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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 essential 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 will help us align the 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. This paper demonstrates how DAF can be instrumental in guiding participatory action for the implementation of digitainability practices. This paper summarizes the insights developed during the Digitainable Spring School 2022 (DSS) on "Sustainability with Digitalization and Artificial Intelligence," one of whose goals was to operationalize the DAF as a tool in the participatory action process with collaboration and active involvement of 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 participating experts worked together to identify a DI and gather and analyze evidence by operationalizing the DAF. The four DIs identified in the process are as follows: smart home technology (SHT) for energy efficiency, the blockchain for food security, artificial intelligence

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(AI) for land use and cover change (LUCC), and Big Data for international law. Each of the four expert groups addresses different DIs for digitainability assessment using different techniques to gather and analyze data related to the criteria and indicators. The knowledge presented here could increase understanding of the challenges and opportunities related to digitainability and provide a structure for developing and implementing robust digitainability practices with data-driven insights.

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 toward an era where a significant part of our lives is reliant on digital technologies. These technologies are shaping the future by supporting the sustainable improvement in 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, 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 that enable 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 that contribute 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 UN toward equity and sustainable development with a horizon set in 2030. The 17 SDGs form the backbone of the UN Agenda 2030, providing a guiding framework for worldwide policies to guarantee a good life for present and future generations. To achieve the SDGs, it is crucial to reduce resource consumption, greenhouse gas emissions, poverty, and inequality, while at the same time expanding education and welfare and combating biodiversity loss, to name just a few factors [4]. The SDGs' 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, leading to accelerated transformation in many sectors. Digital interventions (DIs) have been a primary focus in most public discourses and policy circles [6]. The dawn 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 an analysis of the DI as they provide significant opportunities for sustainable development and contribute to all the SDGs within the 2030 Agenda [9–12].

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 toward 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 the environment [14–16] and society [17,18], prompting a call for closer examination of the ethical and political issues associated with its rapid proliferation [16,19].

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 the 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 a 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.

2. Background

Gupta et al. [20] 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 in evaluating 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" that 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. [20] 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. 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 [21], but more from the theoretical perspective rather than a practical one. Quite recently, Gupta and Rhyner [22], in their article, introduced the digitainability assessment framework (DAF) as a practical tool that can help operationalize the digitainability assessment of the DI in great detail with various levels of evidence.

For the timely achievement of Agenda 2030, inclusive and participatory approaches that enable the exchange of resources and knowledge are increasingly crucial [23]. There is a need for assessment tools to cope with collaborative, governance, and context specific uncertainties to harness the opportunities offered by DIs for sustainable development [24]. Recent advances suggest that participatory action as an approach to problem solving that emphasize collaboration and active involvement of stakeholders in the process could help to facilitate the exchange of knowledge and improve the comprehensive understanding of digitainability practices and develop solutions to support sustainable development [25]. As an instrument in the participatory action process, DAF could help improve understanding of digitainability challenges collaboratively, structure problem-solving processes, and increase participation and engagement of diverse stakeholders to make evidence-based decision making.

The DAF draws from and adapts concepts of the Theory of Change (ToC), which lays out the mapping of cause-and-effect pathways that follow the DI. Its incorporation of 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 of DIs. Utilizing several levels of evidence, the DAF approach is instrumental in holistically identifying impacts and detecting potentially unforeseen implications. Please refer to Gupta and Rhyner [22] for detailed insights about the DAF. 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 progress of the SDGs can be understood and used to support sustainable digitalization. Overall, the DAF is an effective tool that helps consolidate and contextualize a vast amount of multidisciplinary knowledge to understand the interlinked direct, indirect, and progressing consequential impact of the DIs for sustainable development in a qualitative manner.

Consideration of the qualitative assessment in our paper is based on the emerging nature of digitainability as the topic, and the limited availability of diverse standardized data sources related to SDG indicators in a specific context and digitalization impact data [24]. The gap exists concerning the availability of sufficiently large time series for sustainability and digitization data to perform a quantitative assessment at the country scale [26]. Given how the digitainability assessment aims to measure the impact of the DI within a specific context considering complex interactions between multiple factors, granular spatial and temporal scale data are often required, where data gaps become more prominent. Taking into consideration the recommendations made by Naudé and Vinuesa [27] for bridging data gaps by increasing the awareness of existing biases in understanding particular contexts and evidence, better domain understanding of the multidisciplinary fields, and effective collaboration between diverse stakeholders at the cross-section of digitalization and sustainability, such as developers, policymakers, and experts (e.g., from business, data, law, and research), our paper aims to address this knowledge gap and demonstrates the concrete step required for bringing experts in the domain together and operationalizing the DAF for gathering essential insights required at the cross-section of digitalization and sustainability, which is highly fragmented at this point in time [28].

This paper provides insights into the operationalization of the DAF in the participatory action process and how it could guide a structured and systematic collaborative exercise to address digitalization and sustainability-related challenges as a community. The DAF as a tool guides the participatory action process and ensure a comprehensive approach to developing the digitainability practitioner community. In this paper, we explore the operationalization of DAF digital technologies in a real-world scenario and how it paves the way toward mindfulness in applying a DI for sustainable development. The paper presents the outcome of the Digitainable Spring School 2022 (DSS), which involved four groups thoroughly analyzing the digitainability of a specific DI selected in the discussion by the experts in light of the SDGs. The DSS aimed to bring together a diverse group of experts and practitioners from different disciplines who have experience working at the intersection of digitalization and sustainability. A participatory analysis of the methodology was deemed appropriate to fully explore and identify the strengths and weaknesses of the DAF and the impacts of a DI on SDGs. 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 3 elaborates on the methodology we have undertaken for this study and further expands on the methodological consideration of the DIs. in Section 4, we present the results after operationalizing the DAF for selected DIs, followed by a detailed discussion on the findings of four studies in Section 5; finally, conclusions are drawn in Section 6.

3. 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 [24]. 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.

To perform the digitainability assessment in our study, we considered participatory action as the context to draw on the expertise of participants of the DSS using DAF as a tool. The qualitative assessment within participatory action was deemed suitable for our work as participants are encouraged to think collaboratively about phenomena. It allows participants to be observers and critical reflectors to explore the role of digitalization in holistic sustainable development. Furthermore, considering the major goal of DSS, the participatory action provides us with the opportunity to develop skills and knowledge to continue working on their own whilst also learning about the value of collaboration and collective knowledge development [29]. Participatory action is a holistic, integrative concept that incorporates related concepts and values such as participation, collaboration, communication, community of practice, networking, and synergy [30]. It include the methods of action learning where a group-based process of engaging, learning, and reflecting exists; 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 [31]. The DSS brought together an international group of real-life practitioners and experts in digitalization and sustainability. Based on their experience with certain technologies, they operationalized the DAF as a tool for understanding the complex impact of the DIs on sustainability. 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.

The DAF is used to systematically analyze the intra- and interlinked impacts of DIs on SDGs [22]. 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 following steps were followed:

1. Participants of the DSS are grouped based on their preference or considering the equal distribution of multidisciplinary experts with diverse experiences in each group;
2. Each group brainstorms and identify the DI, measures, actors, target group, context, and targeted SDG indicator they want to consider for digitainability assessment;
3. Each group performs their research based on the scope decided in previous steps;
4. Each group starts evaluation and gathers relevant information, refining and populating the information in the DAF with group discussion;
5. Collaborative participants discuss the individual findings with the group to analyze the impacts of DI in a particular context and its interlinked effects on all the indicators of SDGs beyond the targeted indicator;
6. External experts' help can be requested to develop coherent insights from the general analysis, and participants can learn about the essential knowledge points;
7. Depending on the level of evidence and type of integration identified, the group starts populating the impacts on DAF;
8. If participants identify any vital information that DAF does not allow incorporating, the comment section could be used to integrate this essential information with other inputs;
9. After various group discussions and consciences, groups summarize the results, map the impact and develop the overall impact profile of DI on SDGs in the DAF;
10. All groups discuss and learn from the digitainability assessment exercise and provide feedback to each other for corrective knowledge synthesis and actions.

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. For detailed insights of the DAF and how it is practically used, we recommend referring to Gupta and Rhyner [22]. 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 chosen by the respective expert groups during the discussions based on their current relevance are as follows: smart home technologies (SHT) for energy efficiency, the blockchain for food security, AI for land use cover and changes (LUCC), and Big Data for international law.

3.1. 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 [32]. In this context, numerous strategies are presented in order to reach resource efficiency and climate responsibility through modern technologies, i.e., smart grid and advanced metering infrastructure, smart buildings, smart home appliances and devices, and environmental control and monitoring [33]. In particular, energy efficiency is considered crucial to overcoming environmental challenges and meeting the growing demands for energy [34].

In this respect, SHTs for energy efficiency exhibit many opportunities for innovative technological solutions by combining Big Data analytics, the Internet of Things (IoT) and associated smart sensors and meters, and machine learning technologies and techniques. Thus, this technology provides better monitoring, control, and conservation of energy [35].

From the perspective of household residents, it will increase awareness, control, and efficient monitoring of energy 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 [36].

Group 1 focused on the question of *how do SHTs impact the achievement of SDGs considering digitainability?* To answer the question, the DAF methodology was applied. The analysis mainly focuses on the SDGs 7 (affordable and clean energy), 8 (decent work and economic growth), 9 (industry, innovation, and infrastructure), 10 (reduced inequality), and 11 (sustainable cities and communities), considering their relevance to the intended application of DI.

3.2. 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 [37]. Following several decades of substantial progress in reducing hunger by several hundred thousand people [38], food insecurity is regaining ground year after year [39]. When world grain prices soared in 2007–2008, the Malthusian specter 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 [40].

DI can help transitions to address the challenges of food and agricultural systems, supporting the timely achievement of SDG 2 (end hunger) and 12 (responsible consumption and production). The blockchain brings commercial transaction standardization to improve security and reduce costs. Several recent studies [37,41–43] have highlighted the positive and potentially transformational nature of the blockchain, particularly concerning the reconfiguration of market exchange. Research suggests that blockchain systems may reduce uncertainty, insecurity, and ambiguity in transactions by providing full transactional disclosure and unified credible information to all participants in the network Zhao et al. [44], Xu et al. [45], van Hilten et al. [46]. The blockchain is also increasingly deployed in areas where traceability and product auditing is essential, such as the supply chain in food systems [42]. Group 2 focused on the question of *how can blockchain technology support the fulfillment of goals 2 and 12 while considering holistic sustainability, socio-economic and environmental aspects?*

3.3. 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 ML, deep learning (DL), agent-based models, and others, are used to empower AI for better tracking of LUCC patterns.

Implementing ML algorithms can help to detect the land type, as well as spatial and temporal trends in land class/type over time. ML 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. As halting and restoring land degradation is a crucial priority to protect biodiversity and ecosystem services that support life on planet Earth [47], in this case, the study group focused on the following SDG Indicators: SDG 15.1.1 (forest area as a proportion of total land area) and SDG 15.3.1 (proportion of land that is degraded over total land area).

According to Vinuesa et al. [6], AI could bring positive contributions for 88% of the targets related to SDG 15 (life on land), and negative impacts for 33% of them; however, sound empirical evidence is lacking so far [48]. The main contribution of AI relies on enhancing the monitoring and surveillance systems by leveraging multiple data sources from remote sensing [49] and satellite-based earth observation and geospatial information [47,48,50,51]. Global datasets suffer limitations in terms of resolution and accuracy, while Earth Observation (EO) information (e.g., LandSat, Sentinel) is mostly free and open access, available for large regions, provides long time series and data continuity, and represents a complement to traditional statistics for SDG monitoring [50,51].

Therefore, merging AI and EO provides reliable and disaggregated data for better monitoring of the SDGs [52,53], and facilitates data analysis, capacity for measurement, and efficient interventions [54]. Nevertheless, despite the progress in geoscience, the net impact of AI on SDG 15 is still poorly understood. Yu et al. [55] claim that the use of AI to determine 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 [56] 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 (by 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests, and substantially increase afforestation and reforestation globally), 15.3 (by 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world), 15.5 (take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity, and by 2020, protect and prevent the extinction of threatened species), 15.7 (take urgent action to end poaching and trafficking of protected species of flora and fauna and address both demand and supply of illegal wildlife products), 15.8 (by 2020, introduce measures to prevent the introduction and significantly reduce the impact of invasive alien species on land and water ecosystems and control or eradicate the priority species)) ranging from predicting deforestation and enhancing forest management [57–60], managing land degradation [47,60], combating poaching and protecting endangered species [61,62], halting biodiversity loss and habitat degradation [63], reducing invasive species [64,65], and spotting plant diseases and fires or identity seeds [66]. Kolevatova et al. [67] 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. [66] 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 [56] 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 are 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. In addition, major forests/habitats (e.g., Amazonia) are also subjected to restrictive national policies [56,66]. Group 3 focused on the question of *how does AI for LUCC monitoring impact holistic SDG achievement?* In this study, we applied and complemented the DAF with the literature from the Scopus database.

3.4. 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 [68]. "Big data" is a broad concept that cannot be reduced only to the notion of an extensive dataset because this concept includes (among other things) the analysis techniques applied to the data [69]. Similarly, Boyd and Crawford [52] 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 [70]. In this regard, target 2.5 (by 2020, maintain the genetic diversity of seeds, cultivated plants, and farmed and domesticated animals and their related wild species, including through soundly managed and diversified seed and plant banks at the national, regional, and international levels, and promote access to and fair and equitable sharing of benefits arising from the utilization of genetic resources and associated traditional knowledge, as internationally agreed) 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 [71]. Unfortunately, according to the UN [72], 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 [73]. The group focused on the question of *what is the possible impact Big Data could have on the achievement of SDG 2 through international policy platforms?* The analysis explores the state-of-the-art within the framework of the DAF methodology.

4. Result/Outcome

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

The results of the digitainability assessment conducted by performing the literature review illustrate (Figure 1 & Table 1) that indicators 7.1.1 (percentage of population with access to electricity), 7.1.2 (proportion of population with primary reliance on clean fuels and technology), 7.2.1 (renewable energy share in the total final energy consumption), and 7.3.1 (energy intensity measured in terms of primary energy and GDP) have a synergistic impact. Data-driven solutions hold great potential for energy security and equity, and environmental sustainability [74,75]. SHTs can identify the best energy sources at the right time, reduce costs and optimize accessibility and sustainability [76,77]. Considering the long-term impact of SHTs, their use over the next ten years will allow us to achieve the objectives of reducing CO_2 emissions at the global level [78,79], enabling households to operate in "zero emission" mode [80]. Further, data-driven solutions through IoT are a potential way to increase the share of renewable energy. Smart grids allow the integration of renewable energies and can ensure energy security and sustainability [81–83].

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 the 7.1.2 and 7.2.1 indicators. In fact, data-driven solutions are linked to high energy requirements and carbon footprints [6]. Notwithstanding the above, indicators 7.a.1 (international financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems) and 7.b.1 (installed renewable energy-generating capacity in developing countries (in watts per capita)) are considered to have an uncertain impact on the DI.

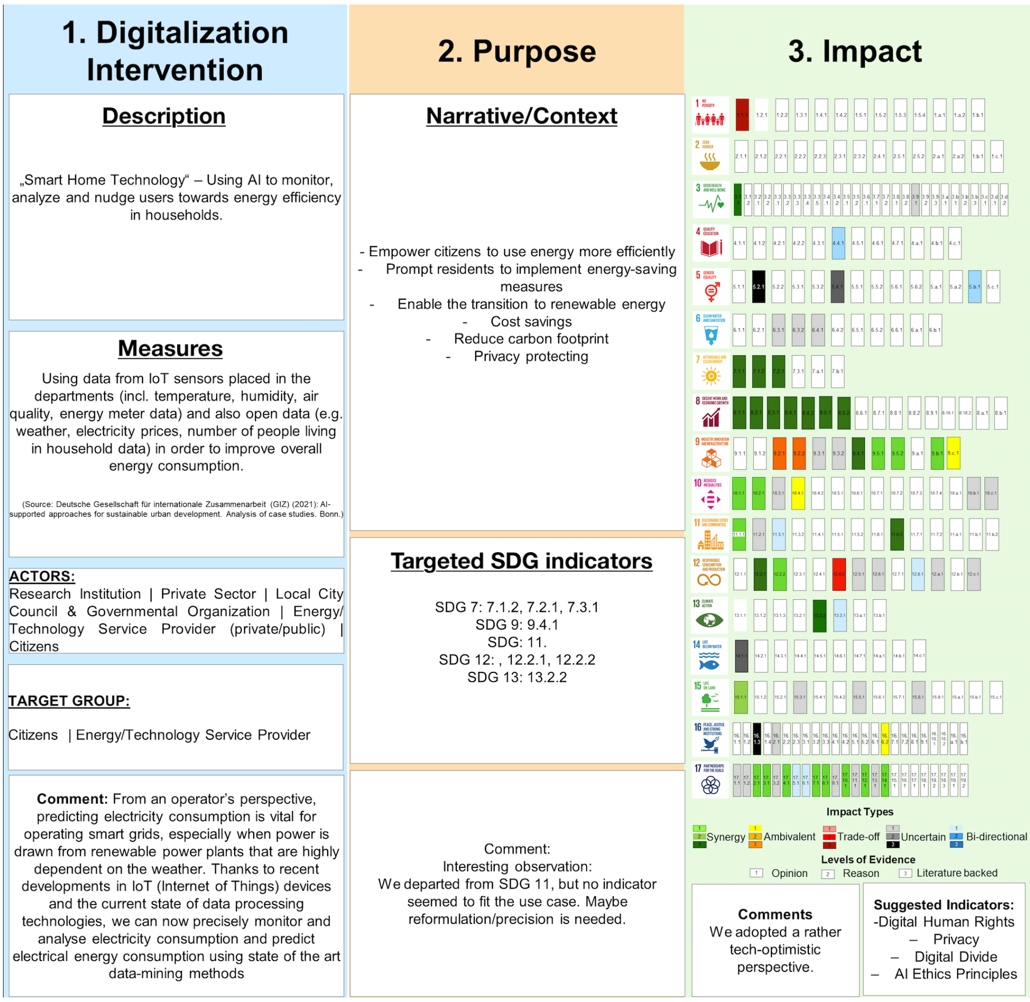

Figure 1. DAF outcome of smart home technologies as DI.

Table 1. Overview of of the impact of SHT as a DI on various SDG indicators. (Text color reflects the Impact type in the DAF).

DAF Outcome for SHT	
Impact Type	**Indicators**
Synergy	3.1.1, 7.1.1, 7.1.2, 7.2.1, 8.1.1, 8.2.1, 8.3.1, 8.4.1, 8.4.2, 8.5.1, 8.5.2, 9.4.1, 9.5.1, 9.5.2, 9.b.1, 10.1.1, 10.2.1, 11.1.1, 11.6.2, 12.2.1, 12.2.2, 13.2.2, 15.1.1, 17.2.1, 17.3.1, 17.4.1, 17.7.1, 17.8.1, 17.10.1, 17.12.1, 17.14.1
Ambivalent	9.c.1, 10.4.1, 16.6.2
Trade-offs	1.1.1, 9.2.1,9.2.2, 12.4.2
Uncertain	3.9.1, 5.2.1, 5.4.1, 6.3.1, 6.3.2, 6.4.1, 9.3.1, 9.3.2, 10.3.1, 10.b.1, 10.c.1, 11.2.1, 12.5.1, 12.6.1, 12.a.1, 12.c.1, 14.1.1, 15.3.1, 15.5.1, 15.8.1, 16.2.1, 17.1.1, 17.1.2, 17.3.2, 17.9.1, 17.11.1, 17.13.1
Bi-Directional	4.4.1, 5.b.1, 11.3.1, 12.8.1, 13.3.1, 17.5.1, 17.6.1

With regard to SDG 8 (decent work and economic growth), a synergistic impact supported by the literature has been reported for indicators 8.1.1 (annual growth rate of real GDP per capita), 8.2.1 (annual growth rate of real GDP per employed person), 8.3.1 (proportion of informal employment in total employment, by sector and sex), 8.4.1 (material footprint, material footprint per capita, and material footprint per GDP), 8.4.2 (domestic material consumption, domestic material consumption per capita, and domestic material consumption per GDP), 8.5.1 (average hourly earnings of employees, by sex, age, occupation, and persons with disabilities), 8.5.2 (unemployment rate, by sex, age, and persons with disabilities). 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 [84–87]. 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 [84]. In Canada, researchers also found that "investing in energy efficiency is a significant net benefit to the economy". It would add 118,000 jobs and increase GDP by 1% over the baseline forecast over the study period (2017–2030) [85]. 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 [84,86].

Nevertheless, other authors suggested that increased energy efficiency should be implemented on a large scale for relevant impacts on energy efficiency [88]. The reason for this is the "rebound effect"; when an item's 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., understanding labeling on appliances based on energy efficiency. Some studies also showed a more positive impact when in-home displays were available [87,89].

The literature review did not disclose a strong correlation between SHT and SDG 9 (industry, innovation, and infrastructure). 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, SHTs 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) [90–92]. In addition, the impact of DI on indicator 9.2.2 (manufacturing value added as a proportion of GDP and per capita) is ambivalent due to the new demand for smart home energy experts and the way the system is maintained and produced. This further triggers the consequential effects on traditional heating/energy systems, and consumers take over work from service providers [93]. Ambivalent impact on indicator 9.c.1 (proportion of population covered by a mobile network, by technology) was also identified, due to the inequality and accessibility of modern mobile infrastructure considering that smart home systems require modern mobile infrastructure to communicate and receive data via the IoT or 5G network [94]. Additionally, considering that smart energy management at home and the energy transition are developing faster, but also the overall growth in ICT energy demand is increasing dramatically, there are synergistic impacts on indicator 9.4.1 (CO_2 emission per unit of value added) [90,95,96]. Indicators 9.5.1 (research and development expenditure as a proportion of GDP), 9.5.2 (researchers (in full-time equivalent) per million inhabitants), and 9.b.1 (proportion of medium and high-tech industry value added in total value added) 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 energy efficiency. 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 in indicators 9.3.1 (proportion of small-scale industries in total industry value added) and 9.3.2 (proportion of small-scale industries with a loan or line of credit).

Regarding SDG 10 (reduce inequality within and among countries), studies are needed on a national level in order to uncover the impact of SHT. Nevertheless, if implemented within a well-crafted national policy in the future, one could assume a positive impact (based on opinion, indicators 10.1.1 and 10.2.1). The same could also 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 (labor share of GDP)). In addition, an uncertain distant 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 (proportion of population reporting having personally felt discriminated against or harassed in the previous 12 months on the basis of a ground of discrimination prohibited under international human rights law), 10.b.1 (total resource flows for development, by recipient and donor countries and type of flow (e.g., official development assistance, foreign direct investment, and other flows)), and 10.c.1 (remittance costs as a proportion of the amount remitted)).

In the context of SDG 11, SHT included within the setting of "data-driven smart sustainable cities" seems to be an optimal representation, thus explaining the distant synergic impact on indicator 11.1.1 (based on opinion). A bi-directional impact is also presented for indicator 11.3.1 (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); previous evidence showed the positive impact of building energy efficiency measures on air quality [97].

In that sense, SHT should be implemented together with smart grid energy-efficient technology, a comprehensive national policy, and other smart home digital interventions monitoring water and air quality, while also integrating renewable energy resources. 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.

4.2. Group 2: Blockchain as a DI

To investigate potential responses to food production, distribution, and consumption challenges, the group undertook an exploratory approach to understanding the 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 [98]. 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 & Table 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 [99]. The technology can help achieve food safety and establish trust between actors by increasing the number of trusted transactions and verifying food provenance [100]. Application of the DI puts in place an infrastructure that fosters a more responsible production and consumption pattern in the food supply chain to reduce food waste [44]. Monitoring and traceability of food can ensure the food is marketed within its life cycle [100].

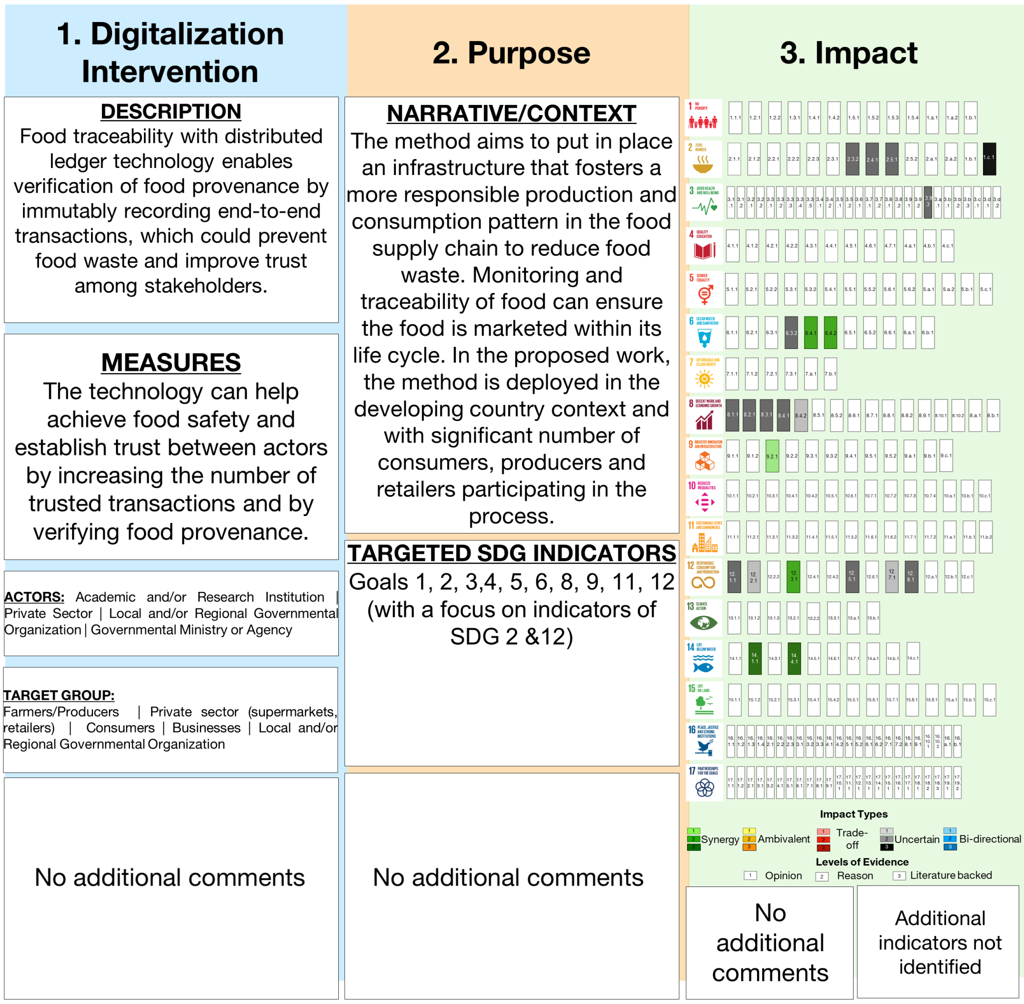

Figure 2. DAF outcome of blockchain as DI.

For SDG 2 (end hunger, achieve food security, and improve nutrition and promote sustainable agriculture), 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., [101]) and other stakeholders (e.g., [102,103]) through data as well as the potential increase in farmers' incomes [104]. 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., [41,105,106]). 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 [107]. 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 [108].

Regarding 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. [109] highlight the need for DNA-based technologies in, e.g., meat markets. In terms of indicator 2.c.1 (food price anomalies), traceability across an extended number of stakeholders improves with blockchain-based trust management [44], bargaining power, and democratization [110], which can be fostered through the involvement of state actors [111]. Additionally, competition between traditional and online channels may prove valuable [112], although the cross-channel information strategy and its relation to performance remain unclear [113].

Table 2. Overview of the SDG indicators impacted by blockchain as the DI. (Text color reflects the Impact type in the DAF).

DAF Outcome for blockchain	
Impact Type	**Indicators**
Synergy	6.4.1, 6.4.2, 9.2.1, 12.3.1, 14.1.1, 14.4.1
Ambivalent	NA
Trade-offs	NA
Uncertain	2.3.2, 2.4.1, 2.5.1, 2.c.1, 3.9.3, 6.3.2, 8.1.1, 8.2.1, 8.3.1, 8.4.2, 12.1.1, 12.2.1, 12.5.1, 12.7.1, 12.8.1,
Bi-Directional	NA

For SDG 3 (ensure healthy lives and promote well-being for all at all ages), indicator 3.9.3 (mortality rate attributed to unintentional poisoning), the blockchain yields a dubious impact on food selection and the spread of polluted foods (e.g., [42,114]), wrongly labeled foods that caused death to customers [45], or improved efficiency while also addressing concerns about animal welfare, environmental sustainability, and public health [115]. As for SDG 6's (Ensure Availability and Sustainable Management of Water and Sanitation for All) indicator 6.3.2 (proportion of bodies of water with good ambient water quality), the blockchain shows limited evidence of impact on real-time water quality monitoring [116]. There is potential for synergistic effects with 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., [117,118]). Additionally, the blockchain may be instrumental in generating insights on the characteristics of soil and 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., [107,119]).

The impact on SDG 8 is stated but not definite by indicators 8.1.1 and 8.2.1, although the potential for a major impact on employment in the agriculture sector is discernible (e.g., [42,120–122]). Indicator 8.3.1 highlights the diversity of affected actors who could nonetheless be expected to benefit from blockchain technology [123], such as SMEs [124]. Using the blockchain can improve indicators 8.4.1 and 8.4.2 insofar as it improves supply chain operations' economic, social, and environmental efficiency (e.g., [42,121,125,126]).

SDG 9 indicator 9.2.1 elaborates on the potential of blockchain technologies for the procurement contract and industrial added value and operational performance [127–129].

For SDG 12 indicator 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 [130] and ensure fairer supply chains [131]. Along those lines, indicators 12.2.1 (material footprint, material footprint per capita, and material footprint per GDP), e.g., optimizing energy consumption [132], 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 [133–136]. As such, the blockchain is seen as a potential solution to contribute to the circular economy (e.g., Tripoli and Schmidhuber [125], Rejeb et al. [137]). Indicator 12.7.1 (degree of sustainable public procurement policies and action plan implementation) discusses blockchain-based digital contracts and their contribution to public procurement [104]. For 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 [138].

For SDG 14's (conserve and sustainably use the oceans, seas, and marine resources for sustainable development) indicator 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 [139,140]. For indicator 14.4.1 (proportion of fish stocks within biologically sustainable levels), blockchains provide added value to determine the provenance and authenticity of seafood [141,142].

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, and 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 [143], and therefore unusable, as it was with the decennial agricultural census in Lebanon, for instance, [144]. 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, the 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.

4.3. Group 3: AI as a DI

The digitainability assessment observed mainly synergistic impacts of AI on SDG 15 targets, as well as relevant connections with many of the SDGs, especially with SDG 2, SDG 6, SDG 11, and SDG 13 (take urgent action to combat climate change and its impacts).

For SDG 1 (end poverty of all forms everywhere), we found by applying the DAF methodology (Figure 3 & Table 3) that most of the indicators of SDG 1 are not relevant to land management, with the exception of target 1.5 (by 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social, and environmental shocks and disasters), where AI can perform a vital role in terms of the exposure to extreme climate events and environmental disasters. For example, AI can predict floods using Artificial Neural Networks (ANNs), which run hydrological models [145] and can model heat waves, as used by Vautard et al. [146].

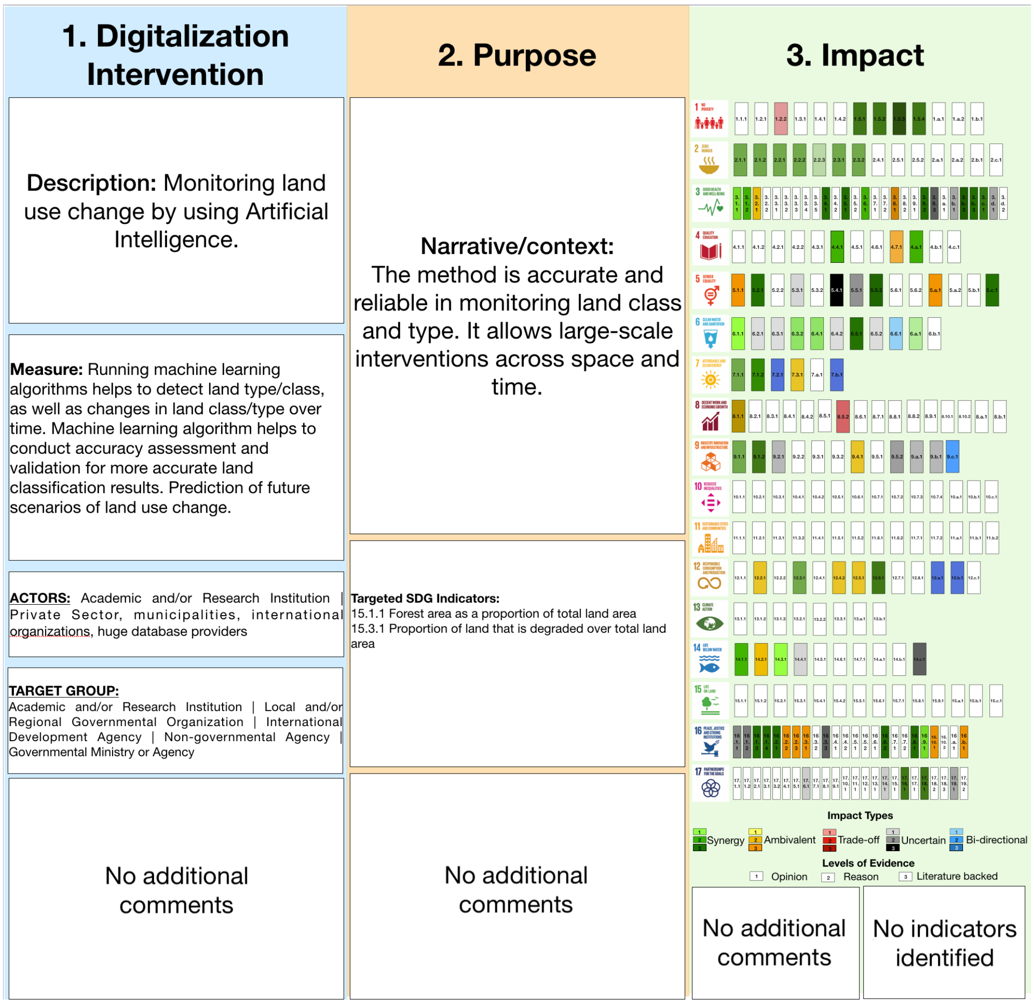

Figure 3. DAF outcome of AI as DI.

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, target 2.3 (end hunger, achieve food security and improved nutrition and promote sustainable agriculture). AI tools are used for crop monitoring, as in the model of Singh et al. [147], who used AI and IoT to detect the most suitable land and conditions for plant growth. AI has been 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 [148].

For SDG 3 (ensure healthy lives and promote well-being for all at all ages), to ensure healthy lives and better well-being intersects 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 [149]. 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 [150,151]. One of the most important factors for better health is accessibility, either for education, medical services, or mental improvement. ANN models are used for measuring land accessibility rates in urban areas, where it serves as the main factor for better well-being [151]. As shown in SDG 2, Soil pollution is being quantified, which serves as some of SDG 3's indicators for reducing the death rate as a result of food pollution [147].

Table 3. Overview of the SDG indicators impacted by AI as the DI. (Text color reflects the Impact type in the DAF).

DAF Outcome for AI	
Impact Type	**Indicators**
Synergy	1.5.1, 1.5.2, 1.5.3, 1.5.4, 2.1.1, 2.1.2, 2.2.1, 2.2.2, 2.2.3, 2.3.1, 2.3.2, 3.1.1, 3.1.2, 3.4.1, 3.5.1, 3.6.1, 3.9.2, 3.b.1, 3.b.3, 3.c.1, 4.4.1, 4.a.1, 5.2.1, 5.5.2, 5.c.1, 6.1.1, 6.3.2, 6.4.1, 6.5.1, 6.a.1, 7.1.1, 7.1.2, 9.1.1, 9.1.2, 12.3.1, 12.6.1, 14.1.1, 14.3.1, 16.1.3, 16.1.4, 16.2.1, 16.6.2, 16.8..1, 16.9.1, 17.16.1, 17.18.1
Ambivalent	3.2.1, 3.8.1, 4.7.1, 5.1.1, 5.a.1, 7.3.1, 8.1.1, 9.4.1, 12.2.1, 12.4.2, 12.5.1, 14.2.1, 16.2.2, 16.2.3, 16.3.1, 16.10.1, 16.b.1,
Trade-offs	1.2.2, 8.5.2
Uncertain	3.9.3, 3.b.1, 3.d.1, 5.3.1, 5.4.1, 5.5.1, 6.2.1, 6.3.1, 6.4.2, 6.5.2, 9.2.1, 9.5.2, 9.a.1, 9.b.1, 16.1.1, 16.1.2, 16.3.3, 17.6.1, 17.14.1, 17.19.1
Bi-Directional	6.6.1, 7.2.1, 7.b.1, 9.c.1, 12.a.1, 12.b.1, 12.a.1, 12.b.1

For SDG 5 (achieve gender equality and empower all women and girls), 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 (proportion of ever-partnered women and girls aged 15 years and older subjected to physical, sexual, or psychological violence by a current or former intimate partner in the previous 12 months, by form of violence and by age) [152], 5.5.2 (proportion of women in managerial positions) [153] and 5.c.1 ((a) proportion of total agricultural population with ownership or secure rights over agricultural land, by sex; and (b) share of women among owners or rights bearers of agricultural land, by type of tenure) [154,155]. Considering SDG 7 and SDG 13, the energy sector is enduring a disruptive transformation toward a more decentralized, digitalized, decarbonized, climate-neutral, and green future, with strong synergies with the building, transport, and infrastructure sectors [156] and large impacts on climate. AI brings huge potential to accelerate the green energy transition [157–159], 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, and demand management and innovation [160–162]. Virtual power plants can boost distributed energy and automation of small, distributed devices such as electric vehicles [156,163].

Vinuesa et al. [6] claim that AI has the potential to contribute to all SDG 7 targets 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 [164–167].

In addition, AI might bring bi-directional impacts on indicator 7.2.1 and indicator 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) [168–170] as well as support the enhanced planning and monitoring of energy facilities [156,163]. 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 [12,156,165,171,172]. Nevertheless, smart grids can suffer cyber attacks and are prone to blackouts in the least developed contexts [66]. On the other hand, renewable energy could help curb the growing carbon footprint of energy-intensive algorithms (e.g., DL) and facilitate more sustainable use of digital technologies by integrating green energy in data centers toward carbon neutrality and green AI [163].

However, an ambivalent impact is observed on indicator 7.3.1, which merits further analysis since the related net effect remains unclear. AI for land management can support the efficient use of resources leading to lower energy consumption and intensity of the economy [173,174]. However, potential rebound effects [175] may arise along with growing energy demand from the DL algorithms [176,177], which might outweigh the benefits. AI systems, particularly DL, require mitigating strategies to reduce their large carbon emissions [178–180]. In addition, a lack of transparency and accountability is observed regarding carbon emissions [181], 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 [161].

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 [160,161,165]. Sætra [182] 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 (number of deaths, missing persons, and directly affected persons attributed to disasters per 100,000 population), providing enhanced disaster prediction and management [160,165,183,184]. An ambivalent impact is identified regarding SDG 13.2.2 (total greenhouse gas emissions per year), 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 (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), AI has indeed the potential to analyze massive educational data (e.g., massive open online course participation data), adapt educational programs to the needs of the students, and provide augmented reality [160]. 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 (number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030), 13.1.3 (proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies), 13.2.1

(number of countries with nationally determined contributions, long-term strategies, national adaptation plans, and adaptation communications, as reported to the secretariat of the United Nations Framework Convention on Climate Change), and 13.b.1 (number of least developed countries and small island developing states with nationally determined contributions, long-term strategies, national adaptation plans, and adaptation communications, as reported to the secretariat of the United Nations Framework Convention on Climate Change) focused on the availability of disaster risk strategies and plans, little evidence is provided in the literature, and these impacts remain uncertain.

With regard to SDG 9 and SDG 11, 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 [185] by monitoring pollution and resource efficiency, enhancing transport and communication infrastructures and boosting research and innovation across all the domains [162,165]. 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 [12,66,186]. 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 (passenger and freight volumes, by mode of transport) since AI for land management might support the mapping and monitoring of population close to road facilities [55,187,188] as well as the volume of passengers and freight from Big Data coming from transportation systems [189–191], and their evolution patterns over time. An ambivalent impact regarding the contribution to indicator 9.4.1 is observed since AI for land could be useful for calculating the carbon footprint based on LCAs from different activities, forest extension, and soil features acting as carbon sinks [192,193]. 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 [165,194,195]. Nonetheless, cybersecurity and privacy represent critical risks that should be wisely considered in critical facilities. In addition, its impact is unclear with regard to indicator 9.5.2 since AI could foster scientific discovery, benefiting many researchers in the realm of SD [196], but no clear evidence has been provided in the literature so far. A bi-directional impact is proved regarding SDG 9.c.1, 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 [197,198]. 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 a citizen-centric approach, as well as for being focused on highly developed economies [186]. Moreover, several targets (11.1 (by 2030, ensure access for all to adequate, safe, and affordable housing and basic services and upgrade slums), 11.4 (strengthen efforts to protect and safeguard the world's cultural and natural heritage), 11.a (support positive economic, social, and environmental links between urban, peri-urban, and rural areas by strengthening national and regional development planning), 11.c (support least developed countries, including through financial and technical assistance, in building sustainable and resilient buildings utilizing local materials)) have been overlooked in the literature on AI for cities, which has been mainly focused on mobility, environmental management and monitoring (water, air, waste, and energy), and disaster responsiveness. Therefore, significant gaps remain in ensuring the social good of AI toward 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, 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 (indicators 10.1.1 and 10.2.1), migration and refugee tracking (SDG 10.7.2 (number of countries with migration policies that facilitate orderly, safe, regular and responsible migration and mobility of people), 10.7.3 (number of people who died or disappeared in the process of migration toward an international destination), 10.7.4 (proportion of the population who are refugees, by country of origin)), fiscal control of markets, financial and economic indicators (SDG 10.4.2 (redistributive impact of fiscal policy), 10.5.1 (financial soundness indicators), 10.a.1 (proportion of tariff lines applied to imports from least developed countries and developing countries with zero tariffs, 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 (proportion of population reporting having personally felt discriminated against or harassed in the previous 12 months on the basis of a ground of discrimination prohibited under international human rights law)) and potential bias [191,199–204]. Indeed, AI has been widely criticized for augmenting inequality, bias, discrimination, and reproducing hierarchies [203]. Even when AI could contribute to fighting discrimination by analyzing massive amounts of data (e.g., social networks, PNL, and sentiment analysis), the negative impact outweighs any benefit. In addition, access to AI systems and digital skills is uneven across geographies [205], 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 toward 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. Sætra [48] 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. [206] 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 indicator 12.2.1 (material footprint, material footprint per capita, and material footprint per GDP), indicator 12.4.2 (number of parties to international multilateral environmental agreements on hazardous waste, and other chemicals that meet their commitments and obligations in transmitting information as required by each relevant agreement), and indicator 12.5.1. 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 [207,208]. AI for land management could improve the monitoring of waste treatment facilities and the detection of illegal landfills [189,209–214]. However, it might also lead to increased waste due to the required digital infrastructures and digital-induced overconsumption [48].

In contrast, synergic impacts are found in relation to the application of AI systems to indicators 12.3.1, 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 [137,215–217]. AI for land management could be useful to support the ESG reporting [218,219], particularly regarding land and soil [220,221], as well as to bring information about the potential impacts of tourism on land and the environment [222]. Bi-directional impacts are observed regarding indicator 12.a.1, the same as SDG 7.b.1. AI for land management could help map and monitor renewable energy facilities by using geospatial Big Data and distilling it into knowledge [223]. In addition, 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 (strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development), Sætra [48] 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 [224–226]. 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 SDG monitoring), since AI systems in combination with Big Data (e.g., earth observation, sensors, and IoP) can be a relevant tool for enhancing statistical capacity and monitoring all the SDGs [74,227–229] 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 make 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 [72,230].

In relation to the potential impacts that AI for land management brings across the 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 [231], 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 SDG 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 SDG 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 [24].

Besides, a relevant limitation of this analysis relies on the potential bias induced when selecting datasets [162], 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 [56]. Ensuring a sustainable, responsible, and inclusive application of AI for the 2030 Agenda will require trustworthy regulation beyond human-centric principles [232] and ethical standards [6,233,234] to halt the "wild west" of unregulated AI [205]. In addition, greening AI is an urgent priority and might be achieved by policy incentives for green algorithms [235], renewable energy and efficiency in data infrastructures, standardized methodologies for carbon and energy accountability embedded within the whole life cycle of AI systems [180], and environmental education. Accountability and transparency should be encouraged using FAIR data, trustworthiness, and 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 [160] and overcome current capacity and accessibility constraints, such as the non-universal access to datasets [236]. 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 [237].

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

The results of this study demonstrate (Figure 4 & Table 4) the opportunities provided by Big Data to achieve the SDGs. It showcases the benefits of participatory action by taking a futuristic perspective on 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.

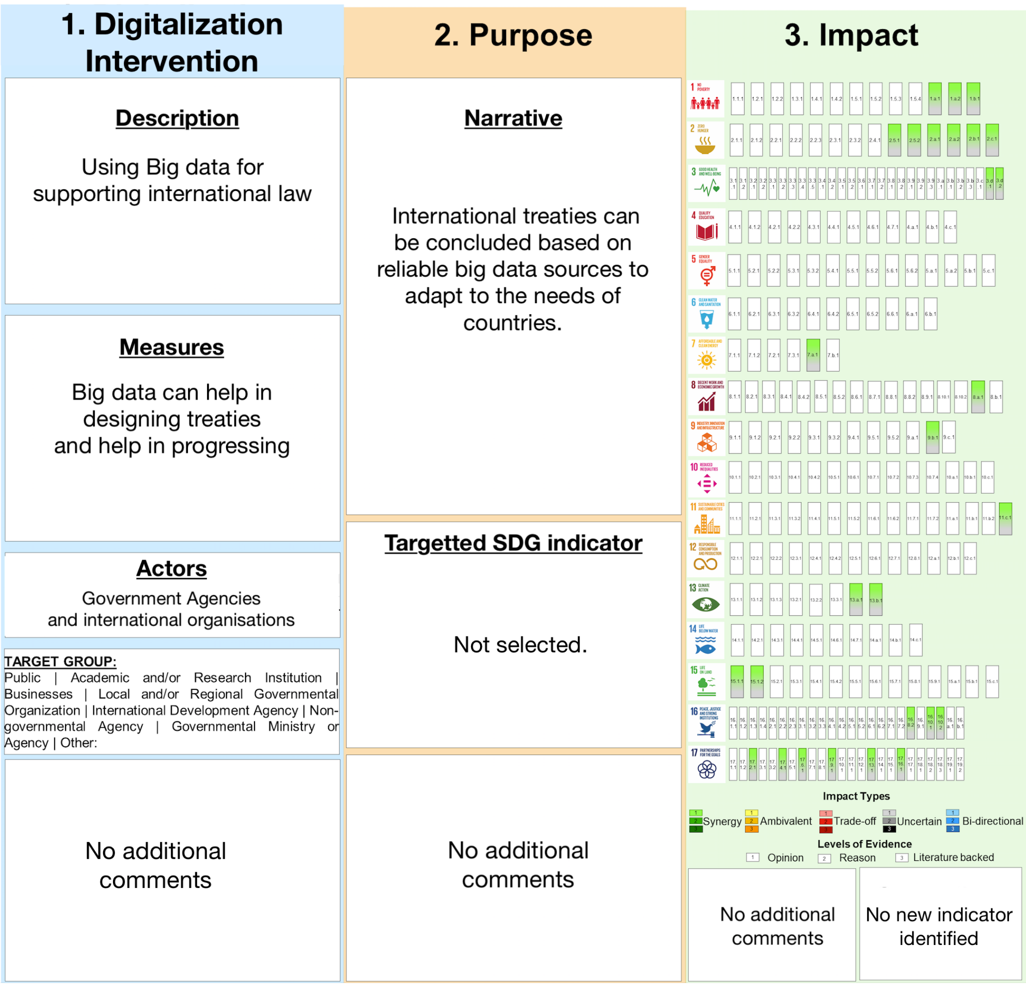

Figure 4. DAF outcome of Big Data as DI.

Implementing Big Data to achieve SDG 2 to create binding international treaties would allow direct compliance with indicator 2.5 (by 2020, maintain the genetic diversity of seeds, cultivated plants, and farmed and domesticated animals and their related wild species, including through soundly managed and diversified seed and plant banks at the national, regional, and international levels, and promote access to and fair and equitable sharing of benefits arising from the utilization of genetic resources and associated traditional knowledge, as internationally agreed), 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.

This would allow the increase in and facilitation of 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 (increase investment, including through enhanced international cooperation, in rural infrastructure, agricultural research and extension services, technology development, and plant and livestock gene banks in order to enhance agricultural productive capacity in developing countries, particularly in least developed countries). 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 (adopt measures to ensure the proper functioning of food commodity markets and their derivatives and facilitate timely access to market information, including on food reserves, in order to help limit extreme food price volatility). The information and improvement in the markets can help to eliminate export subsidies in line with the Doha Development Round and target 2b (agricultural export subsidies).

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, Big Data would help to make policy and organize investment in developing countries, achieving 1.a (ensure significant mobilization of resources from a variety of sources, including through enhanced development cooperation, in order to provide adequate and predictable means for developing countries, particularly in least developed countries, to implement programs and policies to end poverty in all its dimensions) and 1.b (create sound policy frameworks at the national, regional and international levels, based on pro-poor and gender-sensitive development strategies, to support accelerated investment in poverty eradication actions). For SDG 3 (ensure healthy lives and promote well-being for all at all ages), (3.d (strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction, and management of national and global health risks)) would help to reduce risks and health risks. Regarding SDG 7 (7.a (by 2030, enhance international cooperation to facilitate access to clean energy research and technology, including renewable energy, energy efficiency, and advanced and cleaner fossil-fuel technology, and promote investment in energy infrastructure and clean energy technology)), it would help for clean energy investments. For SDG 8 (8.a (increase Aid for Trade support for developing countries, particularly in least developed countries, including through the Enhanced Integrated Framework for Trade-related Technical Assistance to Least Developed Countries)), Big Data can support aid trade for developing countries.

For SDG 9 (9.b (support domestic technology development, research, and innovation in developing countries, including by ensuring a conducive policy environment for, inter alia, industrial diversification and value addition to commodities)) can support technology development. SDG 11 (11.c (support least developed countries, including through financial and technical assistance, in building sustainable and resilient buildings utilizing local materials)) can benefit from sustainable and resilient buildings. For SDG 13 (13.a (implement the commitment undertaken by developed-country parties to the United Nations Framework Convention on Climate Change to a goal of mobilizing jointly $100 billion annually by 2020 from all sources to address the needs of developing countries in the context of meaningful mitigation actions and transparency on implementation and fully operationalize the Green Climate Fund through its capitalization as soon as possible)), it can help to implement committees under the UNFCCC. SDG 15 (15.1 (by 2020, ensure the conservation, restoration, and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains, and drylands, in line with obligations under international agreements)) can benefit from conservation and restoration of ecosystems inland.

Regarding SDG 16 (promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels) (16.3 (promote the rule of law at the national and international levels and ensure equal access to justice for all), 16.8 (broaden and strengthen the participation of developing countries in the institutions of global governance), 16.10 (ensure public access to information and protect fundamental freedoms, in accordance with national legislation and international agreements)), participation in global institutions and governance, particularly for developing countries, ensures access to justice and fundamental freedom. For SDG 17 (strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development) (17.2 (developed countries to implement fully their official development assistance commitments, including the commitment by many developed countries to achieve the target of 0.7 percent of gross national income for official development assistance (ODA/GNI) to developing countries and 0.15 to 0.20 percent of ODA/GNI to least developed countries; ODA providers are encouraged to consider setting a target to provide at least 0.20 percent of ODA/GNI to least developed countries), 17.4 (assist developing countries in attaining long-term debt sustainability through coordinated policies aimed at fostering debt financing, debt relief and debt restructuring, as appropriate, and address the external debt of highly indebted poor countries to reduce debt distress), 17.6 (enhance North–South, South–South and triangular regional and international cooperation on and access to science, technology and innovation and enhance knowledge-sharing on mutually agreed terms, including through improved coordination among existing mechanisms, in particular at the United Nations level, and through a global technology facilitation mechanism), 17.9 (enhance international support for implementing effective and targeted capacity-building in developing countries to support national plans to implement all the Sustainable Development Goals, including through North–South, South–South and triangular cooperation), 17.10 (promote a universal, rules-based, open, non-discriminatory and equitable multilateral trading system under the World Trade Organization, including through the conclusion of negotiations under its Doha Development Agenda), 17.13 (enhance global macroeconomic stability, including through policy coordination and policy coherence), 17.16 (enhance the Global Partnership for Sustainable Development, complemented by multi-stakeholder partnerships that mobilize and share knowledge, expertise, technology and financial resources, to support the achievement of the Sustainable Development Goals in all countries, in particular developing countries)), to aid countries in implementing 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.

Table 4. Overview of the SDG indicators impacted by Big Data as the DI. (Text color reflects the Impact type in the DAF)

DAF Outcome for Big Data	
Impact Type	**Indicators**
Synergy to Uncertain	1.a.1, 1.a.2, 1.b.1, 2.5.1, 2.5.2, 2.a.1, 2.a.2, 2.b.1, 2.c.1, 3.d.1, 3.d.2, 7.a.1, 8.a.1, 9.b.1, 11.c.1, 13.a.1, 13.b.1, 15.1.1, 15.1.2, 16.8.2, 16.10.1, 16.10.2, 17.2.1, 17.4.1, 17.6.1, 17.9.1, 17.13.1, 17.16.1

One of the most important characteristics of international law treaties is that they are concluded by the will of the parties. According to Linares [238], 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. [239] 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.

5. 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. This paper brings forth the operationalization process, how expert groups approached the digitainability assessment process, and their recommendations for digitalization and sustainability practicing communities in a qualitative manner. Participants identified the DI in the discussion from their experience and sought to develop knowledge about digitainability aspects using participatory action. Results from the aforementioned case studies highlight the differences between countries in the application and maturity of the technology. Groups 1, 2, and 3 identify technology impacts at indicator levels covering synergies, ambivalent impacts, trade-offs, bidirectional impacts, and uncertainties, showing potential interlinkages that SDGs have at an indicator level and the diverse impact that DI can have depending on the context where it is applied. The results of Group 4 pointed out that beyond the application of the DI toward 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 provide a sense of having affinities in broader contexts because of the social, environmental, and economic dependencies [240]. For instance, SDG 7 has complex linkages with SDG 12 regarding industrial development and clean energy to sustain a green transition [241]. Achieving SDG 6 may affect the progress of SDG 3 targets, as access to clean water and sanitation is fundamental to delivering health services [242]. In addition, in the case of group 4, the outcomes of 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 leads 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 participatory action process 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 guide 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 to suggest limited attention to the topic, and other potential sources also helped map the multidisciplinary knowledge and existing gaps. Thus, operationalizing DAF for the participatory action exercise with constant 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 types of techniques for evidence-gathering and analysis based on the maturity of the technology and topic. 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 of 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' impacts in a specific context with stakeholders' intent in implementing DI [243]. 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 toward 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 [244]. Furthermore, the crucial trade-offs and ambiguities between the different pillars of sustainability should be noticed due to the focus on a narrow or isolated assessment of the impact of DIs [221]. 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 [245]. 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 from 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 following observation we received from the participants indicates the benefit of using DAF as a tool in participatory action for problem identification, evidence collection, evaluation, reflection, and prioritization of actions.

- 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;

- 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. 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;
- 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. In addition, contexts are highly relevant, and further research is needed in underrepresented countries, especially from the Global South.

The digital practices of the future will play a crucial role in shaping the sustainability and well-being of communities, organizations, and society. Therefore, it is important to ensure that these practices align with sustainable principles and support Sustainable Development Goals. 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 toward the 2030 Agenda milestone, the evolution of new goals needs to consider the digitainability aspect more systemically, toward 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 also help perform estimations required for ex ante and ex post consequential effects of DIs. The DAF can be considered a first step to further develop a mathematical model to understand the numerical impact between indicators, for which a better understanding of the theoretical connections between indicators highlighted by the DAF is needed. For a robust mathematical model that must be calibrated and validated, reliable historical data are needed, which is not available for all cases currently [26]. A mathematical model also needs to work under all contexts, also addressed by the DAF; thus, the access to technology, the energy matrix mix, the political measures in place to achieve certain SDGs, budget, among others, must be represented in the model. Due to the complexity of the model, and the time length to achieve practical results, a mathematical approach to analyze the interconnection between indicators of the agenda 2030 might not be available in the following years, for which the DAF is a valid approach to analyze indicators' interconnections. We strongly believe sustainability data intelligence is a critical next step for operationalizing digitainability to drive initiatives and take coherent measures toward sustainable development.

6. Conclusions and Outlook

This paper demonstrates the operationalization of digitainability by using the DAF as a tool for encouraging mindfulness in utilizing the DIs for sustainable development. Operationalizing digitainability is more than just implementing green technologies or setting sustainability targets. It requires a fundamental shift in understanding how measures with digitalization operate and their maturity in certain contexts, leveraging innovative digital interventions and data-driven insights to redirect costs, optimize resource usage, reduce waste, and enhance actions towards holistic sustainability. DAF provided a coherent structure for evaluating the impact of digital technologies and practices, and helped guide participatory actions. The outcome of the paper demonstrates how a multidisciplinary perspective, with experts from diverse backgrounds, can operationalize the assessment framework to systematically gather evidence reflecting gaps and opportunities DIs can offer for sustainable development. The paper's outcome firstly demonstrates the practical approach to conducting a digitainability assessment using DAF as a tool and supporting the participatory action process. Secondly, it reflects on the digitainability assessment of diverse DIs in specific contexts, reflecting the potential inter-dependencies between SDG progress holistically. The paper further demonstrates how a more inclusive and integrated assessment with practical tools such as DAF could create the mindfulness that organizations and communities can harness to establish a forward-looking understanding of what it means to develop and utilize digital systems, technologies, and practices that support sustainable development. DAF can play a crucial role in transforming the digital practices of the future, helping to promote sustainability, equity, and well-being. Future work should focus on automating some DAF procedures, alleviating the labor-intensive task of evidence-gathering using tools and techniques recognized by various stakeholders. Further development of the assessment framework should consider expanding capabilities from qualitative to quantitative evaluation with interconnected data sources and empirical evidence to make assessment more robust and informative. Furthermore, developing sustainability data intelligence 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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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Meaning
AI	Artificial intelligence
ANN	Artificial Neural Network
DAF	Digitainability Assessment Framework
DIs	Digital Interventions
DL	Deep Learning
DSS	Digitainable Spring School

Abbreviation	**Meaning**
EO	Earth Observation
ESG	Environmental, Social, and Governance
GDP	Gross Domestic Product
GNI	Gross National Income
ICT	Information and Communications Technology
IoP	Internet of People
IoT	Internet of Things
LUCC	Land Use and Cover Change
ML	Machine learning
ODA	Official Development Assistance
PDS	Public Distribution System
SDGs	Sustainable Development Goals
SD	Sustainable Development
SHT	Smart Home Technology
ToC	Theory of Change
UN	United Nations
XAI	Explainable AI

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