AI FOR THE SDGS—AND BEYOND? TOWARDS A HUMAN AI CULTURE FOR DEVELOPMENT AND DEMOCRACY

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SDG1 - No Poverty
SDG2 - Zero Hunger
SDG3 - Good Health and Wellbeing
SDG5 - Gender Equality
SDG8 - Decent Work and Economic Growth
SDG9 - Industry, Innovation and Infrastructure
SDG10 - Reduced Inequalities
SDG11 - Sustainable Cities and Communities
SDG12 - Responsible Consumption and Production
SDG16 - Peace, Justice and Strong Institutions
SDG17 - Partnerships for the Goals

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ABSTRACT

Artificial intelligence (AI) can contribute to the United Nations Sustainable Development Goals (SDGs) and 2030 Agenda to end extreme poverty, advance gender equality, protect natural ecosystems, and promote inclusive societies, among others. One channel involves using AI and new digital "crumbs" to estimate SDG indicators to inform better decisions. Yet, in a world where democracy is increasingly tested, including by the influence of AI on inequalities and polarization, using AI to advance human progress and the SDGs calls for more profound changes than providing better fuel to old engines. The primary pitfalls and potential of AI are not technological, they are political and cultural.

Our chapter critically assesses the key tenets and gaps of the "AI for SDGs" narrative and initiatives. It also discusses the contours and conditions of a human AI culture where societies learn and improve using AI as an inspiration and as an instrument controlled by humans. This requires developing awareness, skills and systems for monitoring all SDGs— including the most politically sensitive ones related to press freedom—as well as considering new goals and fostering the participation and collaboration of all data subject-citizens in AI-enabled and AI-inspired initiatives.

To that end, we call on citizens, policymakers, scientists, educators, donors, journalists, civil society members and employees to read and reflect on the perspectives shared in this chapter, hoping they will help shape and leverage AI to promote and protect human development and democracy by 2030 and beyond.

INTRODUCTION

In September 2021, *Wired* magazine published an article entitled "How Valencia crushed COVID with AI" (Marx, 2021). Describing an award-winning initiative led by Nuria Oliver, one of the co-authors of this contribution, the article described an instance where artificial intelligence (AI), using cell-phone metadata combined with epidemiological and online survey data, was used by the government to inform policy decisions with direct effects on public health and economic activity. It exemplified a positive vision where AI, the new epicenter of the data revolution, could help humanity's march towards shared objectives, including the 17 United Nations (UN) Sustainable Development Goals (SDGs) and their underlying agenda, formally adopted by 193 Member States in September 2015.

In its simple version, the line of argumentation underpinning the mainstream "AI for SDGs" discourse is that the explosion in the quantity and diversity of data related to human actions and interactions collected by digital devices and services (i.e. Big Data), and the parallel improvements in algorithmic systems able to learn from these data (e.g., machine learning) may help policymakers, researchers, non-governmental organizations (NGOs), companies and other relevant groups to better measure, and in turn affect, processes and outcomes that are reflected in or relevant to the SDGs. Many initiatives and publications suggest that there is partial truth in this value proposition: AI-powered indicators, insights and initiatives can of course inform decisions and actions that contribute to the SDGs. But it is time to recognize that this argument and most of its surrounding discussions fail to delve into specifics, nuances, caveats and grey zones (Letouzé, 2015b).

For instance, a major problem with such discussions is the assumption that good intentions from decision-makers or global leaders are primarily hindered by insufficient or inadequate information and that simply alleviating that constraint, thanks to AI methods, would have a major impact. The reality is that the main bottlenecks to making data and AI work for the human development and the SDGs are not fundamentally technological. The main bottlenecks are incentives, power dynamics and imbalances that determine the control and use of key resources. For this reason and more, we believe that the "AI for SDGs" vision needs a clearer, bolder theory of change, and a better plan, based on firm conceptual and contextual grounds.

The present contribution focuses on two topics: (1) the neglected discussion about the role that politics, power, and ultimately culture play in the context of "AI for SDGs" efforts; and (2) the paradigmatic changes and ingredients that we think are required in order for AI to fulfill its expectations and defeat the most ominous predictions.

Our key proposition is to create the conditions for a human AI culture where AI will be used as an instrument controlled by humans and as an inspiration for nurturing learning societies.

To do so, we use an analytical framework referred to as "the Four Cs of AI," or 4Cs, that helps describe and discuss the core constituting elements and requirements of AI in a systematic and structured manner. We also propose a taxonomy of contribution channels—including the "measurement channel"—considering current use cases to unpack the theory of change linking AI applications and human development outcomes in an explicit way. We then use the 4Cs as a framework to summarize the main roadblocks and risks that current efforts face. Last, considering the political and economic resistance to change, we sketch the features of a new theory of change and vision that we call a human AI culture, which we argue may support the SDG and democratic agendas in the next decade and beyond, including the most politically sensitive SDG targets and other objectives.

AI AND THE SDGS: CONCEPTUAL AND CONTEXTUAL CLARIFICATIONS

AI is a discipline within computer science or engineering that encompasses a variety of methods and fields (Vinuesa et al., 2020), such as machine learning, computer vision, natural language processing and speech recognition, applied in a wide range of areas with varying levels of societal impacts. While AI as a discipline has existed since the 1950s, several interconnected factors have given it a boost and reboot in the past fifteen years (Lazer et al., 2009). First, the availability of large and rich sets of digital data provides the fuel of data-driven AI methods. Second, we have seen improvements in computing capacities and the development of sophisticated machine learning algorithms, called deep learning, that can learn from large-scale data by leveraging high-performance computing (King, 2013). Third, we have seen the emergence and growth of ecosystems of companies, research groups, public and international organizations and citizen-customers. Finally, the fourth factor that has boosted AI is the advent of a mindset and culture that values efficiency, predictability, and to some extent accountability, cost-effectiveness and measurement, rooted in the adage "you cannot manage what you cannot measure" (Weigend, 2013). A good example of the power of these factors working together is the improved performance of real-time language translation systems. Accordingly, building on past work (King, 2013; Weigend, 2013; Letouzé 2014; Letouzé 2015a), we propose that rather than a mere technological discipline, AI should be conceptualized and discussed as a socio-technological phenomenon made up of four key elements (Figure 1):

1. Crumbs: the pieces of digital data that humans leave behind (Pentland, 2012) as by-products of actions and interactions involving digital devices and services (Letouzé et al., 2013) (see Table 1 in the Annex). These constitute the raw input to data-driven AI methods.

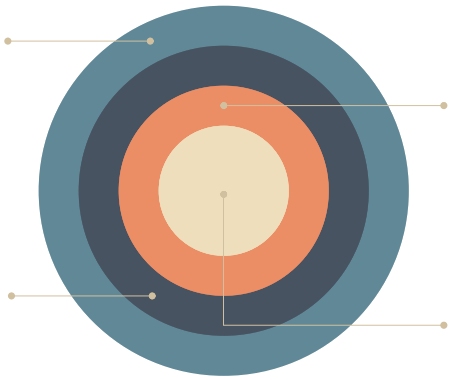
2. Capacities: the tools and methods, hardware and software, know-how and skills necessary to process and analyze these new kinds of data. They can be thought of as AI's infrastructure.

3. Communities: contributors, users and developers of AI systems operating and interacting under specific arrangements and regulations, including UN agencies and other stakeholders of the larger data revolution movement. They may be considered as AI's macrostructure.

4. Culture: the set of incentives, expectations, ideologies, and norms that shape and stem from the use of AI systems, i.e., AI's superstructure, in a Marxist sense.

| FIGURE 1 |

The four Cs of AI as a socio-technological phenomenon, based on Letouzé (2015).



The conceptual framework presented in Figure 1 helps assess and discuss the features and requirements of current and future AI in a structured and holistic manner, as part of a complex ecosystem. It is also useful to describe the genesis and context of the "AI for SDGs" and data revolution narratives and initiatives.

One of the first reports focused on the nexus of AI and SDGs actually predates both. In 2012, UN Global Pulse published a white paper entitled "Big Data for Development: Challenges and Opportunities" (UN Global Pulse, 2012), which laid the foundations of most discussions that have taken place since. In 2013, the High-Level Panel on the Post-2015 Development Agenda called for "a data revolution for sustainable development" (see Figure 2). A year later, an Independent Expert Advisory Group appointed by the UN Secretary General published a report titled "A World that Counts: Mobilizing the data revolution for sustainable development" (IEAG, 2014). The expectation was, and remains, that AI could help fight the dearth of official statistics in developing countries (Letouzé and Jütting, 2015), referred to a "statistical tragedy" (Devarajan, 2013) or "data drought" (*The Economist*, 2014), which would then improve development outcomes, as reflected in the phrases "better data for better decisions and better lives" (Melamed, 2018) and "data are the lifeblood of decision-making and the raw material for accountability" (IEAG, 2014).

| FIGURE 2 |

A New Data Revolution (United Nations, 2013).

"Too often, development efforts have been hampered by a lack of the most basic data about the social and economic circumstances in which people live... Stronger monitoring and evaluation at all levels, and in all processes of development (from planning to implementation) will help guide decision making, update priorities and ensure accountability. This will require substantial investments in building capacity in advance of 2015. A reqularly updated registry of commitments is one idea to ensure accountability and monitor delivery gaps. We must also take advantage of new technologies and access to open data for all people."

Bali Communiqué of the High-Level Panel, March 28, 2013

Many groups and efforts have argued they are leveraging AI for the SDGs (Vinuesa et al., 2020; Tomašev et al., 2020).[47] Yet, the fundamental question of how exactly AI is or may be affecting the SDGs—i.e., the underlying theory (or theories) of change at play—has not been sufficiently investigated and articulated. Authors of this contribution have proposed to examine various functions of AI, such as prediction and prescription (Letouzé et al., 2013), while others have proposed to structure analysis by sectors of impact (Vinuesa et al., 2020). In this contribution, the taxonomy built around four contribution channels and modalities is used with the aim of making the possible causal relationships between AI applications and real-world outcomes explicit: measurement and monitoring; precision and smartness; design, monitoring and evaluation; and all other business.

AI for the SDGs: Four contribution channels

The four main contribution channels that we identify are as follows:

1. A measurement and monitoring channel that aims to fill data gaps and improve situational awareness about specific SDG indicators or closely related indicators.
2. A precision and smartness channel via AI-based products and services that are explicitly designed to have an impact on one or more areas covered by the SDGs.
3. A design, monitoring and evaluation channel with the nascent development of AI-powered approaches that seek to design and deploy evidence-based policies and programs.
4. A channel covering all other business, which includes every other AI system not purposely designed with the SDGs in mind; their developers may never have heard of the SDGs, but these systems affect them down the road.

The list is far from exhaustive but aims to give a summary of the state of play in a structured manner.

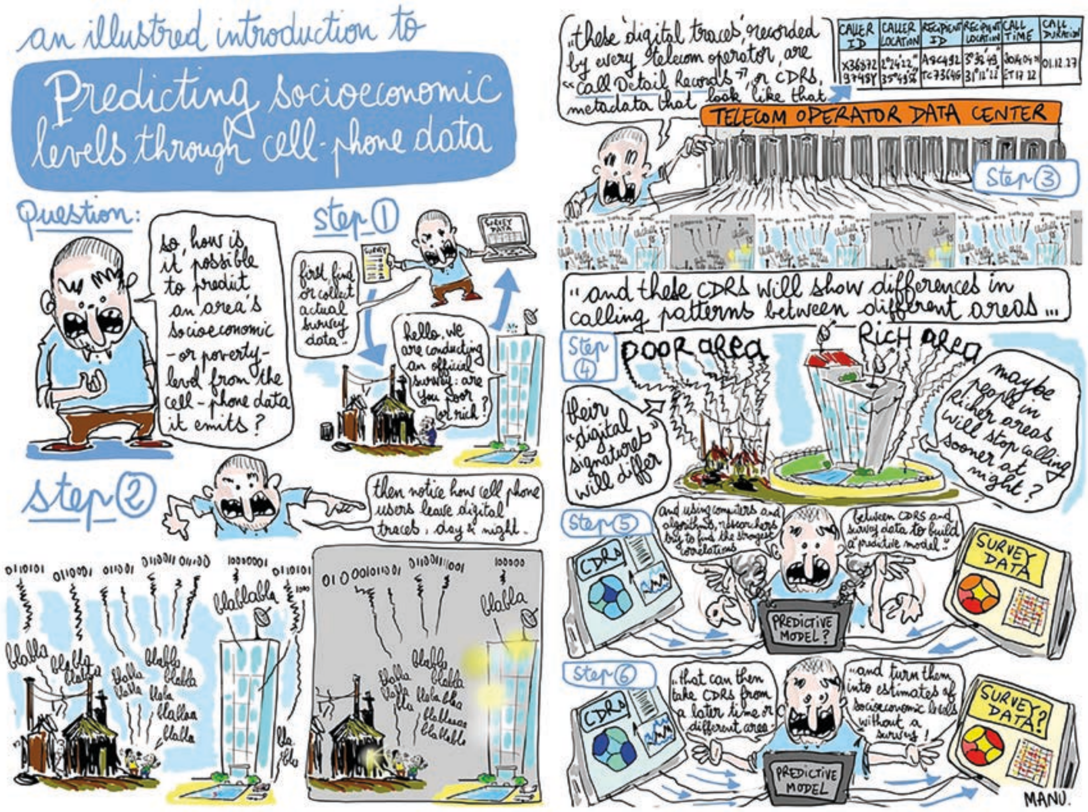
The "measurement and monitoring" contribution channel

As suggested above, it has now long been argued that AI could help promote the SDGs by helping measure and monitor them. Goals and related SDG indicators that have been measured or estimated by AI approaches are typically those that show up in digital crumbs (e.g., electricity consumption tells a lot about socioeconomic status) and are currently monitored through traditional data that provide ground truth. The basic tenets and steps of these approaches are described in Figure 3.

47. Lists of relevant efforts to leverage AI for the SDGs have been compiled in several repositories. For example, the ITU's SDG AI Repository (2021), the database of the AI4SDGs Think Tank (2021) and the database of University of Oxford's Research Initiative AIxSDGs (Saïd Business School, 2021), which lists over 100 projects.

| FIGURE 3 |

Predicting socioeconomic levels through cell phone data
(Emmanuel Letouzé, 2013).



Several problems with the “measure and monitoring” channel can be noted. One is the risk of state and corporate surveillance. Another is the scientific validity of some measures. For example, it is conceivable to develop social cohesion monitoring systems based on the frequency of physical and digital contacts derived from records of call details, but whether such interaction constitutes a meaningful and valid measure of social cohesion remains to be determined. Furthermore, such measurements are limited by and often reflect bias and structural inequalities, as discussed further in the next sections. Furthermore, there is a key question of whether and how better measurements of development outcomes such as the SDGs might affect these very outcomes.

The following section provides selected examples of the many studies and pilots that have used AI to estimate indicators falling under the 17 SDGs (Letouzé, 2015a; Oliver, 2021).

Examples of measurement and monitoring efforts by SDG

SDG1 has been covered by numerous efforts, leveraging Earth observation data such as light emissions and rooftop features (Jean et al., 2016), cell-phone metadata (Sundsoy et al., 2016; Soto et al., 2011), digital bank transactions and online ads (Cruz et al., 2019).

SDG2 has been covered by AI techniques that analyze weather data (USAID, 2010), satellite data, demographic data (Quinn et al., 2010) and socio-economic data (Okori and Obua, 2011) to detect hunger and crop yield in developing countries (Zhu et al., 2018; Ghandi and Armstrong, 2016).

SDG3 has been covered by AI methods through the monitoring of social media data to identify epidemics and outbreaks of various diseases as well as vaccine concerns (Letouzé, 2015b). Affordable wearable devices have also enabled the collection of large-scale longitudinal data (Clifton et al., 2014).

SDG4 has been covered by AI through machine learning methods that have aimed to measure students' attendance and performance levels, for example, through the use of socioeconomic and internet-based data to predict dropout rates (Freitas et al., 2020).

SDG5 has been covered by AI using social media data to identify domestic violence hotspots, as well as using other AI methods to identify gender bias and the participation of women in meetings through speech recognition, natural language processing and conversation analysis (Fedor et al., 2009).

SDG6 has been mapped by AI through different measures to detect and track major sources of water contamination (Wu et al., 2021), including drinking water networks (Dogo et al., 2019), as well as to estimate water consumption in rural and urban areas (Brentan et al., 2017).

SDG7 has been covered by AI through techniques that can estimate energy access for electrification and clean cooking fuel through highly frequent Earth observation (EO) (Pokhriyal et al., 2021).

SDG8 has been mapped by AI using satellite data to estimate GDP at national and sub-national levels, as well as through the use of internet-based data to estimate inflation rates (Letouzé, 2015b).

SDG9 has been covered by AI through techniques that can monitor existing infrastructures by analyzing aerial images (Bao et al., 2019; Ren et al., 2020; Xu et al., 2019), as well as detecting the construction of infrastructures, the production of pollutants in industry (Xu et al., 2015), and energy consumption anomalies.

SDG10 has been covered by analyses using airtime credit and mobile phone datasets to evaluate socioeconomic status (Gutierrez et al., 2013), as well as using mobility data and survey data to assess the inequity of access to urban spaces by different socio-economic groups (Letouzé et al., 2022).

SDG11 has been covered by AI techniques focused on urban planning, estimating urban density from aerial images (Lu et al., 2010), and studying transport use through transport cards data and identifying crime hotspots (Bogomoloy, 2014) and illegal drug trafficking (Li et al., 2019).

SDG12 has been covered by AI through the creation of land-use maps to provide an accurate picture of the state and use of natural resources (Talkudar et al., 2020), as well as inferring socially responsible consumption and disposal behavior (Talkudar et al., 2020).

SDG13 has been mapped by AI through satellite data to measure net primary production, make methane observations and monitor population- and energy-related greenhouse gas emissions (Letouzé, 2015b).

SDG14 has been covered by AI through projects that monitor the quality of oceans using deep learning methods, as well as aerial and satellite image analysis and classification that have enabled the estimation of the volume of plastic debris (Martin et al., 2018), estimate the CO_2 flux (Chen et al., 2019) and detect oil spills (Jiao et al., 2019).

SDG15 has been mapped by AI methods through the monitoring of deforestation (de Bem et al., 2020), forest quality (Zhao et al., 2019) and aboveground biomass (Madhab Ghosh and Behera, 2018), as well as the classification of wildlife (Tabak et al., 2018) and detection of illegal wildlife trade (Di Minin et al, 2019).

SDG16 has been covered by AI focused on corruption, through applying AI algorithms to government corruption (Adam and Fazekas, 2018) and financial transactions (West and Bhattacharya, 2016) and on extremism through language processing of social media content (Johansson et al., 2017).

"Precision and smartness" channel and efforts

Efforts in this channel that use AI do not seek to measure any SDG, but to optimize systems and processes that inform decision-making in areas covered by one or more of the 17 SDGs. They are typically described with the qualifier "precision" or "smart," applied to fields such as agriculture, medicine and healthcare, urban development and more. One example is the Famine Action Mechanism (FAM), which supports risk analysis, financing and programming to fight famine (SDG 2) (Badr et al., 2016). AI can also improve child welfare through the early detection of needs (Schwartz et al., 2017), which impacts inequalities (SDG 10). Other initiatives assist in clinical and public health decision-making, including by offering predictions of cancer, (Esteva et al., 2017), tuberculosis (Doshi, 2017), the probability of intensive care (Kaji et al., 2019) and mental health support needs (Walsh et al., 2017).

Other systems relevant to SDGs 9 and 11 aim to optimize garbage collection and recycling as well as predict solid waste patterns (Kannangara, 2018). Efforts to promote responsible consumption and production and climate action (SDGs 12 and 13) focus on the optimization of production systems, such as the estimation of the impact of logging in forests (Hethcoat et al., 2019) and predicting the occurrence and impact of extreme weather events (Lee et al., 2020; Radke et al., 2019; Wong et al., 2020, Pastor-Escuredo et al, 2014), such as the Artificial Intelligence for Disaster Response project that uses social media data (Ong et al., 2020). Still others include Intelligent Tutoring Systems (ITS) and educational interfaces to help design adequate learning tools for students with disabilities (Abdul Hamid, 2018), which is relevant for SDGs 4 and 10. Another example is *Bob Emploi* (Marion, 2018), a project that promised to help better connect job seekers and opportunities (SDG 8). Concerns associated with this channel are often centered around the fairness and governance of automated systems (Lepri et al.,2017).

"Policy design, monitoring and evaluation" channel and efforts

The possibility of using AI to improve policies and programs throughout their life cycles, from design to evaluation, has received much attention in recent years (Bamberger et al., 2016; Letouzé et al., 2019). One argument is that AI and new data sources offer the possibility to capture a target population's behavioral responses and perceptions using social media and other data sources in almost real-time. This feature helps answering the holy-grail question of policymaking: "Has this intervention worked?" or, better, "Is it working now?", thereby allowing a faster course correction. This line of thinking is summarized by a shift from proving to improving in the field of monitoring and evaluation (Letouzé et al., 2019). However, there are still few real-world applications. One example is the use of AI to better target social assistance (Noriega-Campero et al., 2020) by predicting false positives (i.e., people who benefit but should not according to the rules) and false negatives (i.e., people who do not benefit but should). Another is the use of AI to help detect government fraud (West, 2021).

But AI has contrasting effects on the "evaluability challenge." For instance, it is difficult to know the extent to which causality can be assigned between interventions and outcomes (Bamberger et al., 2016) because AI can create many feedback loops and echoes that further complicate causal inference and predictive power, as in the famous example of the "epic failure" of Google Flu Trends (Lazer et al., 2014). AI is poised to affect policymaking in fundamental ways in the future, including by helping identify new concerns and questions of interest. But it should not mean bypassing careful scientific design based on mixed methods, as guidelines developed to that effect have pointed out (Bamberger et al., 2016), and they cannot be a substitute for well-functioning democratic systems.

"All other businesses" channel and efforts

This final channel includes all AI approaches that are used and impact the SDGs daily in positive or negative ways without having been designed with them in mind (or while considering them only very remotely). Although this may be the single most powerful way in which AI affects the SDGs, it is impossible to say whether overall, and for whom, the net impact is positive or negative, both because of the multitude of effects on different people and groups and because these systems are still very new (Vinuesa et al., 2021). For example, Google Maps may reduce pollution and stress by incentivizing people to avoid driving when traffic is bad, but it can lead to fatalities if drivers are fiddling with their phones. Whether the AI-powered services that Amazon provides are overall positive or negative for people and the planet can be argued endlessly either way depending on perspectives and metrics. An important point is that AI effects must be assessed and discussed much more thoroughly, transparently and respectfully based on available data to maximize their positive impacts (Vinuesa et al., 2021), bearing in mind that there is hardly ever a definitive truth.

Key challenges and limitations in data, capacities, communities and culture

The challenges and limitations of current "AI for the SDGs" initiatives have been the subject of a large body of literature (Letouzé and Oliver, 2019). We summarize these challenges and limitations below using the 4Cs of AI as our framework: crumbs (data), capacities, communities and culture.

Crumbs: Locked, biased, messy and sensitive

We may be swimming in data, yet accessing and using these digital crumbs systematically and safely to train AI systems is a major challenge. Most AI crumbs are controlled—legally, practically or both—by private corporations that are often reluctant to share or facilitate access to them and that frequently collect such data with limited consent or control on the part of those whose data are being collected. One reason is commercial considerations: some companies are or may soon be developing their own commercial data-driven services as part of data monetization strategies, so they fear that sharing data may provide insights to competitors. In addition, some of these datasets contain personally identifiable information, which also raises significant reputational and legal risks that companies may not be willing to take. These concerns are especially salient for companies subject to the European General Data Protection Regulation (GDPR), given what we now know about the limits of data anonymization (de Montjoye et al., 2013; 2015) and even differential privacy in practice (de Montjoye et al., 2019). Some social media platforms have developed APIs (application program interfaces) enabling the automated sharing and standardization of data. However, many only allow the querying of archives of past messages. Although satellite data are usually less expensive than ground mapping—for instance, those provided for free by the United States' *National* Aeronautics and *Space Administration* (NASA) and the European Space Agency (ESA)—some remote sensing products are costly, creating a barrier to access.

A next challenge to data is stability and predictability of access to these data, given that many projects and pilots are yet one-offs, which limits the feasibility and desirability of using AI-based measurement and monitoring of human development indicators over the long run. Irrespective of the size and richness of any dataset, and perhaps especially with large complex ones, one must ask what information they really contain and convey. AI crumbs are typically non-representative of the entire population of interest and may reflect and exacerbate existing biases and structural inequalities (Bradley et al., 2021). As discussed in other contributions in this volume, models trained on such data will typically be irrelevant and in some cases unfair or dangerous to segments of the population that were not represented in the training datasets. These biases will tend to be greater with technologies that have lower penetration rates due to a lack of representativeness. This undermines interpretation and actionability as captured by the concepts of internal and external validities as well as the legitimacy of these systems (Flashcard Machines, 2011).

While all statistics shrink the human experience, leaving aside many of its facets, AI crumbs come from much less controlled collection processes than official statistics do. Many are unstructured and user-generated text, so information might be produced by fake profiles or by real people sharing information that may not accurately reflect their own perceptions or acts. A final challenge is the need to combine crumbs with official statistics in many cases for training and ground-truthing. This requires statistics to be easily available and accessible, which often collides with technical and trust levels (Letouzé and Jütting, 2015).

Capacities: HAIves vs hAIves-not

The second set of challenges and limitations to SDGs is the current extent of AI capacities. These encompass human, technological, scientific and financial aspects. A clear key message is that AI capacities are very unevenly distributed across the globe, with implications that are not yet fully grasped and, even less, addressed. Many nations, institutions and communities neither have nor can afford the kinds of equipment and human resources required to create and run the types of AI systems developed and used by top global universities and corporations. Despite progress in the past decade, Global South countries still lag far behind rich countries in all measures of technological capacities, and it is unclear whether the divide is shrinking or widening as a result of the COVID-19 pandemic (UNCTAD, 2021).

Human capacities are another obvious key limiting factor. An example is the lack or shortage of skilled staff in statistical offices in Global South countries, where young computer science graduates are more likely to be working in a local or global technology company than for an underfunded government agency. Popular analytics software such as Python and R may be free, but local staff may not be equipped or incentivized to use them. In general, the diversity of data sources and techniques involved in developing or using AI implies significant training and retraining needs (Dondi et al., 2021; Brown et al., 2019).

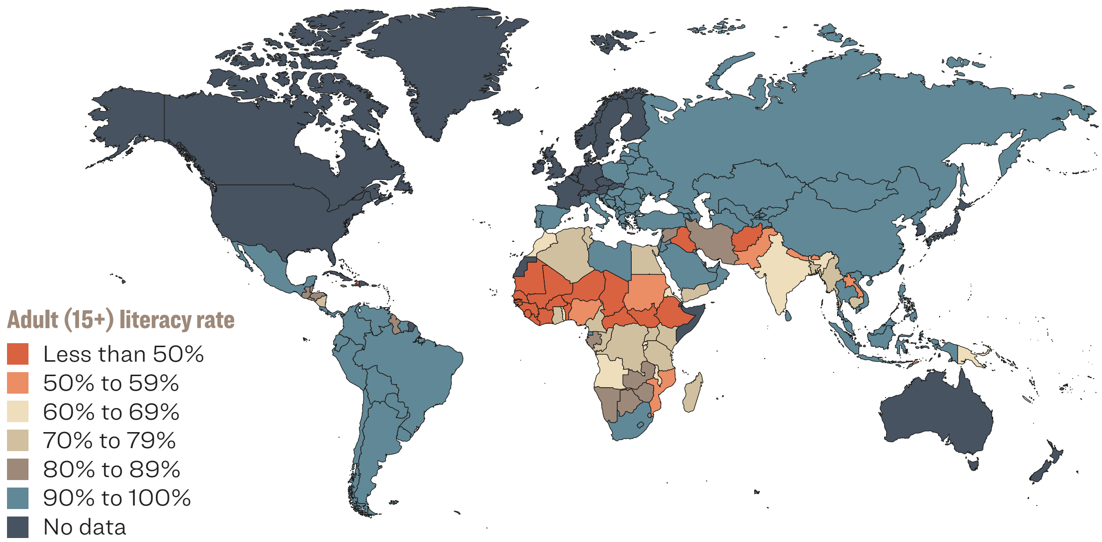
Beyond advanced techno-scientific capacities, key stakeholders generally lack the relevant skills, especially in developing countries—a situation which can be proxied by adult literacy levels (Figure 4). Calls to promote data literacy are welcomed, but these efforts must go beyond simply training students and professionals on how to code (Letouzé et al., 2015). Capacity constraints also include limited standardization of methodologies and technologies to access data in a privacy-conscious manner (de Montjoye et al., 2018), despite the promise of differential privacy[48] (Dwork and Roth, 2014) and attempts such as the Open Algorithm (OPAL) project (Roca and Letouzé, 2016). Techniques to correct for sampling bias using standard statistical techniques and sources are being developed (Zagheni and Weber, 2012; Letouzé et al., 2019), but more needs to be done to ensure that biases are systematically assessed and addressed in the original datasets.

Another capacity issue is the massive energy requirements and carbon footprint of AI-related data storage and processing. According to one study, energy consumption of data centers in Europe may grow 28% between 2018 and 2030 (Montevecchi et al., 2020), while another estimated that training one state-of-the-art Natural Language Processing (NLP) deep-learning model led to an emission of carbon dioxide equivalent to that of the average American in two years (Strubell et al. 2019). On the upside, energy-efficient infrastructures are being developed (Lei and Masanet, 2020), AI may help optimize energy consumption (Gao, 2014), and research is being conducted to better measure the carbon emissions of AI (Lacoste et al., 2019; Henderson et al., 2020; Cowls et al., 2021). However, these trends may still simply be unsustainable.

48. Differential privacy consists of performing a statistical analysis of the datasets that may contain personal data, such that when observing the output of the data analysis, it is impossible to determine whether any specific individual's data was included or not in the original dataset.

| FIGURE 4 |

Adult literacy rates by country (UNESCO, 2017).



Communities: Poor connections and inclusion

As in the case of the Valencian initiative, successful AI efforts require the participation of many stakeholders from the private sector, governments, academia, international organizations and civil society organizations (CSOs), even though their incentives, constraints, and priorities often do not match up well (Letouzé and Oliver, 2019). Some progress has been made in recent years to strengthen connections and trust between stakeholders, including through "data for good" challenges, such as the Data for Refugees Challenge, and other pilots and initiatives, including the European Commission's recent setup of an Expert Group on facilitating the use of new data sources for official statistics, following similar initiatives (Salah et al., 2018; Skibinski, 2020; European Commission, 2022). Collaboration modalities have been proposed to help develop projects within the AI community, such as Data Collaboratives and possible collaboration guidelines and goals (Tomašev et al., 2020). But key obstacles to such initiatives remain, such as the absence of clear business models for data-sharing, as well as regulatory uncertainties, ethical concerns and political calculus (Letouzé et al., 2015; Letouzé and Oliver, 2019).

The woefully inadequate inclusion and participation of marginalized, vulnerable and minority groups—not just in datasets but even (or especially) at the different steps of AI processes and projects—is still a major limitation to applying AI for SDGs. Data and AI systems are neither neutral nor objective; they reflect the questions and preferences of the groups that have the power to put them on the table. Ensuring data protection and individual privacy to mitigate potential harms is of paramount importance, but privacy should also be conceptualized to include group privacy (Kammourieh et al., 2017). Privacy should also include agency, i.e., the capacity of people represented in or affected by AI systems to have a say well beyond simply providing consent when prompted (Letouzé et al., 2015). One attempt at offering a medium for greater local inclusion and representation is the Council for the Orientation of Development and Ethics (CODE) set up by Data-Pop Alliance for all its projects (Letouzé and Yáñez, 2021). But much more needs to be done to promote the appropriate inclusion and participation of data subjects in AI systems.

Culture: When fears, distrust and greed get in the mix

Despite the enthusiasm for AI in some circles, the broad mood in the public space, and to some extent within the "AI for good" community, is one of distrust and fear (Ford, 2015; Ikkatai et al., 2022; Schmelzer, 2019). Mistrust in AI or in AI partners may limit the positive impact of AI on the SDGs and presents a great challenge because it is rooted in legitimate concerns fueled by repeated failure, public scandals and inter-state competition. At the same time, reining in the worst excesses of AI applications may result in overly restrictive legal and regulatory measures that may impede innovation.

Beyond legitimate concerns and grievances, resistance to change is fueled by habits and well-perceived interests. For example, early attempts at leveraging non-traditional data were met with deep skepticism in the official statistical community and government circles, both on scientific grounds and out of fear of losing relevance (Letouzé and Jütting, 2015). At the same time, there are limited incentives for some decision-makers to push for fundamental changes and investments in AI. Even assuming a high-performing AI system, decision-makers may decide to ignore the resulting insights. This decision gap, well known in the humanitarian sector, refers to the disconnect between information and action, which results in part from a lack of a habit of using data for quick decision-making or from a mistrust in such data, and from other political factors, as further discussed in the following section.

The apparent irrelevance of facts could be partly attributed to an overload of data that have "killed facts and truth" (Lepore, 2020). Also, as psychology has shown, it is very difficult for humans to change their minds and actions when such change is at odds with deeply rooted religious, political, economic and other cultural determinants of our identities, or when the behavior stems from an addiction (Kolbert, 2017). For example, over many decades, scientific evidence has proven the detrimental effects of our ways of life on carbon emission and biodiversity, and of alcohol consumption on our own health, but altering hard-wired beliefs and behaviors is very hard.

Trust is a key requirement in order for AI projects to function and for people to slowly come to terms with facts backed by science, which is typically better served by rational and respectful discussions. However, trust is often not strong enough between key stakeholders. An important conclusion drawn from experience and numerous studies is that intangible factors, unrelated to data, technology, skills or regulations, have a significant impact on whether and how AI is used for the purposes of public good (West, 2021).

Towards a human AI culture for human development, learning and democracy in the 21st century

In this section, we aim to propose a longer-term and innovative vision of how AI could contribute to human development objectives, including all the SDGs and beyond, and to democratic principles and processes. We question some of the basic tenets of the standard SDG agenda and discourse in an age of growing distrust and inequality, which are in part fueled by the ubiquity of AI in our lives. In doing this, we sketch the contours and requirements of a vision of a human AI culture.

Restating our problems with the standard "AI for SDGs" narrative

As mentioned above, the argument that AI can help promote human development through the SDGs is weakened by several hard world realities, of which we highlight two.

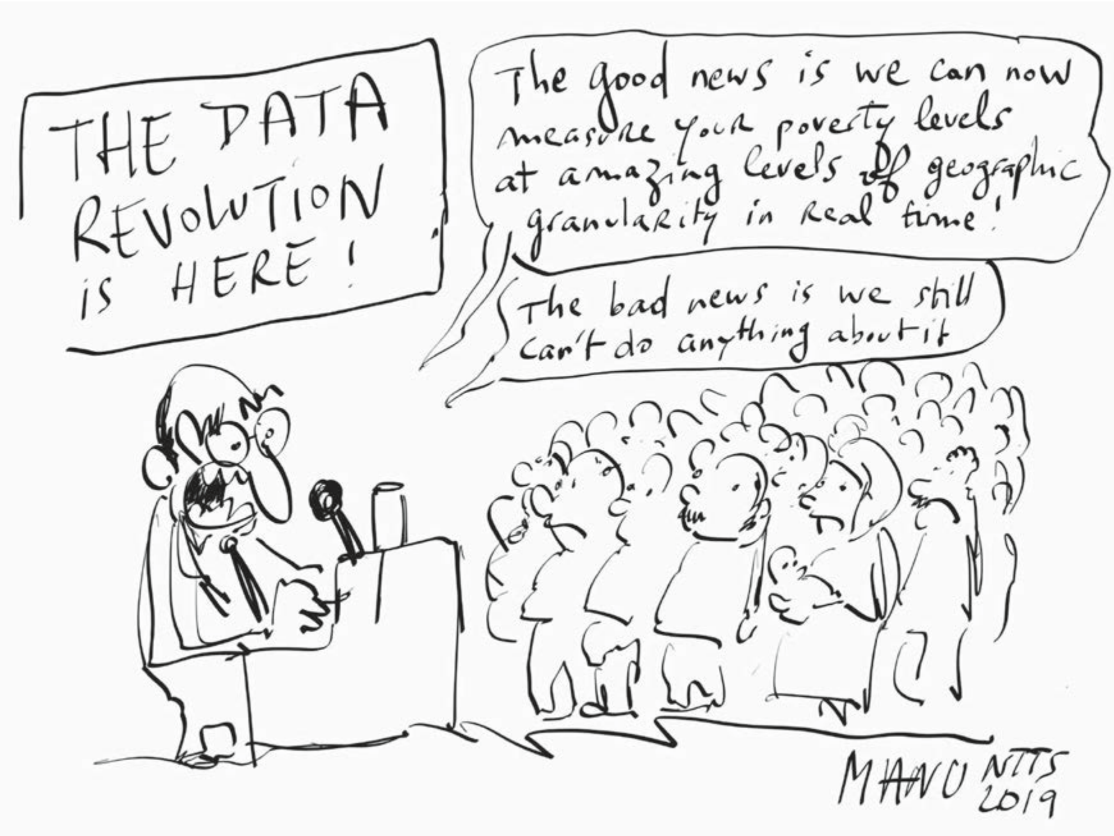
One is the nature and functioning of political regimes around the globe. Indeed, the SDG rationale and the common discourse of the "AI for good" community hinge strongly on the assumption that those making consequential decisions care about the wellbeing of citizens, and that all they lack is high-quality, timely and relevant data to make better decisions. It follows that measurements in this context matter the same way institutions are believed to matter, i.e., they are seen to have a causal effect on outcomes (Przeworski, 2004; Acemoglu and Robinson, 2012; Letouzé, 2018). In contrast, we argue that in the real world, some such leaders have little to no incentive to implement evidence-based policies, especially when the evidence suggests they should implement policies contrary to their political interests or simply leave office. At the same time, they have major incentives to leverage new technologies such as AI for population surveillance and control (Lillis, 2021).

The fact that the SDGs were signed by all 193 heads of governments of UN Members States at the time they were created is both their greatest strength and their greatest flaw. Strength, because, although they are not legally binding, the SDGs help societies hold these signatories accountable regarding commonly set and clearly stated developmental objectives. Flaw, because the nature of many of the signatories' political regimes are such that if any SDG or the whole enterprise had posed a threat to the status quo, they most likely would not have signed them. It has even been argued that the SDGs "undermine[d] democracy" by "pushing an agenda carefully calibrated to avoid upsetting the world's dictators, kleptocrats, and human rights offenders" (Smith and Gladstein, 2019). Although this statement may seem radical, it is not entirely without merit. Democracy appears to be retreating and autocrats have been emboldened by the COVID-19 pandemic. According to the Economist Intelligence Unit (2021), "across the world in 2020, citizens experienced the biggest rollback of individual freedoms ever undertaken by governments during peacetime (and perhaps even in wartime)" and "global democracy continued its precipitous decline in 2021." Income inequality and other forms of inequality continue to widen (Ferreira, 2021; Oxfam, 2022) and, at the time of this writing, the Pandora Papers scandal had just broken (ICIJ, 2021). With all these events combined, it seems naive to argue that the primary obstacle to poverty eradication, gender equality and environmental preservation, among others, is the lack of relevant and timely data or AI algorithms available to political and economic leaders.

The reality is that political and economic interests typically trump scientific evidence and official statistics in determining the priorities and policies that shape real-world outcomes (Figure 5). In this context, the standard "AI or data for good" and "data revolution" narratives may not only be inoperative, but also counterproductive, by providing arguments for development practitioners and politicians to evade accountability. By placing the focus on the dearth of data and the marvels that better AI-powered insights could enable, it is easy for them, especially those who are corrupt, incompetent or both, to claim they failed to improve X because they didn't have the right data on X. To be clear, in our view, poor countries and communities are not poor because their leaders lack good poverty data about them; they are poor and their poverty is not adequately captured because they do not count. When an engine is broken, improving its fuel won't do the trick. The question is, how can it be repaired?

| FIGURE 5 |

The Data Revolution is here! (will it improve all lives?), taken from Emmanuel Letouzé, illustration at the Eurostat NTTS event, March 13, 2019.



In this endeavor, AI can certainly help, though it presents certain challenges. In addition to the barriers to truly advancing AI for the SDGs posed by governments' conflicting political and economic interests, the second major issue is the role of AI-powered platforms in breaking down trust in experts, institutions, neighbors, and, ultimately, facts. A growing body of research suggests that social media platforms and technology giants that are effectively data companies with near complete market dominance are contributing to political polarization, and some fear that they may threaten the very survival of democratic practices and systems (Helbing et al., 2017; Bergstrom and West, 2020; Risse, 2021). This would also mean that objective benefits from AI such as the ability to detect cancer or fraud may be considered suspicious. The result is that AI can hardly be expected to seamlessly help "build back better" after the COVID-19 pandemic, amid multiple compounding ecological and socio-political crises under current conditions, without a fundamental change in how and by whom AI systems are developed, used and regulated—for whom and with what goals.

New legal and regulatory frameworks are emerging around the world to guide the use of data and AI. These developments, however, are largely region- or country-specific and fall short of effectively creating new global rights. Some examples include the right to be forgotten and the European General Data Protection Regulation (GDPR), which are not global norms and in effect result in unequal digital treatment of people. As our physical and digital lives become intertwined, there may be a more fundamental need to rethink our human rights and an equally fundamental need to formalize the rights and responsibilities of AI systems. The Asilomar AI principles[49] are an important first step in that direction (Future of Life Institute, 2017). However, they are limited to AI research and development and are not internationally agreed-upon rules and global norms subjected to enforcement and accountability, which are urgently needed to reduce the risk of a dystopian AI future, including the potential for AI warfare.

A question that is getting more attention is whether AI regulations should focus on ex-ante requirements or ex-post accountability. While the focus is currently on the former, the latter may be more realistic given the distributed nature of AI systems.

Features, requirements and expected benefits of a human AI vision and culture

Despite these worrying trends and growing concerns, we believe that AI can help promote human development and democratic goals. Fundamentally, AI systems are not just powerful tools that can help achieve specific tasks; they also show how data nodes and feedback together enable systems to learn to get better at reaching a set of shared objectives. Somewhat ironically, while AI was inspired by the human brain, we argue that AI could and should now serve as an inspirational analogy for better human systems and societies based on learning, provided the right ingredients are available, nurtured and used.

Following previous contributions, this idea of considering and using AI as both an instrument (narrow AI systems that excel at specific tasks) and an inspiration for human societies based on a renewed desire and ability for collective learning is referred to as “human AI culture” (Pentland, 2017; Letouzé and Pentland, 2018). The human AI culture fosters a vision of how the various parts (nodes) that make up human societies collaborate to learn and reinforce our progress towards shared goals, for which AI could be used as a tool. Such culture would, for example, question whether the goal of building a safer, more peaceful society is best served by the “war on drugs” and related mass incarceration policies that have been taking place in parts of North America over the past decades, or by other means (Pearl, 2018). In doing so, it may leverage AI to help suggest and test alternative approaches, but it may also prefer low-tech solutions.

A human AI culture would also consist of a vision under which the desirability and legitimacy of certain objectives—such as boosting GDP or maximizing profits—would be reassessed in a systematic and continuous fashion based on their effects, as in a learning system. The key requirements and ingredients of such a culture are relatively well known. For instance, it requires nurturing a culture of reasoned and rational discussion, cooperation and, therefore, trust between the nodes far beyond what is observable today between groups, such that measurement has a chance to matter the way it does in AI. In addition, it requires having accurate and timely input data and feedback information from which the system can constantly learn. Furthermore, it requires broad data literacy in societies (Letouzé and Bhargava, 2015), greater control from data subjects over data about themselves—for instance, through the development of data cooperatives or other data-sharing and access mechanisms (Pentland and Hardjono, 2020)—and free press (UNESCO, 2022).

49. See https://futureoflife.org/ai-principles/

The way towards a human AI culture would entail reviving or reinventing democratic principles of participation, self-governance and government by means of discussions based on rational compassion (Bloom, 2016), including and increasingly at local levels. It also requires developing incentives, means and habits for all stakeholders to demand that collective decisions be evaluated systematically. This evaluation should be conducted using the best available data and methodologies in order to adjust future iterations and contribute to a body of evidence on what actions yield which results. In this sense, to avoid deepening the inequalities that the digital economy seems prone to producing, such incentives, means and habits should involve a reconsideration of how different forms of capital—including digital capital—are shared (Gardels, 2022).

It will not be easy to build a human AI culture that places rational respectful discussions based on trust and facts at the core of a new social contract among humans and between humans and machines in 21st-century societies. This is true mostly because it implies addressing the excesses and abuses of powerful actors that are at the root of most humanity's ills and considering dissident voices and the complexities of human realities. As suggested above, it is not just about using AI to provide a better fuel to old machineries; it means and requires upgrading these systems, using AI as an instrument when and as needed, but also as an inspiration.

New indicators and the next SDGs agenda?

One concrete way to start drafting new indicators and the next SDGs agenda is to promote AI efforts that seek to monitor all SDGs' targets, notably the politically sensitive Tier 3 indicators under SDG 16, which seeks to "promote just, peaceful and inclusive societies." These include SDG indicator 16.6.2, "proportion of population satisfied with their last experience of public services' analyzing social media data" (Data-Pop Alliance, 2018) and indicator 16.10.1, "number of verified cases of killing, kidnapping, enforced disappearance, arbitrary detention and torture of journalists, associated media personnel, trade unionists and human rights advocates in the previous 12 months" (Muñoz et al., 2021). These efforts could garner support from international research and advocacy organizations as well as like-minded companies willing to put pressure on governments that are most reluctant to discuss and address these phenomena.

New goals that reflect new societal realizations and priorities should also be considered. Some groups are already suggesting new priorities, such as animal health, welfare and rights (Visseren-Hamakers, 2020), sustainable space (ITU News, 2021) or space for all (National Space Society, 2020), meaningful and safe digital life (Jespersen, n.d), ensuring the Digital Age supports people, the planet, prosperity and peace (Luers, 2020), development and disability (Le Marrec, 2016).

AI may also assist in identifying the SDGs that should be prioritized based on expressed public interests and feasibility studies. Such efforts should take place under human supervision through a carefully participatory design to ensure that they do not reflect structural biases present in datasets. The way to mitigate structural biases could follow a similar line to what has been argued for identifying research priorities in AI (Vinuesa et al., 2020) or for reflecting ethical values in AI systems (Rahwan, 2017).

CONCLUSION

The Data and AI Revolution need to be politicized. The COVID-19 pandemic has exposed and exacerbated pre-existing structural fault lines in our society. Our world is increasingly digital and unequal; while digitalization is steadily increasing, democracy and equality seem to be retreating. In this context, the rise of AI seems to be a perfect case of a Promethean fire. It can certainly help better measure and promote the SDGs and other human development objectives, despite challenges and obstacles in the way, which can be addressed with appropriate investments in data, capacities, collaborations and initiatives. But AI can also further fuel inequities, polarization and the breakdown of trust.

Fundamentally, we argue that the problems to address are not primarily technological. They are primarily political and cultural, rooted in personal greed, elite capture, power hunger and societal distrust. It follows that their solutions must be primarily political and cultural.

Thus, unless there is a recognition that the current standard “AI for SDGs” discourse—according to which the primary constraint is lack of indicators on the dashboards of global leaders—errs on the side of complacency or naivety, AI will not deliver on its promise. In a business-as-usual scenario, where AI remains controlled by individuals and groups driven by power and profit motives, AI is more likely to yield and fuel a future of technological control of citizens, with reduced choices and freedoms and lowered living standards for those on the losing side of rising economic, social, political and environmental inequalities.

But we are not giving up on AI. Paradoxically, while AI mimics the human brain, human societies could now try and take inspiration from AI systems by valuing and nurturing learning capacities and cooperation. We call this a human AI culture, and we describe this culture as using AI as both an inspirational analogy and a set of instruments to measure, monitor and reach commonly set objectives. The most critical objective is to uphold and protect democratic principles and processes. In particular, by giving all people much greater control and transparency over the design and use of AI systems that impact their lives. This must be coupled with clear and firm accountability and compliance mechanisms regarding the design and use of such systems. Perhaps the case of Valencia, Spain, mentioned in the beginning of this chapter, shows that a human AI culture can be achieved.

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| ANNEX | Taxonomy and examples of Big Data sources

Types	Examples	Opportunities
CATEGORY 1: EXHAUST DATA		
Mobile-based	Call details records (CDRs) GPS (fleet tracking, bus AVL)	Estimate population distribution and socioeconomic status in places as diverse as the UK and Rwanda.
Financial transactions	Electronic ID E-licenses (e.g., insurance) Transportation cards (including airplane fidelity cards) Credit and debit cards	Provide critical information on population movements and behavioral response after a disaster.
Transportation	GPS (fleet tracking, bus AVL) EZ passes	Provide early assessment of damage caused by hurricanes and earthquakes.
Online traces	Cookies IP addresses	Mitigate impacts of infectious diseases through more timely monitoring using access logs from the online encyclopedia Wikipedia.
CATEGORY 2: DIGITAL CONTENT		
Social media	Tweets (Twitter API) Check-ins (Foursquare) Facebook content YouTube videos	Provide early warning on threats ranging from disease outbreaks to food insecurity.
Crowd-sourced and online content	Mapping (Open Street Map, Google Maps, Yelp) Monitoring and reporting (uReport)	Empower volunteers to add ground-level data that are useful notably for verification purposes.
CATEGORY 3: SENSING DATA		
Physical	Smart meters Speed and weight trackers USGS seismometers	Sensors have been used to assess the demand for using sensors to estimate demand for high-efficiency cookstoves at different price points in Uganda or willingness to pay for chlorine dispensers in Kenya.
Remote	Satellite imagery (NASA TRMM, LandSat) Unmanned aerial vehicles (UAVs)	Satellite images revealing changes in, for example, soil quality or water availability have been used to inform agricultural interventions in developing countries.

An overview of initiatives addressing SDGs

SDG/impact field	Project or initiative	Organization	Data sources and tools	What is monitored or studied?	Description	Country or region	Implications of using data-driven approaches	Years	Tiers	Type of organization
Goal 16: Peace, Justice and Strong Institutions	FollowTheMoney.org	National Institute on Money in Politics	Campaign finance reports	Campaign financing	Compilation and categorization of **campaign finance reports** made open to the public	USA	Promote transparency in campaign financing, as well as promote open access to large body of cross-jurisdictional reports	2010–present	Tier III	Government
Goal 12: Responsible Consumption and Production, **Goal 8:** Decent Work and Economic Growth	Scanner data in the Swiss CPI: An alternative to price collection in the field	Swiss Federal Statistical Office (FSO)	Price scanner data	Consumer price index	Use **price scanner data** to calculate consumer price index for food and near-food groups	Switzerland	Improve the price collection of the consumer price index: improved quality, reduced costs and reduced administrative burden	2018–present	Not classi-fied	Government
Goal 11: Sustainable Cities and Communities, **Goal 12:** Responsible Consumption and Production	Using satellite imagery and geo-spatial data for the census of agriculture and the census of building and housing	Mongolia NSO	Satellite imagery, geospatial data	Crop production	Use of **satellite imagery and geospatial data** to identify crop types and estimate production to create a first agricultural by-census	Mongolia	Supplement existing data with satellite images	2017	Not classi-fied	Government
Goal 3: Good Health and Wellbeing	Assessment of the Potential for International Dissemination of Ebola Virus through Commercial Air Travel During the 2014 West African Outbreak	Flowminder	International Air Transport Association data, historic traveler flight itinerary	Ebola epidemic	Model the expected number of internationally exported Ebola virus infections, the potential effect of air travel restrictions, and the efficiency of airport-based traveler screening at international ports of entry and exit using **international air transportation data and historic traveler flight itineraries**	Guinea, Liberia, and Sierra Leone	Inform decision-makers on the potential harms of travel restrictions and most efficient screening sites	2014	Not classi-fied	Academic
Goal 2: Zero Hunger, **Goal 3:** Good Health and Well-Being, **Goal 5:** Gender Equality	Big Data and the Cloud – Piloting “eHealth” for Community Reporting of Community Performance-Based Financing in Ghana	World Bank Group	Mobile-based surveys	Effectiveness of Maternal Child Health Nutrition Improvement Project	Report performance of community-level health teams by using **Android-based software survey tools**	Ghana	Circumvent the time delay, capacity constraints and data quality challenges associated with paper-based reporting	NA	Tier III	International, government

SDG/impact field	Project or initiative	Organization	Data sources and tools	What is monitored or studied?	Description	Country or region	Implications of using data-driven approaches	Years	Tiers	Type of organization
Goal 1: No Poverty	Forecasting Poverty and Shared Prosperity Using Cell Phone Data	World Bank Group	Call-detail records (CDR)	Estimate and forecast poverty and shared prosperity	Measure population "digital footprints" by analyzing **cell phone records** using data mining and computer-learning techniques to estimate and forecast poverty and shared prosperity	Guatemala	Provide an affordable, practical and scalable solution for mapping poverty	2019	Tier III	International, government, private organization
Goal 1: No Poverty, **Goal 2:** Zero Hunger, **Goal 11:** Sustainable Cities and Communities, **Goal 13:** Climate Action	Predicting vulnerability to flooding and enhancing resilience using big data	World Bank Group	Google cloud data (elevation, satellite imagery, census data)	Flooding risk	Use of **Google cloud data, census data and satellite imagery** to refine surface risk predictions of flooding in Bangladesh	Bangladesh	Identify and define at-risk populations as well as improve DRM planning	2019	Tier III	International
Goal 11: Sustainable Cities and Communities	Fragile Cities	Igarape Institute	Structured and unstructured sources	Fragility	Rate cities on a fragility index using **structured and unstructured sources**	Worldwide	Understand the dimensions of city fragility through a data visualization platform	2010–2017	Tier I	Academic, NGO, international
Goal 5: Gender Equality	Chega de FiuFiu	Chega de FiuFiu	Crowd-sourced reports on harassment and gender-based discrimination	Gender discrimination, violence against women	Geolocate citizen reports to create a map that informs hotspots for dangerous and uncomfortable places for women using **crowd-sourced and geo-located reports of harassment incidents**	Brazil	Render visible gender-based street harassment hotspots	2013–present	Not classi-fied	NGO
Goal 5: Gender Equality	Mapping eVAW	Hamara Internet	Crowd-sourced reports on electronic harassment	Gender discrimination, violence against women	Geolocate **citizen reports** of Electronic Violence Against Women (eVAW) to map incidents of gender violence in different cities of Pakistan	Pakistan	Render visible gender-based street harassment hotspots	2014–2016	Not classi-fied	NGO, International

SDG/impact field	Project or initiative	Organization	Data sources and tools	What is monitored or studied?	Description	Country or region	Implications of using data-driven approaches	Years	Tiers	Type of organization
Goal 16: Peace, Justice and Strong Institutions	Ibrahim Index of African Governance	Mo Ibrahim Foundation	International agency information, data projects, surveys	Governance performance	Measure and monitor governance performance using **data aggregated, clustered and weighted from multiple sources**, including international agencies, data projects and surveys	Africa	Enhance the transparency and accountability of governance by joining multiple sources of data	2016–present	Tier II	International
Goal 5: Gender Equality	Hollaback!	Knight Foundation	Crowd-sourced reports on harassment	Harassment	Collect and track **crowd-sourced reports of online, street and other forms of harassment**	USA, Bosnia and Herzegovina, Canada, Colombia, and 12 other countries	Render visible rarely reported and culturally accepted harassment	2019	Not classi-fied	NGO