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Applying emerging data-driven technologies in social security. Country experiences and ISSA guidelines

The application of ICT (information and communication technologies) is enabling the implementation of increasingly comprehensive social security systems throughout the world as well as the transformation of social security services.

In particular, the so-called data-driven innovation enables social security institutions to improve products, processes and organisational methods. In this line, social security institutions are progressively applying emerging technologies, such as Analytics, Big Data, and Artificial Intelligence. While the pairing of analytics and big data allows for the performing of sophisticated analyses on increasingly large databases, Artificial Intelligence enables for automating processes and assisting staff in tasks requiring human decisions.

However, the application of such emerging data-driven technologies brings with it many challenges, mainly the complexities of combining the adoption of not fully tested technologies with the required stability of critical operational processes and differences in the application of development processes.

This paper addresses these issues and presents an overview of emerging data-driven technologies and their current application in social security institutions. It also presents guidelines supporting the application of data-driven technologies in social security developed by the International Social Security Association (ISSA).

Key words: analytics, artificial intelligence, big data, digital governance, social security

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Introduction

The application of information and communication technologies (ICT) enables the implementation of increasingly comprehensive social security systems throughout the world and the transformation of social security services. At the same time, the so-called data-driven innovation is enabling social security institutions to improve products, processes and organisational methods. It can also meet global social policy challenges in areas including health and the social protection needs of vulnerable populations. In recent years, the accumulation of institutional data in addition to external data obtained through inter-institutional collaboration is enabling the development of Big Data systems.

Social security institutions are progressively applying emerging technologies, such as Analytics, Big Data, and Artificial Intelligence (AI) to put data-driven innovation into practice. Although the potentials of these technologies have not yet been fully tested nor explored, they are already enabling relevant outcomes in key social security areas such as addressing error, evasion and fraud as well as developing proactive approaches and automated solutions to improve social services.

Nevertheless, their adoption conveys many challenges mainly related to the differences in the application development processes – based on data management rather than in software development – and because they require specialised staff and quality data. Furthermore, their application in social security requires putting into practice institutional innovation strategies that combine the adoption of not fully tested technologies with the required stability of critical operational processes. For that, institutions need digital governance frameworks prioritising business requirements and developing an innovation roadmap. To help meet such challenges, the International Social Security Association (ISSA) has developed Guidelines on Information and Communication Technology.[1]

This descriptive paper addresses these issues and presents an overview of emerging data-driven technologies applied in social security. The main goals of the article are to review the current adoption of these technologies by social security institutions, highlight key challenges and present existing guidance material, notably ISSA guidelines supporting institutions in their technology adoption journey.

The remainder of this article is organised as follows. The following section presents emerging data-driven technologies, their application in social security and related ISSA guidelines. This is followed by Governance considerations and an overview of Digital governance frameworks. Finally, conclusions are presented.

1 International Security Systems Association, *ISSA Guidelines on Information and Communication Technologies*, Geneva 2019.

Emerging data-driven technologies

Developing a data-driven administration

The concept of data-driven administration in the public sector has been developed in recent years. The Organisation for Economic Co-operation and Development (OECD) defines it as:

> A data-driven public sector recognises that data are an asset, integral to policymaking, service delivery, organisational management and innovation.[2]

More specifically, a truly data-driven public organisation applies data to transform the design, delivery and monitoring of public policies and services. The OECD also highlights the importance of applying sound Data Governance to capitalise on the value of data to deliver better services and policies.

Data-driven administration approaches can be applied to social security, where data constitutes the basis for operations and decision making. Data play a crucial role, as most current operations and management decisions are based on data about enrolled persons, their working activities, their contributions and the received benefits. Accurate and reliable data are, therefore, the basis for effective social security systems.[3]

Consequently, Data Governance and Management have become key disciplines for social security institutions, involving not only technological aspects but also business-related ones, especially data governance and data quality. Developments in this area consist of implementing master data and decision support systems in social security institutions across the world.[4]

Implementing data-driven administration requires technologies for managing and analysing data as well as for implementing solutions through data rather than traditional software development processes. Some of these data-driven technologies, such as Analytics, Big Data and Artificial Intelligence, are new or emerging. Such emerging technologies are enabling institutions to implement value-added functionalities and social security services, taking advantage of the growing social security data.

Analytics and Big Data

The pairing of analytics and big data allows social security institutions to take advantage of their increasingly large databases to perform sophisticated analyses ranging from detecting unusual phenomena to developing predictive models.

Data analytics can support social security institutions to improve their administrative effectiveness and efficiency by enabling them to understand the past, trace the cause

2 Organisation for Economic Co-operation and Development, *The Path to Becoming a Data-Driven Public Sector*, OECD Digital Government Studies, Paris 2019, https://doi.org/10.1787/059814a7-en.

3 International Security Systems Association, *Managing social security data*, Geneva 2016.

4 *Ibid.* and *idem*, *ISSA Guidelines on Information…*, *op. cit.*

of events, predict what are likely to happen, and suggest actions that could be taken. Institutions could apply data analytics in a wide diversity of areas, including healthcare, detecting and preventing error, evasion and fraud, proactive social policy and programme design, actuarial projections, improving service delivery, among others.

Data analytics is mainly based on an institution's data and could potentially include external ones which, after ensuring quality, are analysed in order to gain insights using various analytic approaches, in particular:

- Descriptive analytics, which tries to answer "What happened?". It provides an understanding of the past transactions that occurred in the organisation.
- Diagnostic analytics, which tries to answer the question "Why or how did it happen?". It involves an understanding of the relationship between relatable data sets and the identification of specific transactions along with their behaviour and underlying reasons.
- Predictive analytics, which tries to predict "What, when, where can it happen?" based on past data. Forecasting techniques can be used to predict, to a certain extent, the future outcome of an activity. These predictions can be applied to inform and influence proactive measures.
- Prescriptive analytics, which recommends a range of possible actions as inputs such that outputs in future can be altered to the desired solution. In prescriptive analytics, multiple future scenarios can be identified based on different input interventions.

This way, Descriptive, Diagnostic, Predictive and Prescriptive analytics provide different types of support for complex decision making.[5] Furthermore, the application of Prescriptive analytics should be aligned with the organisational management strategy to effectively create value by transforming data-driven analytical models into decisions.[6]

In turn, Big Data analytics leverages very large volumes of data usually going beyond individual institutional transactions.[7] Big Data is characterised by the 4 V's: Volume, Variety, Velocity and Veracity.

For instance, a potential source of Big Data would be medical home devices monitoring patients' vital signs. Big Data analytics requires a revisit of data analysis techniques in fundamental ways and at all stages, from data acquisition and storage to data transformation and interpretation. In particular, the task of collecting and analysing data is at the heart of the Big Data analytics pipeline.

In spite of the potential of Big Data, there are also a number of challenges and drawbacks, notably: data source fragmentation in siloed government systems, poor data quality and inconsistencies across silos, the impact of analytical processing on the performance

5 D. Frazzetto, T.D. Nielsen *et al.*, *Prescriptive analytics: a survey of emerging trends and technologies*, "The VLDB Journal" 2019, Vol. 28(4), pp. 575–595.

6 T. Brandt, S. Wagner, D. Neumann, *Prescriptive analytics in public-sector decision-making: A framework and insights from charging infrastructure planning*, "European Journal of Operational Research" 2021, Vol. 291(1), pp. 379–393.

7 K. Vassakis, E. Petrakis, I. Kopanakis, *Big data analytics: applications, prospects and challenges* [in:] *Mobile big data*, 2018, pp. 3–20.

of operational systems, and trade-offs between providing up-to-date information and not interfering with operational systems. This last issue can be addressed by real-time computing techniques, which enable analytical processes to be applied to transactional databases and systems, without impacting the performance of operational systems.[8]

The ISSA Guidelines on ICT[9] provide orientations for applying analytics in social security through a specific chapter that includes the following guidelines:

- Guideline 53. *Institutional framework for applying data analytics*. The institution establishes a framework for the application of data analytics, which defines the main procedures, duties and responsibilities, as well as technical standards.
  The framework should comprise the following activities: (i) Data lifecycle management, which comprises: data identification, data acquisition and filtering, data extraction, data validation and cleansing; (ii) Developing metadata mapping databases to business concepts; Data modelling aligned with business objectives; (iii) Managing the data repository and data warehouses accessible to business users; (iv) Data analysis and model development responding to business needs; (v) Performance measurement evaluating business-oriented outcomes of data analytics; (vi) Interoperability with institutional Master Data and business information systems.
- Guideline 54. *Descriptive analytics – Understanding the past*. The institution applies descriptive analytics to look at data and to analyse past events for insight on how to approach future decisions.
  Descriptive analytics examines the institution's data and past performance. The most robust use of descriptive analytics is using data exploration tools and developing alerts when certain criteria or trends emerge.
- Guideline 55. *Diagnostic analytics – Explain the cause of it all*. The institution applies diagnostic analytics to look towards the processes and causes of an event instead of the result.
  Diagnostic analytics can provide an answer to questions such as "How can we avoid this problem?" and "How can we replicate this solution?".
- Guideline 56. *Predictive analytics – What is likely to happen*. The institution applies predictive analytics to develop preventive approaches and related measures based on predictive models at strategic, operational and tactical levels.
  The term "predictive analytics" describes the application of statistical or machine learning techniques to create a quantitative prediction about the future through a predictive model. Predictive models alone do not create business value, but rather need to be effectively deployed into business decision-making processes.
  Potential areas of application are: preventing error and fraud, the proactive launch of social programmes and services based on preventive approaches targeting vulnerable population groups, and predicting service demands including budgeting, *etc*.

8 R. Van Leent, *Emerging technologies enabling data-driven policy and practice*, SAP Institute for Digital Government, 2018.

9 International Security Systems Association, *ISSA Guidelines on Information…, op. cit.*

- Guideline 57. *Prescriptive analytics – What action to take*. The institution applies prescriptive analytics to obtain decision options on how to take advantage of a future opportunity or to mitigate future risks.
  Prescriptive analytics differs from predictive analytics in that it does not stop at showing a likely outcome, but continues to present suggested actions. Prescriptive analytics incorporates a feedback loop in which descriptive and predictive models are combined to influence one another and direct the trends instead of simply detecting them.
- Guideline 58. *Analytics of big data*. The institution assesses the adoption of big data analytics, which consists of applying analytics techniques on such very large data sets. The most common big data analytics techniques are association rule learning, classification tree analysis, genetic algorithms, machine learning, incremental learning algorithms, granular computing, feature selection, regression analysis, sentiment analysis, and social network analysis.
- Guideline 59. *Machine learning on big data – Supporting decision making*. The institution assesses the application of machine learning techniques on big data to support decision making. The main goals are reducing the time between data collection, analysing it for relevant information, and using the outcome to make well-informed decisions.
  Machine learning algorithms are quite adaptive in nature. The more data you feed, the more they learn and their predictive modules become more precise and the results become more accurate than applying other techniques. Therefore, big data and machine learning may support social security managers planning new social programmes.
  The main types of machine learning techniques for decision making support are: Inductive learning in which models are built from the generalisation of examples; Deductive learning in which deduction is applied to obtain generalisations from a solved example and its explanation; Genetic learning in which algorithms are inspired in the theory of evolution are applied to find general description to groups of examples; Connexionist learning in which generalisation is performed by the adaptation mechanisms of artificial neural networks.

A growing number of social security institutions have been applying analytics and big data to address relevant social security functions.

Addressing evasion and fraud are some of the main applications of analytics. Social security institutions are applying discovery and profiling techniques for detecting evasion and fraud in contribution collection as well as in the delivery of benefits, particularly in detecting complex fraud operations. In addition, institutions are developing their capacity on Business Intelligence and Analytics as reported by the National Social Security Administration of Argentina (Administración Nacional de la Seguridad Social), the Public Authority for Social Insurance of Oman, the Social Security Administration of USA, Social Security Technology and Information Company (Empresa de Tecnologia e Informações da Previdência Social) of Brazil. Furthermore, Big Data and analytics is utilised for developing preventive approaches as well as for improving programmes and services.[10]

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10 *Idem*, *Applying emerging technologies in social security*, Geneva 2019.

In the context of the COVID-19 crisis, the application of analytics has enabled institutions better to evaluate the health and social impact of the pandemic and improve decision-making processes.[11]

Table 1 summarises application experiences. Other ISSA reports provide further detailed descriptions.[12]

Table 1. Application experiences of analytics and Big Data

Approach	Projects	Institutions
Discovery	Detection of complex fraud manoeuvres and no-take-up Analysing beneficiaries' "itineraries" for service improvement	National Family Allowances Fund, France
	Detecting evasion and fraud in contribution collection	Federal Administration of Public Resources, Argentina Social Insurance Bank, Uruguay General Treasury of Social Security, Spain Central Agency of Social Security Bodies, France
	Detecting complex fraud operations involving registration, contributions, and benefits delivery	National Social Security Institute and General Treasury of Social Security, Spain
	Detecting fraud in unemployment benefits	National Employment Office, Belgium
	Detecting fraud in temporal disability benefits	National Social Security Institute, Spain
	Detecting fraud in work injury and accidents claims	National Employment Accident Insurance Institute, Italy
	Detecting fraud in family benefits	Department of Human Services, Australia
	Detecting fraud in registration, contribution collection, occupational diseases and unemployment	General Organization for Social Insurance, Saudi Arabia
Prevention	Institutional Big Data system covering insured persons and beneficiaries developed in the context of a Digital Transformation programme. System's capabilities range from fraud detection to supporting the prevention of chronic diseases especially diabetes mellitus and hypertension	Mexican Social Security Institute, Mexico
	National Big Data system covering Health and Social Security data, supporting health preventive measures	National Health Insurance Service, Korea

Source: innovative practices carried out by ISSA members

11 *Idem*, *The use of analytical technology in social security systems during the pandemic – Experiences from Latin America*, Geneva 2021.

12 *Idem*, *Ten Global Challenges for Social Security – Africa*, Geneva 2017; *idem*, *Ten Global Challenges for Social Security – Americas*, Geneva 2017; *idem*, *Ten Global Challenges for Social Security – Asia and Pacific*, Geneva 2018; *idem*, *Ten Global Challenges for Social Security – Europe*, Geneva 2019; *idem*, *Ten Global Challenges for Social Security*, Geneva 2019; *idem*, *Compendium of Innovative approaches*, Geneva 2019.

Artificial Intelligence

Artificial Intelligence aims to interpret events and to support decisions as well as to automate actions. AI systems make decisions when predictions are sufficiently accurate and the risk of error is sufficiently mitigated.

While AI initially used logic-based techniques, it evolved to using techniques that leverage Big Data, such as Machine Learning. In fact, in terms of the underlying technical disciplines, AI is an "umbrella" area that continues to evolve such that the boundaries of AI are not quite clearly defined. In fact, there is a continuum of data-driven innovation techniques ranging from Business Intelligence, Analytics and some approaches of Artificial Intelligence. In particular, Machine Learning is a type of Artificial Intelligence extending predictive analytics which can be used to refine predictive models over time.[13]

Advanced Machine Learning algorithms are composed of many technologies used in unsupervised and supervised learning (such as deep learning, neural networks and natural-language processing) and guided by lessons from existing information. Thus, Machine Learning allows AI applications to become progressively more accurate in predicting outcomes, without being explicitly programmed by learning autonomously from previous applications and outcomes. This enables recommending interventions that have proved to be successful under similar circumstances in the past.[14]

The selection of AI techniques should be based on the adequacy to the actual case scenario. For instance, while Deep Neural Networks (aka Deep Learning*)* are appropriate for text and image analyses and processing Internet of Things (IoT) data, other techniques such as Rule-based systems or traditional machine learning enable the solving of many other problems.

The large spectrum of AI applications ranges from low-intelligence scenarios like rule-based automation to higher-end intelligence capable of non-deterministic and evolving decision making. More concretely, AI can be broken down into five levels of sophistication[15]:

- Reactors, which are based on simple rules but can respond to some limited changing contexts (*e.g.* basic drones);
- Categorizers, which can recognise types of objects and can deal with them through simple actions within a controlled environment (*e.g.* warehouse robots);
- Responders, which enable support for others' needs by figuring out questions and situations (*e.g.* driverless cars, personal assistants);
- Learners, which are capable of solving complex problems by gathering information from multiple sources (*e.g.* IBM Watson applications);

13 R. Van Leent, *Rise of the Machines*, SAP Institute for Digital Government, 2019.

14 *Ibid.*

15 Gartner, *Build the AI Business Case. A CIO's Guide to Building the Strategy and Business Case to Implement AI in the Enterprise*, 2018.

- Creators, which may be initiating a paradigm shift. As the application of creators may have an important impact on humans' relationship to technology, they require profound thought before development.

AI application could not only automate processes but also augment human capabilities for decision making by providing high-performance information classification and prediction functionalities. In this vein,[16] points out that AI currently stands for "Augmented Intelligence" for social security agencies.

Some expected trends on AI are:

- Improve communication among persons by improving natural-language processing through contextual interpretation.
- Deepen and broaden integration with IoT applications, such as home movement detection sensors for long-term care.
- Further improvements on autonomous agents and intelligent devices.

Key success factors for AI application are data availability and quality, understanding the nature of developing AI solutions as well as skilled staff. While AI outperforms humans in certain complex cognitive functions such as image recognition in radiology, it requires huge datasets for training the systems.[17] In addition, AI's "business logic" is based on the representation of a decision model rather than on a procedural algorithm. In this line, model testing – which requires large datasets – also constitutes a key factor and challenge for AI application.

The application of AI in social security is promising but also challenging. From a business application perspective, the greatest challenge to AI success is the operationalisation of AI as part of an automated business decision-making system.

In addition, the transparency and "explainability" of the AI application constitutes an important issue, especially regarding decisions that impact people and/or involve relevant risks (*e.g.* economic, environmental, *etc.*).[18] However, there is a trade-off between explainability and accuracy/performance in AI techniques because black-box models are more accurate than Interpretable Models. Briefly, the former provides a lower number of false positives and negatives than the latter. This trade-off could be tackled by assessing the need for explainability when selecting techniques and by enabling business stakeholders to choose (explainable *versus* accurate). In any case, stakeholders should always have access to training data.

Finally, there are other security and data protection issues that also constitute relevant challenges for AI applications. While security threads may involve poisoning/contaminating training datasets, complying with data protection regulations may be compromised if data is used for purposes other than those for which it was collected.

The formidable power unleashed by AI has limitations in the scenarios to which they could be successfully applied and the types of problems which could be tackled. Firstly,

16 R. Van Leent, *Rise of…, op. cit.*

17 B. Lake, T. Ullman *et al.*, *Building machines that learn and think like people*, "Behavioral and Brain Sciences" 2017, Vol. 40, E253.

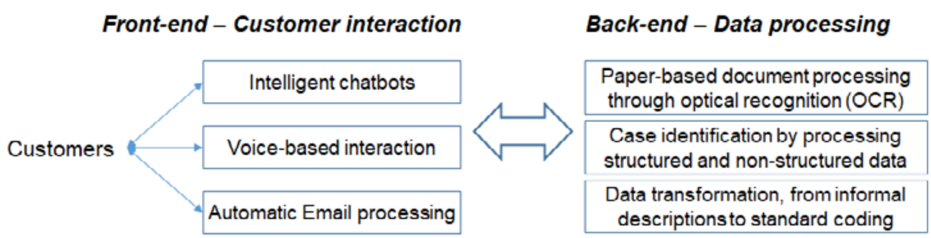
18 F. Xu, H. Uszkoreit *et al.*, *Explainable AI: A brief survey on history, research areas, approaches and challenges*, CCF international conference on natural language processing and Chinese computing, 2019, pp. 563–574.

the critical requirements for quality data may constitute a barrier for applying AI in scenarios without enough quality data (*e.g.* new types of images or IoT information). Similarly, weaknesses in HR capacity for preparing and training the AI systems may also constitute a barrier for such application. As regards the nature of the problems that could be tackled, AI may be able to tackle narrow types of problems. However, when the application areas are broader, the use of AI may not be feasible, especially when this requires interpreting a totally unknown environment. Furthermore, AI may not be capable of considering contextual elements that were not included in the training.

Finally, when compared with humans, AI lacks "judgement criteria" and intuition capabilities, which are usually based on long time experience, broad contextual information and on non-linear reasoning. In addition, it is not capable of exercising critical or ethical judgment or exercise empathy.

Beyond analytics, the emerging use of Artificial Intelligence in social security institutions is enabling the automation of more proactive and automated social security services.[19] This application is enabling one to improve customer services through automated 24/7 front-end support and also, more incipiently, automating back-end processes (Figure 1).

Figure 1. Types of AI applications in social security institutions



A growing practical application of AI consists of developing "chatbots", which are intelligent assistants to support self-e-services. The so-called chatbots are robot software capable of dialogue with customers in order. Chatbots enable one to respond to users' autonomously inquires on specific topics simulating human behaviour. They analyse and understand a user's questions in free natural language as well as managing the conversation flow. The implementation involves training an AI system using knowledge based on the responses and a very large dataset of potential questions and responses.

There is a significant interest in chatbots and they are increasingly being used by social security institutions. This trend is apparent in the good practices and experiences reported by ISSA members from Latin America[20] as well as from other regions.

Practical experiences include a chatbot called Julieta implemented by the Superintendency of Occupational Risks of Argentina to respond to questions about work

19 International Security Systems Association, *Artificial Intelligence in Social Security: Background and Experiences*, Geneva 2020.

20 *Idem*, *The application of chatbots in social security: Experiences from Latin America*, Geneva 2021.

injury benefits while the Social Security Bank of Uruguay (Banco de Previsión Social) implemented one to respond to the domestic workers scheme.[21]

In turn, the intelligent chatbot implemented by the Norwegian Labour and Welfare Administration (Nye arbeids- og velferdsetaten) has enabled the response to an increased demand for information in the context of the COVID-19 crisis. Concretely, during the period March to May 2020, the chatbot responded to more than 8,000 daily inquiries, which compares to a pre-COVID number of 2,000. The key success factors were the chatbot training based on a daily updated knowledge-base, the focus on a specific type of information, and a seamless connection from the chatbot to a human expert. The chatbot is being extended to new topics, and notably to support employers and the self-employed.[22]

The General Organization for Social Insurance (GOSI) of Saudi Arabia launched an experimental use of intelligent chatbots for service delivery. The objective was to develop an intelligent agent to respond to customers' inquiries and to simplify certain services and transactions. The agent communicates with customers through different chat and social networking applications.[23]

Some institutions are also using AI to improve back-end processes, notably to process large volumes of data comprising traditional databases as well as unstructured text and images of digitalised paper-based documents.

Employment and Social Development Canada (ESDC) applied AI to identify beneficiaries of the Guaranteed Income Supplement (GIS). Box 1 synthesises such experience.

Box 1. Employment and Social Development Canada experience applying AI

Employment and Social Development Canada applied AI to identify beneficiaries of the Guaranteed Income Supplement, which is a cash benefit targeting low-income old-age persons. In two months, Machine Learning models identified over 2000 vulnerable Canadians to be entitled to the GIS by processing more than 10 million records of unstructured text data.

In order to maximise the coverage of vulnerable beneficiaries, the business experts of the GIS programme decided that the model should have a high degree of inclusion and intentionally accepted false positives that would have to be reviewed manually.

The experience showed the importance of using representative data and capturing nuances as well as determining the adequate metrics and thresholds for the business needs by building the training dataset together with business experts.

As lessons learned, the ESDC highlighted that the quality of the underlying data is crucial and that AI projects require multidisciplinary teams with data scientists and business experts. The main identified risks comprised the selection of proper tools and the data literacy gaps among the staff in the organisation.

Source: International Security Systems Association, *Artificial Intelligence in Social Security: Background and Experiences*, Geneva 2020; *idem*, *Using artificial intelligence (AI) to identify vulnerable Canadians. Good practice of Employment and Social Development Canada*, ISSA Good practices database, https://ww1.issa.int/gp/198044 (online access: 22.9.2021)

21 *Ibid.* and *idem*, *The use of analytical…*, *op. cit.*

22 *Idem*, *Artificial Intelligence…*, *op. cit.*

23 *Ibid.*

Finland's Social Insurance Institution (Kela) is starting to apply AI in two ways: (i) improving customer services by combining e-services with intelligent chatbots, and (ii) using AI-based image recognition to automate administrative processes by recognising documents.

Similarly, the National Social Security Institute of Brazil (Instituto Nacional do Seguro Social, INSS) implemented an intelligent chatbot – called Helô – for providing automated responses 24/7 to customers' inquiries in the context of the myINSS personalised e-services. The first version deployed in May 2020 has already processed about a million inquiries. The INSS also uses AI to speed up beneficiary death detection to prevent undue payments.[24]

In turn, the Austrian Social Insurance (Dachverband der österreichischen Sozialversicherungsträger, SV) is applying AI for multiple purposes. Box 2 synthetises the Austrian experience applying AI.

Box 2. Austrian Social Insurance experience applying AI

The Austrian Social Insurance is applying AI for multiple purposes.

- Firstly, to deploy an intelligent chatbot – OSC Caro – which provides digital assistance to customers in various areas such as childcare allowances, sick pay and reimbursements.
- In addition, a voice recognition system supports call centre services by automatically forwarding customer inquiries to the corresponding offices.
- The system's language model, which is based on AI, was trained to recognise specific terms.
- Furthermore, AI is also used to implement the automatic dispatching of emails to the corresponding departments with up to 93 percent of accuracy.
- Finally, an ongoing project is implementing an AI-based semi-automatic reimbursement process of medical services fees. In this case, AI is applied to automate several tasks such as the recognition of the submitted documents, encoding diagnosis using the standard ICD-10, and extracting required data for the reimbursement (*e.g.* invoice amount, IBAN). This semi-automatic treatment enables one to speed-up the reimbursement process as well as support the involved staff.

Source: International Security Systems Association, *Webinar on AI*, Geneva 2020

Applications of Machine Learning in social security administration are reported in.[25] They include predicting customers' debt risks by an Australian government agency and proactive eligibility assessment by a UK government for additional social security benefits among vulnerable population groups receiving households benefits.

At the governmental level, several countries are defining national strategies on Artificial Intelligence. In particular, the Estonian strategy aims at enabling a proactive government based on a life-event service design and delivering personalised services

24 *Idem, The application of…, op. cit.; idem, The use of analytical…, op. cit.*

25 R. Van Leent, *Rise of…, op. cit.*

with zero bureaucracy through an intensive application of AI. The Estonian vision of AI-based digital public services is being put into practice through #KrattAI, which is an interoperable network of AI applications enabling citizens to use public services through voice-based interaction with virtual assistants. The more than 70 ongoing projects under this strategy, with 38 already operational, cover a wide range of areas including environmental applications, emergency support, cybersecurity and social services. In particular, an intelligent chatbot for customer services and processing long-term unemployment risk cases is applied in the context of unemployment insurance.[26]

The lessons learnt concerning AI application comprise ensuring the quality and privacy of the involved data, provide metadata, and manage the scalability of AI-based applications by using cloud infrastructure and developing adequate procurement models. Furthermore, the limits of automation for public services have to be correctly assessed.

Among the critical factors, data availability and quality are highlighted as a must in order to train the AI systems appropriately. Such "data needs" require establishing an organisational strategy to use internal data as well as potentially data from other organisations, and also involves assessing the compliance with data protection regulations. AI adoption requires specific institutional capacities. Institutions need to have a detailed understanding of the goal of the project, select data that is representative of the real world, choose simple solutions, pay special attention to the explainability of the algorithms used,[27] choose models that not only have the best results but also pass fairness standards that need to be carefully designed, and finally ensure transparency to ensure accountability.

In addition, institutions applying AI emphasised the importance of having projects developed by multidisciplinary teams involving business staff and data scientists. In this line, staff literacy on AI and data management also becomes a key factor. Business owners and project managers have to understand the implications of AI application in order to define what processes could be automated and which decisions must be in human hands.

Governance considerations

Although there are a growing number of success stories, the adoption of technologies in social security institutions is always complex and challenging. In particular, it requires strategic visions on developing a digital journey in the medium and long-term aligned with the institutional goals. This approach, called Digital Governance, involves the institution's decision-makers, in particular the CEOs, as they are increasingly leveraging ICT to carry out strategic institutional transformations and develop innovation capabilities.

26 International Security Systems Association, *Artificial Intelligence…*, *op. cit.*

27 F. Xu, H. Uszkoreit *et al.*, *op. cit.*

The ISSA Guidelines address these issues and provide orientations to carry out a sound Digital Governance in social security organisations.

At the institutional level, the ISSA Guidelines on Good Governance[28] calls for the board and the management to develop a shared vision of the institution's digital future and define broad, universal digital standards for service. It suggests the establishment of a Digital Governance framework that ensures that even as digital solutions are offered and prioritised, due care should be taken that a digital divide is not created. It also calls for established policies on the protection of personal data and the ethical use of Big Data and Artificial Intelligence, in particular, the prevention of such risks as misuse and the unintended consequences of data mining and algorithmic biases.

Concretely, Guideline 10, *Digital Governance,* recommends that

> The board and the management develop a shared vision of the institution's digital future and defines broad, universal digital standards for service. This includes a digital governance framework which prioritises user needs while balancing the business requirements of the institution, the sharing of information and the protection of personal data. The framework prioritises digital solutions and ensures that a digital divide is not created.

Furthermore, the ISSA guidelines state that ICT Governance constitutes a central responsibility for the board and management to apply technologies successfully. ICT governance can be defined as a

> framework for the leadership, organisational structures and business processes, standards and compliance to these standards, which ensure that the organisation's IT supports and enables the achievement of its strategies and objectives.

Chapter B.9 of the ISSA Guidelines on Good Governance[29] guides the board on developing an ICT Governance:

- Guideline 63. *ICT governance framework*. There is a single, integrated framework for ICT governance that establishes ownership, duties and responsibilities at the highest levels of the board and management.
- Guideline 64. *Strategic goals of ICT application*. The strategic goals of ICT application are aligned with and enable the institution's overall strategic plan. The goals reflect the strategic direction to be taken in the use of ICT, the Internet and the World Wide Web, as determined by the board and management.
- Guideline 65. *Innovations based on ICT and emerging technologies*. The ICT governance framework enables the institution to innovate the use of ICT, the Internet and the World Wide Web. There are established management processes to monitor emerging technologies and assess their potentials to improve the institution's business processes and services.

28 International Security Systems Association, *ISSA Guidelines on Good…, op. cit.*

29 *Ibid.*

As mentioned before, a sound Data Governance is crucial to implementing a data-driven administration, mainly to ensure data quality. The ISSA Guidelines on ICT include a section on Data and Information Management, which addresses data governance and data quality, mechanisms to enable information retrieval and analysis, and the implementation of master data systems in social security.[30]

At the government level, political leadership and support is essential at the national, federal and local levels. Creating connectedness across the different levels of government is fundamental to jointly developing digitisation strategies and creating that common ownership and shared commitment in order to achieve sustainable results. Socio-cultural and political factors will influence the structure of these governance frameworks. There are relevant examples in Australia, Canada and Estonia.

Box 3. Government of Canada Digital Standards – Improving government services in the digital age

The goal of these standards is to provide public services to Canadians that are simple to use and trustworthy. The Government of Canada's Digital Standards constitute the foundation of the government's shift to becoming more agile, open, and user-focused. They will guide teams in designing digital services in a way that best serves Canadians.

These digital standards were co-created with the public and key stakeholder groups. They are living standards and they will continue to evolve over time as we better understand the complexities involved in putting them into practice.

1. Design with users. Research with users to understand their needs and the problems we want to solve. Conduct ongoing testing with users to guide design and development.
2. Iterate and improve frequently. Develop services using agile, iterative and user-centred methods. Continuously improve in response to user needs. Try new things, start small and scale up.
3. Work in the open by default. Share evidence, research and decision making openly. Make all non-sensitive data, information, and new code developed in delivery of services open to the outside world for sharing and reuse under an open license.
4. Use open standards and solutions. Leverage open standards and embrace leading practices, including the use of open source software where appropriate. Design for services and platforms that are seamless for Canadians to use no matter what device or channel they are using.
5. Address security and privacy risks. Take a balanced approach to managing risk by implementing appropriate policy and security measures. Make security measures frictionless so that they do not place a burden on users.
6. Build in accessibility from the start. Services should meet or exceed accessibility standards. Users with distinct needs should be engaged from the outset to ensure what is delivered will work for everyone.

30 *Idem*, *ISSA Guidelines on Information…*, *op. cit.*

7. Empower staff to deliver better services. Make sure that staff have access to the tools, training and technologies they need. Empower the team to make decisions throughout the design, build and operation of the service.
8. Be good data stewards. Collect data from users only once and reuse wherever possible. Ensure that data is collected and held in a secure way so that it can easily be reused by others to provide services.
9. Design ethical services. Make sure that everyone receives fair treatment. Comply with ethical guidelines in the design and use of systems which automate decision making (such as the use of artificial intelligence).
10. Collaborate widely. Create multidisciplinary teams with the range of skills needed to deliver a common goal. Share and collaborate in the open. Identify and create partnerships which help deliver value to users.

Source: https://www.canada.ca/en/government/system/digital-government/government-canada-digital-standards.html (online access: 22.9.2021)

Conclusions and perspectives

There is a growing application of emerging data-driven technologies in social security organisations. Despite the involved complexities, such as emerging data-driven technologies, they are enabling institutions to implement value-added functionalities and social security services, taking advantage of the growing social security data.

The ISSA has developed guidance material to support institutions in applying such emerging technologies, notably guidelines on Analytics and Digital Governance complemented by several technical reports.

While many institutions worldwide are already applying analytics, Artificial Intelligence is gradually becoming a key technology for social security organisations. It enables them to increase administrative efficiency by automating processes and assisting staff in tasks requiring human decisions. However, although positive developments can be observed, several challenges also arise. These relate especially to the limitations and risks of AI, and the trade-off between process automation *versus* human control. Furthermore, the methodological differences between AI and traditional software development pose challenges to institutions carrying out the projects.

These outputs all serve to underline the key role of emerging technologies in social security and the importance of developing the institutional capacity to adopt them. While the intensive application of cutting-edge and emerging ICT may constitute a success factor, these also involve risks and challenges.

Therefore, institutions should have well-defined strategies and structured plans aligned with institutional objectives to adopt emerging data-driven technologies and implement a sound Digital Governance. Guided by a deep-seated culture of innovation, the progressive adoption and innovative use of new technologies and the continuous value-added role of well-trained staff to enhance service delivery offer a smart approach to address emerging challenges.

Future research directions comprise defining practical approaches to automate social security processes by applying data-driven technologies. Notably, AI explainability and Big Data quality issues should be further analysed to enable a reliable application of emerging technologies matching good governance principles.

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Zastosowanie w zabezpieczeniu społecznym nowych technologii opartych na wykorzystaniu danych. Doświadczenia poszczególnych krajów oraz wytyczne Międzynarodowego Stowarzyszenia Zabezpieczenia Społecznego (ISSA)

Zastosowanie technologii informacyjno-komunikacyjnych (*information and communication technologies*, ICT) umożliwia wprowadzanie coraz bardziej wszechstronnych systemów zabezpieczenia społecznego na całym świecie, jak również transformację usług z tego obszaru.

W szczególności tzw. innowacje oparte na wykorzystaniu danych umożliwiają instytucjom zabezpieczenia społecznego ulepszanie swoich produktów, procesów oraz metod organizacji. Podążając tą drogą, instytucje te stopniowo wprowadzają nowoczesne technologie, takie jak analityka, *big data* oraz sztuczna inteligencja. Podczas gdy połączenie analityki oraz *big data* pozwala na przeprowadzanie skomplikowanych analiz coraz obszerniejszych zbiorów danych, wykorzystanie sztucznej inteligencji umożliwia automatyzację procesów oraz wspomaga pracowników podczas zadań wymagających podjęcia decyzji przez człowieka.

Stosowaniu takich nowych, opartych na wykorzystywaniu danych technologii towarzyszą jednakże liczne wyzwania, głównie w postaci trudności wynikających z połączenia takich nie w pełni przetestowanych technologii z wymaganym poziomem stabilności procesów operacyjnych oraz różnic w zastosowaniu procesów rozwojowych.

Tekst ten omawia wyżej wymienione zagadnienia oraz przedstawia przegląd nowych technologii opartych na danych, a także ich obecne zastosowanie w instytucjach zabezpieczenia społecznego. Przedstawia on także opracowane przez Międzynarodowe Stowarzyszenie Zabezpieczenia Społecznego (International Security Systems Association, ISSA) wytyczne wspierające wykorzystywanie takich technologii w zabezpieczeniu społecznym.

Słowa kluczowe: analityka, sztuczna inteligencja, *big data*, zarządzanie cyfrowe, zabezpieczenie społeczne