



From Readiness to Regulation: Practice-Oriented Measures to Increase the Adoption of Generative AI in the Swiss Public Administration

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RESEARCH

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ABSTRACT

This article outlines practitioner-identified and prioritized measures to support the adoption of Generative Artificial Intelligence (Gen AI) in the Swiss public administration. Despite growing interest, empirical guidance on how decentralized and compliance-oriented administrations can effectively increase the use of Gen AI remains limited, underscoring the need for practice-oriented research. Using a sequential mixed-method study design, a nationwide survey first assesses the use of Gen AI among Swiss public servants, followed by a Delphi study in which experts identified and prioritized measures to increase adoption. The results were mapped onto the Consolidated Framework for Implementation Research (CFIR) providing a theoretically grounded basis for categorizing the identified measures into key implementation domains. Survey findings show very low adoption rates, with experts highlighting “Ensuring access” and “Training” as top priorities to promote broader use. The CFIR analysis indicates that Gen AI implementation should focus on strengthening individual capacity and organizational readiness rather than relying on external mandates or purely technical adjustments. This has important implications for the sequencing of Gen AI implementation activities, especially in early-stage adoption phases.

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Generative Artificial Intelligence (Gen AI) refers to a computational technique capable of autonomously generating new text, images, audio, and videos based on training data, often indistinguishable from human-crafted outputs (Wang et al., 2025; Epstein et al., 2023; Feuerriegel et al., 2024; Chun & Noveck, 2025). The emergence of Gen AI as a cross-sector, transformative tool is not only impacting the labor market but also government operations (Beltran, Mondragon & Han, 2024). Despite growing scholarly and political interest in Gen AI, research on its adoption in the public sector remains limited and fragmented (Alshahrani, Dennehy & Mäntymäki, 2022; De Sousa et al., 2019). While the private sector has long been the primary focus of AI research, only recently has attention begun to shift toward the public sector, driven by technological advances, policy pressures, and post-pandemic digital demands (Mergel et al., 2024).

This shift raises important questions for countries with complex governance systems, such as Switzerland, where strong decentralization and strict data protection laws create distinct implementation challenges (Füglister & Wasserfallen, 2014). Although the Swiss public administration has published its first AI sub-strategy, a detailed implementation plan specifying concrete measures and their sequencing has not yet been released (Bundesrat, 2025a). Comprehensive strategic guidance for scaling and governing Gen AI across the federal administration is therefore still lacking. This also complicates the systematic introduction of a secure, government-operated Swiss “Gov-GPT” system that is currently under development.

Beyond these practical challenges, there is also a pronounced theoretical gap. While recent studies have examined applications of Gen AI across sectors such as healthcare (e.g. Zhang & Boulos, 2023), education (Qadir, 2023), and public administration (e.g. Madan & Ashok, 2023), much of the literature remains largely theoretical and conceptual (Neumann, Guirguis & Steiner, 2024; Selten & Klievink, 2024; Wirtz, Weyerer & Geyer, 2019). Systematic empirical investigation into the extent to which Gen AI is used within Switzerland’s distinctive political, administrative, and regulatory context is missing, leaving key theoretical questions about AI adoption in highly decentralized and compliance-oriented administrations unresolved.

Together, these practical and theoretical gaps motivate the present study, leading to the following research question: *Which practice-oriented measures are perceived to increase Gen AI adoption in the Swiss public administration?* To address this research question, the study employs a sequential mixed-method design that integrates empirical and expert-based insights. First, a nationwide survey investigates the use of Gen AI among Swiss public servants, establishing an empirical baseline. Second, it conducts a multi-round Delphi study to systematically gather expert insights into strategic priorities to increase Gen AI adoption in the Swiss public administration. In the final step, the findings are mapped onto the Consolidated Framework for Implementation Research (CFIR), providing a theoretically grounded basis for categorizing the identified measures across key implementation domains.

This study provides several contributions tailored to the institutional context of the Swiss public administration. Methodologically, the study demonstrates how a sequential mixed-method design enables the systematic identification and prioritization of measures to facilitate adoption of Gen AI. Building on this approach, it contributes theoretically by extending the CFIR framework to the public sector context, showing that in decentralized and compliance-oriented administrations, individual attitudes and organizational readiness are more decisive for increasing the use of Gen AI than regulation or purely technical upgrades. For policymakers and public sector managers, the study offers empirically grounded insights by identifying key implementation domains that enable the evidence-based sequencing of measures to foster Gen AI adoption, thereby supporting initiatives such as a Swiss Gov-GPT.

The remainder of this article is structured as follows. Chapter 2 introduces the theoretical background on the use of Gen AI in the public sector, which is then complemented in Chapter 3 by an examination of the empirical context of Switzerland. Building on this foundation, Chapter 4 elaborates on the sequential mixed-methods design, outlining each step of the methodology and presenting the corresponding results. Finally, Chapter 5 situates these findings within a broader discussion.

2.1 INSIGHTS FROM EXISTING RESEARCH

For years, researchers have been engaged in AI research ([Zuiderwijk et al., 2021](#); [Yigitcanlar et al., 2024](#); [Wirtz & Müller, 2019](#)). Since AI's impact on daily life has grown increasingly significant, it has become a popular field of study ([Wirtz, Weyerer & Geyer, 2019](#)). The focus of AI research has traditionally been within the field of computer science, emphasizing the technology itself and its functionality ([Simon, 1995](#); [Xu et al., 2021](#)). In contrast, AI research with a focus on social sciences, particularly within the context of the public sector, has been largely neglected ([Aoki, 2020](#); [Sun & Medaglia, 2019](#); [Wirtz, Weyerer & Geyer, 2019](#); [De Sousa et al., 2019](#); [Janssen & Kuk, 2016](#)). Historically, research emphasis has been placed on the private sector ([Desouza, Dawson & Chenok, 2020](#); [Neumann, Guirguis & Steiner, 2024](#)). Zuiderwijk et al. (2021) attribute this to the significantly more advanced adoption of AI in the private sector compared to the public sector.

Despite the limited attention, Yigitcanlar et al. (2024) demonstrated in their scientometric analysis that AI adoption in the public sector spans five decades, dating back to the late 1980s. They identified four key phases of AI literature in the public sector over the last 50 years: The foundational era (late 1980s), the conceptual era (mid-1990s), the exploratory era (mid-2000s), and the booming era (mid-2010s to late 2023). In recent years, during this “booming era”, AI adoption research in the public sector has gained significant momentum ([Zuiderwijk et al., 2021](#); [Wirtz, Weyerer & Geyer, 2019](#); [Mikhaylov, Esteve & Campion, 2018](#)). For example, to understand the sector-specific challenges and drivers of AI adoption in the public sector, Neumann, Guirguis and Steiner (2024) conducted an empirical analysis of the AI adoption process in eight Swiss public organizations.

This new surge of AI adoption research in the public sector is partly driven by rapid technological advancements ([Aoki, 2020](#)) and the corresponding increase in attention from policymakers ([Mergel et al., 2024](#)), closing the gap with the private sector ([Desouza, Dawson & Chenok, 2020](#)). This trend has been further accelerated by the COVID-19 pandemic. As Mergel et al. (2024) note, the pandemic amplified calls for more citizen-friendly service delivery, which led to significant government investments in AI technologies. Together, these developments have set the stage for a growing focus on Gen AI within public sector organizations.

Building on this interest, current literature primarily addresses the economic and societal impacts of Gen AI in the public sector ([Bright et al., 2024](#)). Economically, McKinsey & Company (2023) estimates that Gen AI could contribute a productivity benefit of approximately \$480 billion within the public sector and related fields. Boston Consulting Group similarly projects substantial financial gains, estimating global annual productivity improvements from Gen AI in the public sector could be worth up to \$1.75 trillion by 2033 ([BCG, 2023](#)). Beyond purely economic aspects, Mellouli, Janssen and Ojo (2024) emphasize that Gen AI offers significant benefits to the public sector. These include gains in productivity (e.g. [Margetts, Dorobantu & Bright, 2024](#); [Beltran, Mondragon & Hun, 2024](#); [Wang et al., 2025](#)), improved communication ([Chun & Noveck, 2025](#)), better internal services and automation of tasks (e.g. [Yigitcanlar et al., 2024](#); [Wirtz, Langer & Fenner, 2021](#)), enhanced citizen engagement (e.g. [Mellouli, Janssen & Ojo, 2024](#)), service co-design and delivery (e.g. [Wang et al., 2025](#)), personalized public services (e.g. [Chun & Noveck, 2025](#)), and improved decision-making and forecasting (e.g. [Maragno et al., 2023](#)). This potential translates into concrete productivity gains by reducing bureaucratic workloads, allowing civil servants to focus on higher-value tasks ([Margetts, Dorobantu & Bright, 2024](#)), and shifting up to one-third of their time from routine to more impactful work ([Berryhill et al., 2019](#)), ultimately contributing to increased public value ([Wang, Teo & Janssen, 2021](#); [Criado & Gil-Garcia, 2019](#)).

Recently, research has also begun to explore the risks and unintended adverse effects of Gen AI in the public sector. Several studies have emphasized the negative consequences of AI adoption, addressing legal, regulatory, ethical, political, technical, social and organizational challenges ([Agarwal, 2018](#); [Bannister & Connolly, 2020](#); [Janssen & Kuk, 2016](#); [Wirtz, Weyerer & Geyer, 2019](#); [Wirtz, Langer & Fenner, 2021](#); [Selten & Klievink, 2024](#); [Sun & Medaglia, 2019](#); [Hopster & Maas, 2024](#); [Bright et al., 2024](#); [Margetts, Dorobantu & Bright, 2024](#); [Taeihagh, 2025](#)). For instance, Cantens (2025) emphasizes the inevitability of Gen AI adoption while also underscoring its associated challenges, including limited explainability of outputs, confidentiality constraints, and persistent mistrust among civil servants toward this emerging technology. Neumann, Guirguis and Steiner (2024) even refer to “justified scepticism and fear of governments using AI” as it may reinforce

existing inequalities (Margetts, Dorobantu & Bright, 2024), compromise citizens' privacy (Hopster & Maas, 2024), and ultimately threaten democracy (Allen & Weyl, 2024). Collectively, these studies underline that Gen AI adoption is best understood as a "Double-Edged Sword" (Salah, Abdelfattah & Al Halbusi, 2024; Neumann, Guirguis & Steiner, 2024), promising transformative opportunities but simultaneously carrying profound social, political, and organizational risks for the public sector (Kuziemski & Misuraca, 2020).

2.2 GAPS IN THE EXISTING LITERATURE

Despite the progress made in recent years, research on Gen AI in the public sector remains scarce (Sun & Medaglia, 2019; Wirtz, Langer & Fenner, 2021; Yigitcanlar et al., 2024). Mergel et al. (2024) observe, "Even though we were able to bring together a range of new papers on AI implementation in the public sector, there is still an immense research gap to be filled (...)." Similarly, De Sousa et al. (2019) note that, despite the recent increase in AI initiatives across government sectors worldwide, there remains a lack of systematic understanding regarding the motivations, processes, outcomes, and impacts of AI implementation in the public sector. Taihigh (2025) attributes this to the literature's inability to keep pace with the rapid technological advancements, leaving the study of AI management in public administration still underdeveloped relative to the field's evolution.

Similar to broader AI research in the public sector, scholarly investigation into the adoption of Gen AI, specifically in public administration, remains in its infancy. So far, much of the current knowledge on Gen AI adoption in public administration stems from theoretical discussions, often focused on in-depth case studies of individual AI tools (Neumann, Guirguis & Steiner, 2024; Selten & Klievink, 2024). Beltran, Mondragon and Han (2024) highlight a "notable gap in the academic literature concerning a systematic understanding of governments' roles and functions in this AI-infused era." Bright et al. (2024) state that only a few studies explore the implications of Gen AI for public sector workers, emphasizing that "Answers to these questions will be vital in helping us to safely and robustly actualize the potential of Gen AI technologies in the public sector."

This "widening empirical evidence gap" (Mergel et al., 2024), particularly on everyday use by public sector employees, creates a disconnect between academic discourse and practical application (Newman, Cherney & Head, 2016). In response, recent studies have begun to examine specific applications of Gen AI across different sectors (e.g. Zhang & Boulos, 2023; Qadir, 2023; Madan & Ashok, 2023) and national contexts (e.g. Guenduez & Mettler, 2023; Wang et al., 2025; Alshahrani et al., 2022), providing early insights into how the technology is being integrated and the factors shaping its adoption.

While these studies highlight important sectoral and national variations, little attention has been paid to the adoption of Gen AI within the distinctive political, administrative, and regulatory framework of Switzerland.

3. EMPIRICAL CONTEXT OF THE STUDY

This study adopts a qualitative single-case study design (Gerring, 2004; Baxter & Jack, 2008), situated within a public governance research perspective as conceptualized by Scupola and Zanfrei (2016). Drawing on the case selection logic outlined by Seawright and Gerring (2008), the Swiss public administration constitutes the national-level case under investigation and serves as the empirical context for identifying governance-related implementation domains to enhance the adoption of Gen AI. The development of Gov-GPT is examined as a concrete institutional initiative embedded within this broader context.

3.1 THE SWISS CONTEXT

Switzerland offers a well-suited empirical context for analysis due to its highly decentralized federal system, consensus-based governance, linguistic and cultural diversity, and strong subsidiarity principles (Fleiner, 2009). In comparative analyses, Switzerland consistently ranks at the top for both fiscal and policy decentralization (Füglister & Wasserfallen, 2014). Given this strong federal structure, all levels of government are endowed with significant autonomy. The Swiss constitution enshrines the principle of subsidiarity, stipulating that all responsibilities not explicitly allocated to the federal level fall under the jurisdiction of the cantons (Linder & Vatter, 2001; Füglister & Wasserfallen, 2014).

This high level of decentralization also presents challenges for digital transformation in the public sector. According to Schedler and Summermatter (2005), it partly explains Switzerland's consistently moderate rankings in e-government performance. With approximately 3,000 political authorities deciding independently on their e-government initiatives, there is limited national coordination. Furthermore, Switzerland has an advanced regulatory framework, particularly in data protection, which adds further complexity. These challenges are reflected in international benchmarks. For example, the 2024 eGovernment Benchmark Report by the European Commission, shows that Switzerland lags significantly behind the European average in the availability and maturity of digital public services, ranking 29th out of 35 (Capgemini et al., 2024).

To address this fragmentation, the organization Digital Administration Switzerland (DVS) was established to coordinate and promote digitalization efforts across all levels of government. Within the strategy Digital Administration Switzerland 2024–2027, DVS develops annual implementation plans to advance its objectives. The most recent plan for 2026 also includes the Coordination Body for Data Science & AI as an active working group composed of experts from public administration that can be engaged as needed by the executive steering committee. The establishment of this coordination body signals a growing institutionalization of AI-related issues within the Swiss public administration. At the same time, it reflects a broader political acknowledgement of AI's strategic relevance.

In its policy agenda for the 2023–2027 legislative period, the Swiss Federal Council highlighted both the challenges and risks that AI poses for Switzerland as a business hub, as well as the need to explore appropriate regulatory responses. In this context, the Federal Council mandated the Federal Chancellery to develop a dedicated strategy for the use of AI systems within the federal administration. Published in 2025, this initial strategy is structured around three guiding pillars: strengthening institutional competencies, ensuring trustworthy application, and enhancing efficiency through the use of AI systems (Bundesrat, 2025a). Together, these pillars establish the foundational framework for AI adoption in the Swiss administration.

In light of this growing institutional awareness, discussions have begun to emerge around the development of a dedicated national Gen AI system tailored to the specific needs and values of the Swiss public administration.

3.2 DEVELOPMENT OF A SWISS GOVERNMENTAL GPT

In March 2025, the Swiss newspaper *Tagesanzeiger* revealed that the Swiss federal government has been developing and operating a proprietary, isolated AI system called Gov-GPT since November 2024. This system runs in a specially secured IT environment within the federal administration. Developed by the Federal Office of Information Technology, Systems and Telecommunication (FOITT), Gov-GPT is based on the open-source language model LLAMA by Meta AI (Knellwolf, 2025).

Gov-GPT has similar functionalities to ChatGPT and other large language models, but its protected environment allows it to process data that would not be permissible under current data protection and information security regulations (Anz, 2025). According to the official guidelines on the use of Gen AI tools in the Swiss federal administration dated January 18, 2024, inputting many types of information into Gen AI tools is prohibited. Specifically, information classified as “internal,” “confidential,” or “secret” may not be processed. Even non-classified documents containing sensitive content, including any form of personal data, are excluded from use in public Gen AI systems (Bundesrat, 2024). This stands in sharp contrast to Gov-GPT, where only “secret” information remains prohibited which implies that Gov-GPT can process data that was previously off-limits to conventional AI systems (Landis, 2025).

The emergence of Gov-GPT coincides with a growing political debate on digital sovereignty in Switzerland, which the Federal Council defines as the state's ability to retain control and autonomy in the digital domain (Bundesrat, 2025b). This debate has intensified following the recent introduction of Microsoft 365 within the Swiss federal administration. While aimed at increasing efficiency, this initiative has also raised concerns related to data control. In response, the Federal Chancellery launched a feasibility study in 2024 on the use of open-source software (OSS) for office automation, assessing its suitability as a fallback solution. This line of inquiry is further reflected in the Swiss Federal Council's 2025 report “Digital Sovereignty of Switzerland”

(Bundesrat, 2025c), which emphasizes the promotion of OSS as a key governmental measure to reduce technological dependencies and identifies AI as a particularly sensitive domain to ensuring Switzerland's digital sovereignty.

Against this backdrop, Gov-GPT can be interpreted as an early institutional response to the challenge of developing more sovereign Gen AI tools. It thus serves as a practical example of how Switzerland seeks to advance the broader implementation of Gen AI within its federal administration while embedding the abstract concept of digital sovereignty into concrete administrative practice.

4. METHODOLOGY

To address the research question, this study applies a sequential mixed-methods design consistent with Creswell et al. (2023) and attentive to the procedural considerations discussed by Ivankova, Creswell and Stick (2006), aimed at analyzing the institutional conditions enabling the wider adoption of Gen AI. Illustrated in Figure 1, the research design consists of three-steps: (1) a nationwide survey investigates the current use of Gen AI among Swiss public sector employees; (2) a Delphi study with experts explores and prioritizes measures to enhance adoption; and (3) the findings are integrated into the interpretative CFIR framework to identify concrete domains for implementing Gen AI in the Swiss public administration.

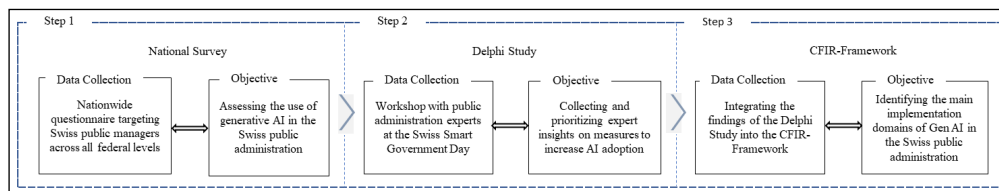


Figure 1 Sequential Mixed-Methods Design.

4.1 NATIONWIDE SURVEY

Data Collection and Analysis

Ahn and Chen (2022) view government employees as the driving force behind the implementation and evaluation of AI technologies, arguing that their perceptions and attitudes largely determine the extent to which these technologies are adopted and regulated. Therefore, meaningful organizational uptake depends on whether public servants integrate these tools into their everyday work practices. Since Gen AI requires continuous interaction and experimentation to generate value (Kanbach et al., 2024), individual use can be understood as a valid proxy for organizational adoption. Building on this premise, a survey about the use of Gen AI provides a baseline assessment of the extent to which Gen AI has been adopted in everyday Swiss administrative practice, thereby helping to determine the urgency and scale of measures required to foster broader uptake.

To generate such an empirical adoption rate, this study draws on a nationwide survey conducted by Guenduez and Stübi, which examines how public servants currently use Gen AI in their daily work. An anonymous questionnaire was distributed to public managers across all 26 Swiss cantons between May 13 and August 21, 2024. The survey deliberately targeted individuals in leadership positions across all tiers of government, including federal, cantonal, and municipal administrations. To ensure broad representativeness across the Swiss public sector, the survey was administered in German, French, and Italian (Guenduez et al., 2025). A total of 3,740 invitations were sent out, and 702 valid responses were received, resulting in a 19% response rate. The participants were asked: How often do you use Gen AI at work for work purposes?

Main Findings

The survey indicates a limited level of Gen AI adoption in the Swiss public administration: Over one-third of respondents (35.9%) have never used Gen AI at work, while almost the same proportion (36%) use it only rarely. Overall, more than 70% of public sector employees use Gen AI either never or only occasionally (see Figure 2). In contrast, 12.4% of respondents reported using the technology approximately once a week, 13.2% several times per week, and only 2.4% reported daily use in their work.

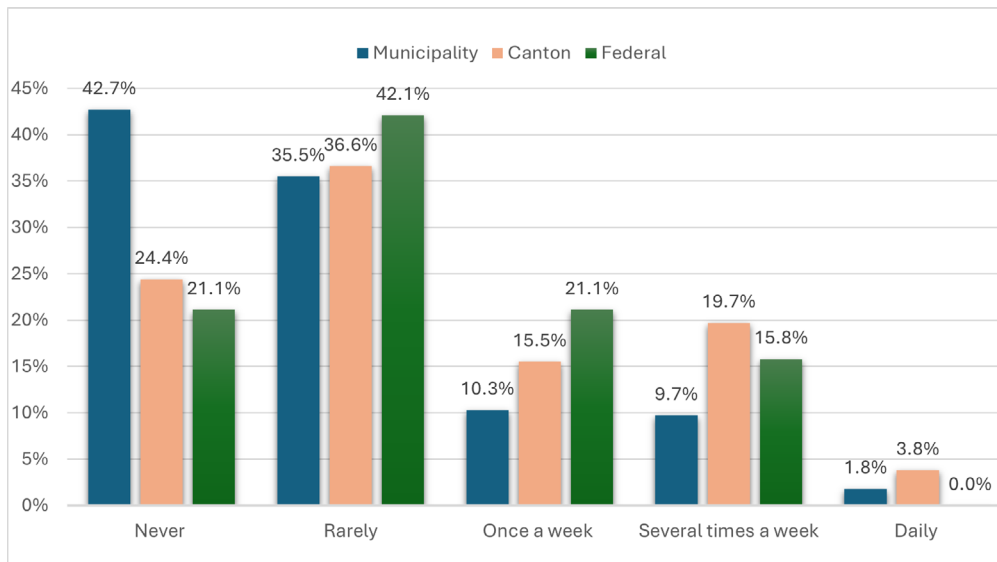


Figure 2 Gen AI Use of Swiss Public Sector Employees at Work (n = 702).

The survey shows that, while the overall adoption of Gen AI is comparably low across municipalities, cantons, and the federal level, some differences emerge between administrative tiers. At the municipal level, 42.7% of respondents reported never having used Gen AI at work, whereas the proportion was lower at the cantonal (24.4%) and federal levels (21.1%), indicating that a higher share of employees at these levels had at least experimented with the technology. Cantonal employees also appeared to use the technology more frequently, with 19.7% reporting multiple times per week and 3.8% daily usage, compared to 9.7% and 1.8% at the municipal level. For a detailed breakdown of response distributions, including the number of responses per category, see Appendix Table A1.

After controlling for gender, professional experience, and education level, only minor variations in Gen AI usage were found. Men reported slightly higher usage than women, with 33.5% of men and 41% of women never having used the technology. Usage was most common among employees with 1–5 years (around 17%) and 5–15 years (around 13%) of experience, while beginners (<1 year, 43%) and very experienced employees (>15 years, 41%) most often reported no use. Higher education levels were generally linked to slightly more frequent usage.

In summary, the adoption of Gen AI among Swiss public sector employees remains very low, indicating a need to strengthen its adoption across public administration. Without broad uptake, the potential benefits of Gen AI are unlikely to be fully realized. This highlights the importance of targeted, evidence-based measures that reflect the specific needs and capacities of Swiss public sector employees. Such measures are essential to support the effective use of Gen AI and have direct implications for the further development of Gov-GPT as a concrete institutional initiative.

4.2 DELPHI STUDY

Data Collection and Analysis

A Delphi Study is a structured, multi-round survey method that uses anonymous questionnaires, with each round building on the previous one (von der Gracht, 2012; Barret & Heale, 2020; Day & Bobeva, 2005). After each round, the participants review each other's responses. By considering the contributions of other participants, the experts are encouraged to reflect on and adjust their previous answers if necessary (Diamond et al. 2014; Barrett & Heale 2020). The process aims for consensus without the influence of dominant individuals and allows for statistical analysis of group responses (Day & Bobeva, 2005).

On September 17, 2024, the “Swiss Smart Government Day” took place, which is an annual conference specifically aimed at practitioners. According to its website, it serves as a dialogue platform for experts from public administration, industry, and academia to discuss pressing issues in government under the motto “Shaping smart administration.” Following Dhillon, Smith & Dissanayaka (2021), I conducted a live Delphi Study at this conference to gather and rank expert opinions based on their relevance. Given the event's target audience, it can be assumed that the Delphi participants were experts in the Swiss public administration. They were asked: How can the use of AI be increased among Swiss public sector employees?

Main Findings

My Delphi Study followed a two-step approach. The first step involved broadly collecting expert ideas on how to facilitate the adoption of Gen AI tools and consolidating them into concrete, actionable issues. In line with Dhillon, Smith and Dissanayaka (2021), I began the process with a blank sheet approach: The experts were asked to name measures that might increase the adoption of Gen AI within the Swiss public administration. This survey was conducted using the “Mentimeter” software. A total of 75 answers, from 34 participants were reported back. I independently grouped all answers and discussed them with the participants until reaching a consensus on 8 relevant issues. For example, responses such as “reduce licensing costs,” “grant permission to use,” and “approve tools” were grouped under the measure “Ensuring Access.” The clustered final results of the brainstorming round are listed in Table 1.

ISSUES	SHORT DESCRIPTION
Reduce stigmatization	Aims to counter fears, misconceptions, and social biases of Gen AI
Demonstrate benefits	Highlights the tangible advantages of Gen AI in the public sector
Training	Focuses on structured programs that help understand how Gen AI works and how to use it effectively
Set an example	Encourages visible use and endorsement by public sector managers
Communication	Emphasizes transparent and proactive communication about the purpose, use, and limits of Gen AI
Clear guidelines	Covers the development and implementation of coherent operational, ethical, and legal frameworks
Coercion	Refers to regulatory or institutional measures that require the adoption of Gen AI
Ensure access	Seeks to guarantee equitable and inclusive access to Gen AI tools

Table 1 Final Issues from the Brainstorming Round.

In a second step, the issues identified were ranked according to their priority by the same Delphi panel. I conducted three rounds. As outlined by Paré et al. (2013), the issues were presented in a random order in the first round and subsequently ranked according to their mean value in the following rounds. In the Delphi ranking, lower mean values indicate higher perceived importance, as items were ranked in ascending order of priority. In the event that no additional input was provided after the first round, this was interpreted as agreement with the presented ranking. Consensus was measured using Kendall’s Coefficient of Concordance (W) (Schmidt, 1997). The coefficient ranges from 0.1 (very weak agreement) to 0.9 (unusually strong agreement). A high agreement ($W > 0.7$) was reached after the third round with a W of 0.72. The final ranking of all eight digital government issues is presented in Table 2. Respondents attributed the greatest importance to *Ensure Access* (Mean Rank [MR]: 2.18) and *Training* (MR: 2.24). Conversely, *Coercion* (MR: 6.97) and *Reduce stigmatization* (MR: 6.45) were ranked lowest in importance. The remaining themes were ranked in between these extremes.

ISSUES	ROUND 1 K = 8		ROUND 2 K = 8		ROUND 3 K = 8	
	MEAN RANK	D2	MEAN RANK	D2	MEAN RANK	D2
Training	2.94	2.28	2.58	3.12	2.24	3.22
Demonstrate benefits	2.94	2.28	2.39	3.79	2.39	2.70
Ensure access	2.97	2.19	2.42	3.67	2.18	3.44
Set an example	3.70	0.57	4.06	0.08	4.06	0.00
Clear guidelines	4.27	0.03	4.39	0.00	3.18	0.73
Communication	4.48	0.00	4.55	0.04	4.82	0.61
Reduce stigmatization	6.64	4.78	6.85	6.29	6.45	5.84
Coercion	7.67	10.34	7.48	9.88	6.97	8.60
Totals	35.61	22.48	34.73	26.88	32.27	25.25
Grand Means	4.45		4.34		4.04	
	W	χ^2	W	χ^2	W	χ^2
p < .001	0.54	123.65	0.68	152.43*	0.72	152.15*

Table 2 Results of the Delphi Panel.

4.3 CONSOLIDATED FRAMEWORK FOR IMPLEMENTATION RESEARCH

Data Collection and Analysis

Damschroeder et al. (2009) developed the Consolidated Framework for Implementation Research (CFIR) in response to the observation that many implementation efforts fail despite careful planning, often because contextual factors are insufficiently considered. The CFIR seeks to uncover factors that may either facilitate or hinder implementation processes (Breimaier et al., 2015). The framework synthesizes key constructs from 19 well-established implementation theories, providing a comprehensive structure for analyzing and guiding implementation processes across diverse settings. CFIR was therefore designed as a theoretical framework to systematically analyze and support the implementation of innovations within organizations (Damschroeder et al., 2022). The updated CFIR consists of five major domains, which are further divided into 39 constructs (Lam et al., 2021; Keith et al., 2017).

The CFIR-Dimension “Intervention characteristics” refers to the attributes of a given intervention that influence its adoption and implementation within an organization. Constructs such as the *intervention source*, *relative advantage*, and *trialability* shape how feasible and appealing an intervention appears to stakeholders. The “Individual setting” refers to the individual-level factors that shape how people perceive, engage with, and ultimately implement a given intervention (Keith et al., 2017; Damschroeder et al., 2009). “Inner setting” factors describes the internal organizational environment that influences implementation efforts. “Outer setting factors” are external influences that shape how and why an organization implements an intervention. Its construct *peer pressure* involves the influence of competitors or peer organizations. *External policies and incentives* include regulations, mandates, guidelines. Lastly, the CFIR Dimension “Implementation Process” consists of four key constructs: *planning*, *engaging*, *executing*, and *reflecting and evaluating*, implying that the successful implementation of an intervention relies on a cyclical process (Keith et al., 2017).

Overall, the purpose of the CFIR is to provide a theoretically grounded structure for examining factors that influence implementation effectiveness, rather than to prescribe a specific implementation process (Reardon et al., 2025). Following Damschroeder et al. (2009), the framework was therefore not applied exhaustively across all five domains and 39 constructs in this study. Instead, it was used as an analytical lens to structure and interpret the empirical findings of the Delphi study, allowing for the systematic identification of those implementation domains that are most relevant for advancing Gen AI adoption within the Swiss public administration. This approach moves the results beyond a purely descriptive ranking by situating Delphi-identified measures within a coherent conceptual framework and translating expert priorities into higher-order implementation domains relevant to fostering Gen AI adoption within the Swiss public administration.

The integration and synthesis were conducted through a structured mapping process, with the results presented in Table 3, illustrating the practical implications of the analysis using Swiss Gov-GPT as a concrete example. Each Delphi-identified issue was assigned to the CFIR domain and construct that best reflected its underlying mechanism, following the official CFIR construct definitions and user guide (Reardon et al., 2025). Where necessary, issues were allocated to the construct with the closest conceptual fit to ensure internal consistency.

ISSUES (DELPHI)	CFIR DOMAIN	CFIR CONSTRUCT	EXPLANATION FOR SWISS GOV-GPT
Ensure Access	Inner Setting	Available Resources	Ensure that the necessary infrastructure, tools, and support are available so that Gov-GPT can be accessed in an equitable manner.
Training	Individual Setting	Self-Efficacy	Provide targeted training to enable employees to use Gov-GPT in their daily work.
Demonstrate Benefits	Intervention Characteristics	Relative Advantage	Clearly communicate the added value, efficiency gains, and functionality of Gov-GPT compared with existing tools to strengthen its perceived usefulness.
Clear Guidelines	Outer Setting	External Policy & Incentives	Develop clear internal guidance for the appropriate use of Gov-GPT, aligned with applicable legal and regulatory frameworks.

Table 3 Alignment of Delphi Results to the CFIR Domains and Constructs.

(Contd.)

ISSUES (DELPHI)	CFIR DOMAIN	CFIR CONSTRUCT	EXPLANATION FOR SWISS GOV-GPT
Set an Example	Process	Engaging Opinion Leaders/ Champions	Encourage leaders and key users to actively apply and promote Gov-GPT, fostering trust and normalization within the Swiss public administration.
Communication	Inner Setting	Networks and Communications	Strengthen internal communication and exchange on Gov-GPT implementation and maintain dialogue with other offices to ensure coordination.
Reduce Stigmatization	Individual Setting	Knowledge & Beliefs about the Intervention/ Implementation Climate	Address concerns and misconceptions (e.g. job displacement, data security) transparently to promote trust and openness toward Gov-GPT.
Coercion	Inner Setting	Tension for Change/ Incentives	Recognize that pressure for adoption may arise from political or regulatory requirements. Internally, ensure that implementation is guided by clear rationale.

Main Findings

Figure 3 provides a synthesized representation of the Delphi-informed CFIR results and aggregates these findings into a layered visualization that highlights where adoption-relevant issues cluster in shaping Gen AI use within the Swiss public administration. The figure not only illustrates the structural relationships between domains but also makes visible the interconnections among the Delphi results and their empirical prioritization, thereby revealing the key areas that are most critical for the effective implementation of Gen AI in Switzerland.

As illustrated in Figure 3, the measures identified through the Delphi process are primarily assigned to the “Individual setting” and “Inner setting” domains of the CFIR Framework. These two domains stand out not only quantitatively, due to the number of associated issues, but also qualitatively, as they encompass the two issues rated as most important by the Delphi study participants (1 Ensure Access; 2 Training).

The issues clustered around the “Individual Setting” underscore the central role of personal attitudes and competencies in influencing adoption. Constructs such as *Training* (MR 2.24) and *Reduce Stigmatization* (MR 6.45) reflect key individual-level prerequisites for engagement, suggesting that successful implementation hinges on lowering both cognitive and psychological barriers among users.

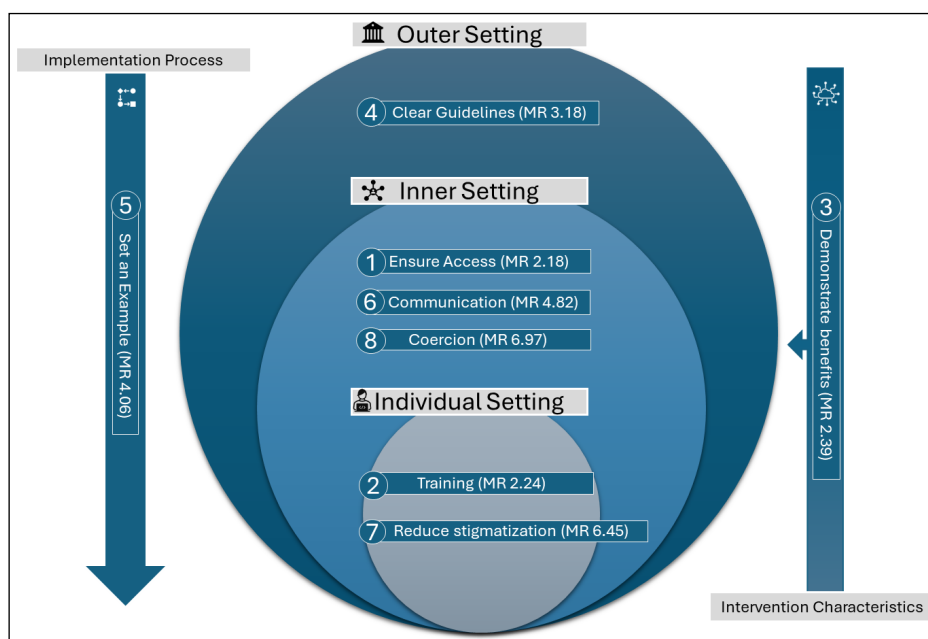


Figure 3 Positioning Delphi-derived Results within the CFIR Framework.

Simultaneously, the measures mapped to the “Inner Setting”, such as *Ensure Access* (MR 2.18), *Communication* (MR 4.83) and *Coercion* (MR 6.97), underscore the importance of a supportive organizational environment that provides access to Gen AI, emphasizing the role of internal

communication and the availability of appropriate tools within the Swiss public administration. These findings resonate with established implementation science literature, which emphasizes the mediating function of the inner setting between broader contextual pressures and individual adoption behaviors (Liang et al., 2007; Coelho, August & Lages, 2011).

Each of the remaining three CFIR dimensions is represented by only one measure, each of which received a medium priority rating from the Delphi experts. For the dimension “Intervention Characteristics”, the relevant factor was *Demonstrate Benefits* (MR 2.39). The “Outer Setting” was most strongly associated with *Clear Guidelines* (MR 3.18). Finally, the inclusion of *Set an Example* (MR 4.06) under the CFIR Dimension “Implementation Process” highlights the strategic importance of role modeling and leadership engagement in fostering legitimacy and trust in AI tools.

Taken together, embedding the Delphi results within the CFIR framework highlights a clear concentration of adoption-relevant measures within the “Individual” and “Inner Setting” domains. This suggests that Gen AI adoption in the Swiss public sector is primarily driven by human and organizational conditions rather than by characteristics of the technology itself or external pressures. By comparison, the “Intervention Characteristics,” “Outer Setting,” and “Implementation Process” domains play a more supportive role, indicating that while these elements contribute to implementation of Gen AI in the Swiss public administration, they are less decisive than individual and organizational determinants.

5. DISCUSSION

While academic interest in Gen AI adoption in the public sector has surged in recent years, most contributions remain theoretical, conceptual, or normative (Wirtz, Langer & Fenner, 2021). Empirical analyses that capture actual patterns of use and readiness are markedly scarce (Mergel et al., 2024). This lack of evidence is particularly problematic in the Swiss context, where substantial public resources are being invested in building a secure, large-scale governmental Gen AI system. Without robust insights into the current state of adoption and the organizational conditions that shape it, policymakers risk designing measures that fail to address practical barriers faced by employees and institutions regarding Gen AI.

This study therefore asked: *Which practice-oriented priorities are perceived to increase Gen AI adoption in the Swiss public administration?* To answer this, a sequential mixed-methods approach was applied. A nationwide survey revealed low adoption: Over one-third of Swiss public sector employees had never used Gen AI at work, and more than 70% used it only occasionally or never. This highlights both a strong need for intervention and the importance of prioritizing immediate measures to build familiarity and engagement. A Delphi study with experts then identified and prioritized strategies to enhance adoption. *Ensure Access* and *Training* emerged as the highest priorities, whereas *Coercion* and efforts to *Reduce Stigmatization* were rated lowest by the practitioners. Intermediate priorities, such as *Communication* and *Demonstrating Benefits*, emphasize the combined importance of individual support and organizational facilitation.

These insights were mapped onto the CFIR framework to provide a theoretically grounded interpretation of the empirical Delphi findings and to identify the most relevant implementation domains for Gen AI adoption in the Swiss public administration. The findings indicate that the most influential factors cluster within the “Individual Setting” and “Inner Setting” domains. “Individual Setting factors”, including *Training* and *Reducing Stigmatization*, emphasize the importance of personal attitudes, competencies, and perceived agency for implementation success (Damschroeder et al., 2009). These results align with those of Arduini et al. (2010), whose analysis of local public administrations demonstrates that the advancement of e-government depends on a favorable interaction between organizational conditions and internal competencies, emphasizing the importance of investment in public sector employee training.

In addition, “Inner Setting” elements, such as *Ensure Access* and *Communication*, emphasize the availability of infrastructure, tools, and support for equitable, user-friendly access to Gen AI. Effective internal communication further plays a critical role in fostering coordination and shared learning. These findings are consistent with the broader literature on digital innovation in both public and private sector organizations, which repeatedly highlights internal communication as a key enabler of successful digital innovation efforts (e.g., Ciriello, Richter & Schwabe, 2018; Scupola & Zanfei, 2016). Beyond these domains, issues associated with “Intervention

Characteristics”, “Outer Setting”, and “Implementation Process”, such as *Demonstrating Benefits*, *Clear Guidelines*, and *Set an Example*, point to the relevance of leadership, visibility, and participatory strategies in fostering legitimacy and trust.

Collectively, these results suggest that successful implementation of Gen AI tools such as Gov-GPT in Switzerland depends primarily on the individual readiness and organizational capacity, while structural pressures (such as *Coercion*) and further technological advances play a secondary role at this early stage. International evidence from Australia (Jones, Jimmieson & Griffiths, 2005), the US (Chen, Gascó-Hernandez & Esteve, 2024), or Switzerland (Neumann, Guirguis & Steiner, 2024) shows similar patterns.

5.1 CONTRIBUTIONS TO LITERATURE

This study makes three key contributions to literature. The first is its empirical contribution, which advances the understanding of Gen AI adoption in the public sector by providing evidence from the Swiss context. Whereas prior studies have been mostly conceptual or normative (Wirtz, Langer & Fenner, 2021; Mergel et al., 2024), this study grounds theory-building in a highly decentralized and compliance-oriented setting and demonstrates the stage of adoption in the Swiss public administration, revealing how public sector employees are beginning to engage with and apply Gen AI in their work.

The second is its methodological contribution, which demonstrates how a sequential mixed-method design can strengthen theory development, by reducing bias (Dzwigol, 2022) and providing a more comprehensive understanding of the phenomenon (Nanthagopan, 2021). By combining a nationwide survey of public servants with a Delphi study of experts and embedding the findings within the CFIR framework, the study illustrates how methodological triangulation can reveal individual and organizational conditions of adoption that might remain hidden in single-method designs.

Damschroder et al., as the developers of the framework, explicitly conceptualized CFIR as a “living, evolving, and improving set of propositions” and already emphasized in their original publication (2009; updated 2022) the need for deeper contextual knowledge. Building on this evolutionary perspective, the third contribution of this study offers technological refinements by extending the CFIR framework to the context of Gen AI adoption in the public sector. It identifies individual attitudes and organizational readiness as particularly critical implementation domains, especially during early-stage adoption within highly decentralized and compliance-oriented administrations.

5.2 IMPLICATION FOR PRACTICE

First, the study offers context-specific guidance for the Swiss public sector by highlighting differences in Gen AI adoption across municipalities, cantons, and the federal administration. Delphi experts consulted at the Swiss Smart Government Day provided tailored priorities to increase Gen AI adoption addressing structural, cultural, and institutional conditions unique to Switzerland. Aligning these measures with observed adoption patterns allows public sector leaders to prioritize interventions that are both practical and locally relevant.

Second, this study provides practical insights for public sector organizations considering the adoption of Gen AI technologies such as Gov-GPT (see “Explanation for Swiss Gov-GPT” in Table 3). For policymakers and managers, secure access to Gen AI tools and targeted employee training emerged as the most critical interventions. The findings differentiate high-impact from low-impact measures, guiding where to focus resources for effective early-stage adoption and avoiding strategies unlikely to influence outcomes, such as coercive approaches or purely technical refinements.

Finally, the study implies a structured approach for implementing the identified priorities within public sector organizations. It emphasizes the combination of individual-level measures with organizational support, ensuring that initiatives like a Swiss Gov-GPT are implemented effectively. This approach allows for a possible sequencing of interventions, highlighting which implementation domains should be addressed first to maximize Gen AI adoption and which can follow once foundational conditions are in place. These findings provide an evidence-based foundation for policy action, suggesting that the Federal Chancellery AI strategy and

its implementation plan should incorporate these insights, directly linking individual and organizational measures to broader national initiatives such as Gov-GPT.

5.3 LIMITATIONS AND FUTURE WORK

Several limitations must be acknowledged when interpreting the findings of this study.

First, the generalizability of the results is limited because the study is based solely on the Swiss public administration case. Institutional arrangements, regulatory frameworks, and administrative cultures differ across countries, so the adoption patterns and effective measures identified here may not fully translate to other national contexts. While the insights are relevant for governments with similar decentralized or compliance-driven environments, caution is required when applying them beyond Switzerland.

Second, the selection and composition of the Delphi panel may have influenced the study's conclusions. Participants were recruited from the Swiss Smart Government Day, but it cannot be conclusively determined that all attendees were experts in public administration. The real-time format of the Delphi process also limited opportunities for reflection between rounds, and the overlap between the initial pool of experts and the final panel may have constrained the diversity of perspectives, potentially affecting the prioritization of measures.

Third, the study did not include a longitudinal analysis. Evolving institutional conditions, such as the gradual reduction of the “confidentiality barrier” (Cantens, 2025) through the deployment of Gov-GPT, may naturally influence perceived risks and adoption behavior independently of targeted interventions (Ajayi et al., 2025). Even without specific measures, rapid adoption of Gen AI is already observable (Arce-Urriza et al., 2025). As a result, the survey data used in this study, collected in 2024, can no longer be considered fully current.

Future Work

Future research could build on these insights in several directions. Longitudinal studies tracking the adoption of Gen AI in public administrations would provide a better understanding of how organizational and individual conditions evolve over time, and how initial measures influence subsequent adoption patterns. Comparative analyses across national contexts could uncover broader trends, helping to determine which strategies are transferable to other public sector environments with different institutional arrangements and regulatory frameworks.

Prior research emphasizes that, given the growing importance of digital government innovation, further work is needed to develop practical implementation strategies (Hong, Kim & Kwon, 2022). Therefore, future work should consider the development of a clear implementation plan that incorporates monetary and temporal prioritization alongside measures of effectiveness. Specifically for Switzerland, all measures included in the government's AI implementation plan should be clearly documented, and their impacts systematically monitored to assess adoption trajectories over time. Beyond the Swiss context, these findings would provide transferable insights for other governments seeking to deploy Gen AI effectively within public administration.

6. CONCLUSION

This study identified key measures to promote the adoption of Gen AI in the Swiss public administration by linking empirical evidence with implementation theory. A nationwide survey revealed currently low use among Swiss public sector employees, underscoring the urgent need to define concrete measures for further Gen AI initiatives such as the potential rollout of a Swiss Gov-GPT. A Delphi study with experts identified and prioritized eight measures, with *Training* and *Ensuring Access* emerging as the most critical interventions to increase Gen AI use in the Swiss public administration. Situating the findings within the CFIR framework highlighted the emphasis experts placed on individual and organizational issues, with the most critical elements clustering in the “Individual” and “Inner Setting” implementation domains. The results suggest that, at this early stage, increasing the use of Gen AI in the Swiss Public Administration depends on addressing both individual and organizational conditions rather than focusing on regulatory or technical dimensions.

FREQUENCY	MUNICIPALITY	CANTON	FEDERAL	TOTAL
Never	190 (42.7%)	58 (24.4%)	4 (21.1%)	252 (35.9%)
Rarely	158 (35.5%)	87 (36.6%)	8 (42.1%)	253 (36%)
Once a week	46 (10.3%)	37 (15.5%)	4 (21.1%)	87 (12.4%)
Several times a week	43 (9.7%)	47 (19.7%)	3 (15.8%)	93 (13.3%)
Daily	8 (1.8%)	9 (3.8%)	0 (0%)	17 (2.4%)
Total (N)	445	238	19	702

Table A1 Swiss Public Sector Employees Gen AI Usage at Work – Survey Results.

COMPETING INTERESTS

The author has no competing interests to declare.

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