PARIS21 Discussion paper 17

AI through the lens of official statistics and the Sustainable Development Goals: The benefits and risks

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About PARIS21

The Partnership in Statistics for Development in the 21st Century (PARIS21) aims to improve the production, quality, availability, and use of statistics for informed decision making for sustainable development. It was established in 1999 by the United Nations, the European Commission, the Organisation for Economic Co-operation and Development (OECD), the International Monetary Fund, and the World Bank as a response to the need for accurate and reliable data to achieve and track progress toward development goals.

PARIS21 works with governments, international organisations, civil society, and other stakeholders to strengthen national statistical systems, promote the use of data for policy making, and foster partnerships and networks in low and middle-income countries.

PARIS21 recognises the critical role that accurate and timely data play in addressing global challenges, making informed policy decisions, and monitoring progress toward sustainable development. By working to improve statistical capacities and systems, PARIS21 contributes to more effective and targeted development efforts worldwide.

About this paper

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Foreword

Launched in 2015, the United Nations Sustainable Development Goals (SDGs) represent an ambitious framework for guiding global efforts in achieving sustainable development by 2030. As this deadline draws near, many countries still grapple with producing the data needed to track progress toward the SDGs. For example, for SDG 13 Climate Action; SDG 5 Gender Equality; and SDG 16 Peace, Justice, and Strong Institutions, less than half of the 193 countries or areas have internationally comparable data since 2015, and less than 30% of the latest available data on the SDGs are from 2022 and 2023 (United Nations, 2023[1]). Even when data are available, they tend to not be adequately disaggregated, which makes it difficult for policy makers to monitor and compare the circumstances of different demographic groups and communities. For instance, only 42% of countries with recent official statistics on monetary poverty have gender-disaggregated poverty data (UN Women and United Nations Department of Economic and Social Affairs, Statistics Division, 2023[2]). This leaves a fundamental question unanswered: How can we know if we are making progress toward achieving the SDGs and which areas require urgent policy action and additional resources?

The OECD defines artificial intelligence (AI) as “a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments” (OECD, 2024[3]). AI has the potential to address the data gaps and needs related to the SDGs while at the same time contributing to their achievement. More specifically, AI can help improve people’s well-being; contribute to economic productivity; increase innovation; and help respond to key global challenges, including those from health and education to climate change and hunger (OECD, 2019[4]). This paper discusses the potential of AI through three case studies, focusing on national statistical office (NSO) practices related to sustainable development. Its intention is to spark a debate around the following questions and prompt concrete actions toward realising the full potential of AI for sustainability: “What are the potential benefits and risks of AI for sustainable development?” and “How can we leverage these potential benefits while at the same time minimise its risks?”.

The first section provides a brief description of AI and the SDGs. The paper then presents the case studies in which AI is being used by NSOs before discussing the benefits and risks of the use of AI in this area. It concludes with actionable recommendations targeting NSOs on how to leverage AI for sustainable development.

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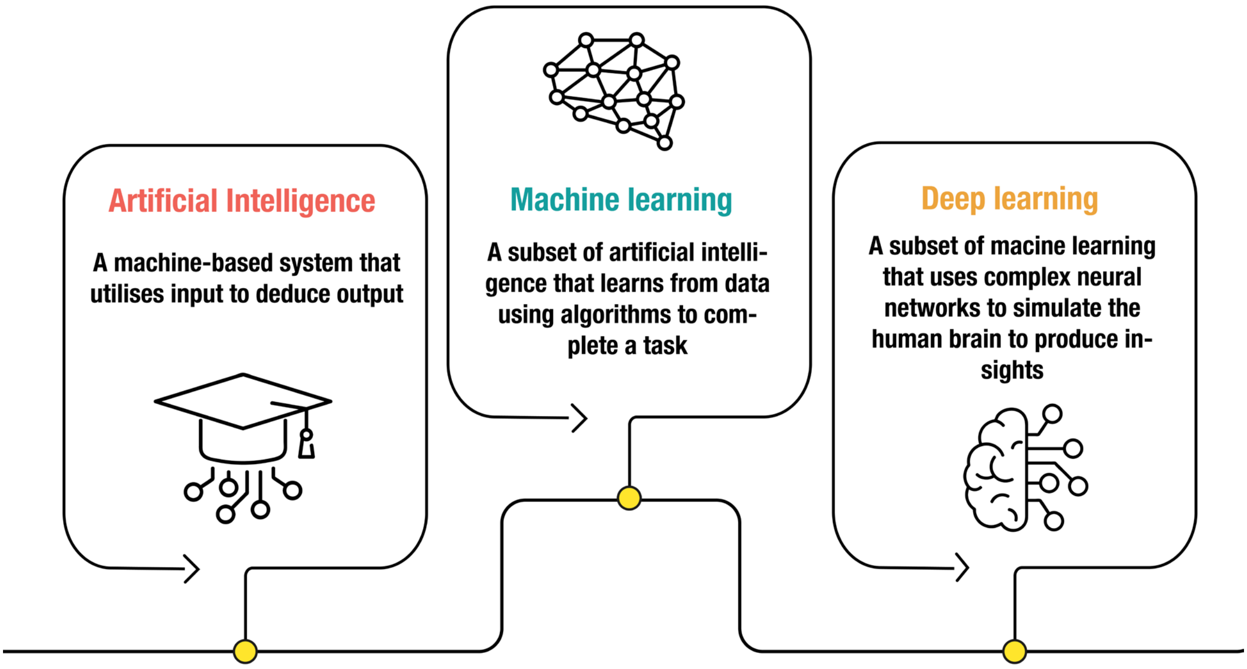
The Sustainable Development Goals and artificial intelligence

The SDGs address global challenges across 17 key focus areas including climate change, environmental degradation, food security, health, inequality and poverty alleviation (United Nations, 2015[5]). Progress toward achieving them is evaluated through 169 targets, which are underpinned by 231 indicators (United Nations, 2024[6]). With only six years left to achieve the SDGs, data still lack for many countries, there are issues with data quality, or the data sources used to monitor and report on the SDG indicators are not frequently updated (Nilashi et al., 2023[7]). This is because many countries rely on traditional data sources such as censuses and surveys, since they have either comprehensive coverage or are representative of the population. They also follow rigorous data collection protocols and confidentiality rules required of official statistics (Proden, Fraisl and See, 2023[8]), which are statistics generated or compiled by governments and public agencies, more specifically NSOs, and are used as the foundation for policy decisions (Eurostat, 2017[9]).

To address this challenge, new sources of data, such as Earth observation and citizen science and novel technologies including AI can be utilised (Fritz et al., 2019[10]; Fraisl et al., 2020[11]; Fraisl et al., 2023[12]). AI techniques are comprised of a series of methods, tools and algorithms that have been developed to loosely emulate some aspect of human intelligence (e.g. neural networks as emulators of the human brain) or that perform tasks that require human-like intelligence (e.g. playing chess, identifying and sorting objects, or having conversations) (Xu et al., 2021[13]; Sarker, 2022[14]).

Figure 1 provides a basic overview of AI. Machine learning is a specific branch of AI that focuses on methods that learn from data or past experiences to, for example, gain knowledge from the data or make predictions (Alpaydin, 2020[15]). This includes pattern recognition methods such as classification and clustering, which can be undertaken using different approaches such as neural networks, decision trees, support vector machines and statistical models such as regression. These methods can be trained using supervised, unsupervised or reinforcement learning. More recently, deep learning approaches have been developed, which are essentially further developments on neural networks (Patterson and Gibson, 2017[16]). They are used in many different applications, from computer vision (e.g. for image and facial recognition, and autonomous driving, etc.) to natural language processing of large bodies of text. The latest advances in AI have been in the form of large language models such as ChatGPT, developed by OpenAI, Google's Gemini and Meta's LLaMA family of models (Chang et al., 2024[17]). Large language models use deep learning and natural language processing in combination with massive data sets to infer relationships and generate new types of content. These models can also be interfaced with other applications, such as Python programming, to generate code, or Dall-E, to generate new images (Brockman, 2023[18]).

Figure 1. Basic overview of artificial intelligence



Case studies

This section presents the three case studies selected according to the methodology outlined in Annex A.

1. The Ghana Statistical Service feasibility study for marine litter detection and reporting

Background

Plastics make up about 85% of all marine litter, which poses an increasing threat to the environment, human health and the economy (Haward, 2018[19]; UNEP, 2021[20]; Nelms et al., 2022[21]). However, because plastics are so widely dispersed and reach even the most remote parts of the globe, it is impossible to determine the true scope of the issue (Cózar et al., 2014[22]). Ghana has made the elimination of plastic and marine pollution a high priority and is devoting resources to addressing this issue because the country is very susceptible to the negative impacts of marine litter. For example, Ghana was the first country to integrate citizen science beach litter data into its official statistics to address the lack of data in this area. It also used these data in its 2022 Voluntary National Review and reported them to the UN SDG Global Database as country-validated data for SDG indicator 14.1.1b Plastic Debris Density ((Fraisl et al., 2020[11]; United Nations, 2021[23]; United Nations Ghana, 2022[24]). The results are also being used to inform Ghana's integrated coastal and marine management policy. However, there is a need for a comprehensive understanding of the marine litter situation, including where and which litter items and plastic pieces are accumulated along Ghana's coastline, in order to better target interventions.

Aim

Building on the work of integrating citizen science beach litter data into Ghana's official statistics, the project aims to understand the feasibility of using drones, citizen science and AI to collect data along Ghana's coastline, identifying marine litter hotspots – areas where litter and plastics accumulate (Fraisl et al., 2023[25]). The aim is also to complement the official methodology outlined for SDG indicator 14.1.1b and help civil society organisations and other volunteer networks in Ghana organise more targeted beach clean-up and data collection activities for subsequent SDG monitoring and reporting. Last but not least, the ultimate aim is to eliminate plastic pollution through partnerships and innovation and address data and policy gaps for that purpose.

Methodology

The proposed methodology includes the integration of various technologies, such as drones, AI and geo-visualisation techniques, along with citizen science to produce litter density maps.

Results

Different scenarios were proposed regarding the next step for implementation based on the results of the feasibility study and the case study. Considering the budget constraints, the scenario that suggests mapping the coastline around the coastal cities of Ghana once, each for about 50 kilometres long, or a total of 200 km, was found to be the most favourable option. This will provide a good understanding of the extent of the marine litter problem in areas with high population density in the country while at the same time enabling better planning for management and clean-up efforts in the areas with a high risk of marine litter accumulation.

Relevant SDGs

The project can contribute to the monitoring and achievement of the following SDG target and indicator:

- Target 14.1: By 2025, prevent and significantly reduce marine pollution of all kinds, particularly from land-based activities, including marine debris and nutrient pollution
  - 14.1.1b Plastic Debris Density.

2. Colombia’s approach to better understand poverty and inequalities

Background

Colombia is one of the countries the most severely impacted by COVID-19. Its economy shrank by 6.8% in 2020, resulting in 2.4 million job losses (DANE, 2021[26]; DANE, 2020[27]; PARIS21, 2022[28]). According to the National Administrative Department of Statistics of Colombia (DANE), 18.3 million people out of the 50 million in the country live in poverty, 6.9 million of which live in extreme poverty (Griffin, 2023[29]). According to DANE, there is an urgent need to understand who are the most vulnerable, as poverty affects different communities and individuals in different ways, leading to extreme inequalities. One of the Colombian government’s primary goals is to eradicate poverty through an inclusive strategy to ensure that no one is left behind, including in official statistics. DANE is, therefore, specifically working on expanding the availability of data on marginalised communities. However, traditional methods such as censuses and surveys are not sufficient to make estimates at a more granular level, as needed, but they are still useful due to their ground-truthing possibilities (Oviedo et al., 2021[30]).

Aim

The aim of the initiative is to obtain a more nuanced and up-to-date understanding of poverty in a cost-efficient way.

Methodology

The methodology involved combining existing data from traditional sources with geospatial information. More specifically, an AI algorithm was trained to connect daytime and nighttime satellite images. This algorithm was then used to predict poverty rates based on daytime satellite imagery. In the final stage, these predictions were combined with the results from the latest census to verify their accuracy.

Results

The result was a 70-fold increase in data points related to poverty, or 78 000, compared to the 1 123 data points in the previous estimates. This approach to measuring poverty also resulted in much more granularity in capturing nuances within and between municipalities.

Relevant SDGs

The examples of SDG targets and indicators that the project can contribute to are:

- Target 1.1: By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than USD 1.25 a day
  - Indicator 1.1.1: Proportion of the population living below the international poverty line by sex, age, employment status and geographic location (urban/rural).
- Target 1.2: By 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions
  - Indicator 1.2.1: Proportion of the population living below the national poverty line, by sex and age
  - Indicator 1.2.2: Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions.
- Target 10.2: By 2030, empower and promote the social, economic and political inclusion of all, irrespective of age, sex, disability, race, ethnicity, origin, religion, or economic or other status
  - Indicator 10.2.1 Proportion of people living below 50% of median income, by sex, age and persons with disabilities.

3. Swiss Federal Statistical Office and Swiss Conference of Regional Statistical Offices StatBot.swiss chatbot for sharing statistical information

Background

The central portal opendata.swiss lists the government's open data sets and makes them publicly available. However, the general public may still find it difficult to understand and use these data due to a lack of technical skills in some cases. There is a need to facilitate the exploration of open government data and statistical information for the public (Lavrynets, 2023[31]).

Aim

In addition to bringing data sets into a common data space and supporting the harmonisation of statistical data from several official sources, the project aims to develop a chatbot system that will enable users to query these harmonised data (Ruiz, 2023[32]).

Methodology

There are two stages to the methodology. The objective of the first stage is to gather, process and ingest data from diverse government data sources into a shared and standardised data space. In the second stage, a machine learning system converts user questions into natural language as Structured Query Language (SQL) queries. It then retrieves an answer to the queries from a database and presents the results to the user in a natural language form.

Results

A Minimal Viable Product chatbot was ready by the end of 2023. A final report including lessons learnt will be published in 2024.[1]

Relevant SDGs

In addition to contributing to open data and science principles, data awareness, and literacy, the project can support the achievement of the following SDG target:

- Target 16.10: Ensure public access to information and protect fundamental freedoms, in accordance with national legislation and international agreements.

[1] Swiss Federal Statistical Office Data Science Competence Center, 2024. Personal correspondence.

Benefits of artificial intelligence

Although many AI applications are commercial, it can also be employed to achieve socially beneficial outcomes. Referred to as AI for Social Good, AI systems can help solve problems related to human and environmental well-being in a sustainable way, which does not harm or worsen existing inequalities. For example, (Cowls et al., 2021[33]) used the SDGs as an assessment benchmark to evaluate AI for Social Good initiatives, finding 108 projects in total, and showed that every SDG is being addressed by at least one project involving AI. In a study by Vinuesa et al. (2020[34]), experts were consulted about the potential of AI for the SDGs. The consensus was that 134 targets across all SDGs had the potential to be accomplished if AI was employed. At the same time, however, the experts identified 59 targets that could be inhibited by using AI. For example, the potential impact of climate change can be better understood and modelled through AI, which is necessary to achieve SDG 13 Climate Action. However, the high energy requirements of AI could jeopardise the efforts to achieve this SDG, particularly if non carbon-neutral energy sources are deployed (Vinuesa et al., 2020[34]).

Xu et al. (2024[35]) outlined another example of the potential benefit of AI. They showed that fertiliser management and tillage practices optimised at a local scale using machine learning and big data could reduce emissions from fertiliser by up to 38%. Hence, this use of AI could positively contribute to SDG 2 (Target 2.4) and SDG 13 (Target 13.2)[2] if successfully applied. More specifically, examples of the benefits of AI for development include improved healthcare through accuracy and speed of diagnosis and reduced cost of treatment, climate change mitigation by increasing energy efficiency, and economic growth due to increased innovations and labour productivity, among others.

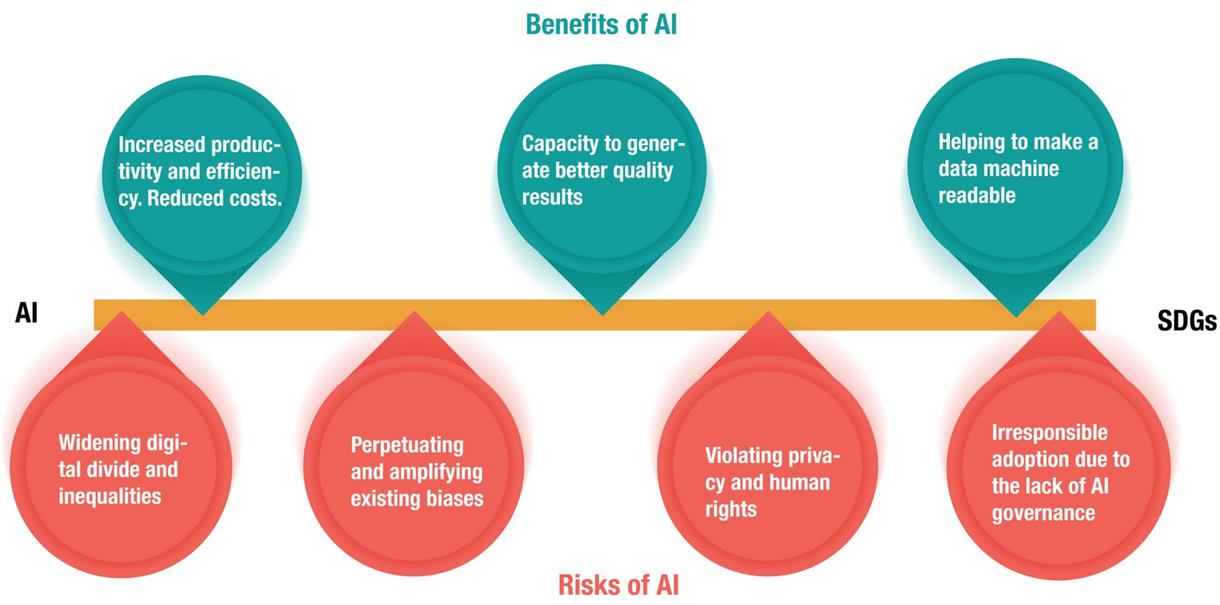
As a result of these types of benefits, AI is receiving more and more attention from the official statistics communities and policy makers because it is increasingly affecting people’s lives as its capabilities and use expand. Additionally, statistical institutions and policy makers need AI for more efficient, accurate and insightful results. In fact, AI can be examined through the lens of the data value chain to better contextualise these actors’ growing interest in AI. The data value chain is a framework outlining the stages and steps of data production and use, including collection, publication, uptake and impact (Open Data Watch, n.d.[36]). AI can contribute to all stages of the data value chain. For example, it can help collect data much faster, more accurately and more efficiently than humans and other methods. It can support the publication of data, such as through visualisation in real time and in a more understandable and interactive way. It can support the uptake of data by, for example, automating the processing of complex and large data sets more consistently and accurately to derive new insights from existing data. Finally, AI can help track if certain policies have an impact on people’s lives, such as through social media sentiment analysis.

[2] Target 2.4: By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality. Target 13.2: Integrate climate change measures into national policies, strategies and planning.

Discussing AI in the context of the data value chain can help to identify, structure and further expand the understanding of the ways in which diverse AI approaches can contribute to the monitoring and achievement of sustainable development. However, the data value chain, in its current state, may not meet the unique circumstances of AI. For example, the progression of AI may not be linear and may not always depend on earlier stages, as presented in the data value chain. Instead, a wide range of factors can impact AI, making it difficult to predict its direction and how it will develop as the circumstances, such as data availability and AI-related regulations and policies, evolve. Nevertheless, examining AI in relation to the data value chain is still useful, as this can help advance our understanding of AI, such as for impact assessments.

Figure 2 shows the most notable benefits and risks of AI in the context of the SDGs and sustainable development, presented through the lens of the aforementioned case studies. The following sections will discuss both these benefits and risks in more detail.

Figure 2. Benefits and risks of artificial intelligence in the context of the Sustainable Development Goals



1. Increasing productivity and efficiency while reducing costs

AI can improve the productivity and efficiency of official statistics by providing enhanced computational capacity, increased access to data, improved data collection, automation of tasks, access to real-time data, enhanced data visualisation and more accurate insights, among others. For example, it can automate the data collection process, which saves time and reduces costs while gathering large amounts of data. AI can also assist statistical institutions in leveraging the potential of new data sources, such as social media, to gather additional insights and a more comprehensive understanding of an issue, which can supplement official statistics and contribute to productivity.

Looking at the benefits of AI using the case studies from the previous section as a guide, for example, the use of AI in Ghana could allow data gaps in marine plastic litter to be addressed much quicker compared to other methods such as individual beach surveys, which can be quite labour-intensive and expensive to conduct regularly. Additionally, they can only cover small areas and are problematic to carry out in remote locations that are not easy to access. Because the project includes a citizen science component where volunteers will assist in classifying drone imagery, AI approaches can also support efforts to improve decision-making processes by highlighting inclusive data ecosystems and citizen participation. In the case of Colombia, the 1 123 data points on poverty obtained from census data have grown to 78 000 through the use of AI, increasing the amount of data available, particularly on marginalised communities, which is more up-to-date than traditional methods can offer.

Gathering data at a high granularity to an extent not possible through the use of traditional sources of data can help to address disparities, allowing the government to formulate and implement policies that focus on the most vulnerable. This contributes to the 2030 Agenda's principle of leaving no one behind and is one of the highest priorities of the Colombian government. In the Swiss Federal Statistical Office and CORSTATS StatBot.swiss chatbot example, improved productivity and efficiency can be attained through the ability of the chatbot to interact with multiple users at once in comparison to a human performing the same task, which helps to assure quick responses and cut down on response times. Furthermore, such a service would be available 24 hours a day 7 days a week and not be restricted to working hours; it allows efficiency in delivering statistical information to citizens and reduces the response burden of statistical institutions to relevant queries. Additionally, through the use of AI, it was possible to advance data standardisation and harmonisation for statistical organisations in Switzerland to export their data into a common and standardised data space. The project also provides citizens with easy access to statistical information, making data dissemination, uptake and reuse much easier and more efficient.

2. Capacity to generate better quality results

AI can enhance the quality of official statistics by automating processes like data cleaning and correction. AI approaches can also assist in the analysis and comparison of data across diverse sources, helping to reduce errors and ensure accuracy. Additionally, AI can improve data quality by addressing dimensions such as timeliness (whether data are available when needed), validity (whether the data conform to defined formats), consistency (whether the data are consistent across various data sets) and uniqueness (whether the data are recorded only once in the same data set), among others (GOV.UK, 2021[37]).

Nevertheless, it is important to note that, in principle, the quality of the data and the results from AI depend on the quality of the algorithms and the quality of the data sets used to train them. AI algorithms will not deliver high-quality results if the training data are biased or inaccurate. For example, in the case of Ghana, accuracy would depend on the ability of the algorithm to distinguish and classify plastic items accurately. The AI algorithm that is planned to be used in the Ghana case is highly accurate, which was also tested in Ghana through a pilot study. However, the quality can still be improved through the availability of more and local training data. Therefore, a human-in-the-loop approach through citizen science is planned. This means that volunteers will perform image classification tasks that will be used to improve the AI algorithm. In the Colombian case, data quality was assured by comparing it with data from the latest census. In the Swiss case, the project team reported on potential errors, which can be an issue since statistical organisations strive for the highest quality data to be made available from official sources.

3. Helping to make data machine readable

AI approaches can assist in translating content from paper-based documents and photographic images into machine-readable format, which can help automate the extraction of relevant information from massive amounts of data and make them available for further AI applications. This indicates that in addition to generating data, results and insights as outputs, AI approaches can also assist in producing the input data needed to put AI to work. Because AI needs data to perform, producing data that are understandable by machines is essential. For example, to respond to citizen requests related to properties and property rights, the Swedish Land Registry had to become more productive and efficient because processing these requests mostly involved reviewing handwritten documents, many of which were from the 1850s. The government charged citizens by the hour to fulfill these requests, as the work required to complete this was about 48 000 hours a year. To tackle this problem, the Swedish Land Registry first needed to deal with the issue related to the poor quality and resolution of handwritten documents. To improve the quality of the input data, it performed pre-processing on the handwritten documents. Information was then extracted from the handwritten documents, which was ingested by a neural network for word corrections and associations to complete sentences that lacked words that were not detected in the previous stage. Finally, an AI model was employed to extract important details in documents, such as names and locations (GOV.UK, 2019[38]).

Connecting this benefit to the cases presented in the previous section, for example, the first phase of the StatBot.swiss project was centered on standardising and harmonising data from the opendata.swiss website. The goal of this phase was to render the data machine-readable so that they could be utilised in the second phase of the project as a component of the chatbot that would query this database (Lavrynets, 2023[31]).

Risks of artificial intelligence

Despite its great benefits, AI does not come without challenges and risks, which require considerable attention, because like its benefits, its risks can also be at a greater scale. This section examines the risks of AI both in the context of the case studies presented above and more generally.

1. Widening the digital divide and inequalities due to infrastructural limitations and skill gaps

Not all countries and NSOs have the same level of access to the opportunities offered by AI. In most countries in Africa, AI approaches have not yet been deployed due to infrastructural limitations, including issues related to access to the Internet and electricity (Centre for Intellectual Property and Information Technology Law, 2023[39]). According to the International Telecommunication Union, in 2023, more than 2.6 billion people lacked access to the Internet (ITU, 2024[40]). This limited access to the basic components of AI, such as electricity, connectivity and affordable devices, are contributing to widening the digital divide and inequalities (UN AI Advisory Board, 2023[41]). The achievement of the SDGs, which has a specific goal and targets on reducing inequalities and advancing the idea of leaving no one behind, may be hindered by the lack of fundamental infrastructure required to develop and deploy AI (OECD, 2019[42]; UNESCO, 2021[43]).

It is important to note that the digital divide issue extends beyond borders between the Global North and the Global South; it also has varying effects on countries, communities and demographic groups within a given country or region. For example, given the diversity of the Global South, some countries in this region may be able to leverage the potential of AI sooner than others (Oxford Insights, 2023[44]). It is crucial to address these disparities because the application of AI in this setting may exacerbate existent inequalities between and within regions and among diverse segments of the population.

Another risk that might hinder AI from realising its full potential are technical skill gaps in statistical and government institutions, especially in the Global South. The AI Readiness Index, which attempts to assess the level of government preparedness for integrating AI into the provision of public services, ranks sub-Saharan Africa’s human capital readiness at 22 out of 100, the lowest ranking globally, compared to 68 in North America, which obtained the highest ranking (Oxford Insights, 2023[44]).

There is an urgent need to tackle these infrastructural limitations as well as the skill gaps in order to address existing inequalities and fully realise the transformative potential of AI. The donor community must play a substantial role in this process, collaborating with the public and private sectors. Support from the Global North to the Global South can be the key to eliminating inequality, ensuring true sustainable development on a global scale.

2. Perpetuating and amplifying existing biases

In AI, biases can take several forms, such as those resulting from algorithms that are trained on non-local data. This is also related to the lack of large amounts of data needed to train AI algorithms, especially for the Global South, which may lead to the transfer of algorithms developed in other countries that do not recognise the local context and sensitivities. This could jeopardise the quality of the results, further deepening inequalities (UNESCO, 2021[43]).

Bias related to the lack of local data may be a legitimate concern for the Ghanaian case study. For example, water sachets are used in Ghana to store and sell drinking water; however, this is not common in Europe. The algorithm used in the marine plastic litter project needs to be capable of detecting and classifying such items correctly that are specific to the local context, which requires more and local training data. In the Ghana case, this is planned to be addressed with the use of citizen science approaches that enable rapid classification of drone imagery to increase the accuracy of the AI algorithm. Nevertheless, the aim should be to create local AI solutions rather than simply transferring them from one context to another. If this is not feasible, appropriate steps should be taken, including further training using local data, to guarantee that the local nuances are appropriately considered.

Apart from bias associated with inadequate local data, biases rooted in society, such as on race, gender and ethnicity, might also compromise AI's fairness. For example, research indicates that facial recognition algorithms may not be very accurate in classifying the faces of women of colour (Buolamwini and Gebru, 2018[45]; Buolamwini et al., 2018[46]; Buolamwini, 2023[47]); and models exist that automatically assign he/him pronouns for professions like doctors and pilots and she/her pronouns to nurses and flight attendants (Cho et al., 2021[48]; Shrestha and Das, 2022[49]). One practical way to solve this issue is through algorithmic auditing, the process of assessing each stage of AI development to identify potential bias sources and ways to eliminate them. This approach can assist in developing effective tactics to eradicate bias. Additionally, it is crucial to include inter- and trans-disciplinary perspectives on AI to shift the focus of AI development and relevant conversations from being exclusively technical to being ethical and social (Cheng, Varshney and Liu, 2021[50]). Accordingly, more women and members of diverse demographic groups and communities should be included in AI development to address the bias issue, as they are underrepresented in the field of AI. According to a study conducted by the World Economic Forum and LinkedIn, women make up about 30% of AI experts (World Economic Forum, 2023[51]). It must be noted that, ultimately, it is critical to address gender and other inequalities in society to tackle the root cause of the problem, as algorithms reflect societal biases.

3. Violating privacy and human rights

Another potential risk of AI is the violation of privacy. Privacy cuts across the three case studies covered in this paper. In the Ghana example, the combined use of drones and AI may violate privacy if the regulations governing the protection of privacy and personal data are not respected. Privacy could also be an issue in the Colombian case, as the use of satellite imagery at a high granular level may pose potential threats to privacy. In the StatBot.swiss example, privacy concerns may be related to gathering data on users for statistical purposes with the aim of improving the service or other reasons. Even if such concerns may not apply to this specific initiative, privacy is a fundamental issue for chatbots in general and requires special attention, especially as the use of AI chatbots in public institutions has grown in popularity in recent years.

AI solutions should be developed and deployed ethically and responsibly to ensure that personal data are not collected without active consent and are never used in any manner that could impact individuals or communities negatively. For instance, especially in the case of chatbots, it is important to ensure that users are informed about the data being collected about them, why they are being collected, how they will be stored, and whether or not they can opt out of sharing their data. When statistical organisations engage in the use of AI chatbots, they need to ensure that the relevant laws and regulations are always adhered to, without any potential errors related to collecting data that could jeopardise someone's privacy.

Protecting privacy is crucial for upholding human rights and must be respected throughout the life cycle of AI systems. As a result, all aspects of data collection, use, sharing and archiving must adhere to all applicable international laws, rules and principles, including those set forth in the UNESCO Recommendation on the Ethics of AI. The recommendations emphasise the need to implement privacy impact assessments that embrace the privacy by design approach. It is important to note that the actors who develop and deploy AI bear responsibility for its design and implementation; it is their duty to guarantee privacy protection throughout the entire AI life cycle (UNESCO, 2022[52]).

4. Irresponsible adoption and use due to the lack of AI governance at a global scale

Another risk of AI is irresponsible adoption and use of this technology due to the absence of policy frameworks governing or regulating AI at a global level. As discussed above, this could result in risks regarding data privacy and protection, as well as human rights violations more generically, all of which could jeopardise efforts to achieve sustainable development (UNECE High Level Group on Modernisation of Official Statistics, 2023[53]). Therefore, effective AI governance at a global level is necessary to address the risks and limitations of AI while also capitalising on its benefits, as the processes and results of AI applications can have a global impact for better or for worse. To address this issue, in his report "Our Common Agenda", UN Secretary General António Guterres proposed a Global Digital Compact to be agreed at the Summit of the Future in September 2024 to "outline shared principles for an open, free and secure digital future for all" (United Nations, 2021[54]). As a follow-up, in his policy brief published in May 2023, Guterres elaborated on the ideas presented in "Our Common Agenda", highlighting that AI has immense potential when applied carefully, and that global, multistakeholder co-operation is necessary for addressing governance gaps related to the use of AI and other emerging technologies (United Nations, 2023[55]).

Subsequently, in October 2023, the UN Secretary General launched a High-level Advisory Body on AI, whose recommendations will be inputs to the Summit of the Future and to the negotiations related to the Global Digital Compact followed by stakeholder consultations. The success of the negotiations is highly important, as currently this workstream is the only intergovernmental process related to AI governance (Simon Institute for Longterm Governance, 2023[56]). If the Compact leads to a consensus on the governance of AI it would provide a framework for the responsible use of AI, thereby overcoming or mitigating its risks and leveraging its potential for sustainable development globally and for all.

Some of the principles that the High-level Advisory Body on AI put forward cover:

- inclusive governance of AI, including the participation of all for the benefit of all
- AI for the broader public interest involving diverse actors
- data governance, including data privacy and security and the promotion of the data commons to help address societal issues
- the need to govern AI in a way that is universal, networked and based on collaboration with diverse stakeholders
- the need to anchor AI governance in the UN Charter, the International Human Rights Law and other agreed international commitments such as the SDGs (UN AI Advisory Board, 2023[41]).

Conclusion and recommendations

This paper is an important contribution to the widely debated topic of AI in the context of sustainable development data and official statistics. The paper particularly focused on the NSO practices provided as case studies to explore how AI can enhance sustainable development and identified the potential risks related to its uptake. This paper can provide a foundation for further discussions on the use of AI, especially by NSOs, as well as the data and official statistics communities.

The case studies presented in the paper cover three examples, but the adoption of AI is starting to find its way into many NSO operations, although its full potential has yet to be realised. For example, Statistics Canada is using AI to detect greenhouses from satellite images (Hatko, 2021[57]); Statistics Netherlands is using AI and aerial images to determine the proportion of green to grey areas in inner cities (Braaksma and Offermans, 2021[58]); and Statistics Indonesia is harnessing the potential of satellite imagery and machine learning to map poverty (Wijayanto, 2021[59]). In addition to NSOs, UN agencies are also capitalising on the potential of AI for the SDGs and sustainable development. The UN Refugee Agency is using machine learning to predict the movements of displaced people (UNHCR, n.d.[60]); the World Food Programme is using machine learning techniques and data from diverse sources to monitor and predict hunger in real time in 94 countries (WFP, 2024[61]); and GRID-Arendal, a United Nations Environment Programme partner, is using drones with AI, satellites with optical and synthetic-aperture radar, and other sources to prevent illegal fishing in coastal and small island developing states (GRID-Arendal, 2024[62]). These are just a few examples of how the United Nations and other international organisations are already deploying AI, and the common objective of both the United Nations and the NSO-led initiatives is to use AI to monitor and support sustainable development more efficiently.

This paper argued that the benefits of AI can be manifold, such as climate change mitigation or improved healthcare, which can help better monitor and ultimately achieve the SDGs. In the context of development data and NSO operations, the paper discussed different ways that AI can assist official statistics: by making their operations more productive, efficient and cost-effective; by assisting in producing higher quality results; and by helping to make data machine-readable, Indeed, NSOs need AI, especially because new technologies and global challenges are making fundamental changes to the ways in which they operate.

The paper also highlighted that AI is not without risks that require careful consideration, because like its benefits, its risks can also be quite substantial. Some examples of the risks of AI discussed in the paper include: widening the digital divide and inequalities due to infrastructural limitations and skill gaps; perpetuating and amplifying existing biases; violating privacy and human rights; and irresponsible AI adoption and use due to the absence of AI governance at a global scale.

This study has certain limitations. For example, it could have covered more case studies or broadened its investigation by considering documents published in languages other than English. It is also acknowledged that not all examples of NSOs' use of AI are documented or published on line. The goal, however, was not to compile a comprehensive list of AI cases led by statistical organisations or NSOs. Instead, the case studies serve as a basis for a discussion of how AI may be used to better monitor and accomplish sustainable development. Additionally, as the intention was not to be exhaustive, the paper may not have covered all the potential benefits and risks of using AI in the context of official statistics and sustainable development. An example of an additional risk could be the fact that training and developing AI models may require large computational resources and significant energy and water consumption and this may have a harmful impact on the environment (Strubell, Ganesh and McCallum, 2019[63]; Patterson et al., 2021[64]).

Finally, the following recommendations can be made for NSOs and the official statistics community to leverage the benefits of AI while minimising its potential risks in the context of sustainable development data and official statistics:

Recommendations on strategies, policies and guidelines

- Update national strategies for the development of statistics by integrating the use of AI in all steps, from planning to costing and implementation.
- Advocate for and actively engage in processes related to establishing policy frameworks and regulations for the adoption of AI and data governance that are adaptable to the fast-evolving nature of AI.
- Offer clear guidelines for the responsible and transparent use of AI, taking into account the potential privacy, data protection and other ethical concerns.

Recommendations on documentation and measurement

- Develop an inventory of existing and potential use of AI by NSOs.
- Document and clearly communicate the risks and benefits of AI in each NSO operation where AI has been used.
- Measure the risks and identify ways to mitigate them in the NSO's own AI operations, including those that involve third parties such as tech companies.

Recommendations on practical applications of AI to eliminate risks

- Ensure equal distribution of the benefits of AI, particularly in the Global South and including for vulnerable and marginalised communities.
- Carefully consider issues of safety and security in all AI initiatives, including cybersecurity for potential cyberattacks.
- Ensure that the AI practices and processes deployed by NSOs do not harm human rights, fundamental freedoms or the environment, as the carbon footprint of AI can be significant.
- Ensure that humans are in the loop in AI processes, from training to decision making.
- Conduct inter- and trans-disciplinary analyses on the future directions and potential consequences of AI to enable prompt adjustments as needed.

Recommendations on collaborations and awareness raising

- Build partnerships and initiate a dialogue involving all the key actors, including academia, private companies, government agencies, international organisations, civil society and others, in a way that is inclusive and guarantees the active participation of all, especially those who have traditionally been marginalised, to unlock the full potential of AI for achieving the SDGs by leaving no one behind.
- Promote targeted collaborations across the Global South to jointly develop and implement AI strategies that take into account their unique circumstances, safeguard the most vulnerable and marginalised in their context, and foster responsible innovation.
- Ensure that countries and communities in the Global South are well-represented and have a strong voice during global discussions and converations on AI.
- Work together as a community to raise awareness on and address the necessary infrastructural and financial limitations as well as the capacity-building needs related to the adoption of AI, especially in the Global South.
- Support innovative funding mechanisms in collaboration with the donor community as well as the public and private sectors to address the Global South’s infrastructural and financial constraints and capacity-building needs.
- Raise awareness among the public to enhance both AI and data literacy.

Keeping up with the pace of AI is daunting, especially for NSOs, which are striving to produce high-quality results with limited resources while at the same time upholding high statistical standards. NSOs must embrace AI for its benefits and position themselves as trusted leaders in the responsible use of it in this rapidly evolving field while closely monitoring and mitigating its risks. The risks are particularly important in the context of the Global South and low- and lower middle-income countries, which require further investigation to better understand the unique challenges they face.

Team work and inclusive partnerships that engage everyone, especially local communities, are key to achieving the ambitious goal of realising the full potential of AI for sustainable development. Only through genuine collaborations and trusted partnerships can we unlock the transformative potential of AI; this paper is a call for action to jointly construct such partnerships that enable true collaborations.

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Annex A. Methodology

Desk research is the main methodology used in this paper, including a review of the SDG indicators and case studies that demonstrate AI's potential for the SDGs.

As part of the desk research, first metadata of the SDG indicators and the literature related to the use of AI in the context of the SDGs and sustainable development more broadly were reviewed. The authors have substantive knowledge about the SDG framework, including the SDG indicators, due to previous work on mapping citizen science contributions to the SDGs (Fraisl et al., 2020[11]) and exploring how citizen science can contribute to the monitoring of health and well-being related SDG indicators and the World Health Organization's Triple Billion Targets (Fraisl et al., 2023[12]). Desk research also helped identify the literature on the link between AI and the SDGs, as well as that on AI and sustainable development data and statistics.

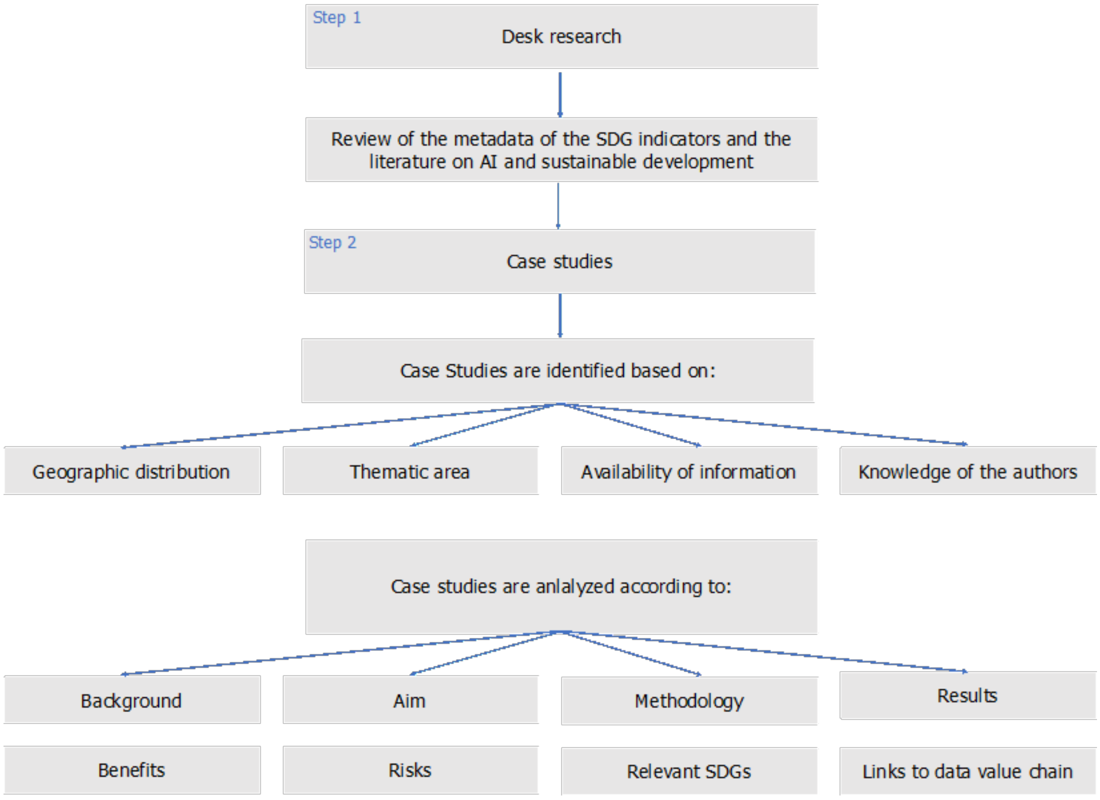
Next the case study method was used to investigate how NSOs are using AI to address their data gaps and needs, and to improve their services.

The three case studies were chosen based on their geographic distribution to ensure a certain degree of representativeness; the thematic area they cover to demonstrate that a diverse range of topics can be supported by AI approaches; the availability of information on line due to the time constraint of drafting this report; and the authors' knowledge, as they have been involved in initiatives in which AI is either used or planned to be used. The authors then analysed the three case studies based on the following criteria to gain better insights into the use of AI by NSOs in the context of sustainable development data and statistics:

- Background: What problem/need does the project address?
- Aim: What is the aim of the project?
- Methodology: What is the methodology of the project and how is AI used in it?
- Results: What are the results?
- Benefits: What are the benefits of using AI in the project?
- Risks: What are the risks associated with the use of AI in the project?
- Relevant SDG: Which SDG indicator and/or target can the project contribute to?
- Links to the data value chain: To which stage of the data value chain is the project related?

Figure 3 shows the methodology applied in this paper.

Figure A A.1. The methodology of the research undertaken in this paper



Based on the results of the case study analysis and the desk research, the authors then identified the benefits and risks associated with the use of AI by NSOs for development data and statistics and outlined the key factors for unlocking the potential of AI by mitigating its potential risks.

AI through the lens of official statistics and the Sustainable Development Goals: The benefits and risks

Artifical intelligence (AI) and its impact on people's lives is growing rapidly. It is already leading to significant improvements in various fields, such as healthcare, education and agriculture; and it can contribute to more efficient monitoring and achievement of the Sustainable Development Goals. AI is also raising concerns because if it is not addressed carefully, its risks may outweigh its benefits. As a result, AI is garnering increasing attention from national statistical offices (NSOs) and the official statistics community more broadly because they are challenged to produce more, comprehensive, timely and high-quality data for decision making with limited resources in a rapidly changing world of data and technologies and in light of complex and converging global issues from pandemics to climate change. Building on case studies that examine the use of AI by NSOs, this paper discusses the benefits and risks of AI with a focus on NSO operations. The objective is to spark conversations around how AI can be leveraged to inform decisions and take action to better monitor and achieve sustainable development.

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