such as risk aversion, the pilot-to-production gap, and organizational change, are common to all types of AI (Selten and Klievink 2024). For non-generative AI, the technical setup in each phase may change, but the basic framework stays the same.

4. Methodology

This study used an interpretive research philosophy (Ayton, Tsindos, and Berkovic 2024; Flick 2007) to explore the development, use, and validation of the framework. Recognizing that reality in organizations is socially constructed, this approach emphasizes understanding events through the personal meanings and views of those involved (Flick 2007). It is especially useful for gaining detailed insights into how AFAIPS worked and was perceived by stakeholders, including managers, technical staff, and end-users, during its use.

The Adoption framework for AI in the public Sector (AFAIPS) was developed using an Elaborated Action Design Research (EADR) methodology (Mullarkey and Hevner 2019). This approach is effective for creating and evaluating solutions to complex problems, like AI adoption in the public sector. As shown in Figure 2, this methodology has two nested iterative cycles. The outer Macro Cycle guided the research project through four distinct phases. (1) Problem Diagnosis, addressed by the literature review, (2) Solution Design and the creation of the AFAIPS framework, (3) Implementation in the public sector AI project , (4) Evaluation and assessment of the effectiveness using a case study design. Progress in each major phase was driven by the quick, iterative inner Micro Cycle of problem formulation, artifact creation, evaluation, reflection, and learning. In practice, each of the eleven development iterations within the AI chatbot project was a complete micro-cycle. A specific feature was planned and built, user feedback was collected and reviewed, and the resulting insights informed the next iteration. This paper focuses on the empirical validation of AFAIPS from the Evaluation phase, using a single explanatory case study design (Yin 2018). The case study allows for an investigation of complex phenomena in their real-world context and is well-suited for exploring our research questions regarding how AFAIPS was implemented and adjusted in public healthcare administration (Yin 2018). The unit of analysis was the process of applying AFAIPS during a specific AI chatbot implementation project. While primarily explanatory, the study also included exploratory aspects to identify necessary organizational and technical changes driven by sector-specific constraints (Runeson et al. 2012).

Figure 2 - EADR Research Framework (Source: author, based on Mullarkey and Hevner, 2019)

To answer the research questions, a multi-method data collection strategy was employed, ensuring triangulation. Each research question was addressed by a specific combination of data sources, as detailed in Table 2.

Table 2 - Mapping of Research Questions to Data Collection Methods (Source: author)

Research Question	Primary Method(s)	Supporting Method(s)	Rationale
RQ1: How does AFAIPS guide the AI adoption process?	Project Documentation (iteration plans, workshop outputs, technical specs)	Participant Observation (meeting notes), Interviews (retrospective process accounts)	Documentation provided a real-time record of how AFAIPS was used in each phase. Observation captured the process as it happened, while interviews collected stakeholder views on the framework's guidance.

RQ2: What organizational and technical adaptations are required?	Semi-structured Interviews (capturing stakeholder reflections), Project Documentation (e.g., guidelines, hosting memos)	Participant Observation, User Feedback (from the wider group)	Interviews were essential for understanding why users needed changes. Documentation offered clear proof of the changes made, such as creating new guidance. Observation and user feedback pointed out new needs that led to these changes.

The case involved an AI implementation project that lasted about 34 weeks, from July 2024 to February 2025, in a Swiss public healthcare department referred to as 'The Office'. The entire department has around 1,400 staff members. The project aimed to create an AI agent (chatbot) using cloud services (Google Cloud Platform) to improve administrative processes for healthcare cost verification. It aimed to solve a knowledge gap by giving correctional facility staff quick access to complex cost coverage rules. This would lower the number of inquiries to a central specialist team.

This case was chosen because of the strong access researchers had to participants and project data, its uniqueness as an early AI agent used in cantonal administration, and how well it reflects common challenges in public sector digitalization, such as issues with information retrieval, sharing expertise, and meeting accuracy requirements. Important contextual factors included managing the differences between the project's iterative framework (AFAIPS) and the administration's usual structured method HERMES (Bürki 2023). Researchers also had to follow strict cantonal data protection rules, especially about cloud usage. This led to a key design choice where the AI agent worked only with non-personal and non-sensitive data.

A qualitative data collection strategy using multiple sources was used to allow triangulation. The primary data for the case study included:

(1) extensive project documentation created during the 34-week implementation, which included eleven iterations. This documentation consisted of workshop materials and outputs, like Miro boards and mock-ups, email exchanges, iteration plans and reviews, technical documents, user feedback logs, presentations, internal messages, and the AI's knowledge base documents. This provided real-time insights into the project's development, decisions, and challenges.

(2) Post-implementation semi-structured interviews were conducted with three carefully chosen key participants representing critical perspectives: a central specialist team member (Key User 1), a person with cantonal IT project management experience (Key User 2), and a primary user involved in testing (Key User 3). The 30-minute interviews took place after the project concluded in March 2025. They examined experiences with AFAIPS, context-specific issues, stakeholder involvement,

and lessons learned. The interviews were audio-recorded with informed consent and transcribed verbatim.

(3) Participant observation notes were taken by the researcher during important project events. These included workshops related to the AI implementation and major team meetings. The notes provide direct insights into AFAIPS's application and team interactions.

(4) The collection of feedback from about 20 potential key users, via email, after presenting to a larger audience that gave first impressions from stakeholders not previously involved in the project.

The data was analyzed using the Thematic Analysis method. We used MAXQDA software to manage and code all data sources, including interview transcripts, project documentation, and observation notes. The initial analysis generated over 150 distinct codes through a two-part approach. First, we established deductive codes based on the AFAIPS framework and the research questions to test the framework's relevance. Second, we created inductive codes to label specific phenomena we observed directly in the data, capturing the practical realities of the project. The coding involved systematically tagging the data. We applied deductive codes like Agenda-Setting or Matching to text segments that described activities within those AFAIPS phases. The inductive coding was more focused on the data itself. For example, the code Language Mismatch (User vs. Official) was created after Key User 2 described the challenge of "mapping from everyday language to... official language" in source documents. Likewise, we applied the AI-Ready documentation code to project records where the team created and shared new guidelines for document formatting. This was a direct response to a technical challenge. Next, we consolidated these specific codes into broader themes. This process involved grouping related codes to tell a larger analytical story. For instance, we combined the code 'Internal Capability Gap', which appeared in interviews about a lack of MLOps skills, with documented project decisions labeled 'External MLOps Support'. Together, they formed the strong theme of 'Strategic Adaptation to Internal Skill Gaps'. We systematically checked the validity of these themes through triangulation. This meant that a theme identified in an interview was actively compared with project memos and our own observation notes to confirm its significance and context. This approach prevented reliance on a single data point and ensured that the findings were well-supported. We used analytical memos to create a formal record throughout this process, documenting how and why we made specific analytical decisions.

Ethical conduct mattered. We obtained formal ethics approval from the relevant institutional review boards before collecting data. All interview participants gave informed consent; they understood the study's purpose, the voluntary nature of their participation, and our promise of anonymity and confidentiality. We stored data securely using encryption and safe platforms, following university policies and data protection laws. Additionally, the AI agent's design focused on non-personal data, which helped address data privacy concerns linked to using cloud services in the public sector.

The case study focuses on a conversational AI agent that uses Knowledge Graph and Retrival-Augmented Generation (RAG) technologies. This illustrates the current trends in public sector AI. A study by the University of St. Gallen found that Generative AI is spreading "bottom-up" in Swiss administration, with staff trying things out in a "regulatory grey area" (Guenduez and Stübi 2025).

At the EU level, chatbots are a key application, and Europe has now overtaken the US in public sector AI projects (StartUps Consortium 2025).

5. Results

First, we explain how AFAIPS guided the project step by step (RQ1). Second, we summarize the main organizational and technical changes that came up during this process (RQ2).

Answering RQ1: Guiding the AI Chatbot Adoption with AFAIPS

The project's Agenda-Setting phase (Iterations 1-3) focused on a hands-on, solution-based approach that quickly produced real results and received positive feedback. It started with a DT workshop, where the team identified six top priority use cases for the chatbot. One key user praised this method as "less complicated, more direct, and more solution-oriented" compared to earlier methods. A major success of the framework was its ability to address the team's initial doubts about AI. By swiftly moving from concepts to a working prototype in just three iterations, the process became "very quickly concrete," as the internal project manager noted. This allowed key users to work with a tangible solution, which one person described as "an exciting thing." The early testing proved "very valuable," providing immediate, useful feedback and highlighting important insights, such as the need for high-quality input data. From a project management view, the biggest benefit was that "results were visible very early on." This was seen as a major advantage over traditional, upfront-heavy methods like HERMES. This also directly countered the pervasive culture of risk aversion identified in the literature (OECD 2025) by demonstrating value quickly and building stakeholder confidence before committing significant resources. The Matching phase (Iteration 4) shows how the AFAIPS framework helps move from user-focused exploration with DT to the ongoing testing of LS. First, the team used DS principles to validate the proposed Knowledge Graph (KG) architecture, with user feedback. At the same time, they discovered important data fragmentation issues for future use. The shift to LS began with the project's first build-measure-learn cycle, where they implemented and tested a new intent. An issue with prompt recognition was not seen as a failure. Instead, it became a successful case of learning that allowed for quick adjustments. In this way, AFAIPS reduced risks in the project by using DT to confirm the strategic direction and LS to test and improve the technical execution.

The Redefining phase (Iterations 5-9) showed the main principle of LS: iterative development. The framework helped the team go through cycles of building, measuring, and learning to improve both the product and the organization. This phase focused on implementing and refining complex functionalities. The successful launch of the "Unfall" (Accident procedures) intent and new features like automated GTIN (Global Trade Item Number) lookups showed the build-measure-learn loop in action. Iterative releases resulted in positive user feedback. The use of new technologies, such as RAG for the "OSK" intent, tested a technical hypothesis. The challenges faced in combining RAG with the Knowledge Graph provided valuable data points that led to important technical adjustments. This phase was rich with validated learning. Thorough user testing uncovered key issues, such as the bot struggling with everyday language and problems with complex tasks. These insights directly drove improvements in prompt engineering and system optimization. Most importantly, difficulties in processing source material resulted in a proactive organizational change: the creation of new guidelines for making "AI-ready" documents. This outcome is a clear example of the framework facilitating the kind of organizational transformation and capacity building that Selten and Klievink (2024) and the OECD (2026) argue is essential for AI success.

The Clarifying phase (Iteration 10) focused on confirming the solution's broader usefulness and starting the shift toward operational stability, an important step before full deployment. A key activity involved presenting the prototype to a larger audience of 20 representatives from various cantonal correctional facilities. The very positive feedback confirmed the chatbot's potential for significant public value by showing its ability to speed up onboarding and simplify workflows. This user feedback loop, a vital part of the framework, also provided clear guidance for the final technical improvements needed to ensure consistent reliability at scale. This phase marked the project's first real steps into MLOps. Technical consolidation involved rewriting code and, importantly, adding strong logging and monitoring features, which are essential for sustainable AI operations. This practical use of MLOps principles quickly revealed a critical insight: the specialized knowledge needed to manage these systems was currently not available within the internal IT team. This illustrates AFAIPS functioning as a diagnostic tool, proactively identifying the specific skills gaps that the literature warns can derail projects (OECD 2026). This confirmed learning led to the strategic choice to secure external hosting and support, showing how AFAIPS influences not only technical development but also important, long-term organizational and sourcing decisions.

The Routinizing phase (Iteration 11 and ongoing) initiated the shift from a development project to a sustainable, operational service. The main task was the initial launch of the externally hosted chatbot on the Kanton's intranet. With support from internal IT, this step moved the solution into its intended production environment. Afterward, integration testing confirmed that the chatbot worked as expected. The framework's iterative nature continued at this stage, with ongoing discussions about final functional improvements. While the research wrapped up as this phase started, the final activities highlighted the project's shift toward long-term governance. Securing permanent external support and implementing the MLOps logging and monitoring capabilities were identified as the main remaining steps. This shows how AFAIPS offers a clear path not only for building and deploying a solution but also for ensuring its routine, sustainable operation and continuous delivery of value.

Answering RQ2: Required Organizational and Technical Adaptations in the Public Sector Context

A primary change for the organization is the shift toward proactive data governance. The framework showed that existing data is often not "AI-ready." This finding pushed the organization to create new guidelines for organizing source documents. This change shifts the organization from a reactive stance to a proactive approach on data quality, which will support current and future AI initiatives. Additionally, the ongoing process points out internal skills gaps, leading to a need for more flexible sourcing and governance models. The case study illustrated this by showing the decision to outsource long-term MLOps and hosting after recognizing a lack of specialized internal expertise. This move ensures the project's sustainability.

On the technical side, a key change is using prompt engineering. Public sector AI often depends on formal source documents that cannot be altered. This makes it essential to create effective prompts that connect informal user queries to the exact terminology in those texts. Additionally, the strong need for reliability calls for hybrid and dependable AI systems. The project demonstrated that a constant, ongoing balance between a structured Knowledge Graph (KG) for precision and RAG for flexibility was necessary to ensure the final system met the strict standards of public accountability.

While the case study confirmed the main principles of AFAIPS, it also revealed several limitations in the framework as it currently stands. The framework assumes an agile-friendly environment and does not provide clear guidance for dealing with conflicts with strict external governance structures, such as the canton's HERMES methodology. Additionally, it often identifies important data and readiness issues during development rather than through a structured assessment early on. Future research and updates to the framework should aim to include a proactive Readiness Gate and create tools that help connect agile practices with traditional public sector budgeting to improve its practical use.

Table 3 - Limitations of the AFAIPS framework (Source: author)

Limitation of AFAIPS	Impact on the Project	Proposed Framework Augmentation
Assumes an Agile-Friendly Governance Environment	This created extra management work and needed informal "translation" to satisfy strict HERMES reporting standard	Add a "Governance Alignment" sub-phase to Agenda-Setting to identify and handle any external process friction.
Lacks a proactive readiness assessment gate.	Data quality issues and gaps in MLOps skills were found late. This led to quick technical and strategic changes.	Introduce a mandatory "Readiness Assessment Step" that covers data, skills, and ethics before the Matching phase.
No Guidance on Securing Agile Funding	The project struggled to meet its changing needs while sticking to traditional, fixed budget expectations.	Develop a "Value-Based Budgeting Toolkit" to help teams explain ongoing funding needs to non-agile finance departments.

6. Discussion

AFAIPS showed strong flexibility in the public healthcare area by balancing its structured DOI-based phases with agile, iterative principles like DS and LS. This combination was important for handling the uncertainties that come with AI implementation. For example, technical issues such as poor data quality and LLM volatility were effectively addressed not through strict upfront planning, but by closely collaborating with users and quickly prototyping solutions. This approach allowed for fast fixes, like refining prompts. The framework's iterative aspect also served as a key driver for significant organizational learning, which is an important yet often neglected success factor. Ongoing feedback cycles not only improved user AI skills but also led to real changes within the organization. The most notable instances included creating "AI-ready" documentation guidelines in response to data processing failures and deciding to seek external MLOps support after realizing a crucial internal gap in skills. These results indicate that the framework's usefulness extended beyond just technical implementation to building readiness for AI throughout the system. The framework's ability to show incremental value through MVPs was essential for maintaining momentum and offered a realistic alternative to the traditional "all-or-nothing" funding approach. Accountability measures in the public sector significantly influenced technical design, making it necessary to prioritize reliability over flexibility and requiring early attention to compliance and data governance. Managing leadership expectations about this non-linear journey from prototype to production also became a vital management task for successfully using agile methods in a traditionally cautious environment.

From a theoretical standpoint, this study contributes in three key ways. First, it refines DOI theory for AI adoption by showing how integrating agile methods and iterative experimentation can make DOI actionable for complex, emerging technologies. It does this by managing uncertainty and enabling both the technology and the organization to adapt. Second, the study enhances agile adoption models for the public sector by offering a framework that tailors DT, LS, and MLOps to the AI lifecycle within a DOI structure. Finally, this research adds to the broader field of public sector innovation by providing insights into overcoming bureaucratic obstacles, emphasizing the role of organizational learning, and demonstrating how accountability demands affect AI design in government. It connects the often-separated areas of organizational change and technical implementation.

This study focuses on the adoption process, not outcome evaluation. A longitudinal cost-benefit analysis would require a separate study design. The framework's generalizability is intentional—AFAIPS is designed to inform practitioners beyond the Swiss context. Importantly, the value of a structured adoption process extends beyond the success or failure of any single AI system. Through AFAIPS, the organization developed AI literacy, identified capability gaps, and established governance practices—organizational assets that persist regardless of the specific project's ultimate ROI. The process itself builds institutional readiness for future AI initiatives.

Also, this study validated AFAIPS through a single generative AI case. Future research should test its applicability to other AI categories, such as predictive analytics or computer vision, in different public sector domains. While this study offers valuable insights into the adoption process, it has limitations that shape its contribution. The single case study design, which was necessary for a detailed analysis, limits the statistical generalizability of the findings. Importantly, the study period ended as the Routinization phase began; therefore, we could not observe the long-term sustainability and development of the AI tool in everyday use. Future long-term research is needed to fill this gap by tracking framework applications through full routinization and beyond. This research should use a solid measurement framework to assess lasting impact. For example, sustained adoption could be evaluated through user engagement rates and the tool's formal integration into onboarding processes. Organizational change could be monitored by the use of AI-ready data standards and through qualitative analysis of shifts in organizational attitudes towards agile governance. Lastly, public value could be measured through efficiency gains (ROI) and reductions in error rates, while qualitative assessments could evaluate improvements in the fairness and transparency of administrative decisions. A long-term evaluation using these indicators is crucial for understanding the lasting value generated by AI adoption frameworks like AFAIPS.

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