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Article

Operationalizing Digitainability: Encouraging mindfulness to harness the power of digitalization for sustainable development

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Abstract: Digitalization is globally transforming the world with profound implications. It has enormous potential to foster progress toward sustainability. However, in its current form, digitalization also continues to enable and encourage practices with numerous unsustainable impacts affecting our environment, ingraining inequality, and degrading quality of life. There is an urgent need to identify such multifaceted impacts holistically. Impact assessment of digital interventions (DIs) leading to digitalization is important specifically for Sustainable Development Goals(SDGs). Action is required to understand the pursuit of short-term gains toward achieving long-term value-driven sustainable development. We need to understand the impact of DIs on various actors and in diverse contexts. A holistic understanding of the impact it creates will help us align it with visions of sustainable development and identify potential measures to mitigate negative short and long-term impacts. The recently developed Digitainability Assessment Framework (DAF) unveils the impact of DIs with an in-depth context-aware assessment and offers an evidence-based impact profile of SDGs at the indicator level. We performed the impact assessment of diverse technologies using DAF. This paper summarizes the insights from the Digitainable Spring School 2022 on "Sustainability with Digitalization and Artificial Intelligence," one of whose goals was to operationalize the DAF as a tool in the action learning process with diverse professionals in the field of digitalization and sustainability. The DAF guides a holistic context-aware process formulation for a given DI. An evidence-based evaluation within the DAF protocol benchmarks a specific DI's impact against the SDG indicators framework. The operationalization of the DAF was carried out by looking at four different DIs: smart home technologies (SHT) for energy efficiency, blockchain for food security, artificial intelligence for land use cover and changes (LUCC), and big data for international law. Each of the four studies addresses different DIs for digitainability assessment using different techniques for a diverse group of indicators, demonstrating the potential of the DAF but also outlining the existing data gaps that limit a comprehensive analysis.

Keywords: Digitainability; Digitalization; Sustainability; Artificial Intelligence; Blockchain; Smart homes; Big data; Sustainable Development; SDGs; Technology Assessment Framework; Agenda 2030; Digital Age;

1. Introduction

Digitalization is driving the world towards an era where a significant part of our lives are reliant on digital technologies. These technologies are shaping the future by supporting the sustainable improvement of socio-economic, environmental, and climate-related concerns through more effective use of existing processes [1]. From fostering equitable access to education, to reducing poverty and improving healthcare services, digital technologies are instrumental in raising the quality of life and increasing access to resources. With internet access expanding to four billion people, almost twice as many as ten years ago, digitalization is breaking barriers by enabling prompt communication and networking, access to knowledge, and improved cost-efficiency. Digitalization brings together an innovative set of tools and techniques which enables the process of converting physically collected information and knowledge into a machine-readable language. As a result, robust integrated workflows that connect physical objects to the internet are being developed using embedded sensors, software, and other technologies that enable real-time data collection and analysis. Massive data analysis capability enables timely and informed decisions contributing to sustainable development [2]. Several challenges, however, have been left largely untapped to meet the Sustainable Development Goals (SDGs).

The United Nations (UN) Agenda 2030 [3] is a global roadmap defined by the United Nations (UN) toward equity and sustainable development with a horizon set in 2030. The 17 SDGs form the backbone of the UN Agenda 2030. They present a guiding framework for worldwide policies that guarantee a good life for present and future generations. In order to achieve the SDGs, it is crucial to reduce resource consumption, greenhouse gas emissions, poverty, and inequality, while at the same time expanding education, welfare, and combating biodiversity loss, to name just a few [4]. The SDG targets and indicators call for timely observation and reporting of the progression in member states of the UN [5]. Recent literature emphasizes that SDG progress can be aided by adopting innovative technologies for digitization, leading to accelerated transformation in many sectors. Digital interventions (DIs) have been a primary focus in most public discourses and policy circles [6]. The emergence of artificial intelligence (AI) and the development of machine learning (ML) have been deemed instrumental in achieving the Agenda 2030 [6–8]. However, it needs to be clarified how and to what extent these DIs provide opportunities and where they could lead to challenges limiting the progress of SDGs. This calls for the impact assessment for meeting the SDGs [6], given that AI promises significant opportunities for sustainable development and contributes to all the SDGs within the 2030 Agenda [9–14]. This potential gave birth to various initiatives such as the "AI for social good" paradigm [15,16]. AI is interpreted as the interaction of computing and cognitive science, providing insights by modeling and pattern detection, prediction, and optimization [17]. In combination with Big Data, AI catalyzes innovation through massive data processing, advanced computing, and clever algorithms able to untangle complex problems, thus augmenting human knowledge and decision-making and paving the way to sustainable governance [18].

Applying the DIs in specific contexts is often "wicked" with interlinked technological, social, environmental, and governance-related challenges. They are associated with positive and negative impacts [13]. On the one hand, the DIs can serve as levers and set off dynamic transformation towards sustainability in different sectors. For instance, various reports point to the potential of digitalization to boost energy productivity, avert resource waste, improve access to sustainable services, and establish new sustainable practices [4]. On the other hand, its development and use could trigger knock-on effects with a negative impact on environment, society, prompting a call for closer examination of the ethical and political issues associated with its rapid proliferation [19,20]. Given the fast evolution of technologies and the influence of both corporate interest in technology and policy-making towards this crucial crossroads for humanity, the existing literature is primarily concerned with the benefits of AI-based technology. As there are little empirical evidence of its inevitable trade-offs and unclear net benefits, these are often overlooked in the literature [21]. Moreover, most of the studies focus on the development prospects of the Global North while overlooking the infrastructure and capacity constraints of the Global South [10].

Much of the foregoing work has centered on identifying the role of the DIs for SDGs. However, most scholarly attention has been directed at identifying their relevance at goal level. Given that SDGs are composed of various targets and indicators, this approach is rather superficial. As a result, insight into the impacts of DI is limited by the fact that, to date, they have been measured from a narrow perspective. The gap also exists in understanding the context that defines the relation of the DI to SDGs progress. Nevertheless, it has been widely acknowledged that SDGs are interlinked, and the impact on one SDG can have cascading negative or positive impacts on other SDG targets and indicators. Thus, it is crucial we uncover the interlinked impact of the DI on SDGs in a more holistic manner, moving beyond the impact measurement of DIs on isolated SDGs. Instead of measuring the impact on a particular goal or target, the aim should be to establish a multidisciplinary view of the direct and indirect impacts the DI may have on all SDGs in the certain context. The context-specific assessment of the DI requires analyses in a broader system, whereby the impacts on most of the SDGs are considered integral to it.

Gupta *et al.* [22] and Vinuesa *et al.* [6] identified the role of the DIs at the target level, one level deeper. The limitation of these works is their consideration to evaluate the impact of selected DI on a specific target at a time but not exploring the interlinked consequential impact of the particular DI on all other targets and indicators of SDGs. Since sustainable development requires holistic actions on all the essential aspects, the most meaningful way to identify the real impact of technology is to identify where and how it supports bringing the change required for the advancement of all the SDGs. Indicators of the SDGs are the impact measures, reflecting the "what" has been achieved thus far. Therefore, it is essential to measure the 'what' change at the indicator level is achieved when the DI is utilized to measure consequential impact. As digitalization combines the individual, organizational and societal transformation brought by the multitude of algorithms and data-driven interfaces, utilizing it for sustainable development also needs diverse stakeholders' inclusiveness and active involvement with their perspectives. We need to understand the consequential impacts and mindfulness in using digitalization to support the achievement of SDGs and their specific targets. Digitainability is introduced by Gupta *et al.* [22] as the effort to uncover the impact of digital tools considering their interlinked impacts in a specific context with a multidisciplinary perspective to secure the mindful application of digital technology to foster sustainable development. This is a crucial step to investigate in-depth if and to what extent the potential offered by the DIs can be leveraged for sustainable development, particularly for achieving the goals of Agenda 2030 [23]. After its introduction, digitainability has been perceived as essential to capturing the cross-fertilization potential of digitalization and sustainability, the two mega-trends for innovation and new sustainable business development [24], but more from the theoretical perspective rather than a practical one. Quite recently, Gupta and Rhyner [23] in their article introduced the digitainability assessment framework (DAF) as a practical tool that can help operationalize the digitainability assessment of digital intervention (DI) in great detail with various levels of evidence. Assessing digitainability is essential to shape the development process for a more intelligent and sustainable digital future.

The DAF that incorporates context, the potential direct impact, indirect impacts, and cascading effects mapped for the SDG indicator(s) could be considered a practical approach to assess the impact

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of DIs. Utilizing several levels of evidence, the DAF approach is instrumental in holistically identifying impacts and detecting potentially unforeseen implications. This comprehensive assessment further facilitates the mapping of impacts, taking into account long-term and short-term priorities in a given context. By undertaking a holistic assessment, the potential pathways that enable or inhibit the growth of the SDGs can be measured and used to support sustainable digitalization. Overall, the DAF is an effective tool that helps consolidate a vast amount of multidisciplinary knowledge to deeply understand the interlinked direct, indirect and progressing consequential impact of the DIs for sustainable development.

In this paper, we explore the operationalization of DAF digital technologies in a real-world scenario and how it paves the way towards mindfulness in applying a DI for sustainable development. We operationalize the DAF to assess the digitainability of the DIs to encourage mindfulness in their application. The paper presents the outcome of the Digitainable Spring School 2022 (DSS), which involved four groups thoroughly analyzing the digitainability of a specific DI in light of the SDGs. The DSS aimed to bring together a diverse group of experts and practitioners from different disciplines having experience working at the intersection of digitalization and sustainability. In order to fully explore and identify the strengths and weaknesses of the DAF and the impacts of a DI on SDGs, a study-based analysis of the methodology was deemed appropriate. The primary outcome of the DSS was a practical application of digitainability as a concept and an enriched analysis of the impacts of DIs for SDGs, considering different perspectives and contributions using the DAF as a methodology.

The paper is structured as follows: Section 2 elaborates on the methodology we have undertaken for this study and further expands on the methodological consideration of the DIs. in Section 3, we present the results after operationalizing the DAF for selected DIs, followed by a detailed discussion on the findings of 4 studies in Section 4; finally, conclusions are drawn in the Section 5.

2. *Method: Digitainability* assessment

Considering the overarching topic of digitalization and sustainability, diverse stakeholders such as practitioners are usually not typically inclined to engage with research that they consider the realm of specialized academic researchers. They are more favorably prone to ‘doing’ and experimenting using trial and error, discussions, reflection in, on, and after taking action, considering the action cycles for transformation. To foster sustainable development, it is paramount to promote exchanges between diverse disciplines and the research community to convert concepts into practices focusing on inclusion, collaboration, and participation. This is all the more important considering the importance of digitainability for mindful sustainable digital transformation. Identifying and defining the key aspects and processes of digitalization and sustainability that are interdependent and vital for maximizing holistic sustainable development is essential.

In order to conduct the digitainability assessment, we utilized the action learning approach [25], a participatory approach that drew on the expertise of participants of the Digitainable Spring School (DSS). Action learning is a group-based process of engaging, learning, and reflecting, where a group of peers interact under the guidance of a facilitator for a given time-frame to address a specific real-world issue in real-time [26]. Participants identify real problems in the discussion from their experience and seek to develop innovative and creative ways to solve them [27]. The DSS brought together an international group of real-life practitioners and experts in digitalization and sustainability for action learning. Based on their experience with certain technologies, they operationalized the DAF as a tool for understanding the complex impact of the DIs on sustainability. In this section, we discuss the detailed assessment and evidence they have gathered based on the DAF methodology. Given their diverse background, disciplines, and expertise, the DSS participants combined into a single arena their multidisciplinary views on standardization processes, reflections, and perspectives on the theoretical and practitioner contexts that supported the process of digitainability assessment. This paper brings forth the operationalization process, how expert groups approached the digitainability assessment process, and their recommendations for digitalization and sustainability practicing communities.

The DAF is used to systematically analyze the intra- and interlinked impacts of DIs on SDGs [23]. It is designed to help perform technology impact assessments and map them considering various synergies, trade-offs, and complex interlinkages between SDGs at the indicator level within certain contexts. The analysis results are visualized in the form of a heatmap or matrix, presenting not only the impact results (synergy, ambivalent, trade-off, bi-directional or uncertain) but also including the context and the main SDG indicators under focus. Four groups conducted the digitainability assessment using various forms of evidence from a multidisciplinary perspective and identified strengths and weaknesses in the methodology and data gaps regarding DI and SDGs. The four DIs are: Smart Home Technologies (SHT) for energy efficiency, Blockchain for Food Security, AI for Land Use Cover and Changes (LUCC), and Big data for International Law.

2.1. Group 1: Smart Home Technologies (SHTs) as DI for energy efficiency

The concept of "data-driven smart sustainable cities" has emerged from the advancements in information and communications technology (ICT), particularly big data, coupled with alarming worldwide challenges related to the environment, climate change, natural resources and energy consumption [28]. In this context, numerous strategies are presented in order to reach resource efficiency and climate responsibility through modern technologies. These include "smart grid and advanced metering infrastructure", "smart buildings", "smart home appliances and devices", and "environmental control and monitoring" [29]. In particular, energy efficiency represents a crucial, effective method to overcome environmental challenges and meet the growing demands in energy [30].

In this respect, SHTs for energy efficiency exhibit many opportunities for innovative technological solutions by combining big data analytics, the IoT and associated smart sensors and meters, and machine learning technologies and techniques. Thus, this technology provides better monitoring, control and conservation of energy [31].

From the perspective of household residents, the implication would be greater awareness, control, and efficient monitoring of energy/electricity consumption. From the operator's perspective, this approach allows not only for precise monitoring and analysis of electricity consumption but also enables forecasting electrical energy consumption using data mining and machine learning methods; this is beneficial specifically when power is drawn from renewable power plants that are highly dependent on the weather [32].

Group 1 focused on the question of *how STHs impact the achievement of SDGs considering digitainability?* To answer the question, the DAF methodology was applied. The analysis mainly focuses on the SDGs 7, 8, 9, 10, and 11 considering their relevance to the intended application of DI. In order to analyze using the DAF, grey literature was used.

2.2. Group 2: Blockchain as a DI for food security

Recent trends in global food sustainability and improved nutrition show growing concern, and food security is far from guaranteed for all [33]. Following several decades of substantial progress in reducing hunger by several hundred thousand people [34], food insecurity is regaining ground year after year [35]. When world grain prices soared in 2007-2008, the Malthusian spectre of a "global food crisis" was brandished by the media. Ever since, the problem of food insecurity has returned to the agenda while the rise in the price of food commodities, of which Russia and Ukraine are major producers, is at its highest level since 2008 [36].

DI can help transitions for addressing the challenges of food and agricultural systems, supporting the timely achievement of SDG 2 (End Hunger) and 12 (Responsible Consumption and Production). The DI, such as blockchain, brings commercial transaction standardization to improve security and reduce costs. Several recent studies (e.g., Tyczewska *et al.* [33], Feng *et al.* [37], Nurgazina *et al.* [38], Patidar *et al.* [39]) have highlighted the positive and potentially transformational nature of blockchain, particularly concerning the reconfiguration of market exchange. Research suggests that

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blockchain systems may reduce uncertainty, insecurity, and ambiguity in transactions by providing full transactional disclosure and unified truth to all participants in the network Zhao *et al.* [40], Xu *et al.* [41], van Hilten *et al.* [42]. The blockchain is also increasingly deployed in areas where traceability and product auditing is essential, such as the supply chain in food systems [38]. Group 2 focused on the question of *how blockchain technology can support the fulfillment of goals 2 and 12 while considering holistic sustainability, socio-economic and environmental aspects?*

2.3. Group 3: AI as a DI for Land Use Cover and Changes (LUCC)

Given the high level of interest and the need to understand various processes that are triggered in one part of the globe and affect certain processes in another part of the globe, AI has been introduced as a powerful information tool to address this issue. Many approaches, such as Machine Learning, Deep Learning, Agent-Based models, and others are used to empower AI for better tracking of Land Cover/Use patterns.

Implementing machine learning algorithms can help to detect the land type, as well as spatial and temporal trends in land class/type over time. Machine learning algorithms can be used to assess the accuracy and validate the results of land classification. Thus, the method can benefit from predicting future scenarios of land use change and implementing an accurate and reliable system to monitor land class and type. It has the potential to allow large-scale interventions across space and time. In this study, we consider the following SDG Indicators: Forest area as a proportion of total land area (SDG 15.1.1) and the Proportion of land that is degraded over total land area (SDG 15.3.1).

Halting and restoring land degradation is a crucial priority to protect biodiversity and ecosystem services that support life on planet Earth [43]. AI is heralded to serve this purpose by encouraging "conservation biology" [44]. According to Vinuesa *et al.* [6], AI could bring positive contributions for 88% of the targets related to the SDG 15 (life in land), and negative impacts for 33% of them; however, sound empirical evidence is lacking so far [21]. The main contribution of AI relies on enhancing the monitoring and surveillance systems by leveraging multiple data sources from remote sensing [45] and satellite-based earth observation and geospatial information [21,43,46,47]. Global datasets suffer limitations in terms of resolution and accuracy, while EO information (e.g., LandSat, Sentinel) is mostly free and open access, available for large regions, providing long time series and data continuity, representing a complement to traditional statistics for the SDGs monitoring [46,47].

Therefore, merging AI and EO provides reliable and disaggregated data for better monitoring of the SDGs [48,49] facilitates data analysis, capacity for measurement and efficient interventions [50]. Nevertheless, despite the progress in geoscience, the net impact of AI on SDG 15 is still poorly understood. Yu *et al.* [51] claim that the use of AI to determine land use and cover change (LUCC) in arid ecosystems has not been sufficiently researched but can provide predictions about land degradation and guide policies to mitigate potential issues. Isabelle and Westerlund [52] explore AI's role in positively contributing to the SDG 15 targets. Indeed, the literature evidence contributions of AI to several SDG 15 targets (SDG 15.2, 15.3, 15.5, 15.7, 15.8) ranging from predicting deforestation and enhancing forest management [53–56], managing land degradation [43,56], combating poaching and protecting endangered species [57,58]; halting biodiversity loss and habitat degradation [44], reducing invasive species [59,60], spotting plant diseases and fires or identity seeds [61]. Kolevatova *et al.* [62] claim the relevance of explainable AI (XAI) to support the climate effects of land changes (land cover, deforestation, urbanization) with enhanced computational time and data usage. Palomares *et al.* [61] underscore the great potential of AI systems for SDG 15 while claiming the need for high-quality open data and infrastructures.

Nonetheless, some limitations are also observed. Isabelle and Westerlund [52] stress that ML and DL training is complex and time-consuming, demanding large amounts of data and skills which are not always available (e.g., endangered species), particularly in the least developed countries with a lack of universal access to datasets, computing power and capacity. High-resolution data is needed, but its costs are beyond the reach of small farmers. Using AI for deforestation or even maintaining digital infrastructures are perceived as a challenge in these contexts due to logistic problems. Besides, major forests/habitats (e.g., Amazonia) are also subjected to restrictive national policies [52,61]. Group 3 focused on the question of, *how AI for LUCC monitoring impacts the holistic SDGs achievement?* In this study, we applied and complemented the DAF with literature from the Scopus database.

2.4. Group 4: Big Data as DI for International Law

The analysis of Big Data as DIs in the context of International Law is intended to examine its potential role in designing treaties and how it impacts the progressing SDGs. In the field of International Law, there is a growing academic interest in the phenomenon of "big data." However, the relationship between International Law and the massive use of data has not yet been explored [63]. "Big data" is a broad concept that cannot be reduced only to the notion of an extensive data set because this concept includes (among other things) the analysis techniques applied to the data [64]. Similarly, Boyd and Crawford [48] concluded that "less about data that is big than it is about a capacity to search, aggregate, and cross-reference large data sets." Under those considerations, carrying out the analysis of the SDGs in the light of Big Data and International Law is an opportunity to study and propose an effective mechanism for compliance with the SDGs. When two or more States agree on a specific object and wish to give legally binding value to said agreement, they conclude a treaty [65]. In that sense,D

Target 2.5 and its indicators propose international cooperation at various levels. It aims to promote access to fair and equitable education as well as share the benefits derived from the use of genetic resources and associated traditional knowledge. It also seeks to increase investment, correct and prevent trade restrictions and distortions in world agricultural markets, adopt measures to guarantee the proper functioning of the markets for primary food products and their derivatives, and facilitate timely access to information on the market, including on food stocks, to help limit extreme volatility in food prices [66]. Unfortunately, according to the United Nations [67] the quantity of people suffering from hunger and food insecurity has been rising continuously since 2014. Due to the inadequate solutions at the international level, it is urgent to update and adjust the mechanisms of international law in order to achieve SDGs [68]. The group focused on the question of *what are the possible impact of Big Data could have on the achievement of the SDG 2 through international policies' platforms?* The analysis explores the state-of-the-art within the framework of the DAF methodology.

3. Result/Outcome

3.1. Group 1: Smart Home Technologies (SHTs) as DI

The results of the digitainability assessment conducted by performing the literature review illustrate (Figure 1) that indicators 7.1.1, 7.1.2, 7.2.1, and 7.3.1 have a synergistic impact. Data-driven solutions hold great potential for energy security, energy equity, and environmental sustainability [69,70]. Energy savings of 12%-20% can be obtained by introducing smart household products [71]. According to an Australian study, SHTs can identify the best energy sources at the right time, reduce costs and optimize accessibility and sustainability [72,73]. Another synergetic impact shows that it is possible to identify and predict energy poverty based on satellite images accessible through big data technologies [74]. Considering the long-term impact of SHTs, their use over the next ten years will allow us to achieve the objectives of reducing CO2 emissions at the global level [75,76], enabling households to operate in "zero emission" mode [77]. Further, data-driven solutions through IoT are a potential way to increase the share of renewable energy. Smart information systems (smart grids) allow the integration of renewable energies and can ensure energy security and sustainability[71,78,79]. In the renewable energy context, meteorological data can be used to forecast production and thus support the decision-making of the energy systems [80].

Nevertheless, the question of whether data-driven solutions promote energy sustainability remains. This question highlights the ambivalent and bi-directional impact of the different data-driven solutions on the energy sector, focusing on 7.1.2 and 7.2.1 indicators. In fact, data-driven solutions

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require high energy requirements and carbon footprints [6]. Notwithstanding the above, indicators 7.a.1 and 7.b.1 are considered to have an uncertain impact on the DI.

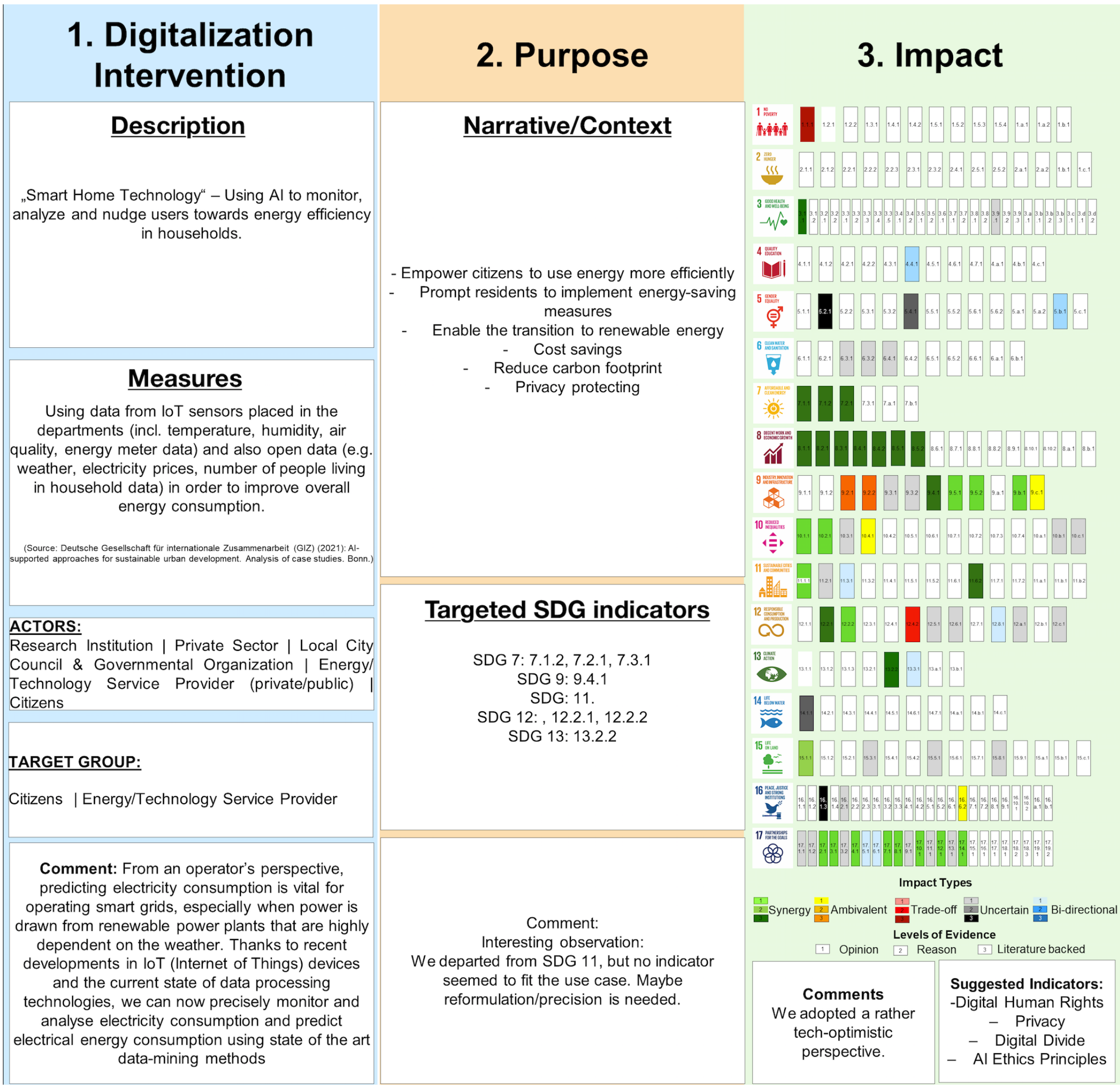

Figure 1. DAF outcome of Smart Home Technologies as DI.

With regard to SDG 8, a synergistic impact supported by the literature has been reported for the indicators 8.1.1., 8.2.1., 8.3.1., 8.4.1., 8.4.2., 8.5.1., 8.5.2.; whereas no impact was noted for the other indicators. Previous evidence showed that household energy efficiency could help boost the economy and increase national GDP; this was conveyed in studies and use cases from the UK and Canada [81–84]. For instance, in the UK, a potential 5% improvement in energy efficiency (through technological improvements), would result in an increase in the national GDP by 0.10% in the long term [81]. In Canada, researchers also found that "investing in energy efficiency is a significant net benefit to the economy". It will add 118,000 jobs (average annual full-time equivalent), and increase GDP by 1% over the baseline forecast over the study period (2017-2030) [82]. Moreover, the impact of SHTs is observed in creating jobs and employment. Direct jobs will arise from recalling energy service companies, as well as indirect jobs for skilled professionals along the supply chain, such as energy auditors and home energy raters, contractors, as well as retailers, and product distributors. In addition, workers hired into new direct and indirect jobs would spend their income on goods and services in the local economy, hence positively impacting the economy through the redistribution of savings [81,83].

Nevertheless, other authors suggested that "the introduction of increased energy efficiency should be spread over all or at least a wider range of households for more effective impacts on energy efficiency" [85]. The reason for this suggestion is the “rebound effect” (when an item price decreases, users tend to use it more, eroding the benefits of household energy efficiency). Furthermore, energy efficiency would indeed have a positive impact on the economy if users were correctly educated on the effective ways of dealing with energy efficiency, i.e., not using the income coming from energy saving to buy appliances that are not energy-efficient. Some studies also showed a more positive impact when in-home displays were available [84,86].

The literature review did not disclose a strong correlation between SHT and SDG 9. SHT impact is ambivalent owing to potential new business models that can again have positive as well as negative impacts on the value-added by manufacturing processes. Indeed, Smart Home systems are often part of a larger socio-technical system of the Smart Home bubble that triggers the introduction of other systems into the 'home' (indicator 9.2.1) [87–89]. In addition, the impact of DI on indicator 9.2.2 is ambivalent due to the new demand for smart home energy experts and the way the system is maintained and produced. This leads to other trigger effects of household demand for traditional heating/energy systems and consumers take over work from service providers [90]. Another ambivalent impact is for indicator 9.c.1 due to controversy in the inequality and accessibility of modern mobile infrastructure, knowing that the Smart Home system needs a modern mobile infrastructure to communicate and receive data via IoT or 5G network [91]. From the point of view of synergistic impact, smart energy management at home and the need for a transition to renewable energy are more probable, especially since the overall growth in ICT energy demand is increasing dramatically (indicator 9.4.1) [87,92,93]. Indicators 9.5.1, 9.5.2, and 9.b.1 have a synergistic impact based on opinion due to public and private sector funding and research, as well as the high interest in implementing these systems, as they are deemed necessary for the energy transition. The DI is being implemented by large energy providers and established technology providers, with little room for smaller-scale industries. It is possible to create start-ups or new digital business models that can leverage smart home energy. This aspect brings an uncertain impact based on opinion (indicators 9.3.1, 9.3.2).

Regarding SDG 10, more studies are needed on a national level in order to prove a synergy impact of the DI overall. Nevertheless, if implemented within a well-crafted national policy, one could argue for such a positive impact (based on opinion, indicators 10.1.1, 10.2.1). The same could be argued for the labor share of GDP, especially when it comes to the green jobs created through this technology. However, the consequent loss of traditional jobs should also be accounted for, hence leading to a potentially ambivalent impact of the DI (based on opinion, indicator 10.4.1.). In addition, an uncertain long-term impact of the DI could be observed regarding the proportion of discrimination or harassment, alongside the total flow of development resources between countries and the costs of remittances (based on opinion, indicators 10.3.1., 10.b.1., and 10.c.1.).

In the context of SDG 11, i.e., to “make cities and human settlements inclusive, safe, resilient and sustainable”, the SHT included within the setting of “data-driven smart sustainable cities” seems to be an optimal representation, thus explaining the synergy impact on indicator 11.1.1 (based on opinion). A bi-directional impact is also presented for indicator 11.3.1, the “ratio of land consumption rate to population growth rate”, given that it could influence and be influenced by the DI (based on opinion). One additional interesting synergy impact of this DI is on indicator 11.6.2 (annual mean levels of fine particulate matter (e.g., PM2.5 and PM10) in cities (population weighted), literature-backed); previous evidence showed the positive impact of building energy efficiency measures on air quality [94]. While this DI is promising on the environmental and sustainable development level in smart cities, much more is needed to observe an impact on the other indicators in this goal, showcasing other crucial - even more urgent - problems that this particular DI could not solve, namely disaster risk reduction, providing personal safety, especially for women, children, older persons and persons with disabilities, waste management, and supporting least developed countries.

As such, the smart-grid energy-efficient technology may best be introduced as part of a comprehensive national policy, along with other smart home digital interventions such as energy-efficient appliances and monitoring water and air quality, while also integrating renewable energy resources. In addition, this DI needs to be established in a wider range of households for an optimal impact. Further, policies are needed to ensure the SHTs are implemented in the right way while respecting the ethical aspect of the DI, including the privacy and security of residents.

At the indicator level, there are few similarities between several indicators of the same goal, while the potential for synergy and trade-offs between them has not been considered. In addition, the multidimensional aspect of the indicators makes their interpretation ambiguous and contradictory. Another aspect of the different limitations is that the indicators have been formulated at a global level, with countries having different, sometimes contradictory, interests, actors, and technologies. The independence between national statistical offices, the prioritization of the SDGs, and the different reporting systems of the countries are also aspects that limit SDGs and potential indicators.

The DAF helped to assess the impact of the SHT on the SDGs and provided a means of examining this association more scientifically and adopting a broader, multidimensional perspective of analysis. Hence, it provides the foundation for a more purposeful, wiser, and inclusive implementation of digital interventions for sustainability.

3.2. Group 2: Block chain as a DI

To investigate potential responses to food production, distribution, and consumption challenges, the group undertook an exploratory approach to understanding state-of-the-art regarding the potential of blockchain technology as a DI in the context of food systems using DAF. To make the data interact, the group undertook a literature review at the intersection of these three contexts: distributed ledger technology (blockchain), zero hunger, and sustainable consumption and production. We focused on the context of developing countries with a significant number of consumers, producers, and retailers participating in the process. E.g., household food waste could indeed increase by 50% by 2030 due to the growing consumption of the middle classes in developing countries [95]. We examined the interactions between the various goals and targets and the extent to which they reinforce or conflict with each other.

Overall, the result (Figure 2) of this group exercise demonstrates that food traceability with distributed ledger technology enables verification of food provenance by immutably recording end-to-end transactions, which could prevent food waste and improve trust among stakeholders [96]. The technology can help achieve food safety and establish trust between actors by increasing the number of trusted transactions and verifying food provenance [97]. Application of the DI put in place an infrastructure that fosters a more responsible production and consumption pattern in the food supply chain to reduce food waste [40]. Monitoring and traceability of food can ensure the food is marketed within its life cycle [97].

For SDG 2, we identified four indicators that were found to be relevant but were somewhat ambiguous as to their potential impact. For indicator 2.3.2 (Average income of small-scale food producers, by sex and indigenous status), the literature pointed to the empowerment of farmers (e.g., Ekawati *et al.* [98]) and other stakeholders (e.g., Kochupillai *et al.* [99], Patel *et al.* [100]) through data as well as the potential increase of farmers' income [101]. Regarding indicator 2.4.1 (Proportion of agricultural area under productive and sustainable agriculture), several papers underscored that food safety traceability systems which are backed up by big data and the IoT ensure agility, transparency, integrity, reliability, and safety of traceability information (e.g., Feng *et al.* [37], Vivaldini [102], Zheng *et al.* [103]). Furthermore, the connections between food security and climate change, as well as related risks and their respective stress on water and soil resources, are acknowledged [104]. A particular emphasis in this regard was placed on the context of developing countries such as India, where the public distribution system (PDS) could be explored [105]. Regarding the indicator 2.5.1 (Number of (a) plant and (b) animal genetic resources for food and agriculture secured in either medium- or long-term conservation facilities), Rao *et al.* [106] highlight the need for DNA-based technologies in, e.g., in meat markets. In terms of the 2.c.1 Indicator of food price anomalies, traceability across an extended number of stakeholders improves blockchain-based trust management [40], bargaining power, and democratization [107], which can be fostered through the involvement of state actors [108]. Additionally, competition between traditional and online channels may prove valuable [109], although the cross-channel information strategy and its relation to performance remain unclear [110].

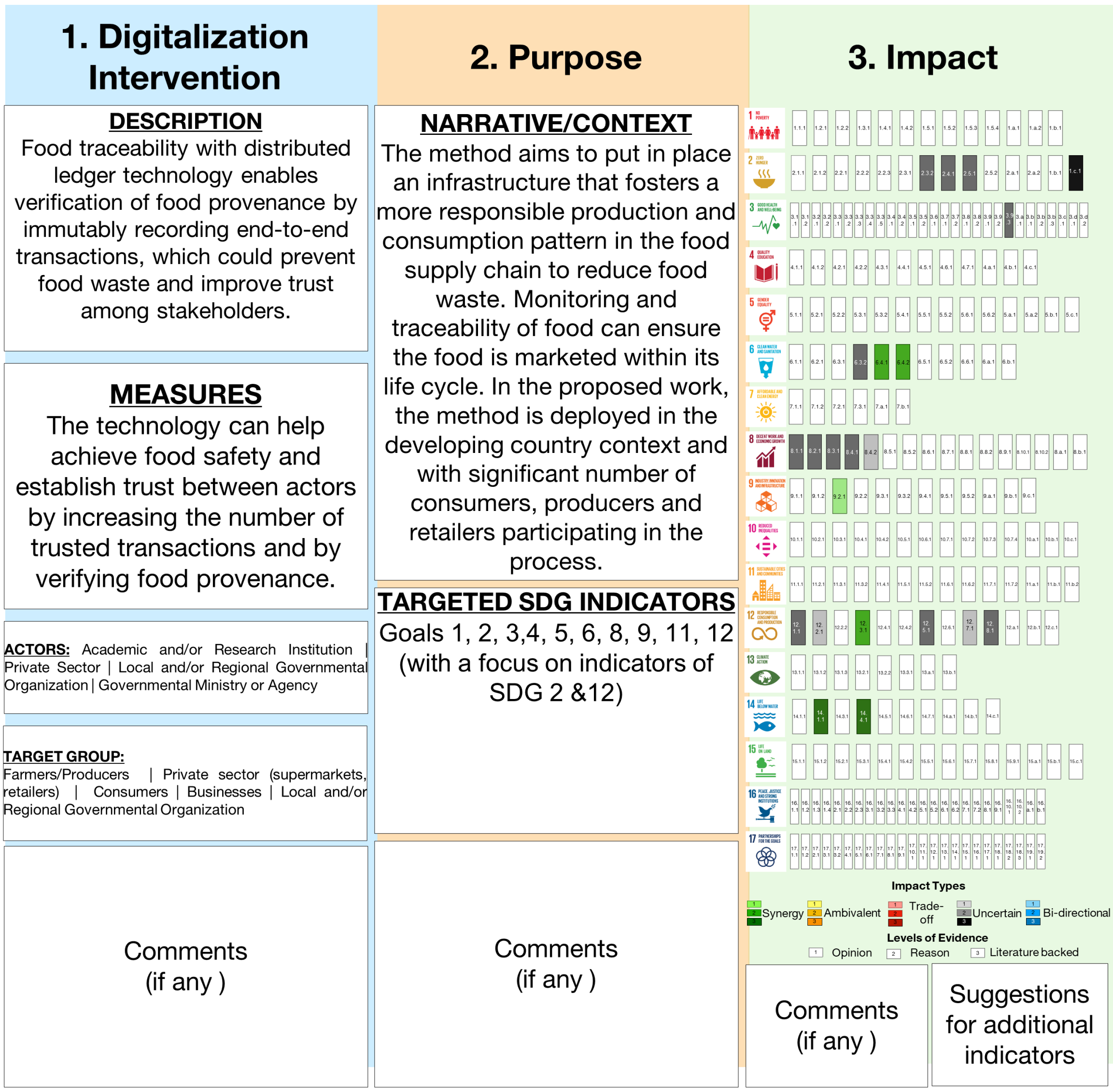

Figure 2. DAF outcome of Blockchain as DI.

For SDG 3, 3.9.3 (Mortality rate attributed to unintentional poisoning), blockchain yields a dubious impact on food selection and the spread of polluted foods (e.g., Nurgazina *et al.* [38], Behnke and Janssen [111]), wrongly labeled foods that caused death to customers [41] or improved efficiency while also addressing concerns about animal welfare, environmental sustainability, and public health [112]. As for SDG 6, 6.3.2 (Proportion of bodies of water with good ambient water quality), blockchain shows limited evidence of impact on real-time water quality monitoring [113]. There is potential for synergistic effects with the indicators 6.4.1 (Change in water-use efficiency over time), and 6.4.2 (Level of water stress: freshwater withdrawal as a proportion of available freshwater resources), as crops can be irrigated and managed with higher precision (e.g., Arsyad *et al.* [114], Duan *et al.* [115]). Additionally, blockchain may be instrumental in generating insights on the characteristics of soil and

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water, climate conditions, treatment with pesticides and fertilizers, production process, traceability, transparency, labor and human rights, quality and safety, waste reduction, authenticity, relationship with stakeholders, etc. (e.g., Iftekhar *et al.* [104], Luzzani *et al.* [116]).

The impact on SDG 8 is stated but not definite by the indicators 8.1.1 (Annual growth rate of real GDP per capita) and 8.2.1 (Annual growth rate of real GDP per employed person), although the potential for a major impact on employment in the agriculture sector is discernible (e.g., Nurgazina *et al.* [38], Chen *et al.* [117], Fan *et al.* [118], Guo *et al.* [119]). The indicator 8.3.1 (Proportion of informal employment in total employment, by sector and sex) highlights the diversity of affected actors who could nonetheless be expected to benefit from the blockchain technology [120], such as SMEs [121]. Using blockchain can improve the indicators 8.4.1 (Material footprint, material footprint per capita, and material footprint per GDP) and 8.4.2 (Domestic material consumption, domestic material consumption per capita, and domestic material consumption per GDP) insofar as it improves supply chain operations economic, social, and environmental efficiency (e.g., Nurgazina *et al.* [38], Fan *et al.* [118], Tripoli and Schmidhuber [122], Yadav *et al.* [123]).

For SDG9, 9.2.1 (Manufacturing value added as a proportion of GDP and per capita) elaborates on the potential of blockchain technologies for the procurement contract and industrial added value and operational performance [124–126].

For SDG 12, 12.1.1 (Number of countries developing, adopting, or implementing policy instruments aimed at supporting the shift to sustainable consumption and production), integrating organic, kosher, or halal certification into the blockchain could reassure stakeholders [127] and ensure fairer supply chains [128]. In that line, indicators 12.2.1 (Material footprint, material footprint per capita, and material footprint per GDP), e.g., optimizing energy consumption [129], 12.3.1 ((a) Food loss index and (b) food waste index) and 12.5.1 (National recycling rate, tons of material recycled) highlight food waste issues [130–133]. As such, blockchain is seen as a potential solution to contribute to the circular economy (e.g., Tripoli and Schmidhuber [122], Rejeb *et al.* [134]). The indicator 12.7.1 (Degree of sustainable public procurement policies and action plan implementation) discusses blockchain-based digital contracts and its contribution to public procurement [101]. For the indicator 12.8.1 (Extent to which (i) global citizenship education and (ii) education for sustainable development are mainstreamed in (a) national education policies; (b) curricula; (c) teacher education; and (d) student assessment), the work of agricultural development cooperatives has been mentioned [135].

For SDG 14, 14.2.1 (Number of countries using ecosystem-based approaches to managing marine areas), examples outlined in the literature demonstrate the use of blockchain technology to inform consumers and society, providing more transparency throughout the fish product value chain [136,137]. For the indicator 14.4.1 (Proportion of fish stocks within biologically sustainable levels), blockchains provide added value to determine the provenance and authenticity of seafood [138,139].

However, when we contrast these research findings with the general expectations regarding the potential of blockchain technology in this particular field, we find that the evidence is still lacking. Thus, our assessment mostly sits in the "uncertain" impact category. Additionally, SDGs 1-3 (no poverty, zero hunger, health and well-being) were rather underrepresented compared to the purported potential in these domains.

The SDGs are universal in their application and their scope aims to transcend the boundaries between the developed and developing world. They provide a policy framework that aims to ensure greater coherence between social, environmental and economic objectives, where such issues had previously been addressed in various diplomatic, political and institutional arenas. However, keeping track of progress is hampered by the difficulty of measuring sustainable development in all its complexity, partially due to broadly defined objectives, the achievement of which is measured through a wide array of narrowly outlined indicators. However, gathering data to monitor these indicators, intended to assess the achievement of the SDGs, is a major data challenge that fails to account for local contexts: available data are, in many instances, outdated [140] and, therefore unusable, as it was with the decennial agricultural census in Lebanon, for instance, [141]. Moreover, the sheer number of indicators risks tilting the implementation of the SDGs into a technocratic exercise far from the transformative ambition it was set out to achieve. Finally, besides its technological challenges, blockchain raises legal and regulatory issues, which lawmakers are only beginning to tackle: the cross-border aspect of the technology hinders the enforcement of set rules.

Transforming and improving the efficiency, inclusiveness, and sustainability of agricultural and food systems is necessary to ensure that food loss and waste do not undermine efforts to eradicate hunger, improve nutrition, and reduce pressure on natural resources and the environment. To reconcile the challenges of food security and equity, decision-makers must be able to make informed strategic choices among a range of options for managing food systems. However, the knowledge gaps found in the literature impede estimates of the sustainable exploitation potential of blockchain technology. To this end, international and interdisciplinary applied research from a broad spectrum of thematic expertise is needed to fill the knowledge gaps on ecological, economic, and social processes interacting with blockchain technology in the context of food security. At the same time, we need to critically assess the usefulness of specific indicators which lack contextual country-level application potential or explore avenues for qualitative assessment which could complement the picture. Thus, a more holistic impact assessment using the SDGs as a compass or navigating framework is deemed an advisable starting point which, however, needs to be enhanced through qualitative means of SDG assessment. However, we believe that the SDGs and the associated focus on the indicators provide an interesting avenue for further exploration, as the indicators offer an impact-based assessment and contribution to the grand challenges of our time.

3.3. Group 3: AI as a DI

The digitainability assessment observed mainly synergistic impacts with on SDG 15 targets, as well as relevant connections with many of the SDGs, especially with SDG 6 (water), SDG 2 (agriculture), SDG 13 (climate), and SDG 11 (cities).

For SDG 1 (End poverty of all forms everywhere), we found by applying the DAF methodology (Figure 3) that most of the indicators of SDG 1 are not relevant to Land Management, with the exception target 5, where AI can perform a vital role in terms of the exposure to Climate extreme events, and environmental disasters. For example, AI can predict floods using the Artificial Neural Network (ANN), which runs hydrological models [142] and can model heat waves as used by Vautard *et al.* [143].

In the case of SDG 2, which is related to the function of our soil and its productivity for crop production, and the fairness of its distribution, we found that all targets related to land use, such as target 2.3 of increasing agricultural productivity. AI tools are used for crop monitoring as the model done by Singh *et al.* [144], who used AI and IoT (Internet of Things) to detect the most suitable land and conditions for plant growth. AI has shown to be a powerful tool in terms of big data analysis for soil quality, as shown in the review by Eli-Chukwu and Ogwugwam [145].

For SDG 3 to ensure healthy lives and better well-being is cross-cutting with land management in some of its targets. Consequently, there may be potential trade-offs in the application of AI on these indicators. SDG 3 is targeted to ensure good mental health for all, mental health is directly associated with recreational activities which are directly affected by Land management. Therefore, AI is being used to quantify and map recreational sites for better well-being and good health [146]. Not only this, but since SDG 3 targets reducing deaths caused by road injuries, AI-enhanced models in road management, predictions, and transportation are offered for safety and for tracking injuries [147,148]. One of the most important factors for better health is accessibility, either for education, medical services, or mental improvement. AI (ANN) models are used for measuring land accessibility rates in urban areas where it serves as the main factor for better well-being [148]. As shown in SDG 2, Soil pollution is being quantified, which serves as some of SDG 3 indicators for reducing the death rate as a result of food pollution [144].

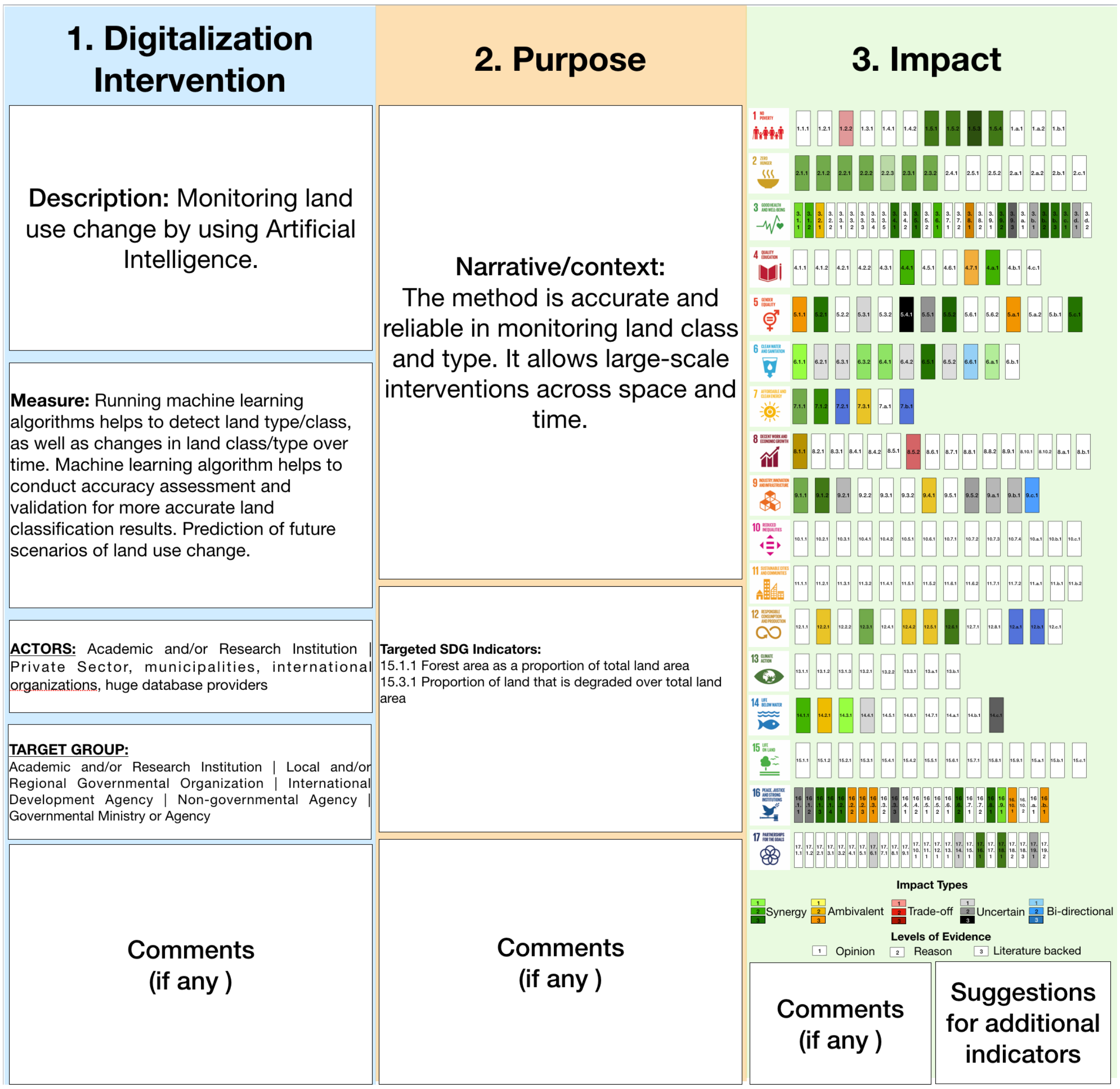

Figure 3. DAF outcome of AI as DI.

For SDG 5, synergistic impacts exist between three of the indicators and AI use in relation to only one indicator relevant to land and its ownership. These include 5.2.1 [149], 5.5.2 [150] and 5.c.1 [151,152]. Considering SDG 7 (sustainable energy) and SDG 13 (climate action), the energy sector is enduring a disruptive transformation towards a more decentralized, digitalized, decarbonized, climate-neutral and green future, with strong synergies with the building, transport, and infrastructure sectors [153], and large impacts on climate. AI brings huge potential to accelerate the green energy transition [154–156], but its current application is limited to pilots, with barriers to scaling up. AI applications for energy cover consist of high-fidelity models for predicting renewable generation and demand, grid and systems optimization, operation and maintenance, demand management and innovation [157–159]. Virtual Power Plants can boost distributed energy and automation of small, distributed devices such as electric vehicles [153,160].

Vinuesa *et al.* [6] claim that AI has the potential to contribute to all SDG 7 ambitions positively but at the same time might be an inhibitor for 40% of the same targets. According to the group analysis, AI could contribute positively to enhancing access to electricity (7.1.1.) and clean fuels (7.1.2). Particularly, AI for land management can help to identify better supply needs and coverage of clean energy facilities (e.g., solar roofs) and match them according to the population and available resources in the area [161–166].

Besides, AI might bring bi-directional impacts on SDG 7.2.1 (renewable energy share) and SDG 7.b.1 (installed renewable energy capacity in developing countries). Firstly, ML and DL could help assess the availability of renewable energy resources (e.g., wind and solar irradiation) [167–170] as well as supporting enhanced planning and monitoring of energy facilities [153,160]. Secondly, it is widely recognized that AI drives resource efficiency gains and enables the flexible matching of supply and demand in real-time through smart grids and microgrids [14,153,163,171–173]. Nevertheless, smart grids can suffer cyber-attacks and are prone to blackouts in the least developed contexts [61]. On the other hand, renewable energy could help curb the growing carbon footprint of energy-intensive algorithms (e.g., Deep Learning) and facilitate more sustainable use of digital technologies by integrating green energy in data centers toward carbon neutrality and green AI [160].

However, an ambivalent impact is observed on SDG 7.3.1 dedicated to energy intensity (primary energy) which merits further analysis since the related net effect remains unclear. AI for land management can support efficient use of resources leading to lower energy consumption and intensity of the economy [174,175]. However, potential rebound effects [176] may arise along with growing energy demand from the DL algorithms [177,178], which might outweigh the benefits. AI systems, particularly Deep Learning, require mitigating strategies to reduce their large carbon emissions [179–181]. Besides, a lack of transparency and accountability is observed regarding carbon emissions [182], which are generated in three ways: by its use for applications with negative impacts (e.g., Oil and Gas); system-level impacts; the life cycle of software and hardware [158].

Regarding SDG 13, AI brings huge potential for understanding the climate crisis, and the literature provides evidence of its positive role in supporting crisis and disaster management, early prediction of natural events, as well as opportunities for education on climate responsibility and action [157,158,163]. Sætra [183] claims that AI shines in dealing with complexity and enhancing climate science and policy, but the political harms of algorithmic governance should be avoided. Vinuesa *et al.* [6] argue that AI systems could bring benefits to 70% of the targets, causing negative effects on 20% of them.

According to our analysis, AI systems bring positive synergies to SDG 13.1.1 (deaths and missing persons due to disasters), providing enhanced disaster prediction and management [157,160,163, 184,185]. An ambivalent impact is identified regarding SDG 13.2.2 on GHG emissions, in analogy with SDG 7, due to the yet unclear net effects of AI systems in terms of energy consumption and related carbon footprint. In combination with earth observation (i.e., Land and Sentinel Satellites), AI could help assess the emissions and their effects, while algorithms generate a high carbon footprint. Several experts call for more transparency in terms of the climate impacts of AI. Regarding the contribution to SDG 13.3.1 (education for sustainable development), AI has indeed the potential to analyze massive educational data (e.g., MOOC), adapt educational programmes to the needs of the students, and provide augmented reality [157]. At the same time, nonetheless, it could aggravate extant inequalities and biases. However, limitations are observed with regard to most SDG 13 metrics as they are considered narrow and mainly focused on the countries with established climate strategies and financial resources. SDG 13 targets and indicators do not reflect the complexity of this crucial goal and do not provide suitable means for measuring progress. Even when AI has the potential to contribute to a better understanding and monitoring of SDG 13.1.2, 13.1.3, 13.2.1, and 13.b.1 focused on the availability of disaster risk strategies and plans, little evidence is provided in the literature and these impacts remain uncertain.

With regards to SDG 9 (industry, infrastructure, innovation) and SDG 11 (sustainable cities), AI systems in combination with Big Data, IoT, and Digital Twins, could contribute to support both a resilient, sustainable, and circular industry and smart manufacturing [186] by monitoring pollution and resource efficiency, enhancing transport and communication infrastructures and boosting research and innovation across all the domains [159,163]. In the urban sphere, the great potential of AI in combination with the Internet of People (IoP) for smart and low-carbon cities is widely recognized

[14,61,187]. Therefore, a positive contribution to SDG 9 and SDG 11 is evinced with benefits to SDG 12 by a more sustainable production supply chain.

In our analysis, a synergic impact is observed in relation to SDG 9.1.1 (rural population near an all-season road) and SDG 9.1.2 (transport) since AI for land management might support the mapping and monitoring of population close to road facilities [51,188,189] as well as the volume of passengers and freight from Big Data coming from transportation systems [190–192], and their evolution patterns over time. An ambivalent impact regarding the contribution to SDG 9.4.1 (CO2 emissions) is observed since AI for land could be useful to calculate the carbon footprint based on LCAs from different activities, forest extension, and soil features acting as carbon sinks [193,194]. At the same time, however, large GHG emissions are associated with AI systems, as aforementioned. AI could support the optimization of supply chains and energy systems, improve quality, and reduce defects, leading to resource efficiency but rebound effects could increase the net emissions and material footprint [163,195,196]. Nonetheless, cyber-security and privacy represent critical risks that should be wisely considered in critical facilities. Besides, its impact is unclear with regard to SDG 9.5.2 since AI could foster scientific discovery, benefiting many researchers in the realm of SD [197], but no clear evidence has been provided in the literature so far. A bi-directional impact is proved regarding SDG 9.c.1 (population covered by the mobile network) since AI for land can help monitor the mobile network and population coverage while better mobile connectivity could also be an enabler for enhancing AI capabilities and better access to mobile Big Data [198,199]. AI systems are already contributing to SDG 11 in numerous cities around the world, but their use for smart cities has been criticized for lacking genuine sustainability and citizen-centric approach as well as for being focused on highly developed economies [187]. Moreover, several targets (11.1, 11.4, 11.a, 11.c) have been overlooked in the literature on AI for cities, which has been mainly focused on: mobility, environmental management, and monitoring (water, air, waste, energy), disaster responsiveness. Therefore, significant gaps remain in ensuring the social good of AI towards sustainable smart cities for all. Despite the potential benefits, SDG9 and SDG 11 metrics represent a fragmented and incomplete perspective of infrastructures, industry, and cities, hindering the outstanding potential of AI and digital paradigms in these domains and lacking evidence for a relevant number of indicators.

For SDG 10 (inequality), one of the well-known menaces of AI systems is its potential to exacerbate inequalities, bias, and discrimination. Vinuesa *et al.* [6] argue that in SDG 10, most impacts of AI systems are considered negative, causing trade-offs in 55% of the targets. Admittedly, uncertain impacts are identified in most targets, and a potential trade-off in terms of potential discrimination is caused by extant algorithms. Again, limitations are observed in relation to narrow targets and metrics. AI systems could support better and more efficient monitoring of metrics about people below-median income (SDG 10.1.1, 10.2.1), migration and refugees tracking (SDG 10.7.2, 10.7.3, 10.7.4), fiscal control of markets, financial and economic indicators (SDG 10.4.2, 10.5.1, 10.a.1., ODA flows, remittances) but a clear, direct impact is not evidenced in the literature due to a lack of empirical evidence. The most relevant impact of AI systems on SDG 10 is a trade-off related to discrimination (SDG 10.3.1.) and potential bias [192,200–205]. Indeed, AI has been widely criticized for augmenting inequality, bias, discrimination, and reproducing hierarchies [204]. Even when AI could contribute to fighting discrimination by analyzing massive amounts of data (e.g., social networks, PNL, sentiment analysis), the negative impact outweighs any benefit. Besides, access to AI systems and digital skills is uneven across geographies [206], and AI-based automated work could also amplify inequalities against vulnerable people.

According to Vinuesa *et al.* [6], AI systems can be expected to have a positive impact on 59% of SDG 12 targets and a negative impact on 16% of them. They could support tracking consumption towards sustainable patterns and better ESG monitoring, facilitating a circular economy. However, severe uncertainties emerge regarding the well-known negative trade-offs of digitalization in terms of material footprint and e-waste. Saetra argues that the positive effects seem negligible with a lack of evidence and empirical data, and the negative impacts outweigh the benefits. Di Vaio *et al.* [207] claim that AI could drive a cultural drift in SDG 12 by enabling sustainable business models, but relevant gaps remain, and ethical considerations should be integrated to ensure the proper use of this paradigm for the 2030 Agenda. Indeed, we observe three ambivalent impacts regarding the contribution of AI systems to SDG 12.2.1 (material footprint), SDG 12.4.2 (hazardous waste), and SDG 12.5.1. (Recycling rate). AI could increase the need for data centers and related digital infrastructures leading to an increase in material footprint, land use, and e-waste, while at the same time, ML and DL systems could support an optimized production system, resource efficiency, and environmental awareness [208,209]. AI for land management could improve the monitoring of waste treatment facilities and the detection of illegal landfills [190,210–215]. But it might also lead to increased waste due to the required digital infrastructures and the digital-induced overconsumption [21].

In contrast, synergic impacts are found in relation to the application of AI systems to SDG 12.3.1 (Food Loss and waste), SDG 12.6.1 (corporate sustainability reporting), and SDG 12.b.1 (accounting tools for sustainable tourism). Indeed, AI for land management can help to monitor agricultural fields and crops, influencing the availability of food on the market. Yet, the relationship between food supply chains and related losses is not clearly established [134,216–218]. AI for land management could be useful to support the ESG reporting [219,220], particularly regarding land and soil [221,222] as well as to bring information about the potential impacts of tourism on land and environment [223]. Bi-directional impacts are observed regarding SDG 12.a.1, linked to SDG 7.b.1 (installed renewable energy in developing countries). AI for land management could help map and monitor renewable energy facilities by using Geospatial Big Data and distilling it into knowledge [224]. Besides, more renewable energy could help AI to be more sustainable by reducing its carbon footprint. Again, SDG 12 metrics are considered narrow and unable to represent the complexity of the sustainable consumption and production paradigm, hindering the potential of AI to contribute to the 2030 Agenda.

Considering SDG 17 (means of implementation and partnerships), Sætra [21] underlines the relevance of the partnerships' support for monitoring systems and compliance but claims that despite its outstanding relevance for governance, the role of AI in SDG 17 has been overlooked. Vinuesa *et al.* [6] argue that AI could positively contribute to just 15% of the subgoals while causing a negative contribution to 5% of them. We observed that most impacts are uncertain due to a lack of evidence and empirical data, along with strong limitations and shortcomings featuring SDG 17 targets and metrics. AI systems could support SDG 17.6.1 (fixed Internet broadband subscriptions) and SDG 17.8.1. (Individuals using the Internet) by enhancing the monitoring and operating of digital infrastructures [225–227]. On the other side, proper Internet broadband coverage supports cloud-based AI systems. However, the literature in this area is sparse. Synergies can be observed regarding SDG 17.16.1 (monitoring frameworks) and SDG 17.18.1. (Statistical capacity for SDGs monitoring), since AI systems in combination with Big Data (e.g., earth observation, sensors, IoP) can be a relevant tool for enhancing statistical capacity and monitoring all the SDGs [69,228–230] and particularly SDG 15 targets.

Overall, AI offers exceptional potential for enhancing land-related metrics (SDG 15) in combination with remote sensing and satellite earth observation data. However, several limitations, barriers, and risks remain to leverage and mainstream the full potential of AI systems for social good, particularly in the least developed countries constrained by a lack of resources and capacities and unsuitable logistics and regulations. AI requires synergic integration with other digital paradigms (e.g., IoT, Digital Twins, Big Data, 5G, blockchain), trustworthy regulation, transparent accountability, and cross-fertilization with multidisciplinary domains such as climate change agriculture, water, ocean ecosystems, and urban planning. The impacts of AI on land management are mainly positive synergies, but several trade-offs and ambivalent impacts are also evidenced. This is particularly the case with regard to the net carbon footprint, material footprint, as well as unsolved social dilemmas and ethical implications [67,231].

In relation to the potential impacts that AI for land management brings across the whole SDG indicators, most observed interactions can be considered synergies and ambivalent impacts, including trade-offs with unclear net impact. These ambivalent impacts are mainly related to the "Janus faced" nature of AI in terms of the carbon footprint from energy-eager algorithms (e.g., DL), material footprint, and e-waste from supporting data-driven infrastructures subjected to early obsolescence, rebound effects causing overconsumption, cyber-security vulnerabilities, but also social and ethical threats such as capacity constraints, asymmetry of power, malicious use [232], misinformation, discrimination, inequalities, bias, security, safety, privacy and greenwashing. A few interesting bi-directional impacts are also observed due to the enabling nature of both digitalization (broadband and mobile connectivity) and renewable energy, which deserve further exploitation.

In addition, a significant number of uncertain impacts have been identified due to the intrinsic limitations of the SDGs targets and indicators and the lack of literature and empirical data for many of them. One of the main barriers to the application of AI to SD and the 2030 Agenda stems from the drawbacks of the SDGs targets and indicators themselves. It is widely accepted that SDG indicators are narrow and reductionist and do not reflect the complexity of the domains they are expected to cover [18].

In addition, a relevant limitation of this analysis relies on the potential bias induced when selecting datasets [159], applying black-box algorithms and when evaluating interactions and impacts based on expert opinions and pilots whose results are difficult to extrapolate and could lead to spurious conclusions [52]. In conclusion, there exists a burgeoning research landscape and huge opportunities but also several caveats, data and reporting gaps, lack of accountability, and limited literature on the contribution of AI to most SDG metrics that merit further research. Besides, contexts are highly relevant, and further research is needed in underrepresented countries, especially from the Global South.

Ensuring a sustainable, responsible, and inclusive application of AI for the 2030 Agenda will require trustworthy regulation beyond human-centric principles [233] and ethical standards [6,234,235] to halting the "wild west" of the unregulated AI [206]. Besides, greening AI is an urgent priority and might be achieved by policy incentives for green algorithms [236], renewable energy and efficiency in data infrastructures, standardized methodologies for carbon and energy accountability embedded within the whole life cycle of AI systems [181] and environmental education. Accountability and transparency should be encouraged using FAIR data, trustworthy and Explainable AI (XAI) to fight discrimination and biased outcomes. Further research on social dilemmas and ambivalent impacts is needed and should cover all relevant contexts and communities, particularly the Global South, to reduce digital divides. Alliances for social good might bring relevant stakeholders together, including civil society and vulnerable communities, to share data [157] and overcome current capacity and accessibility constraints such as the non-universal access to data sets [237]. Finally, the SDG framework and metrics should be revisited through the lenses of digitalization to accommodate the opportunities brought by AI in combination with EO and Big Data. This evolution of the 2030 Agenda monitoring should bear in mind the systemic nature of sustainability and digitalization; therefore, methodologies and standardization are needed for this purpose [238].

3.4. Group 4: Big Data as DI for International Law

The results of this study demonstrate (Figure 4) the opportunities provided by Big Data to achieve the SDGs. It showcases the benefits of action learning by taking a futuristic perspective about the potential impact of DIs. This study aims to demonstrate how DAF can help innovate while anchoring insights in a mindful consideration of DI impacts on SDGs.

Implementing Big Data to achieve SDG2 to create binding international treaties would allow direct compliance with indicator 2.5, which seeks to promote access to fair and equitable sharing of benefits arising from the utilization of genetic resources and internationally recognized traditional knowledge. Its implementation is primarily aligned with the "means of implementation" targets.

It would allow to increase and facilitate investments to improve international cooperation in rural infrastructure, agricultural research facilities, technology and research development, research, and gene banks to increase agricultural productive catalyzing target 2a. Proper management of Big

Data can facilitate access to transparent, updated, and complete information for trade and global agricultural markets and fair prices aligned with Target 2c. The information and improvement of the markets can help to eliminate export subsidies in line with the Doha Development Round and 2b Target.

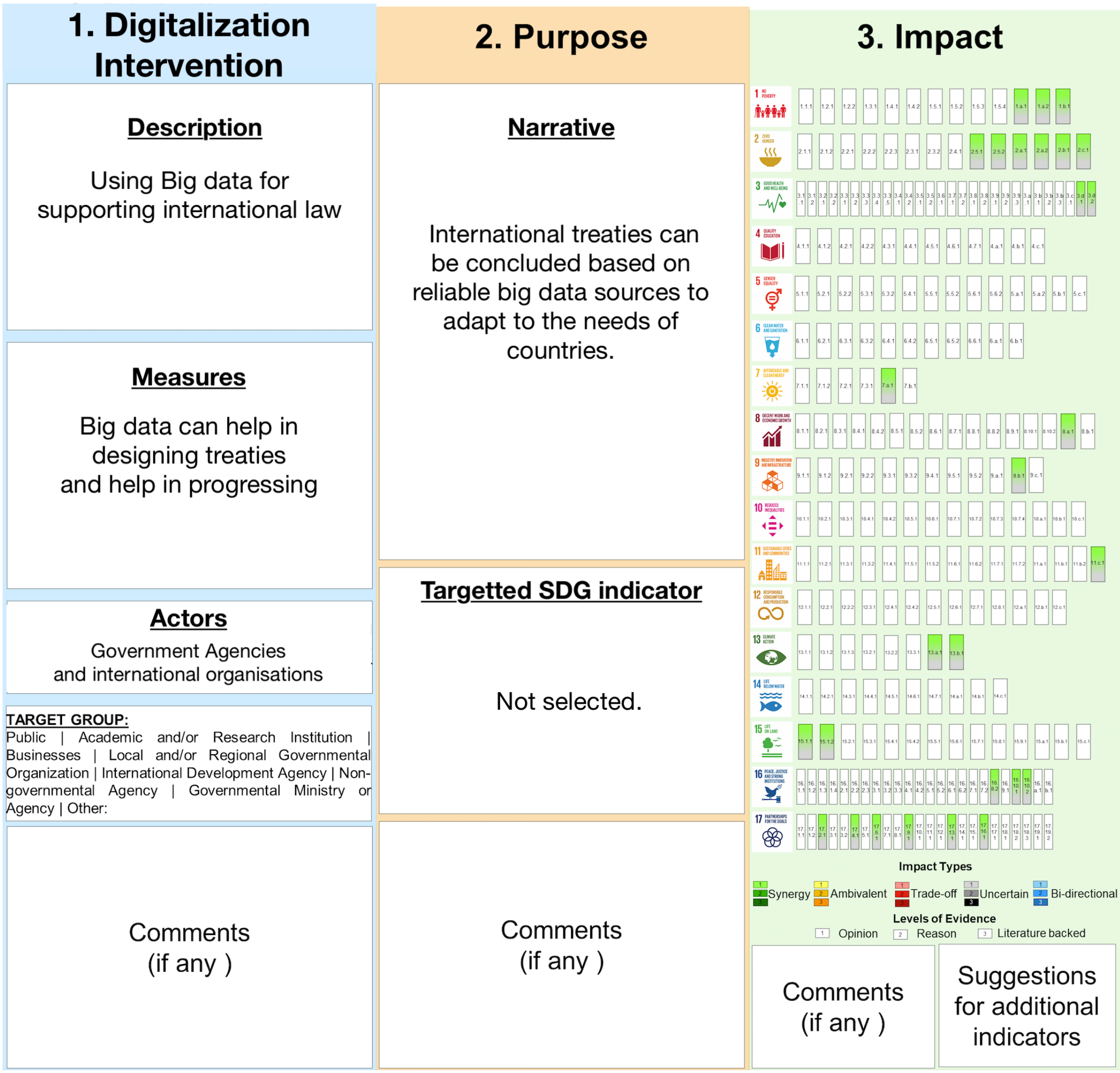

Figure 4. DAF outcome of Big Data as DI.

Beyond SDG 2, Big data and international law can be adopted for other targets, especially the "means of implementation" targets, that seek to ensure significant mobilization of resources. For SDG 1 (1.a and 1.b) on policy-making and investment in developing countries, SDG 3 (3.d) to reduce risks and health risks, SDG 7 (7.a) for clean energy investments, SDG8 (8.a) aid trade for developing countries, SDG 9 (9.b) for technology development, SDG 11 (11.c) for sustainable and resilient buildings, SDG 13 (13.a) to implement committees under the UNFCCC, SDG 15 (15.1) for conservation and restoration of ecosystems inland, SDG 16 (16.3, 16.8, 16.10) to ensure access to justice, participation in global institutions and governance particularly of developing countries, and fundamental freedom, and SDG 17 (17.2, 17.4, 17.6, 17.9, 17,10, 17.13, 17.16) to aid countries to implement the assistance commitments, coordinate coherent policies for long-term sustainability, enhance international cooperation and capacity building, implement the non-discriminatory multilateral trading system, improve global macroeconomic stability and enhance the Global Partnership for Sustainable Development.

One of the most important characteristics of International Law Treaties is that they are concluded by the will of the parties. According to Linares [239], an international treaty "is an instrument where provisions are freely agreed between two or more subjects of International Law to create, modify or extinguish obligations and rights." Therefore, if the developing States do not have the will to sign treaties, the countries that need help and cooperation will not be able to implement the proposed measure even when big data demonstrate to the parties the benefits of signing the treaty. Pulido-Ortiz *et al.* [240], mention that "normative language suffers from indeterminacies caused by the ambiguities, vagueness, and inaccuracies of the words and sentences, and by the contradictions, redundancies, and gaps in the set of legal norms". In this order of ideas, the indeterminacy of the language of the SDGs can mean that the creation of a binding international treaty does not achieve its objective; even with the help of Big Data, the indeterminacy of the ODS would prevent meeting some of the 2030 goals, and nothing ensures compliance with the goals.

Another great challenge is that the States provide the correct and adequate information to be able to create the database of the needs that some States have in order to carry out a treaty and obtain a benefit. Additionally, developing countries do not have sufficient technology to collect the necessary information to identify their needs and eventually create an international treaty. As long as the technology gap is not overcome, big data for International Treaties may be ineffective.

4. Discussion

DIs has the potential to accelerate sustainable development. However, implementation actions still need to be improved in several areas for some technologies to fully utilize their potential for achieving the SDGs. Results from the case studies highlight the differences between countries in the use and maturity of the technology. Groups 1, 2, and 3 identify impacts at indicator levels covering synergies, ambivalent impacts, trade-offs, bidirectional impacts, and uncertainties, showing the interlinkages that SDGs have at an indicator level and the diverse impact that DI can have depending on the context where those DI are applied. The results of Group 4 pointed out that beyond the application of the DI towards the achievement of the SDGs, the legal wording and language used in the 2030 Agenda may hinder the application of the DI and collaboration at the international level. Results also showed the scarcity of literature when it comes to evaluating and supporting the DAF analysis. Furthermore, the interlinkages between SDGs have yet to be fully understood, which hampers a fully comprehensive DAF analysis. For example, the interlinkages between targets and indicators of SDG 1, 8, 9, 11, 13, and 15 are unclear but seem to have affinities in broader contexts because of the social, environmental, and economic dependencies. For instance, SDG 7 has complex linkages with SDG 12 regarding industrial development and clean energy to sustain a green transition. Achieving SDG 6 may affect the progress of SDG 3 targets, as access to clean water and sanitation is fundamental to delivering health services. In addition, in the case of group 4, outcomes on Big Data for International Law results showed that the potential of DI remains unexplored. The analysis of group 4 also demonstrated two crucial aspects, first the methodological aspect about how lack of clarity on indicators and context lead to a surface interpretation of DI implications, and second the advantage of the method to help identify the importance of big data to facilitate the identification of partners and pathways to create robust policies to advance the SDGs.

The action learning undertaken through the DAF tool, as presented in this paper, has facilitated the in-depth identification of the complex and interrelated impacts of DI for sustainable development. The process helped peers in each group to question, reflect and generate actionable learning that would flow into the mindful application of DIs. The process also helped improve the current understanding of the peers in a multidisciplinary manner and kindled a new strategic approach for sustainable transformation. Throughout the DSS, participants worked on their identified DI for digitainability assessment with the support of other participants and insights from experts and advisors on various aspects at the intersection of sustainability and digitalization. Feedback from guest specialists during the DSS also helped participants make sense of their multidimensional experiences through real-time reflection and relevant theories. The flexibility to incorporate information from scientific literature, grey literature, and other potential sources also helped in mapping the multidisciplinary knowledge and existing gaps. Thus, operationalizing DAF for action learning with feedback enriches participants' practices and values to ensure that any multidimensional actions identified in the assessment are seen not as neutral or positive stances but as positions with specific impacts. As can be noticed from the group work and outcomes, each group used different techniques for evidence gathering and analysis. Despite this, the result demonstrates the versatility of DAF in facilitating inclusive, diverse voices to be heard at different levels during the digitainability assessment of technology, leaving no one behind for sustainable development.

The findings also demonstrate the extent to which analysis of the actual impacts on the SDGs is limited. It is crucial to navigate between intra- and inter-administrative boundaries at the micro, meso, and macro levels to analyze the DIs impact in a specific context with stakeholders' intent in implementing DI. It helps realize the scale and dependence between administrative levels and the overall impact those have on the target and goal, with hints to understanding the impacts of administrative boundaries. Results also indicate that analysis focusing on varying levels and contexts should consider the information in great detail to understand the short and long-term impacts of the DIs in intra- and interdependent forms and contexts.

When considering sustainable development, it is also crucial to balance the progress towards all the key dimensions of sustainability because substantial adverse effects in one could lead to a chain reaction of repercussions on overall progress. DAF provides a method for assessing impact along several dimensions. However, current data gaps pose several limitations to a comprehensive analysis. Furthermore, the crucial trade-offs and ambiguities between the different pillars of sustainability should not be overlooked due to the focus on a narrow or isolated assessment of the impact of DIs. Evaluating the impact of the DIs considering the SDGs help address potential gaps that arise between various multi-stakeholder actions for sustainable development. However, due to the complexity of the SDGs, there is some overlap between the different DIs applications and indicators. At the indicator level, there are few similarities among indicators of the same goal, and the potential for synergy and trade-offs between them has not been adequately investigated. The interdisciplinary aspect of the SDG indicators also makes their interpretation ambiguous or even contradictory. Another aspect that needs consideration in the assessment is formulating the indicator in a global perspective, with different and sometimes conflicting interests, actors, and technologies. In addition, different reporting systems sometimes limit assessment processes. While the DAF helps to overcome these gaps and disparities to some extent, it is also valuable for identifying them and highlighting research imperatives.

The DAF provides a methodology for assessing the impact of DIs, allowing for a more robust evidence-based scientific approach to identifying spatial and temporal effects from a broader multidimensional perspective. These critical and holistic assessments of the DIs' usefulness help to address significant challenges we all face in achieving Agenda 2030. As we move towards the 2030 Agenda milestone, the evolution of new goals needs to consider the digitainability aspect more systemically, towards sustainability in the digital age, stressing the need for more robust methodologies, indicators, standardization processes, and policies accordingly. In that sense, the analysis of DIs impact on SDGs through the DAF can point to hotspots and opportunities tailored to specific contexts and areas, promoting local adaptation and actions required for sustainable development more inclusively and holistically. We believe that DAF can complement other analyses as a valuable tool for performing the ex-ante and ex-post consequential analysis considering all 17 SDGs.

5. Conclusion and Outlook

This paper demonstrates the operationalization of the DAF for encouraging mindfulness in the application of the DIs for sustainable development. It has emphasized how a multidisciplinary perspective, with experts from diverse backgrounds, can operationalize the framework to systematically gather evidence reflecting gaps and opportunities DIs can offer for sustainable development, supporting action learning. The paper's outcome firstly demonstrates the practical approach to digitainability. Secondly, it reflects on the digitainability assessment of diverse DIs in specific contexts recognizing interlinkages for the holistic impact on SDGs. Thirdly, the paper demonstrates the need for a more inclusive and integrated assessment with practical tools for encouraging mindfulness in diverse stakeholders acting toward sustainable development. Future work should focus on automating some of the DAF procedures, alleviating the labor-intensive task of evidence-gathering using tools and techniques recognized by various stakeholders. Expanding the framework with capabilities to interconnect data sources and empirical evidence could make assessment more robust and informative. Furthermore, developing global data sets based on DAF inputs with diverse actors and DIs can help guide context-driven mindful decisions for sustainability in the digital age.

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