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Digital Convergence USP 2030

AI APPLICATIONS IN SOCIAL SECURITY

Building evidence and insights from the AI TechByte

INTERNATIONAL SOCIAL SECURITY ASSOCIATION

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AI applications in social security
Evidence and insights from the TechByte

International Social Security Association
Geneva, 2025

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Digital Convergence Initiative (DCI)

DCI is the global initiative for the digital transformation of social protection systems. Established as part of the USP2030 partnership, the DCI is an open and collaborative platform for governments, development partners, civil society organizations and the private sector united by a shared vision: expanding the coverage of social protection and enhancing its delivery through inclusive, interoperable digital systems.

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1. Introduction and context setting

Artificial intelligence (AI) is no longer a distant prospect for social security; it is already being applied in diverse areas to improve services, efficiency and oversight. The International Social Security Association (ISSA), the Organisation for Economic Co-operation and Development (OECD), the German Agency for International Cooperation (*Deutsche Gesellschaft für Internationale Zusammenarbeit* – GIZ), the Inter-American Development Bank (IDB) and others have all examined this emerging reality (ISSA and UNU-EGOV, 2024; OECD, 2025; GIZ, 2020; Marer et al., 2024). These reports highlight both the opportunities created by AI to improve social security, from enhancing service delivery and quality to strengthening organizational capabilities, as well as the challenges it poses around governance, data quality, implementation and institutional capacity.

The principles found across the related reports are relevant, however, less is known about how AI supports social security institutions address challenges in practice, how they frame the use of AI as opposed to traditional technologies and what lessons can be drawn from current implementation experiences. To address this pressing need, the ISSA has already released a series of AI and digitalization-related documents, namely the newly updated ***ISSA Guidelines on Information and Communication Technology*** (ISSA, 2025b) which includes a new section on AI and *ISSA Guidelines on Good Governance* (ISSA 2025c). Together, they become key references for the effective adoption and use of AI by social security institutions.

To better understand the details of AI implementation, the ISSA Technical Commission on Information and Communication Technology (ICT) developed the new tool "TechByte: Mapping the use of AI in social security" (ISSA, 2025d). The TechByte was developed into a survey tool that provides a practical way to capture and analyse cases of AI adoption in social security institutions. Moreover, the tool goes beyond documenting AI technologies in use, it focuses on unwrapping the rationale, constraints and opportunities that shape institutional choices.

The TechByte objectives are threefold: i) to identify and map AI applications, ii) to understand the motivations linked to the use of specific AI technologies and iii) to make sense of the overall state of play of AI in social security.

This report presents the first results from the TechByte mapping. Understanding these use cases and examples are relevant for social security institutions planning and using AI solutions, offering them greater clarity on the landscape of AI applications and building confidence for informed experimentation and decision-making. Ultimately, this will allow the adoption of AI to be better linked to institutional strategies, align technology with long-term objectives and support the social security institutions mission objectives. TechByte is also envisioned to set the foundations for peer learning and cross-pollinating within and among social security institutions,

TechByte uses a standardized approach to document experiences and establish a foundation for peer learning across institutions. Its reach is further reinforced through collaboration with the Digital Convergence Initiative (DCI, 2025), coordinated by GIZ, which expands the scope of understanding of the use of AI in social security and fosters exchange across a wider community of practice of AI in social protection.

2. AI implementation journey so far

The ISSA carried out a pilot exercise with 37 cases submitted by 28 social security institutions. The institutions represented a wide geographical spread, showing that AI adoption in social security is not confined to a handful of countries but is being explored across different contexts worldwide.

The participating institutions reflect a wide variety of economic, social development and institutional diversity that ensure the cases captured reflect a range of conditions under which AI is being adopted, creating a stronger foundation for understanding the evolving ecosystem of AI applications.

Table 1. *Use case distribution by region and country*

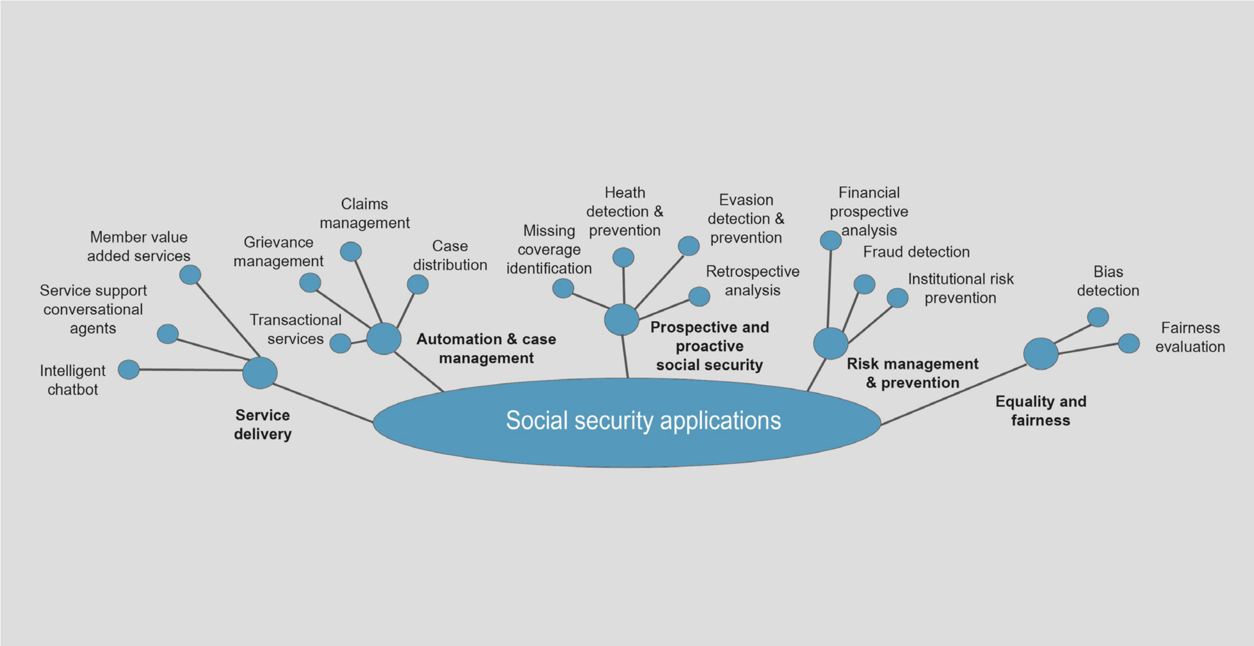
Region	Countries	Social security institutions	Use cases	
			Number	Percentage
Africa	2	2	3	8%
Americas	6	6	7	19%
Asia	5	7	13	35%
Europe	8	13	14	38%
Total	21	28	37	100%

Source: Authors' elaboration based on the TechByte survey information.

3. Insights from TechByte

From the various use cases analysed, different patterns begin to emerge, which can be examined in the following four sections. The report maps the TechByte, identifying the application (or domain) objective of the AI solution using the typology established in the joint report by the ISSA and the United Nations University Operating Unit on Policy-Driven Electronic Governance (UNU-EGOV) *Artificial Intelligence in Social Security Organizations* (ISSA and UNU-EGOV, 2024).

Figure 1. *AI applications in social security*



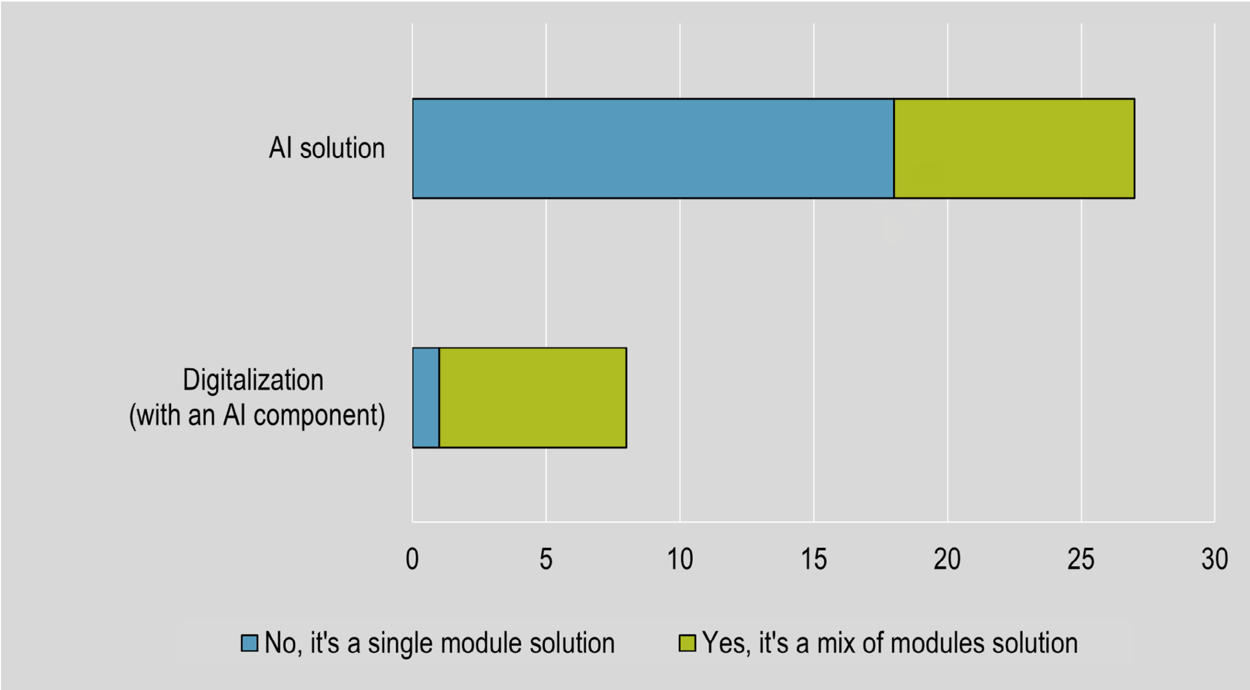
Source: ISSA and UNU-EGOV (2024).

The findings are organized in the following four sections. Section 3.1 provides a general overview of how AI adoption plays a role in the digitalization of services and the adoption of AI in terms of the application objective that the AI was focused on addressing, highlighting the objective areas and secondary objectives being prioritized. Section 3.2 examines how these applications are supported by different types of underlying AI technology solutions. Section 3.3 provides an overview of approaches to building AI solutions as well as alternatives to develop AI capacity. Section 3.4 analyses the business drivers behind AI adoption, with insights about the opportunities and needs that are fuelling momentum and the gaps that could hold it back. Together, these perspectives help us see the contours of emerging patterns.

3.1. General overview: mapping the landscape of AI adoption

Out of 37 cases, 76 per cent were identified as AI solutions driving digitalization and 24 per cent as digitalization projects with an AI component (Figure 2). This highlights two models of adoption: in some institutions, AI is positioned as the core element for solving a problem, while in others it is integrated more cautiously as a supporting layer within broader strategies. The same duality is visible in how solutions are designed. Some are single-module applications (in blue), while others are conceived as multi-module systems (in green). This variation is not merely technical; it signals readiness in institutional, technical and technological capacities, as well as available resources in the uptake of AI.

Figure 2. *Smart contract applications in public and social security institutions*



Source: Authors' elaboration based on various sources.

When mapped against the ISSA's topology of types of AI applications in social security (ISSA and UNU-EGOV 2024), Figure 3 shows the presence of AI across every type of domain of application in social security. The largest concentration of use cases is in service delivery and automation and case management, which are highly client-facing and service-intensive. Chatbots and virtual assistants, such as iConsulto by Spain's National Institute of Social Security (*Instituto Nacional de la Seguridad Social* – INSS) (see Appendix), illustrate a quick-to-deploy, highly visible and strategically appealing solution.

As shown in Figure 3, there are fewer but strategically significant use cases which target inward-looking functions such as risk management, fraud detection or predictive modelling. The German Federal Pension Insurance (*Deutsche Rentenversicherung Bund* – DRV Bund) (see Appendix), for instance, developed KIRA, a risk-based supervisory model that uses AI to identify irregularities in contribution payments, illustrating how AI can enhance oversight and internal efficiency. While tools like the latter example are less visible to the public, they support efficiency, oversight and sustainability in ways that are equally important to fulfil the institutional mandate.

Client-facing applications dominate, as they often provide institutions with the most compelling business case and a pragmatic entry point for adopting AI solutions that can deliver visible and measurable results. These solutions can be built through relatively accessible technologies and skills, they can build internal capacity and are a trusted mainstream solution to connect users and build public trust. Yet the cases observed include more complex applications (e.g. machine learning and generative AI), which suggest that some institutions are already investing in system strengthening and the capacities needed for more complex deployment. Altogether, these findings point to two adoption paths: one focused on quick, visible wins and another experimenting with deeper and more demanding innovations.

Figure 3. *Distribution of associated secondary domains of application within its primary domain as per ISSA's topology*

Source: Author's elaboration based on the TechByte survey information (number of use cases).

As with many technology solutions, one tool is not introduced with only one objective and AI implementation follows the same pattern. While there is a primary objective of application (or domain), there is a secondary objective directly associated with it. Figure 3 provides a view of the relationship between primary and secondary domains of applications in AI. Reviewing this relationship reveals that AI applications are generally multi domain. Cases categorized under one primary domain, such as service delivery or risk management and prevention, often entail a secondary type of application, like risk management, compliance or prospective analysis (even when reported otherwise). This is relevant to understand from a practical point of view regarding the use case and objectives in implementing AI. For example, a chatbot introduced to improve service delivery may require or lead to an additional step of reorganizing existing user data and workflows, effectively extending into case management, triggering change and impacts across the development chain.

The analysis highlights that AI solutions often transcend their initial technical purpose, touching several domains at once and reflecting the interconnected nature of social security. For policymakers and practitioners, this means that AI adoption must be treated as an institutional transformation process; one that depends on good digital and AI governance, design and collaboration to channel the ripple effects of technology into long-term value. In a similar way, this layered reality highlights the need for institutions to anticipate multidimensional outcomes from the outset, as well as to anticipate its full scope of impact, ensuring that AI adoption strengthens institutional capacities rather than recreating silos enabled by AI.

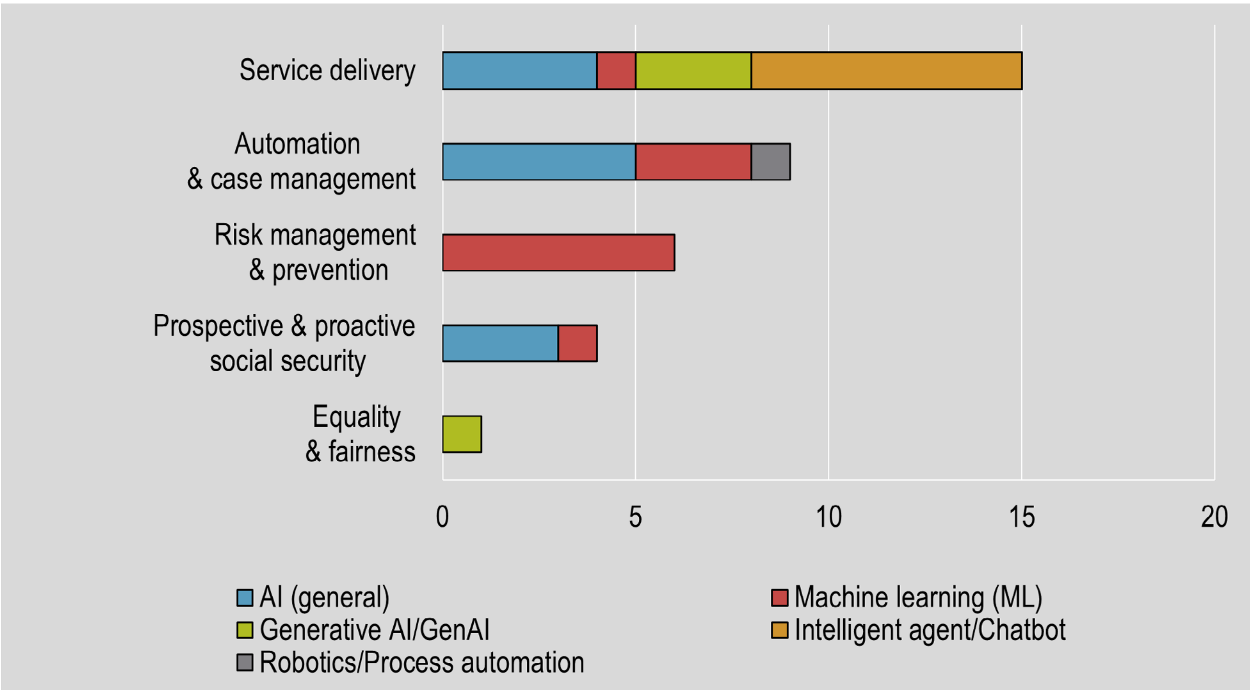
3.2. AI applications: matching technologies to objectives

The multidimensional nature of AI adoption also becomes evident when looking at the distribution of the type of AI technologies used across different domains of application. Associations can be seen between specific AI technology solutions and particular objectives that reflect choices, awareness and expectations of the impact that they can deliver in specific contexts.

The strategic matching of technologies to domains of application (objectives based on the topology described above) illustrates how institutions are already aligning technological choices with the nature of the challenges they face. Figure 4 illustrates how chatbots and virtual assistants are popular in service delivery because they are simpler to deploy and help institutions to better interact with clients, while reducing administrative workload and creating visible improvements in responsiveness. Their appeal lies in their relatively straightforward business case, their ability to scale and build institutional capacity and public trust. Uruguay's Social Insurance Bank (*Banco de Previsión Social* – BPS) (BPS, 2020), for instance, has developed a conversational agent that provides real-time guidance for supporting formalization of domestic workers, demonstrating how virtual assistants can enhance responsiveness in critical social support services.

Compliance and risk management, by contrast, requires a more robust capacity. Machine learning models are most commonly used to support case identification through predictive analytics. Austria's IT-Services der Sozialversicherung (see Appendix) has pioneered this through its KAI reimbursement system which applies machine learning to detect anomalies in medical claims, combining predictive capability with procedural fairness. Solutions like this one are less visible to the public, but they enhance oversight internally, while also strengthening decision-making and institutional performance.

Figure 4. *Distribution of associated secondary domains of application within its primary domain as per ISSA's topology*

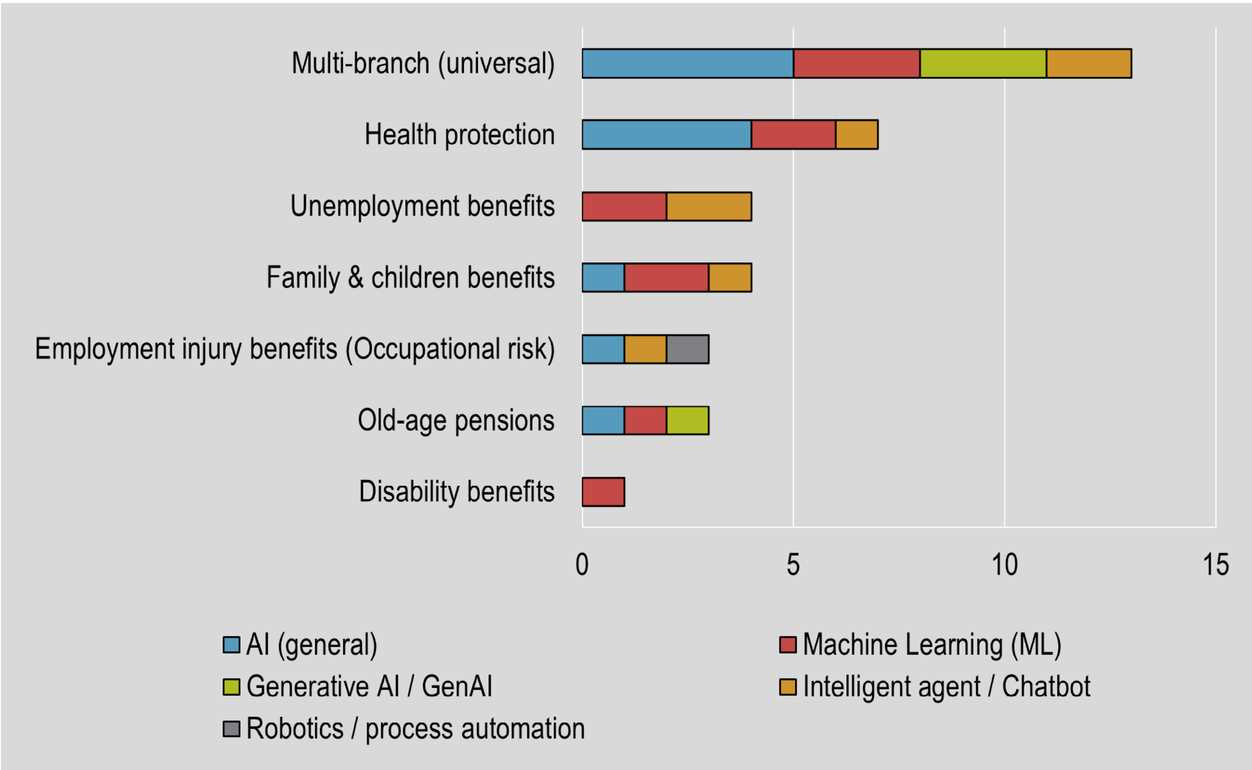


Source: Author's elaboration based on the TechByte survey information (number of use cases) and ISSA and UNU-EGOV (2024).

These associated domain-AI technologies matter for two reasons: First, they highlight the diversity of technological entry points into an institution's AI journey. Some projects start with relatively simple solutions, while others demand more complex undertakings involving data governance, workflow redesign, or organizational change. Second, the mix of technologies deployed reflects on the technical complexity and readiness. While a single AI tool may suffice for a specific challenge, the multidimensional nature of the challenges often requires a layered and more complex approach and technologies and a higher degree of institutional readiness. A similar pattern appears when mapping AI technologies across the branches of social security in Figure 5.

Figure 5 shows that AI technologies tend to concentrate around visible and strategic functions. In unemployment benefits, for instance, chatbots provide real-time guidance to users, while more complex models support internal decision-making by validating eligibility and detecting potential fraud. In health insurance, AI systems are being used for automated claims review and predictive analysis of expenditure patterns, reinforcing the narrative that AI adoption is inherently multidimensional, combining both front-end and back-end improvements and efficiency gains. The coexistence of these tracks is not contradictory; rather, it reflects an adaptive approach where adaptability proceeds at different speeds depending on institutional maturity and readiness.

Figure 5. *Distribution of AI technologies by primary domain of action as per the International Labour Organization's (ILO) definition (ILO, 2025)*



Source: Authors' elaboration based on the TechByte survey information (number of use cases).

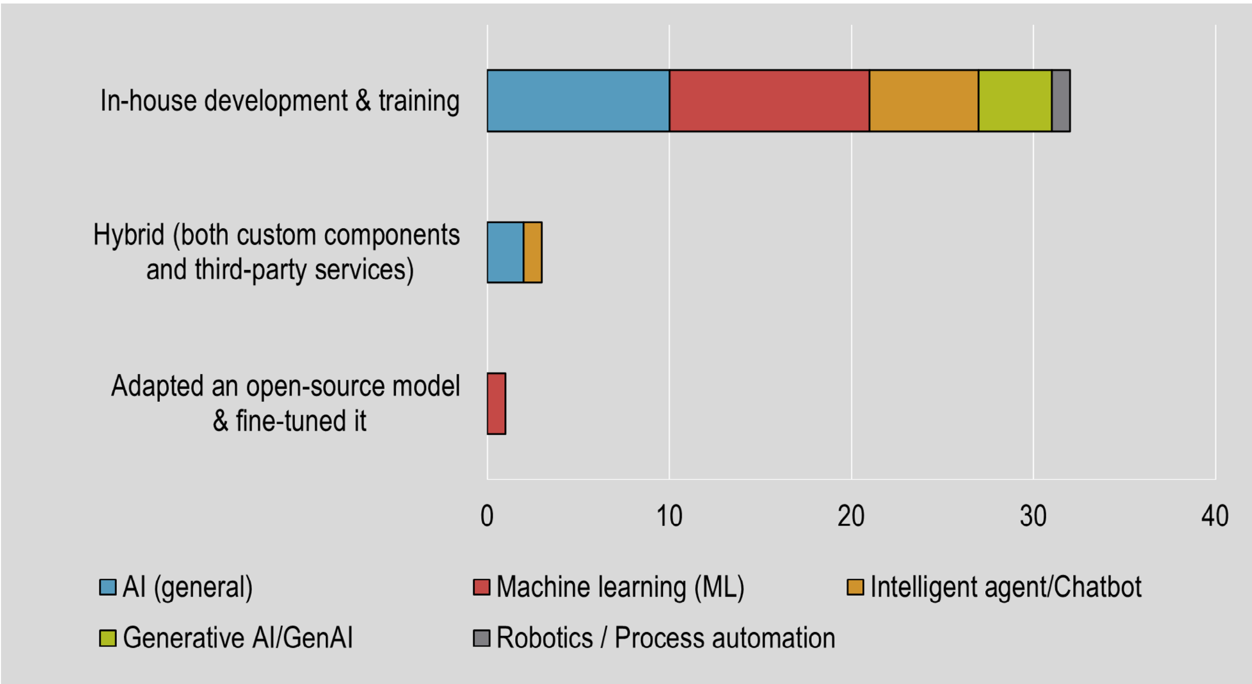
3.3. Development modalities: signals of readiness and capacity building approaches

Capacity remains a decisive factor shaping the direction and depth of AI adoption. The TechByte reveals that most institutions develop their solutions either in-house (with training and development taking place internally) or through hybrid models that include partnerships, vendors and other sources of external support. For example, Germany's DRV Bund combines two approaches, in-house expertise for projects such as "rvRecht" with external partnerships for technical development and testing (see Appendix).

Even though further analysis of the use cases is required, this indicates the importance of building capacity internally. There is still a need to carry out a further study in order to understand how this capacity is built and how external collaborations, partnerships, outsourcing training and/or expanding external research and development capacities with for-profit and non-profit organizations help build institutional capacities. The overall picture is nonetheless one of growing autonomy and technical acumen within institutions.

The high-level of in-house development and training shown in Figure 6, signals that institutions have the technical and organizational foundations needed to initiate an AI journey. Hybrid approaches, combining custom components with third-party services, are also common, further underlying that institutions mix internal capacity with external support to get projects off the ground. This signals a need to further understand the strategies and approaches around synergies established between social security institutions in leveraging third-party products and services as well as hybrid development approaches. The capacity building approach shows that institutions are not passive recipients of AI tools that are implemented as "off the shelf" solutions but establish teams that drive processes. Technology adoption remains an institutional imperative behind actively exploring, developing, adapting and taking up AI.

Figure 6. *Distribution of AI technologies by technology development capacity*



Source: Authors' elaboration based on the TechByte survey information (number of use cases).

When this is further broken down by technology type, as in the previous exercises, the data shows that institutions can implement not only relatively simple tools such as chatbots, but also more demanding technologies such as machine learning or, in some cases, generative AI. This suggests that capacity exists and is being built to support a wide spectrum of AI applications. The open question, however, is the extent of this capacity. Is it sufficient to sustain more ambitious projects, those that go beyond specific use cases and push toward systemic AI adoption or institutional transformation?

At the same time, while the skills required to design and deploy single-use applications are present, broader uses of AI – those demanding coordination across domains of application, stronger data governance, or multi-technology integration – require stronger capabilities and integration with institutional and strategic plans for digitalization. These include robust AI governance frameworks, institution-wide approaches to capacity building and partnerships that can leverage innovation and research within their jurisdictional ecosystems.

This need to develop in-house capacity should therefore be seen as a systemic need that builds on further experimentation, but complemented by mechanisms that sustain learning, ensure quality and trustworthiness of AI models and enable scalability. Malaysia's Employees Provident Fund (EPF) (Mustaffa, 2021) illustrates this well with its hybrid approach, which combines internal AI expertise with partnerships from the private technology ecosystem. This model enables progressive adoption while maintaining control over data and outcomes. Over time, such mechanisms transform localized technical ability into a more strategic, system-wide capability for innovation.

3.4. How are AI technologies being applied

A closer look at the primary and secondary objectives of the use cases by using AI applications presented in Figure 1 provides deeper insight into the types of technologies used to support interrelated objectives across domains. Table 2 illustrates how AI technologies are increasingly aligned with specific objectives. It provides an overview of the combinations of objectives supported by different technologies, indicating in brackets the number of cases using that type of technology. A closer examination of the subdomains reveals that similar technologies often support multiple functions, even when those secondary objectives fall under different primary domains. This suggests that institutions are learning to adapt AI technologies to diverse operational needs. Also, institutions are generating cross-cutting applications that respond to the interconnected nature of social security systems. For example:

- *Machine learning* is most frequently associated with retrospective analysis and claims management, where predictive capacity and fairness are crucial. These applications enhance accuracy and transparency in decision-making and reduce the administrative burden associated with manual reviews. For instance, Chile's Mutual for Safety CChC (*Mutual de Seguridad CChC*) (CChC, 2023) applies machine learning to detect and identify occupational respiratory diseases enabling earlier interventions.
- *Chatbots and intelligent agents* dominate in service-support sub-domains where direct communication with clients is key. Here, the advantage lies in scalability and improved user interaction, allowing institutions to handle large volumes of requests while maintaining quality of service.
- *Conversational technologies* providing grievance management and member value-added services, where rapid, context-aware interaction is integral to the service proposition.

Table 2. *Pairing of primary and secondary sub-domains by types of AI technologies*

	Transactional services	Claims management	Institutional risk prevention	Case distribution	Fairness evaluation	Grievance management	Member value added services	Service support conversational agents
Transactional services		AI-General (1)						AI-General (1)
Prospective analysis	Machine Learning (2)							
Fraud detection		Machine Learning (1)	Machine Learning (2)	AI-General (1)	Machine Learning (1)			
Intelligent Chatbot				Intelligent Chatbot (1)		Intelligent Chatbot (1) Generative AI (1)	Intelligent Chatbot (1) Generative AI (1)	AI-General (2) Machine Learning (1) Intelligent Chatbot (3)
Case distribution		Machine Learning (1)						
Fairness evaluation		Machine Learning (2)						
Member value added services				Process Automation (1)				Intelligent Chatbot (1)
Evasion detection & compliance					AI-General (1)			
Bias detection					Generative AI (1)			

Source: Authors' elaboration based on the TechByte survey information (number of use cases).

- *Generative AI*, although its footprint is still smaller, appears alongside these functions, typically to draft responses, summarize interactions or power more adaptive dialogue flows. EPF Malaysia's "WhatsApp for Business" (WABA) (see Appendix) assistant illustrates this emerging use, employing generative AI models to tailor responses and maintain conversational coherence across multiple interactions.

Table 2 shows how institutions have developed a range of AI technologies that can be used together. A use case reported under service support may rely on an intelligent agent at the front end, a retrieval layer over institutional knowledge bases and a machine learning model to route cases or predict resolution time.

This layering is important as it helps explain why AI technologies support primary and secondary sub-domains concurrently and why seemingly simple interfaces often require upstream work on data models, taxonomy and workflow orchestration. Moreover, this level of granularity showcases how institutions are beginning to develop recognizable "routes of solution" and "technology combinations" that address recurring objectives. These routes are important beyond demonstrating what could work, mainly by signalling the technical and institutional conditions needed that are useful for transferable learning across institutions. For example, Uganda's National Social Security Fund (NSSF, 2020) has implemented chatbots to support member services, offering a scalable example of how conversational AI can be adapted to improve communication while addressing end-to-end transparency.

At the same time, these associations highlight the growing domain specificity of AI adoption. Institutions are not simply using AI as a generic tool; they are learning how to use the right type of AI for each context. As institutions move from single challenges to bundled ones, hence bundled domains and sub-domains, the stack becomes more complex and the bar for institutional readiness rises. That is where governance, service design and cross-functional teams turn these patterns from isolated fixes into platforms that can be scaled.

3.5. Business drivers behind AI implementation

The qualitative evidence gathered through the TechByte survey was organized into a set of eighteen "business drivers" that represent the strategic conditions enabling or constraining AI implementation. Fourteen of these drivers were captured with concrete examples from the use cases and illustrated in Table 3 below. Five of these drivers account for more than one-third of all mentions: i) improving responsiveness, ii) enhancing personalization, iii) improving decision intelligence, iv) expanding reach and coverage and v) boosting institutional agility.

Together, these indicate a strong emphasis on visible, service-level improvements that deliver value directly to users, while also pointing to early signals of more strategic objectives. The top four drivers reflect the logic of client-facing quick wins, which help institutions secure political backing, build internal technological know-how and demonstrate tangible results. They also suggest a growing interest in linking AI adoption to the broader missions of social security institutions. The rest of business drivers account for internal and institutional objectives that are emerging as institutions expand their bet on AI.

Table 3. *Matching of business drivers by AI technologies*

	AI (general)	Generative AI	Intelligent agent/Chatbot	Machine learning (ML)	Robotics/ process automation
Improving responsiveness	6	2	4	4	1
Enhancing personalization	4	1	6	4	1
Improving decision intelligence	5		1	7	
Expanding reach and coverage	3		1	4	1
Boosting institutional agility	2	2	2		
Enabling operational sustainability	4			2	
Operational efficiency	2	1		3	
Facilitating inclusion			1	3	
Improving strategic communication	1		3		
Strengthening workforce capabilities		3		1	
Building citizen trust	2	1			
Enabling equitable access	2			1	
Strengthening targeting	2			1	
Supporting institutional coordination	1	1			

Source: Authors' elaboration based on the TechByte survey information (number of use cases).

However, the analysis also shows that structural enablers, such as workforce development, coordination mechanisms and structured adoption frameworks, remain underrepresented in terms of drivers for AI adoption. These elements are critical for scaling beyond isolated exercises and ensuring that AI becomes a sustained part of institutional transformation. Their relative absence underscores the need for AI innovation to transcend siloed projects that may stall efforts to institutionalize broader capacity conditions.

Equally important is the way technologies align with these drivers. Machine learning often corresponds to drivers like decision intelligence and operational efficiency, while chatbots align with responsiveness and personalization. This consistency suggests that technologies are being selected to meet concrete institutional needs, while it also illustrates that AI adoption in social security is not driven by technological enthusiasm alone, but problem-solving grounded in organizational realities and challenges. In this sense, clarifying why AI solutions are relevant before designing an AI application is key and can be supported by asking questions such as: why a given challenge needs to be addressed,why AI is chosen as a tool to address it and why resources are allocated to its deployment.

Another insight from the TechByte survey is that most institutions take a conservative approach to AI adoption and use. They primarily apply it to address existing, well-defined problems (mostly operational or service-related) where the risks are lower and the benefits more immediate. This approach reflects prudence as well as practicality: institutions are seeking to learn through manageable use cases that deliver quick and visible results. Recurrent applications such as AI-enabled chatbots and virtual assistants exemplify this pattern, providing a tested and trusted entry point for AI adoption.

At the same time, this cautious approach reveals both a limitation and an opportunity. The evidence suggests that institutions are gravitating toward technologies with proven track records, partially answering the “why” behind AI adoption but also signalling that experimentation remains concentrated within a narrow set of use cases.

As data foundations, technical capacities and governance frameworks continue to mature, AI will be better positioned to move upstream; for example, towards informing strategic planning, forecasting and service (re)design. The gradual shift from operational support to strategic intelligence represents not only the next step, but the next frontier for AI in social security, one that will depend on its ability to prove trustworthy, transparent and safe for both users and institutions alike.

4. Key considerations from an institutional point of view

The findings reveal that AI is advancing rapidly yet unevenly across social security. Institutions are gaining technical and organizational experience in identifying the application areas where AI can add value. The evidence also suggests that sustaining this progress will depend on how experimentation connects with broader enablers such as capacity, data, technology and governance. The following considerations outline the main takeaways from the TechByte survey and signal a possible way forward as AI becomes increasingly embedded in social security systems.

- **Governance.** Many use cases demonstrate success at the service level but might face challenges when scaled across institutional structures. The findings point to the importance of maintaining a portfolio perspective on AI initiatives, supported by evolving governance frameworks. These mechanisms help align projects, manage risks and embed responsible AI principles from the start. Over time, the adoption of a robust AI governance framework can be integrated into social security institutions, where lessons and safeguards are shared and will be relevant to build systemic approaches to leveraging AI.
- **Human and technology capacity.** Institutional capacity is expanding through both in-house and hybrid models, marking a turning point in how social security institutions approach technological innovation and adoption. Embedding these skills into everyday practice remains a gradual process, but the momentum is clear. Cross-functional collaboration, partnerships with technology providers and continuous training mechanisms are necessary requirements to transform AI experimentation into durable AI-related capabilities. Here the concept of humans-in-the-loop

should apply both at early and later stages. As these practices consolidate, the next step will be to connect them with system-wide workforce strategies that make AI readiness part of institutional culture rather than an isolated initiative.

- **Data quality and governance.** Across all cases, the quality and integrity of data consistently emerge as decisive enablers. Reliable, secure and sovereign data availability and management are fundamental for any AI endeavour. While attention to privacy, consent, cybersecurity and data governance are present, they cannot be taken for granted and, in some cases, these are less tangible than in others. Looking ahead, the priority should be to align data governance with interoperability standards, safeguards and institutional enablers to ensure outcome fits the desired result, ensuring that the growing use of AI also strengthens public trust in social protection.
- **Technology choices.** The diversity of reported use cases shows that institutions are navigating a dynamic landscape of build, buy, adopt and adapt technology. This diversity reflects a pragmatic approach where technological choices are tailored to institutional realities. Modular IT architectures, lifecycle discipline and evolving procurement models are proving essential to manage risk while maintaining flexibility. As AI becomes more central to operations, institutions may need to reimagine procurement and capacity building not just as a transaction but as a tool for innovation and AI uptake, enabling long-term partnerships that help institutions build agility and accountability as part of the process.
- **From patterns to strategy.** The growing alignment between technologies, sub-domains and institutional drivers suggests that AI adoption will gradually transition towards a more mature stage. The challenge ahead is to use these emerging patterns as signals for strategy development rather than templates for replication. Strengthening collaboration, investing in institutional readiness and experimenting by linking AI experimentation to meet social security objectives will be essential. This evolution marks the next chapter for AI in social security: one where technologies are not simply adopted to solve problems, but leveraged to shape smarter, more adaptive and inclusive social security.

5. Concluding remarks

Social security institutions are increasingly implementing AI solutions, adding significant value to their services and processes to enhance effectiveness and efficiency while supporting their mandate to achieve improved social outcomes. The TechByte draws on the ISSA-UNU-EGOV report *Artificial Intelligence in Social Security Organizations* and the *ISSA Guidelines on Information and Communication Technology*, including a dedicated chapter on artificial intelligence, along with extensive ISSA webinars and events, to provide practical insights on when and how AI generates value for social security objectives.

AI has demonstrated a proven track record in leading and supporting broader digitalization efforts, notably improving service delivery and case automation. However, institutions should adopt a strategic and proactive approach to AI implementation and governance, ensuring that AI initiatives are integrated systematically across their organizations and within their institutional ecosystem. The *ISSA Guidelines on Information and Communication Technology* (Section B.5, Guidelines 60, 61 and 65) offer clear guidance on establishing effective governance structures and identifying business processes where AI adds the most value and do so with responsibility and accountability.

Capacity-building efforts in AI adoption display a diverse landscape, from fully in-house developments to strategic partnerships and external collaborations. Regardless of the model, maintaining high-quality data and establishing business cases are essential, requiring social security institutions to be firmly in the driving seat of AI strategy to ensure relevance and impact. Looking ahead, the future of AI in social security will depend not just on technology, but on institutions' ability to align capacity, governance, technology and data to deliver trustworthy, user-centric public services. This highlights the importance of supervision of AI solutions and decision-making, which require significant human intervention (human-in-the-loop) as a crucial element to ensure they remain fit-for-purpose and to prevent undesirable outcomes, as emphasized in ISSA webinars and international conferences (ISSA, 2024; ISSA 2025e).

In the rapidly evolving landscape of AI technology, incorporating emerging trends, such as AI agents and multimodal AI, can further support social security objectives. This underscores the importance of moving beyond a use-case-centric focus, such as automation and efficiency, toward a systemic transformation leveraging AI as a transformative technology while focusing on accountability, inclusion and citizen-centric design. This trajectory supports the ISSA's emphasis on strategic governance and institutional capacity to enable smarter, fairer, more efficient and more adaptive service delivery.

The ISSA Technical Commissions on ICT and on Organization, Management and Innovation continue to make efforts to understand the business drivers and innovation of the use of AI in social security through the TechByte survey established to capture adoption and use cases of AI. This report was developed by the ISSA, in collaboration with the Digital Convergence Initiative, coordinated by GIZ.

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Appendix: Case studies

Topology of solution	
Main topology category	**Sub-Category**
1 – Service Delivery	A – Intelligent Chatbot
	B – Service Support Conversational Agent
	C – Member Value Added Services (non chatbot)
	D – Other (please specify)
2 – Automation & Case Management	A – Transactional Services
	B – Grievance Management
	C – Claims Management
	D – Case distribution
	E – Other (please specify)
3 – Prospective and Proactive Social Security	A – Missing coverage identification
	B – Financial literacy & Sustainable Society
	C – Evasion detection and prevention
	D – Retrospective analysis
	E – Other (please specify)
4 – Risk Management & Prevention	A – Financial prospective analysis
	B – Fraud detection
	C – Institutional Risk prevention
	D – Other (please specify)
5 – Equality and Fairness	A – Bias Detection
	B – Fairness Evaluation
	C – Other (please specify)

Federation of Social Insurances, Austria: *Reimbursement with artificial intelligence*	
Topic	Automatic processing of reimbursement requests for medical invoices with Artificial Intelligence.
Business problem	Support the Austrian Health Insurance Fund (ÖGK), the Austrian Social Security Service for Entrepreneurs (SVS) and the Austrian Social Security Service for Public Servants, Railways and Mining Industry Employees (BVAEB) in processing incoming reimbursement requests for medical invoices from private practitioners and therapists.
Use case objective	Incoming medical bills from insurants for medical services of private practitioners and therapists are sent to the aforementioned social security branches via mail, e-mail and centralized electronic plattforms on non-standardized invoices, forms and letters, which have to be processed manually by civil servants. It intends to support this time-consuming process semi-automatically with the help of artificial intelligence by recognizing and identifying the provided data and presenting it to the civil servants for further inspection and completion or fully automatically sending the data to subsequent downstream technical systems.
Topology of solution	2C (Automation & Case Management – Claims Management)
Expected/Achieved benefit to the organization/staff	Insurance organizations: Expand the organizational efficiency by reducing the amount of data to be entered manually, increase the capacity of invoices processed in a shorter time and as a result reduce financial costs.
Expected/Achieved benefit to the beneficiaries/target population	Insurant/Customer: faster reimbursement of medical costs through increased efficiency of case processing.
Key technological tools (technology stack)	• Multiple container solution with underlying architecture of microservices and message queuing • Webservice technology with Vue.js (frontend), Python, Kotlin (backend) and developer toolchain consisting of Jetbrains IntelliJ, Apache Maven, Jenkins (continuous delivery/ continuous deployment), Sonatype Nexus
Technological objective	Considering the non-standardized invoices and forms to be processed, a supervised training of various AI models at regular intervals outweighs a traditional software developing approach.
Challenges and considerations	A most accurate and efficient detection, recognition, identification and mapping of different elements and entities demands the deployment, training and coordination of various models for their respective advantages.
Data considerations	Data security is of uttermost importance since patients’ medical data processed is considered to be of highest vulnerability, sensibility and confidentiality (Social Security Class 3). High recognition accuracy guarantees no data breach as well as higher processing performance of reimbursements for insurants (end-customer).
Complexity	Start in 2019 with an average of 10-12 employees per year.
Results obtained (estimated) and KPIs	During the period of three years with an increasing number of processed cases the data recognition has been improved considerably by using and adapting and training various AI models.
Scalability	Application for other use cases in the field of social security has been considered and evaluated constantly and other information systems will be able to adapt the underlying AI technologies.

Key enablers and dependencies	ITSV Management as the main driver and customers (social security branches) as receiving parties.
Internal capacity used & external partners leveraged	The company's internal AI team consists of various data scientists and developers with different specializations with technical and software developing backgrounds and is widely recognised as the AI competence centre in the Austrian social security. External partner companies and consultants extend this expertise. Infrastructure services, system management and system maintenance are also provided by the company itself.
Contact information	Alexander Zeiss and Samantha Brodbeck

Agency for Sustainable and Operative Social Provision (DOST Agency), Azerbaijan: ***Enhancement of Interactions with Citizens through AI in Labour & Social Protection***	
Topic	The project aims to enhance the efficiency and effectiveness of citizen interactions by integrating AI-powered chatbot and Call Center systems. This implementation will lead to higher user satisfaction ratings and improved service delivery metrics for the Ministry of Labour and Social Protection of Population of the Republic of Azerbaijan and its subordinate institutions.
Business problem	The Ministry and its subordinate institutions, including the Agency for Sustainable and Operative Social Provision (DOST Agency), State Social Protection Fund, Social Services Agency, State Employment Agency, and others maintain a presence on their websites and various social networks, where they receive daily inquiries from citizens. To manage these requests efficiently, the DOST Digital Innovations Center introduced the Social Bot function, which automatically redirects inquiries from social media to the chatbot. The bot responds using pre-defined template responses, while questions it cannot address are forwarded to Call Center staff. Although the template responses are continuously updated, analysis of data from calls and social media inquiries reveals that many questions are repetitive. As a result, operators often spend time addressing the same issues – such as pension payment schedules – leading to delays in handling unique inquiries. A similar pattern emerges with questions received through social media. Implementing AI can streamline this process, enabling quicker and more efficient responses to frequently asked questions. The institution is well-equipped for this enhancement, as the Call Center has recorded all calls since its establishment in 2014, generating millions of data points and conversations. This wealth of data can be leveraged to develop a more responsive AI system, improving overall service delivery.
Use case objective	The integration of AI in the labour and social protection sectors of Azerbaijan aims to improve interactions with citizens by providing timely, personalized, and efficient services. This initiative will leverage AI technologies to streamline processes, enhance service delivery, and foster better communication between government agencies and citizens. Various case studies were researched, but none have been directly applied in country's context. The Center is focused on establishing a completely new mechanism that leverages insights from these experiences while being tailored to local context and needs.
Topology of solution	1A (Service Delivery – Intelligent Chatbot)
Expected/Achieved benefit to the organization/staff	**Expected benefit to organization:** Implementing an AI solution is supposed to significantly enhance organizational performance in several ways, including increasing overall productivity and efficiency, providing 24/7 availability and faster resolution times, optimizing services and reduce operational costs. **Expected benefit to staff:** The enhancement of interactions with citizens AI can offer several significant benefits to staff, such as reducing workload, facilitating better communication between staff and citizens, leading to clearer and more efficient interactions.

Expected/Achieved benefit to the beneficiaries/target population	All the relevant institutions receive calls made by citizens through a single and unified DOST Call Center 142. The Call Center 142 serves with the purpose of receiving and promptly responding to inquiries and complaints about the issues related to the activities of the Ministry, including social security, identification of disability, medical and social rehabilitation, employment, compliance with labor legislation in workplaces, citizens' information regarding the use of e-services in these areas. During the first six months of 2024, the Call Center 142 received a total of 812,589 applications. Of these, 771,320 were incoming calls, with 769,891 of these calls being answered. Additionally, there were 648,327 registered calls. The average number of incoming calls per day was approximately 7,100. In the social media channels, there were a total of 190,566 appeals over the first nine months of the current year. Of these, approximately 132,983 (69.8%) were responded to by social bot, while 57,583 (30.2%) were handled by live operators.
Key technological tools (technology stack)	The Artificial Intelligence Application Division has been established within the structure of the DOST Digital Innovations Center. Currently, it is engaged in investigating needs assessments and selecting key technological instruments for project implementation
Technological objective	Call Center often experiences high volumes of calls, leading long wait times for customers. AI chatbot and virtual assistant can handle routine inquiries and provide instant responses, reducing the load on human agents and improving response times. AI solution enables chatbots to handle a large number of simultaneous conversations without a decrease in performance or quality. Variability in agent performance can lead to inconsistent service quality and customer dissatisfaction. AI can monitor calls in real-time, providing feedback and identifying areas for improvement, ensuring a uniform quality of service. Call Centers generate vast amounts of data that can be overwhelming to analyze manually. AI-driven analytics tools can process and analyze call data to uncover trends, insights, and areas for improvement.
Challenges and considerations	The main challenge observed at the beginning of this journey is the lack of experts specialized in this field. As the country gradually transitions to AI, many experts are still in the process of learning.
Data considerations	**Date cleanliness:** Since 2014, enough data has been collected considering the data recording. For AI, there is enough material to study it. **Data source:** Centralized Call Center 142 acts as the main data source. **Data privacy:** The Law on Personal Data Protection in Azerbaijan, adopted in 2019, establishes comprehensive principles and requirements for the collection, processing, storage, and transfer of personal data. This law aims to safeguard the privacy and security of personal information.
Complexity	It will be defined due to course.
Results obtained (estimated) and KPIs	The creation of a department in the relevant field and the use of the first artificial intelligence-enabled chatbot are among the expected results. KPIs will be determined according to the questions answered when the services are provided.
Scalability	It will be defined due to course.
Key enablers and dependencies	Implementing this project requires several organizational enablers and dependencies across various institutions, including the DOST Digital Innovations Center and the 142 Call Center.
Internal capacity used & external partners leveraged	**Internal:** DOST Digital Innovations Center and the 142 Call Center. **External:** Not currently planned.

ISSA Guidelines	ISSA has developed guidelines on information and communication technology (ICT) to improve the efficiency of social security systems. These Guidelines cover governance, data security, interoperability, user-centric design, capacity building, innovation, and monitoring and evaluation. They emphasize the importance of training personnel, adopting new technologies, and assessing the effectiveness of ICT implementations.
Contact information	Sabina Huseynova – Advisor to the Director, DOST Digital Innovations Center

German Federal Pension Insurance, Germany: *KIRA – Artificial intelligence for risk-based employer audits*	
Topic	Artificial intelligence for risk-based employer audits
Business problem	One central task of Deutsche Rentenversicherung Bund is to regularly check all German employers whether they have paid their social security taxes correctly. Currently, an auditor has less than one day on average to audit an employer. This is far too little to search through the entire wealth of audit documents for irregularities. The auditors can therefore only carry out spot checks and must decide where to prioritise their audits. The challenge will continue to increase due to the demographic challenges, i.e. fewer people for equal or even more work.
Use case objective	Development and deployment of an machine learning model that supports auditors by analysing audit documents in order to generate two things that should make the auditors' work easier: a) an assessment of irregularities in the form of a risk score and b) concrete indications of found anomalies in the audit documents.
Topology of solution	4B (Risk Management & Prevention –Fraud Detection), 5B (Equality and Fairness – Fairness Evaluation)
Expected/Achieved benefit to the organization/staff	Based on the machine's outcomes (risk score and detailed indications), employer audits can be processed in a prioritized manner and the process is accelerated.
Expected/Achieved benefit to the beneficiaries/target population	Auditors can complete tasks more quickly. The workload is reduced.
Key technological tools (technology stack)	Python libraries: kedro, pytorch, tensorflow, scipy, scikit-learn, random forest, xgboost etc. VSCode, JupyterNotebook, Redhat, Angular/node.js/npm, Oracle database, SQL, Apache Webserver
Technological objective	We are using supervised learning to analyze hundreds of thousands of historical closed audit cases and learn from them where and what anomalies can be found in the data. The model is then applied to new data and probabilities are calculated for score and indications. This type of analysis, classification and output of accurate employee-level notices would not be possible with traditional technologies such as rule-based systems.
Challenges and considerations	There were some challenges in implementing the first AI use case in our organization – technical, organizational, and cultural. On the one hand, access to many technologies and tools within the organization is restricted for security reasons, such as Python. Python was not released at the start of the project and had to be introduced. A new infrastructure had to be set up due to lack of servers with GPUs within the organization. The database had to be created and anonymized. Stakeholder management was as time consuming as the pure technical development: the biggest efforts were made to address regulatory demands of IT security and data protection issues. Furthermore, another challenge was to convince workers council. This required a great deal of educational work in the departments mentioned, but also in the organization in general, to explain what AI is, which AI is being used here and how it should be handled. We had to engage in a great deal of communication and change management in order to counter septicism about the use of AI in general and concerns about our own workplace.
Data considerations	The training data was anonymized and stratified before use. Numerous analyses were performed regarding data completeness, data consistency, uniformity, relevance, data privacy and general bias in the data.

Complexity	Preparation and provision of historical data and development environment: 3 months 100 PT Pure development time so far was 7 months with 100h Data Engineer, 200h Data Scientist, 100h ML Engineer
Results obtained (estimated) and KPIs	The machine makes it possible to reduce the number of audit cases by approx. 50%, as these are inconspicuous (score 1). And the error rate is less than 1%. This means that we miss less than 1% of the financial impact due to incorrect classification while reducing the number of audit cases significantly.
Scalability	The AI solution for the tax audit service could be expanded to various other types of audits (e.g. collection agency audits, audits of direct contributors, audits for specific reasons, insolvency audits). With the appropriate database, it would also be conceivable to use KIRA for other types of checks in addition to pension insurance issues.
Key enablers and dependencies	Key enablers and dependencies for us were the external service provider for the development, the IT security and data protection department, the IT department for providing the infrastructure and interfaces to existing systems, the staff representatives, the team for compliance with accessibility standards, the involvement of the domain specialists in the project team, and the support of the respective department heads and directors.
Internal capacity used & external partners leveraged	On the technical side external support was heavily used. The development took place with an external partner. Internal know-how is currently being developed.
Contact information	Dr. Michael Tekieli

German Federal Pension Insurance, Germany: *rvRecht' – GenAI within "rvRecht", the legal literature system of DRV*	
Topic	Proof of concept for demonstrating the use of GenAI within "rvRecht" – the legal literature system of Deutsche Rentenversicherung.
Business problem	The legal literature system 'rvRecht' contains a well-maintained collection if legal texts, legal interpretations, legal judgements, and further documents. The database is used daily by up to 9000 clerks in the various departments of the Deutsche Rentenversicherung Bund. The database supports clerks in their decision making, especially when replying to a customer. Typically, clerks use a standard keyword search for navigating through the various documents. This approach is time consuming and finding relevant information can be difficult.
Use case objective	The proof of concept aimed at building internal knowledge regarding the new technology, as well as showcasing potential advantages for employees working with the literature system.
Topology of solution	1A (Service Delivery – Intelligent Chatbot)
Expected/Achieved benefit to the organization/staff	Efficiency gains by supporting employees in their daily work.
Expected/Achieved benefit to the beneficiaries/target population	Clerks can make use of AI functionality to find relevant information in the literature database faster. Furthermore, the system can also generate personalized answers based on the existing documents in the literature database and individual preferences of the clerks. Clerks will spend less time searching for information – the extra time can be used for more demanding work.
Key technological tools (technology stack)	Retrieval augmented generation (RAG) approach based on open-source technologies: Python, LLMs, embedding models, vector databases, et cetera
Technological objective	Introducing GenAI capabilities to the technology stack of the Deutsche Rentenversicherung. Defining a GenAI tech stack, that can be used for multiple business use cases.
Challenges and considerations	The main challenge is maintaining a high-quality output of the GenAI solution. The RAG approach aims at avoiding typical drawbacks of LLMs, such as hallucinations. Data quality in the source system is another concern because poor quality and high complexity of the source material significantly complicates correct data retrieval. Ethical and organizational considerations also play an important role, such as avoiding bias, implementing guardrails for a human-centred system design, empowering employees by providing adequate training, et cetera. To conform the high standards of IT security and data protection is necessary but can be challenging.
Data considerations	The PoC only used publicly available data. In the resulting project, confidential data will also be used. Hence, in contrast to the PoC, the solution must be implemented within the infrastructure of DRV Bund. The confidential data must not leave the internal IT infrastructure.
Complexity	The PoC for showcasing GenAI potential was executed in 5 months. The actual project for setting up an IT system for productive use is set to start in January 2025 and is supposed to last for around one year.
Results obtained (estimated) and KPIs	A first simulation within the proof of concept quantified expected time savings for GenAI-supported literature research in the database to around 25%.

Scalability	The legal literature system 'rvRecht' is used by all 16 of the German pension insurance provides. Hence the technical solution aims at being easily scalable and applicable to other parts within the organization.
Key enablers and dependencies	Broad interest and willingness to investigate possibilities of a new technology, management buy-in, support of all affected department heads, thorough testing of the system demo with the potential users, participation of relevant stakeholders like IT security, data protection, staff council et cetera from day one.
Internal capacity used & external partners leveraged	The technical part of the proof of concept has been realized with the support of an external service provider. The core project teams (internal and external resources) consisted of less than 10 people.

Employees Provident Fund, Malaysia: ***Resource Intelligent Search Engine (RISE)***	
Topic	EPF faces increasing challenges in efficiently identifying internal talent for job functions, projects, or temporary assignments. Skills data is often fragmented across HR systems, CV repositories, and internal platforms, making manual searches slow, inconsistent, and prone to oversight. This results in underutilisation of internal capabilities, missed opportunities for internal mobility, upskilling, and retention and delays in project initiation and delivery
Business problem	Enable fast, accurate, and intelligent matching of internal employees to job functions, project assignments, and cross-functional opportunities by leveraging AI-powered semantic search, skills extraction, and contextual ranking – supporting agile workforce deployment, enhancing internal mobility, and reducing dependency on external recruitment.
Topology of solution	5A (Equality and Fairness – Bias Detection, 5B (Equality and Fairness – Fairness Evaluation)
Expected/Achieved benefit to the organization/staff	RISE will reduce internal talent search time by over 60%, increase internal placement rates to lower external recruitment costs, enable agile workforce planning and project staffing, and enhance employee engagement through improved internal mobility opportunities.
Expected/Achieved benefit to the beneficiaries/target population	RISE will reduce internal talent search time by over 60%, increase internal placement rates to lower external recruitment costs, enable agile workforce planning and project staffing, and enhance employee engagement through improved internal mobility opportunities.
Key technological tools (technology stack)	Microsoft Azure AI Foundry, LLM: GPT-4o, retrieval augmented generation (RAG).
Technological objective	**1. Language Model Limitation:** The current large language model (LLM) powering RISE is primarily tuned for English, while a significant portion of internal employee data (resumes, profiles, job descriptions) is in Bahasa Malaysia (BM). This may impact the accuracy of semantic search and skill extraction in BM until further model tuning or multilingual support is implemented. **2. Pilot Stage Constraints:** RISE is still in the pilot phase and has not yet been deployed to production. As such, many operational challenges (e.g., system scalability, user adoption, integration stability) are not fully observable at this stage. **3. Internal-Facing Scope:** Since RISE is designed for internal use only, external risks (e.g., customer data privacy, external cyber threats) are minimal at this point. However, considerations for future scaling and compliance (e.g., PDPA) should remain in focus.
Challenges and considerations	In this phase, we are focusing only on screening non-HR talent data, as we need to first secure stakeholder buy-in given the sensitivity and confidentiality of HR data. The available data is structured and ready for use
Data considerations	Leveraging AI foundry engine has significantly reduce the complexity
Results obtained (estimated) and KPIs	RISE has demonstrated a reduction of at least 60% in the time spent on internal talent searches
Scalability	The design pattern is extendable to other applications and use cases, provided that the prompts and underlying documents are aligned with the core objective of enabling effective search and discovery

Key enablers and dependencies	**Key Enabler:** Enhancement of the language model for multilingual (BM + English) capability, and integration with HR systems within a secure, scalable, and compliant infrastructure. **Key Dependency:** Stakeholder approval to access and process HR data, supported by robust data governance, security validation, and budget allocation for production deployment.
Internal capacity used & external partners leveraged	RISE was developed 100% internally, leveraging a lean team consisting of one data scientist, one business analyst, and one HR subject matter expert (SME)
Contact information	Afhzal Abdul Rahman, Chief Digital Technology Officer, EPF, and Muhammad Nurhakim (Hakim), Centre of Excellence, EPF

Employees Provident Fund, Malaysia: *SARA (Seamless AI Retirement Advisory)*	
Topic	SARA
Business problem	Retirement advisors face challenges in delivering timely, personalized financial planning to members because comprehensive member information is not readily available in one place. While some data exists within the core system (e.g., contributions, age, salary), critical inputs such as external savings, liabilities, or financial commitments are missing. Preparing tailored retirement advisory is time-consuming due to manual effort to gather, validate, and analyse multiple data points – including economic trends – hindering the ability to provide instant, holistic retirement guidance.
Use case objective	To enable the delivery of instant, personalized retirement advisory by integrating available core system data with member-provided inputs and external economic trends, leveraging AI and analytics to generate tailored financial planning recommendations that support informed and confident retirement decisions.
Topology of solution	1C (Service Delivery – Member Value Added Services (non chatbot)), 1D (Service Delivery – Other), 2E (Automation & Case Management – Other)
Expected/Achieved benefit to the organization/staff	The solution increases member engagement and trust in retirement services, reduces manual advisory workload for staff, and enhances data-driven decision-making for retirement policy development.
Expected/Achieved benefit to the beneficiaries/target population	It provides members with personalized, actionable retirement guidance and improves confidence in retirement readiness.
Key technological tools (technology stack)	Custom-built application on Microsoft Azure AI Foundry leveraging GPT-4o LLM, Azure AI Search, Azure Vector DB and n8n.
Technological objective	To build a secure, scalable platform that analyses member-provided data alongside pre-filled data extracted from the core system, enabling the generation of personalized, data-driven retirement advisory insights through advanced analytics and AI models
Challenges and considerations	**1. Fragmented data:** Member information is spread across multiple systems, requiring consolidation to enable comprehensive analysis. **2. Dependency on advisor expertise:** Retirement advisors still need to be sufficiently knowledgeable to interpret AI/system-generated insights, as responses may at times lack accuracy, local context, or the level of hyper-personalization required. **3. Data security:** Handling sensitive personal and financial data requires strict adherence to security protocols and compliance with data protection regulations. **4. Input accuracy and member behaviour dependency:** The quality of the analysis depends heavily on the accuracy of both pre-filled and member-provided inputs; ultimately, outcomes rely on member decisions, and adherence to advice cannot be guaranteed. **5. Need for human oversight:** AI-generated plans or analyses require validation and interpretation by retirement advisors before they are shared with members to ensure relevance, clarity, and appropriateness.
Data considerations	The solution will leverage internal data from core systems, economic indicators, and external data provided directly by members. To ensure data consistency and accuracy in analysis, unstructured data will be converted into structured formats wherever possible, enabling seamless integration and reliable insights.

Complexity	High: The solution involves integration with legacy pension systems, AI model development, and adherence to regulatory compliance requirements. In the pilot stage, the use case was made fully functional within 3 months by initially integrating with the Customer Experience System instead of the Core System to reduce complexity and accelerate deployment.
Results obtained (estimated) and KPIs	From 30-45mins to instantaneously, but will require the RA to analyse and interpret before advising members
Scalability	The design pattern is modular and API-driven, enabling the solution to scale from retirement advisor-assisted advisory to self-service capabilities within the Member Interaction Platform (MIP). This allows members to directly access personalized insights, expanding the solution's reach while reducing dependency on manual advisory support.
Key enablers and dependencies	**1. Robust Data Integration Layer:** Seamless connection between internal core systems, customer experience platforms, and external data sources (e.g. economic indicators) to enable a holistic view. **2. AI Model Localisation and Tuning:** Enhancement of AI models to handle local context, languages, and member-specific needs, improving relevance and accuracy of recommendations. **3. Secure and Compliant Infrastructure:** Enterprise-grade security architecture with strict data privacy controls (e.g., PDPA compliance) to protect sensitive member data. **4. Advisor Enablement and Training:** Structured training to equip retirement advisors with skills to interpret AI outputs and deliver meaningful, personalized guidance.
Internal capacity used & external partners leveraged	The pilot model were co-developed with Microsoft Global Black Belt team, internal EPF full-stack developers, data scientist and subject matter experts.
Contact information	Afhzal Abdul Rahman, Chief Digital Technology Officer, EPF and Muhammad Nurhakim (Hakim), Centre of Excellence, EPF

Employees Provident Fund, Malaysia: *TROVE (Trusted Retrieval of Verified Endorsements)*	
Topic	TROVE
Business problem	Approvals, decisions, and endorsements captured in minutes of meetings are often stored in unstructured text formats, making them difficult and time-consuming to search manually. This slows down internal processes such as governance checks, audit readiness, and decision tracking, increasing operational risk and effort in retrieving critical approvals.
Use case objective	To develop an AI-based search engine that enables staff to quickly locate, verify, and retrieve approvals or decisions from minutes of meeting, reducing search time from hours to minutes and supporting faster, more accurate internal governance activities.
Topology of solution	2E (Automation & Case Management – Other)
Expected/Achieved benefit to the organization/staff	TROVE delivers significant benefits to the organization by reducing the time and manual effort required to locate approvals, improving the accuracy and consistency of governance reporting, and supporting more efficient compliance, legal, and operational processes.
Expected/Achieved benefit to the beneficiaries/target population	It provides a more streamlined experience for reviewers and auditors.
Key technological tools (technology stack)	Azure Cognitive Services, Azure Search for indexing and retrieval
Technological objective	To build a secure, AI-powered search engine that can parse and index unstructured meeting records, enabling accurate, real-time retrieval of approvals and decisions, and integrating seamlessly with existing internal systems.
Challenges and considerations	1. Variability in how approvals and decisions are recorded across different minutes of meeting formats. 2. NLP accuracy in interpreting organizational language, acronyms, and approval structures. 3. Ensuring data privacy and access controls for sensitive governance records.
Data considerations	1. Primarily unstructured text data from minutes of meetings (PDF, Word, or plain text). 2. Need for pre-processing and normalization to enable accurate tagging and indexing. 3. Secure storage and processing aligned with internal data governance policies.
Complexity	Moderate to high: The solution must handle unstructured data, natural language nuances, and integration with legacy document management systems while ensuring compliance with data governance requirements.
Results obtained (estimated) and KPIs	1. Estimated reduction of approval search time by >80%. 2. Increased retrieval accuracy rate (target: >90% precision on approval search).
Scalability	The design pattern supports extension beyond Procurement Committee minutes to other committees, boards, and governance documentation. The API-driven architecture enables easy integration with new document sources or workflows.
Key enablers and dependencies	1. Access to historical and current Procurement Commitee minutes of meeting data for model training. 2. Stakeholder buy-in from legal, governance, and IT teams for adoption and integration. 3. Budget for AI model development, infrastructure, and ongoing support. 4. Strong data governance and compliance oversight to manage sensitive information.

Internal capacity used & external partners leveraged	The pilot model were co-developed with Microsot Black Belt team, internal data scientist and subject matter experts.
Contact information	Afhzal Abdul Rahman, Chief Digital Technology Officer, EPF

Employees Provident Fund, Malaysia: *WABA (WhatsApp for Business)*	
Topic	WABA
Business problem	Customers increasingly expect quick and consistent responses when seeking information or support for simple, repetitive queries especially on product offerings.
Use case objective	To reduce call centre congestion by offering a faster support option through WhatsApp. Customers can get instant answers to common questions with AI, without needing to wait on the phone. For more complex issues, the chat can smoothly hand over to a human agent.
Topology of solution	1B (Service Delivery – Service Support Conversational Agent)
Expected/Achieved benefit to the organization/staff	Operational Efficiency – Common questions will be handled automatically through WhatsApp, so customers can get answers quickly on their own. This lets agents focus on more important or personal cases. It helps save time, speed up replies, and gives the team a clearer view of what customers need — making the whole support process more efficient and cost-effective.
Expected/Achieved benefit to the beneficiaries/target population	IThe solution makes it easier for customers to get help using WhatsApp — a platform already used by 89% of Malaysians. By bringing EPF services into a familiar app, it streamlines the customer journey and improves engagement. Customers get quick, accurate answers with less waiting, and can still talk to a human when needed.
Key technological tools (technology stack)	Platform: WhatsApp Business API Backend: REST APIs & Webhook Messaging: Flow Builder (no-code/low-code) NLP: Answers (Chatbot Platform) AI/ML: Infobip's AI Assistant (RAG) Security: End-to-End Encryption, ISO 27001, SOC2 & GDPR-compliant
Technological objective	To build a secure and scalable AI chatbot integrated with WhatsApp for Business, enabling real-time self-service while ensuring seamless handover to human agents for complex or sensitive queries.
Challenges and considerations	1. Ensuring accuracy of AI responses and knowledge base content. 2. Handling multi-language support and local context (e.g., BM + English). 3. Managing data privacy, consent, and security in line with PDPA and other regulations. 4. Avoiding customer frustration during bot-to-human handover.
Data considerations	1. Use of structured knowledge base data, FAQs, and CRM records for bot responses. 2. Secure storage and processing of chat logs and customer interactions. 3. Continuous data refinement through AI learning and feedback loops.
Complexity	Moderate: Requires AI tuning, WhatsApp API integration, multi-system connectivity
Results obtained (estimated) and KPIs	1. Target reduction in agent-handled queries by >50% for simple issues. 2. First-contact resolution rate improvement (target: +30%). 3. Reduced average response time for customers (target: near-instant for common queries).
Scalability	The solution can extend to other messaging platforms (e.g., Telegram, Facebook Messenger) and integrate with broader customer service ecosystems, including voice bots and web chat (ELYA).
Key enablers and dependencies	1. Well-maintained, up-to-date knowledge base and FAQs. 2. Strong change management and customer education to drive adoption.

Internal capacity used & external partners leveraged	The full suite use case is currently under testing and are co-develop with a Meta's BSP.
References	1. Foundational Security Triad – aligns with ISO 27001 standards, emphasizing the classic CIA triad: Confidentiality, Integrity, and Availability – ensuring robust data protection across its messaging platform. 2. Governance & Risk Management – employs a structured security governance model; Board-level ownership of security, Regular external penetration testing (OWASP, NIST, OSSTMM).
ISSA References	1. ISSA also prioritizes the CIA triad as a core principle: maintaining confidentiality, integrity, and availability of information systems in professional conduct and organizational guidelines. 2. ISSA emphasizes governance through its Code of Ethics, advocating for; Strong policy frameworks, Ethical decision-making and Accountability in risk assessments and organizational conduct.
Contact information	Afhzal Abdul Rahman, Chief Digital Technology Officer, EPF, Ahmad Fahmi and Azfar Al Farabi

National Social Security Institute, Spain: iConsulto	
Topic	Proof of concept for AI Implementation in iConsulto, the system of the National Institute of Social Security of Spain (INSS) that collects the legal information and it is used by informers and processors in tasks of citizen service and information, as well as benefit management.
Business problem	The main issue is the need to improve the a**ccessibility and efficiency of information retrieval** within the extensive document corpus of iConsulto. Users have difficulty quickly finding relevant documents and answers to their questions. Additionally, there's an effort to optimize interaction with the knowledge stored in iConsulto through **generative AI**, allowing for more intuitive answers to complex questions.
Use case objective	Implement a **semantic search engine** that enables users to find relevant documents by understanding the meaning of their queries. Develop a **virtual assistant** based on generative AI that answers questions related to the knowledge stored in iConsulto. Offer **AI-generated document summaries**, allowing users to quickly grasp the content. Enable users to provide feedback on summaries to improve their quality. Facilitate the **visualization of tables** contained in documents. Implement a s**ystem for previewing documents** and **benefits sections**. Enhance **navigation** within iConsulto, making access to information more intuitive.
Topology of solution	1A (Service Delivery – Intelligent Chatbot)
Expected/Achieved benefit to the organization/staff	Improves **efficiency in information retrieval**, reducing the time and effort needed to find relevant documents. Provides **faster access** to answers, thanks to the virtual assistant. The INSS staff will spend less time on these tasks, allowing them to dedicate that extra time to higher value-added activities.
Expected/Achieved benefit to the beneficiaries/target population	Faster answers to the citizens needs.
Key technological tools (technology stack)	**Generative AI models**: Mixtral for summaries, GPT-3.5-Turbo for the virtual assistant. **Python libraries:** weasyprint, scrapy for converting HTML to text; textract and tesseract for optical character recognition (OCR); txtai for calculating word similarity. **Search engines:** OpenSearch for the search engine, Azure AI Search for the assistant. **AWS services:** S3, Kinesis, Lambda, EC2. **Azure services:** Blob Storage, AI Search, Functions, Document Intelligence. **Other tools:** Unstructured for extracting table images; text-generation-inference for deploying models.
Technological objective	Implement a **semantic search** system that understands the meaning of queries and returns the most relevant documents. Develop a **virtual assistant** capable of answering questions about the content of iConsulto using generative AI. Ensure the **scalability and reliability** of the solution by using cloud services. Optimize **document processing** using OCR and AI techniques

Challenges and considerations	The **complexity** of the document corpus, which includes documents with different formats and structures. The **need to process** images and tables to extract relevant text. **Optimizing** the semantic search to guarantee accurate and relevant results. Managing user **feedback** to improve the quality of summaries. The **integration** of the solution into the iConsulto environment. The need to migrate to new generative AI models due to the retirement of old models.
Data considerations	A subset of documents from the retirement area of iConsulto is used as a corpus for the proof of concept. Documents are processed to extract text and relevant metadata. Embeddings are generated for semantic search and document indexing. Data is stored in object repositories (S3 and Blob Storage) and search engines (OpenSearch and Azure AI Search). User searches are tracked through logs.
Complexity	The complexity lies in the integration of various technologies and services to process iConsulto's knowledge. The development of a robust and efficient crawler to extract content from iConsulto. Implementing a semantic search system that requires advanced natural language processing techniques. The generation of quality summaries from documents. The management of events and the orchestration of different services.
Results obtained (estimated) and KPIs	A semantic search engine has been implemented that returns the documents most similar to the user's query, ordered by relevance. A virtual assistant has been developed that answers questions based on iConsulto's knowledge and provides links to sources. Summaries of documents have been generated using generative AI. A feedback system for summaries has been implemented. Functionalities for visualizing tables, highlighting keywords, and previewing documents have been implemented. The results of the semantic search were positive, with MAP10, MAP100, NDCG10, and NDCG100 metrics indicating a good ability to retrieve relevant information, although with room for improvement. The OCR evaluation shows an almost perfect text extraction in tables, with a slightly lower performance in images due to factors such as noise in scanning. The quality of the summaries was measured using the readability metric, with a value of 47.15. In summary, the results are promising, although with specific areas identified for optimization.
Scalability	The solution has been designed to be scalable, using cloud services that allow adapting to demand. Cloud services have been used for ingestion, processing, and deployment of the solution. An event manager has been implemented to automate the processing of new documents. Test environments have been created to ensure the stability of the service.
Key enablers and dependencies	GISS/Tech Innovation department & INSS
Internal capacity used & external partners leveraged	The company's internal AI team is composed of diverse data scientists and developers with expertise in various specializations, supported by strong technical and software development backgrounds. The team's expertise is further augmented by consultants. Additionally, the company independently manages infrastructure services, system administration, and system maintenance.

ISSA General Secretariat

Route des Morillons 4, Case postale 1
CH-1211 Geneva 22, Switzerland

E: **ISSA@ilo.org**
T: **+41 22 799 66 17**

www.issa.int

International Social Security Association

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