DIGITALISATION

THE POTENTIAL OF ARTIFICIAL INTELLIGENCE FOR THE SDGS AND OFFICIAL STATISTICS

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The Potential of Artificial Intelligence for the SDGs and Official Statistics

Abstract

Artificial Intelligence (AI) and its impact on people's lives is growing rapidly. AI is already leading to significant developments from healthcare to education, which can contribute to the efficient monitoring and achievement of the Sustainable Development Goals (SDGs), a call to action to address the world's greatest challenges. AI is also raising concerns because, if 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 as 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. This paper has been prepared as an input to the "Data and AI for Sustainable Development: Building a Smarter Future" Conference, organized in partnership with The Partnership in Statistics for Development in the 21st Century (PARIS21), the World Bank and the International Monetary Fund (IMF). Building on case studies that examine the use of AI by NSOs, the paper presents the benefits and risks of AI with a focus on NSO operations related to sustainable development. The objective is to spark discussions and to initiate a dialogue around how AI can be leveraged to inform decisions and take action to better monitor and achieve sustainable development, while mitigating its risks.

Introduction

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* (Goal 16), less than half of the 193 countries or areas have internationally comparable data since 2015, and less than 30 per cent of the latest available data on the SDGs are from 2022 and 2023 (UN, 2023). This leaves the 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?

Defined as a machine-based system that utilizes input to deduct outputs such as, predictions, content, recommendations and decisions (OECD, 2024), Artificial Intelligence (AI) has the potential to address these data gaps and needs related to the SDGs, while at the same time contributing to their achievement. More specifically, AI can help improving people's well-being, contribute to economic productivity at a global level, increase innovation, and help to respond to key global challenges from health and education to climate change and hunger (OECD, 2023). In this paper, we aim to discuss the potential of AI, focusing on NSO practices related to sustainable development presented as case studies. Our intention is to spark a debate around the following questions: "*What are the potential benefits and risks of AI for sustainable development?"* and *"how can we leverage the potential of AI, while at the same time minimizing the risks of AI?".* We hope that our paper, prepared as input to the "Data and AI for Sustainable Development: Building a Smarter Future" Conference, organized in partnership with PARIS21, the World Bank and the International Monetary Fund (IMF), will help to stimulate discussions and prompt concrete actions to realize the full potential of AI for sustainability.

The SDGs and AI

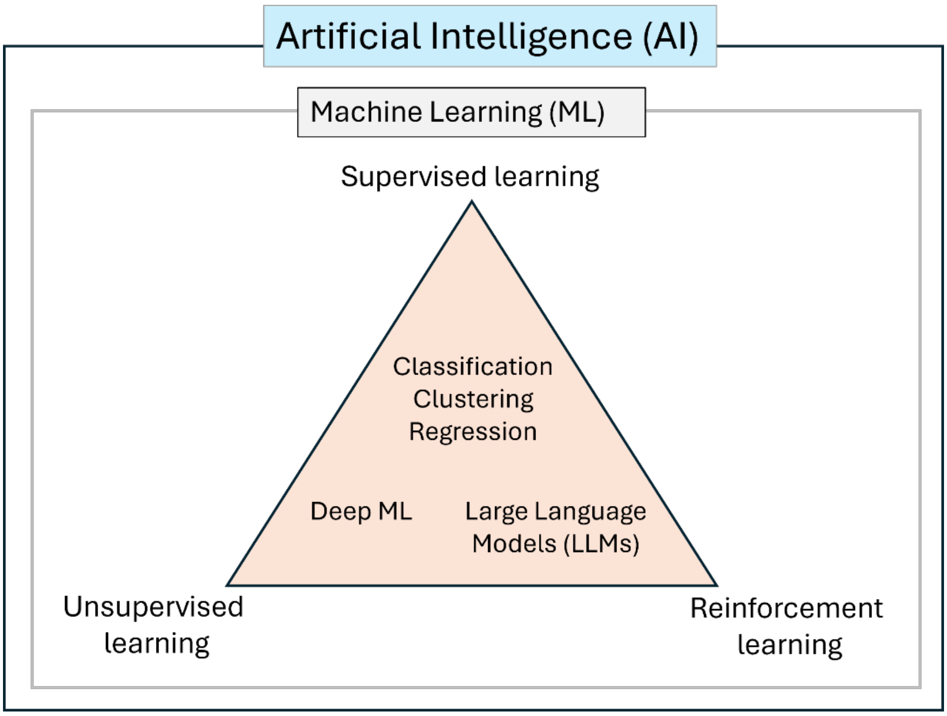
The 17 goals of the SDGs address global challenges across a number of key focus areas including climate change, environmental degradation, food security, health, inequality, and poverty alleviation (UN, 2015). Progress towards achieving the goals is evaluated through 169 targets, which are underpinned by 231 indicators (UN, 2024). Each SDG indicator is described in detailed metadata, which outlines the methodology and data sources that are used to populate them; both the methodologies and the data sources have evolved as the indicator framework has developed over time. However, with only six years left to achieve the SDGs, there is still a lack of data for many countries, there are issues with data quality, or the data sources that are used to monitor and report on the SDG indicators are not frequently updated (Nilashi et al., 2023). 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 et al., 2023), which are statistics generated or compiled by governments and public agencies, more specifically, by National Statistical Offices (NSOs) and are used as the foundation for policy decisions (Eurostat, 2017).

There are now many other sources of data available that could be used to address these data gaps and populate the SDG indicators, including data from Earth Observation (both remote sensing and in situ data collection), different types of social media, and citizen science (Fritz et al., 2019). Data from Earth Observation and citizen science are already directly contributing to some indicators, e.g., in SDGs 11, 14 and 15 (Fraisl et al., 2020, 2023a), but concerns over data quality remain one of the main barriers to the adoption of non-traditional sources of data (Proden et al., 2023). Other challenges include the need for appropriate legislative frameworks that allow for non-traditional sources of data to be used as official statistics as well as the mechanisms for integrating these diverse and heterogeneous data sources into official reporting processes (Fraisl et al., 2023a) .

In addition to non-traditional data sources, AI also has the potential for addressing data gaps and needs related to the SDGs, as well as contributing to their achievement. The OECD defines 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). Indeed, AI is a branch of computer science that investigates how human behavior and intelligence could be integrated into machines or systems (Xu et al., 2021; Sarker, 2022). 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).

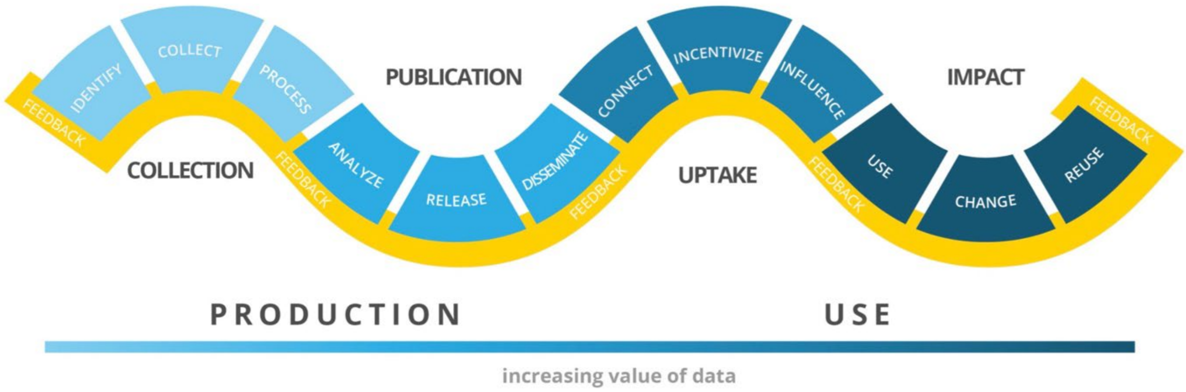
An overview of AI is provided in Figure 1. Machine learning is a specific branch of AI that focuses on methods that learn from data or from past experiences to, for example, gain knowledge from the data or to make predictions (Alpaydin, 2020). This includes pattern recognition methods such as classification and clustering, which can be undertaken using different approaches such as neural networks, decision trees, support vector machines, as well as statistical models such as regression. These methods can be trained using supervised, unsupervised or reinforcement learning. More recently, deep learning approaches, which are essentially further developments on neural networks, have been developed (Patterson and Gibson, 2017), which 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 (LLMs) such as ChatGPT, developed by OpenAI, Google's Gemini and Meta's LLaMA family of models (Chang et al., 2024). LLMs 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).

Figure 1: Overview of Artificial Intelligence (AI)



AI can contribute to the various stages of the data value chain, which is a framework outlining the stages and steps of data production and use, including collection, publication, uptake, and impact (Open Data Watch, n.d.). For example, AI can help collect data much faster, more accurately and efficiently than humans and other methods. It can support the publication of data, such as through visualization 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. Figure 2 shows the various stages and steps of the data value chain.

Figure 2: The stages and steps of the data value chain



Source: Open Data Watch (n.d.)

Discussing AI in the context of data value chain can help to identify, structure and further expand the understanding of the ways diverse AI approaches contributes to monitoring and achievement of sustainable development. However, 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 earlier stages, as illustrated in the data value chain. Instead, a wide range of factors can impact AI, which makes it difficult to predict its direction and how it will develop as the circumstances, such as data availability, algorithmic innovations, and policies evolve. Nevertheless, examining AI in relation to data value chain is still useful as this can help advance our understanding of AI for impact assessments.

Although many applications of AI are commercial, AI can also be employed to achieve socially beneficial outcomes. Referred to as AI for Social Good (AI4SG), AI systems can help to solve problems that are 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) used the SDGs as an assessment benchmark to evaluate AI4SG initiatives, finding 108 projects in total, and showed that every SDG is being addressed by at least one project involving AI. In the study by Vinuesa et al. (2020), 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, high energy requirements of AI could jeopardize the efforts to achieve this SDG, particularly if non-carbon-neutral energy sources are deployed (Vinuesa et al., 2020).

Another example of the potential benefit of AI is outlined in the recent paper by Xu et al. (2024), who showed that fertilizer management and tillage practices optimized at a local scale using machine learning and big data could reduce emissions from fertilizer by up to 38%. Hence, this use of AI could positively contribute to SDG2 (Target 2.4) and SDG13 (Target 13.2) 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 labor productivity, among others.

However, the risks of AI can surpass its potential, if not implemented carefully. Some of these risks include loss of jobs, harmful practices related to privacy, and the rapid spread of misinformation through the exploitation of social media. In order to leverage the benefits of the AI and address its risks and limitations, effective AI governance at a global level is necessary, as the processes and results of AI applications can have global level impact for better or worse. Therefore, in his report “Our Common Agenda”, the 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). 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 a global, multistakeholder cooperation is necessary to address the governance gap related to use of AI and other emerging technologies (United Nations, 2023).

In October 2023, the 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 following 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). If the Compact leads to a consensus on the governance of AI, this would provide a framework on the responsible use of AI overcoming or mitigating its risks and leveraging its potential for sustainable development globally and for all.

In the next section, we provide a brief description of the methodology used to conduct this study, followed by a presentation of the case studies in which AI is being used by NSOs. We then discuss the benefits and risks of the use of AI in this area, along with actionable recommendations targeting NSOs on how to leverage AI for sustainable development.

Methodology

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

As part of the desk research, we first reviewed the 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. We have substantive knowledge about the SDG framework including the SDG indicators due to our previous work on mapping citizen science contributions to the SDGs (Fraisl et al., 2020) and exploring how citizen science can contribute to the monitoring of health and wellbeing related SDG indicators and the WHO’s Triple Billion Targets (Fraisl et al., 2023b). Desk research also helped us identify the literature on the link between AI and the SDGs, as well as AI and sustainable development data and statistics.

We then used the case study method to investigate how NSOs are using AI to address their data gaps and needs, as well as improving their services. Three case studies presented here are as follows:

1. The Ghana Statistical Service (GSS) feasibility study for marine litter detection and reporting;
2. The National Administrative Department of Statistics of Colombia (DANE)’s approach to better understanding poverty and inequalities;
3. The Swiss Federal Statistical Office (FSO) and the Swiss Conference of regional statistical offices (CORSTAT) StatBot.swiss chatbot for sharing statistical information.

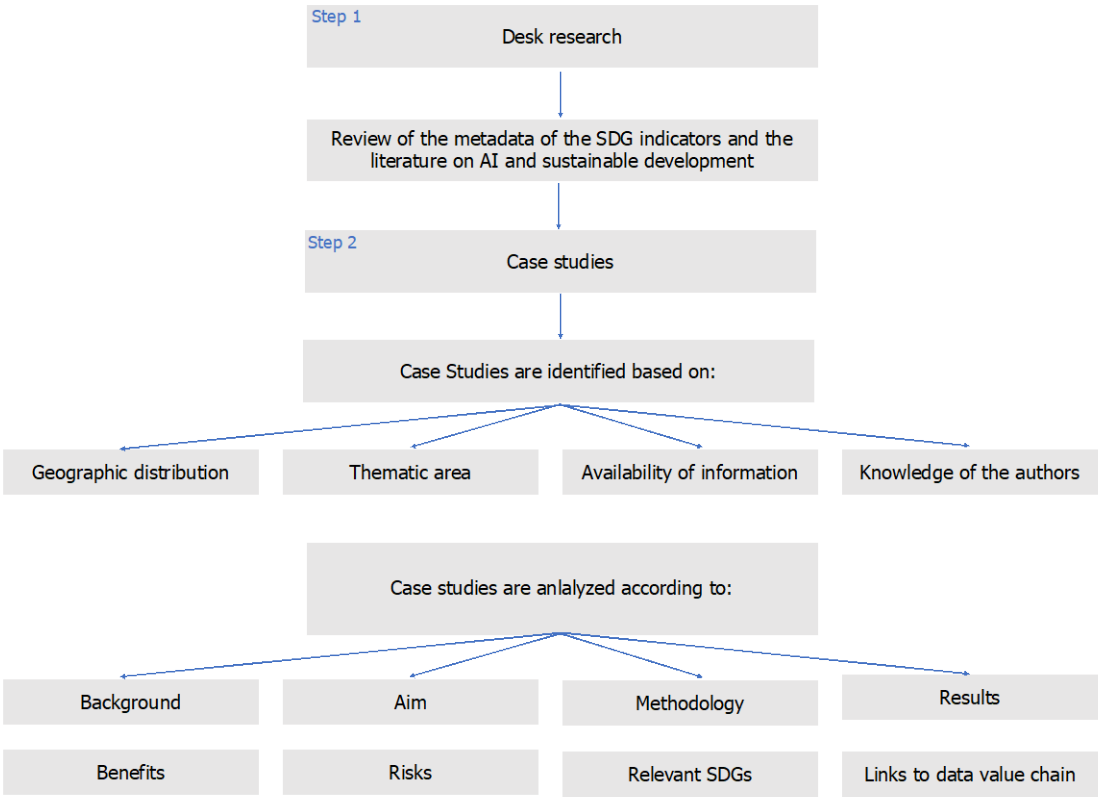
We identified these three cases based on their (i) geographic distribution to ensure a certain degree of representativeness, (ii) the thematic area they cover to demonstrate that a diverse range of topics can be supported by AI approaches, (iii) the availability of information online due to the time constraint of drafting this report, and (iv) our knowledge as we have been involved in initiatives in which AI is either used or planned to be used. We then analysed the three cases 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 is the problem/need the project addresses?
- 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 that has been applied in this paper.

Figure 3: The methodology of the research undertaken in this paper



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

Results

In this section, we present the three case studies according to the criteria selected as outlined in the methodology section.

1. The GSS 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; UNEP, 2021; Nelms et al., 2022). 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). 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 much susceptible to the negative impacts of marine litter. For example, Ghana was the first country to integrate citizen science beach litter data into their official statistics to address the lack of data issue on this matter. They also used these data in their 2022 Voluntary National Review and reported these data to the UN SDG Global Database as country-validated data for SDG indicator 14.1.1b *Plastic Debris Density* (Fraisl et al., 2020; UN, 2021; UN Ghana, 2022). 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 the entire coastline of Ghana in order to better target interventions.

Aim

Building on the work integrating citizen science beach litter data into Ghana's official statistics, the aim of this project is to understand the feasibility of using drones, citizen science, and AI to collect data along Ghana's coastline, identifying marine litter hotspots - areas with significant accumulation of litter and plastics (Fraisl et al., 2023c). The aim is also to complement the official methodology outlined for SDG indicator 14.1.1b and to help civil society organizations and other volunteer networks to organize more targeted beach cleanup 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 to address data and policy gaps for that purpose.

Methodology

The proposed methodology includes the integration of various technologies, such as drones, AI, and geo-visualization techniques, as well as 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 analysis 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 a 50 km extent, for a total of 200 km, was found to be the most favorable 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 cleanup efforts in the areas with high risk of marine litter accumulation.

Benefits

Through the use of AI, data gaps in marine plastic litter in Ghana along with information on what kind of plastics and where they are accumulated can be addressed much quicker in comparison with other data gathering methods such as in-situ data collection. AI approaches can help improve the availability and the quality of the data for addressing the marine litter problem and SDG monitoring needs. They can also support the efforts to improve decision-making processes emphasizing inclusive data ecosystems and citizen participation in decision-making due to the citizen science component of the project.

Risks

Although AI approaches can provide high accuracy for marine litter detection, data quality can still be an issue as the algorithm will rely on training data. Additionally, there may be risks related to data privacy and security as drone imagery will be used to detect marine litter, which means the system will be processing user-uploaded data and may store sensitive information. Additionally, the algorithm that was developed in a European country will be used in the project and it provides high accuracy, but the circumstances may be different in Ghana. For example, water sachets are used in Ghana to store and sell drinking water; however, this is not common in Europe. The algorithm 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. This can be addressed with the use of citizen science approaches that enable rapid classification of drone imagery.

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

Links to the data value chain

The AI approaches that are planned for use in the project have a direct link to the collection stage of the data value chain, as the main objective of the project is to identify, collect and process data on marine litter and harness the potential of new technologies for that purpose. The project also has links to the publication stage of the data value chain because it aims to support the analysis, release, and dissemination of data by producing insights on marine litter and using visualization techniques to communicate them. It also serves in the uptake stage as it can enable data use for decisions. Finally, it can help to achieve impact as part of the final stage of the data value chain, as the results are intended to be used for the development of an integrated coastal and marine management policy in Ghana.

2. DANE's approach to better understand poverty and inequalities

Background

Colombia is one of the countries that has been the most severely impacted by COVID 19. The economy shrank by 6.8% in 2020, resulting in 2.4 million job losses (DANE, 2020, 2021; PARIS21, 2022). According to DANE, 18.3 million people out of the 50 million in the country live in poverty, and among those, 6.9 million live in extreme poverty (Griffin, 2023). According to DANE, there is an urgent need to understand who are the most vulnerable as poverty affects different communities and individuals differently, leading to extreme inequalities. One of the primary goals of Colombia is to eradicate poverty through an inclusive strategy to ensure that no one is left behind including in official statistics. Therefore, DANE is specifically working on expanding the availability of data on marginalized communities. However, traditional methods such as censuses and surveys are not sufficient to make estimates at a higher granular level, as needed, but they are still useful due to their ground-truthing possibilities (Oviedo et al., 2021).

Aim

The aim of the initiative is to get 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.

Benefits

The benefit of the approach is gathering data at a high granularity to an extent that was not possible through the use of traditional sources of data, which can help to address disparities, allowing the government to formulate and implement policies that focus on the most vulnerable. This contributes to the leaving no one behind principle of the SDG agenda and is one of the highest priorities of the Colombian government.

Risks

The risks are not documented for this case study or at least not available online. However, the use of satellite imagery at a high granularity could pose privacy risks in such applications. Additionally, high performance computing resources and the requirement for efficient processing pipelines for large volumes of data could be another risk associated with this case study as this may require high energy use, which may be harmful to the environment.

Relevant SDGs

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

- Target 1.1: By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $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 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 per cent of median income, by sex, age and persons with disabilities

Links to the data value chain

The application of AI in the project contributes to several stages of the data value chain. For example, it helps to collect data from diverse sources and uses new technologies including traditional and non-traditional, making them interoperable. It also contributes to the publication stage as new insights, which were previously not available, are gained from data and visualized for better dissemination. The approach also supports the uptake stage of the data value chain because it has helped to significantly reduce the cost of data gathering, and it demonstrated the value of the data through the considerable increase in the number of data points on poverty. It also provided extensive information on the most vulnerable and marginalized populations at a much higher granularity. Finally, the approach can also support the impact stage of the data value chain as the results are intended to inform relevant policies for addressing the disparities between the rich and the poor and for implementing more focused action towards those who need it the most.

3. FSO and CORSTAT 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 because some technical skills may be required in some cases. There is a need to facilitate the exploration of open government data and statistical information for the public (Lavrynets, 2023).

Aim

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

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 standardized 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 this query from a database and presents the results to the user in a natural language form.

Results

A Minimal Viable Product (MVP) chatbot was ready by the end of 2023. A final report including lessons learned will be published in 2024 (Swiss Federal Statistical Office (FSO) Data Science Competence Center (DSCS), 2024).

Benefits

The benefits of the project include advancing data standardization and harmonization for statistical organizations to export their data into a common and standardized data space. The project also enables citizens to have easy access to statistical information, making data dissemination, uptake and reuse much easier and more efficient.

Risks

These types of tools have a certain error rate that can be problematic when they are used by the public looking for information from official sources (Swiss Federal Statistical Office (FSO) Data Science Competence Center (DSCS), 2024).

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

Links to the data value chain

The AI technique used in the project can support the collection stage of the data value chain as it helps to standardize and harmonize statistical data from various official sources and bring datasets into a common data space. This would then allow statistical information to be disseminated in a way that is easier to access and more understandable by the general public, contributing to the publication stage of the data value chain. AI can also support a reduction in the time-cost of data use and reuse, as otherwise it is not very straightforward to utilize these data, and this would require technical skills. The AI approaches applied here can also contribute to achieving impact by promoting data exploration and literacy and increase interest in the data.

Discussion

This study is an important contribution to the widely debated topic of AI in the context of sustainable development data and official statistics. AI is getting more and more attention from the official statistics communities and policymakers because it is increasingly affecting people's lives as its capabilities and use expand. Additionally, statistical institutions and policymakers need AI for more accurate, efficient, and insightful results. AI can increase the relevance and quality of official statistics by providing enhanced computational capacity, increased access to data, improved data collection, automation of tasks, real-time data, enhanced data visualization, accurate insights and much more. As a result, AI can help make many statistical processes more efficient and less costly. However, despite its great benefits, AI does not come without challenges and risks, which requires considerable attention because just like the benefits of AI, its risks can also be at a greater scale. In this section, we look at the benefits and risks of AI in the context of the case studies presented here and then discuss the benefits and risks of AI more generically.

Improved efficiency in data collection and use is one of the benefits AI approaches provide. For example, in the Ghana marine plastics case, AI can be used to automatically analyze data on the specific locations and types of plastics accumulated along the country's coastlines. In this case, AI approaches provide greater efficiency in comparison to traditional methods, such as individual beach surveys that are labor intensive and expensive to conduct regularly. Additionally, these surveys can only cover small areas and they are problematic to conduct in remote locations that are not easy to access. 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 marginalized communities, which is more up-to-date than traditional methods can offer. In the FSO and CORSTATS StatBot.swiss chatbot example, 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 all the time and not restricted to working-hours, it allows efficiency in delivering statistical information to citizens and it reduces the response burden of statistical institutions to relevant queries. Other benefits of AI in the context of the case studies presented here are increased data availability at a higher granularity, as well as the potential for policy uptake in Ghana and Colombia, and more effective communication and dissemination of data in Switzerland. Reduced costs is another common benefit shared in all three cases, in the Colombian and Ghanaian case in data collection, and in the Swiss case in data dissemination and potential uptake.

More accurate results can be another benefit offered by AI, but this would depend on the quality of the algorithms and the quality of the data sets used to train them. The 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 project has high accuracy, 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 for adoption in the project. This means that the volunteers will perform image classification tasks that will be used to improve the AI algorithm. In the Colombian case, data quality was assured through comparison with the data from the latest census. In the Swiss case, the project team reported on potential errors, which can be an issue as statistical organizations strive for the highest quality data to be made available from official sources.

Another finding from this study is the relevance of AI to the data value chain. By more effectively gathering, disseminating, and reusing data and by potentially producing positive policy and societal outcomes, each of the cases provided here contributes to all four phases of the data value chain, namely collection, publishing, usage, and impact. All of the case studies also touch on one or more SDGs, helping to improve their monitoring and support their achievement.

The case studies presented here are also subject to risks. For example, privacy is one potential risk related to the use of AI that cuts across the three case studies. 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 followed. 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. The use of AI chatbots in public institutions has grown in popularity in recent years. Even if privacy concerns may not apply to this specific initiative, they are a fundamental issue for chatbots in general and need special attention. Therefore, it is important to make sure that users are informed about the data that are 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 organizations engage in the use of AI chatbots, they need to make sure that the relevant laws and regulations are always adhered to, without any potential errors related to collecting data that could jeopardize privacy.

Another potential risk of AI is bias resulting from algorithms that are trained on non-local data. This may be a legitimate concern for example like Ghana, if not carefully addressed. Therefore, it is important not to transfer solutions from one context to another as is and develop AI solutions locally for localized issues if possible. Otherwise, necessary measures should be taken such as more training with local data to ensure that the local nuances are properly taken into account.

The fact that training and developing AI models may require large computational resources and significant energy and water consumption is another potential risk related to the cases presented here and others involving AI, as this may have a harmful impact on the environment (Strubell et al., 2019; Patterson et al., 2021).

The case studies presented here cover 3 examples, but the adoption of AI is starting to find its way into many NSO operations, although its full potential has yet to be reached. For example, Statistics Canada is using AI to detect greenhouses from satellite images (Hatko, 2021); Statistics Netherlands is using AI and aerial images to determine the proportion of green to grey areas in inner cities (Braaksma and Offermans, 2021); and Statistics Indonesia is harnessing the potential of satellite imagery and machine learning to map poverty (Wijayanto, 2021). In addition to NSOs, the UN agencies are also capitalizing on the potential of AI for the SDGs and sustainable development. The UN Refugee Agency (UNHCR) is using machine learning to predict the movements of displaced people (UNHCR, n.d.); the World Food Program (WFP) is using machine learning techniques and data from diverse sources to monitor and predict hunger in real-time in 94 countries (WFP, 2024); and GRID-Arendal, a UNEP 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 (SIDS) (GRID-Arendal, 2024). These are just a few examples of how the UN and other international agencies are already deploying AI, and the common objective of both the UN and the NSO-led initiatives is to use AI to monitor and support sustainable development more efficiently.

While AI has a lot of promise for monitoring and achieving sustainable development, it is important to highlight that if its risks are not carefully managed, these risks may even exceed its benefits. For example, not all the 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). According to the International Telecommunication Union (ITU), in 2023, more than 2.6 billion people lack access to the Internet (International Telecommunication Union, 2024). This limited access to the basic components of AI, such as connectivity, affordable devices and electricity, are contributing to widening the digital divide and inequalities (UN AI Advisory Board, 2023). 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 this (OECD, 2019; UNESCO, 2021). The lack of large amounts of high quality data needed to train AI algorithms is another issue, especially for the Global South, which may lead to the transfer of algorithms developed in other countries that do not recognize the local context and sensitivities. This, in the end, may jeopardize the quality of the results, further deepening inequalities (UNESCO, 2021). The technical skills gap that may exist in many NSOs, together with the financial limitations for setting up and operating AI approaches, is another risk that might hinder AI from realizing its full potential.

Another risk to the responsible adoption of AI is the absence of policy frameworks governing or regulating AI usage. This could result in additional risks regarding data privacy and protection as well as human rights violations more generically, all of which could jeopardize efforts to achieve sustainable development (UNECE High Level Group on Modernisation of Official Statistics, 2023). To address the governance and policy deficit of AI at a global level, the High-level Advisory Body on AI, which was established by the UN Secretary General, put forward some principles that can help expand the benefits of AI while mitigating its risks. These principles cover topics on (i) inclusive governance of AI including participation of all for the benefit of all, (ii) AI for the broader public interest involving diverse actors (iii) data governance including data privacy and security and the promotion of the data commons to help address societal issues, (iv) the need to govern AI in a way that is universal, networked and based on collaboration with diverse stakeholders, and finally (v) the need to anchor AI governance in the UN Charter, the International Human Rights Law, and other agreed international commitments such as the Sustainable Development Goals (UN AI Advisory Board, 2023).

Conclusion

In this paper, we focused on NSO practices provided as case studies to explore how AI can enhance sustainable development and what the potential risks related to its uptake are.

We argued that the benefits of AI range from climate change mitigation to improved healthcare, which can help better monitor and ultimately achieve the SDGs. In the context of development data and NSO operations, we proposed that AI can assist official statistics in becoming more efficient and cost-effective. Indeed, NSOs need AI, especially because new technologies and global challenges are making fundamental changes to the ways in which they operate. We also highlighted that AI is not without risks that call for careful consideration, as just like its benefits, its risks can also be quite substantial. Some examples of risks of AI, if not carefully deployed, include expanding the digital divide, widening inequalities, the violation of people's privacy and human rights and the harmful impact of AI operations on the environment.

In order to leverage the benefits of AI, while at the same time minimizing its potential risks in the context of sustainable development data and official statistics, we provide the following recommendations targeted at NSOs and the official statistics community:

- Develop an NSO or community-based strategy for the adoption and use of AI for sustainable development data and statistics by the NSO and other stakeholders;
- Build partnerships involving all the key actors, including academia, private companies, government agencies and international organizations in an inclusive way to unlock the full potential of AI for sustainable development data and for achieving the SDGs;
- 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;
- Ensure that humans are in the loop in the AI processes, from training to decision-making;
- Document and clearly communicate the risks of AI, as well as its benefits in each NSO and National Statistical System (NSS) operation where AI have been used;
- Ensure that the AI practices and processes deployed by the NSO and NSS do not harm human rights, fundamental freedoms as well as the environment as the carbon footprint of AI can be significant;
- Ensure equal distribution of the benefits of AI including vulnerable and marginalized communities;
- Carefully consider issues of safety and security in all AI initiatives such as cyber security for potential cyber-attacks;
- Measure the risks, and identify ways to mitigate these risks in the NSO's own AI operations, including those that involve third parties such as tech companies, by, for example, setting up agreements and engaging with tech companies that use open-source models and platforms;
- Build capacities among the NSO staff through national and international collaborations and by involving academia and private sector actors;
- Raise funds or invest in infrastructure necessary for AI deployment;
- Encourage the development of locally relevant AI solutions wherever feasible, for example, by training AI models with local data and by refining models developed abroad to better fit local circumstances and nuances;
- Raise awareness among the public to enhance both AI and data literacy.

Keeping up with the pace of AI is daunting, especially for NSOs, who are striving to produce high-quality results with limited resources, while at the same time upholding statistical standards. NSOs must embrace AI for its advantages and position themselves as trusted leaders in the responsible use of AI in this rapidly evolving field, while closely monitoring and mitigating its risks.

Next steps

We have prepared this paper as an input to the “Data and AI for Sustainable Development: Building a Smarter Future” Conference, organized by PARIS21, the World Bank and the International Monetary Fund (IMF). The conference brings together policy makers, NSOs, private sector representatives, foundations, international organisations, civil society, and academia to discuss how to leverage the potential of AI for sustainable development. The paper will serve as a framework for conversations on the application of AI, particularly for NSOs, and the benefits and risks of AI for sustainable development as its applications and capabilities grow. Our aim is to improve this paper based on the results of the conference, including the opportunities, challenges and best practices related to the use of AI presented and discussed at the conference. Any feedback from the attendees is much appreciated. Please get in touch: fraisl@iiasa.ac.at

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