Towards Sustainability of AI: A Systematic Review of Existing Life Cycle Assessment Approaches and Key Environmental Impact Parameters of Artificial Intelligence

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Abstract

Most people are aware of the huge benefits that Artificial Intelligence (AI) brings to humanity in terms of sustainable applications (AI for sustainability). Yet, the fewest face the environmental impacts caused by an AI over its complete lifecycle (Sustainability of AI), e.g., the energy consumption, regardless how beneficial its outputs are. This paper presents a systematic literature review on the existing approaches for conducting a Life Cycle Assessment (LCA) on AI applications, alongside the key factors influencing their environmental impact. The study identifies critical environmental impact drivers of an AI over its life cycle, like the energy and resource consumption of hardware devices which provide the needed computing power. It underscores the importance of a holistic LCA approach considering operational and embodied energy use and the lifecycle impacts of data centers and other physical devices required for AI. The results provide critical insights for stakeholders looking to assess and mitigate the environmental impact of AI applications.

Keywords: artificial intelligence, sustainability, sustainability of AI, life cycle assessment, data center

1. Introduction

Artificial Intelligence (AI) offers huge potential to humanity to operate more sustainably, i.e., more efficiently and thus more resource-efficiently (Schoormann et al., 2021; Vinuesa et al., 2020).

However, the development and use of AI applications do not only result in positive effects. The training of the well-known NLP model GPT-3 alone has emitted approximately 552 t CO_2 equivalents (Patterson et al., 2022) as it requires a lot of computing power from energy- and resource-intensive data centers. This is nearly 425 times the emissions emitted by a single person flying from Los Angeles to Honolulu and back or the lifetime emissions of approximately 17 diesel cars (ADAC & Statista, 2018). The energy consumption of the application in operation, including deployment in millions of households, and other factors, such as environmental impacts from required hardware, of the model are not yet considered.

For this reason, there is a strong need to consider the positive and negative impact of an AI application over the entire life cycle.

With Life Cycle Assessments, an analysis approach exists that provides a framework for determining and comparing positive and negative effects caused over the entire life cycle of a product or service. The application of this approach, which is widely used in practice, is rather rare in AI models (Ligozat et al., 2022) .

This results in the following research questions, which are addressed in this paper regarding the sustainability of AI through a literature review.

RQ1: What approaches exist to perform a LCA of an AI?

RQ2: What are the key influencing factors driving the negative environmental impact of AI that need to be considered in an LCA?

2. State of the Art

2.1. Sustainable AI

According to (van Wynsberghe, 2021), who proposes an initial definition of *Sustainable AI*, the term describes "a field of research that applies to the technology of AI (the hardware powering AI, the methods to train AI, and the actual processing of data by AI) and the application of AI while addressing issues of AI sustainability and/or sustainable development."

The paper also distinguishes between both perspectives "AI *for* sustainability" (AI4S) and the

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"Sustainability *of* AI" (SoAI). To be considered as sustainable, both perspectives must be met by an AI.

AI4S describes research activities on potential applications that sustainable AI applications can have on their environment, regardless of the effort required to implement them and the potential negative environmental impacts triggered through their deployment (van Wynsberghe, 2021). (Rolnick et al., 2019) provide a broad overview on how AI can be used in various areas to achieve sustainable goals.

SofAI, on the other hand, explores the possibility of using metrics to measure the impact of AI over its lifetime, which covers the "design, development, training, validation, re-tuning, implementation and use of AI" (van Wynsberghe, 2021).

However, in any case, the implementation of AI applications requires hardware that provides the computing power needed to compute and deploy an AI application (Strubell et al., 2019). According to (Strubell et al., 2019), this has consequences in financial and especially environmental terms, as resource-intensive data centers must be provided.

2.2. Sustainable ICT and data centers in the context of AI

Since AI models on the software side and computing power providing hardware side are directly interdependent, sustainable information and communication technologies (ICT) is also considered as an umbrella term. According to (Krcmar, 2005), ICT is generally defined as "the totality of resources available for storage, processing, and communication, and the way in which these resources are organized."

(Hilty & Aebischer, 2015) take up the broad concept and, in parallel to (van Wynsberghe, 2021), distinguish between "Green ICT" and "ICT for Sustainability". In this case as well, only the first term "Green ICT" is relevant for the delimitation of this contribution. (Murugesan, 2008) defines Green ICT as "the study and practice of designing, manufacturing, using, and disposing of computers, servers, and related subsystems [...] with minimal or no impact on the environment." He identifies areas of focus as including energy-efficient computing, sustainable data center design and operation, use of renewable energy sources, and monitoring sustainability with green metrics and assessment tools.

Regarding the design of sustainable data centers, efforts are usually reflected in the optimization of energy efficiency, particularly regarding the power consumption of IT equipment, cooling systems and other energy supplies (Laurent & Dal Maso, 2020).

At the same time (Arlitt et al., 2012; Flucker et al., 2018; Whitehead et al., 2015b) emphasize that over the entire life cycle, the energy and resource consumption during manufacturing and transportation, as well as the environmental impact during deconstruction of the required construction and materials for the building of a data center, as well as the IT infrastructure used, must also be considered. In this context, the Life Cycle Assessment approach appears the most suitable.

2.3. Life Cycle Assessment

The Life Cycle Assessment (LCA) is a widely known and accepted method to enable an "assessment of environmental impacts at all stages of a product's life from cradle to grave, i.e. from raw material extraction through processing, manufacturing, distribution and use" (Muralikrishna & Manickam, 2017). The approach to this is prescribed and documented in (International Organization for Standardization 14040, 2006; International Organization for Standardization 14044, 2006).

According to (Hauschild et al., 2018), an LCA has the following four main characteristics: (1) observation of the entire life cycle, (2) coverage of diverse environmental impacts, (3) quantitative results and (4) science-based.

The procedure of an LCA is of a highly iterative character, but still consists of the same three phases (Hauschild et al., 2018) & ISO 14040

Target definition and scope: This phase has an immense impact on the reliability and interpretability of the results, as decisions are made here that affect data selection and product system design.

Inventory Analysis: In this phase, information on material flows or process steps of resources, materials, intermediates and products consumed to produce and provide a functional unit of the product or service under consideration are gathered. The same applies to emissions, waste, and recyclable products. The quantitative scaling of these flows refers to the initially defined functional unit.

Impact Assessment: In the last phase, the identified and quantified flows are "translated" into result values of the assessment categories selected at the beginning.

3. Methodology

3.1. Scope of literature review

The scope of this literature review was defined according to (Cooper, 1988). The aim of this paper is to analyze an overview of the available research on the sustainability of AI applications. The overview takes a neutral perspective and is aimed at researchers who wish to explore methods for sustainability assessment of AI. Due to limited access to databases and narrowing by search terms, this paper does not claim to be complete or representative.

3.2. Preparing the search process

In this paper, a literature review according to (Webster & Watson, 2002) is conducted. First, relevant search terms are defined based on initially found literature (Table 1) and then applied for systematic search in scientific databases.

Search term groups 1, 2, and 3 represent terms to include (1) Artificial Intelligence, (2) data centers, and (3) ICT in the search. The search term groups A-E consider the subject areas of (A) Life Cycle Assessments, (B) Environmental Assessments, (C) other sustainability measurements and (D) Carbon footprint and synonyms, (E) general life cycle.

Similar search terms are connected with the OR operator, and thus summarized to a search term group, to expand the search field. A single search was performed by linking one of each of the topic areas 1-3 and A-E using the AND operator to form the intersection. Due to lacking relevance, the only combination left out of the search process is the intersection of search terms “3” and “E”.

For the search process, the EBSCO Host, AIS eLibrary, ACM Digital Library, IEEE Xplore, and MDPI databases are used. Backward research is applied to found literature, the process of forward research is omitted.

According to (Paez, 2017), gray literature found during the research is also considered.

Table 1: Overview of used search terms

#	Search terms
1	“AI” OR “Artificial Intelligence” OR “ML” OR “Machine Learning”
2	“Data Center” OR “Data Centre”
3	“ICT” OR “Information Technology”
A	“Life Cycle Assessment” OR “Life Cycle Analysis” OR “Lifecycle Assessment” OR “Lifecycle Analysis” OR “LCA”
B	"Environmental Assessment" OR "Environmental Sustainability" OR "Impact Assessment" OR "Ecological Impact"
C	"Sustainability Measurement" OR "Green Performance Indicator" OR "Sustainable Performance Indicator" OR "Sustainability Performance"
D	"Carbon Footprint" OR "Climate Neutral" OR "Resource Consumption"
E	"Life Cycle" OR "Lifecycle"

3.3. Performing the search process

Except for MDPI, all search terms are applied to the title for all databases. For MDPI, the search terms are applied to the keywords area.

As a result, 443 contributions were initially found. Already during the search process, attention was paid to the inclusion of duplicates, which is why only three duplicates had to be removed from the results.

Subsequently, the abstracts of the remaining 440 paper were screened for key terms and relevance in title and abstract. Only those publications were marked as relevant that had a clear reference to the SofAI and did not only consider AI4S. After applying this filter, the number of results is reduced to 25 contributions. The high percentage of discarded search results based on this requirement could be explained by a research gap. By adding the backward search, an additional 23 contributions were added to the collection, of which 7 are considered as gray literature. As a result, 48 contributions could be identified as relevant through the search process.

4. Results

As suggested for IS literature reviews by (Webster & Watson, 2002), a concept matrix is used, to analyze and summarize the contributions found.

The found literature was grouped and analyzed by (1) the technical aspect that is being looked at in the paper such as (1.1) “ICT”, (1.2) “AI/ML” or (1.3) “data centers”, as well as (2) the aspects relevant for an LCA such as (2.1) “taking on a lifecycle approach”, (2.2) “discussing functional units”, (2.3) “system boundaries” and (2.4) “life cycle inventory”. Furthermore, the methods discussed in the papers were identified to create an overview of the current methodological landscape. The results are shown as a concept matrix in Table 2.

5. Findings

During the search process, the ITU-T and ETSI standards were identified as gray literature and searched backwards (ETSI - European Telecommunications Standards Institute, 2015; ITU-T, 2014). Both refer to be technically equivalent and give a comprehensive framework for conducting LCAs in ICT equipment, networks, and services. Specifically, to services, eight categories to be considered are given through the phases *raw material acquisition*, *production*, *use*, and *end of life*.

Complementary to ITU-T/ETSI, an ADEME standard has been published by the French side

(ADEME, 2021). According to its own statement, it complements existing guidelines to meet specific needs and provides rules, assumptions, and secondary data to make LCA easier for users to perform.

Since the standards were written very generically for ICT and only briefly address a regulatory framework for digital services, a first adaptation of the standard to AI approaches was done as part of the contribution of (Ligozat et al., 2022).

5.1. LCA of AI/ML applications

A standard that provides a guideline for conducting life cycle assessments with a dedicated focus on AI applications does not exist currently. Based on the LCA core requirement of considering the entire life cycle, literature containing a framework for the individual life phases of AI applications was also considered during the research. The following contributions are considered particularly relevant.

(Ligozat et al., 2022) offer a first approach in which scope, respectively in which system boundary the SofAI applications should be measured, based on the ITU-T/ETSI standard. For this purpose, they link the individual phases of the AI lifecycle with required physical devices that are basic prerequisites for creating and using AI applications. As a result, for each device involved during an AI's lifecycle, its own resource consumption of each device lifecycle is again included in the calculation on a pro-rata basis.

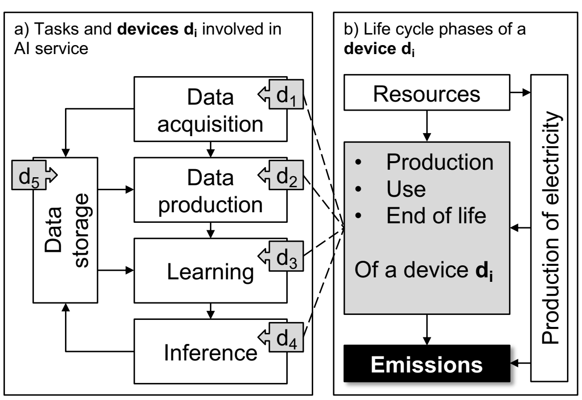

Figure 1: Emissions caused over the AI life cycle related to the life cycle of involved devices (Ligozat et al., 2022).

5.2. Energy consumption of AI/ML applications

Since the direct measurement of AI-caused CO2 emissions is very difficult as the target value depends on the local energy mix and time of day. (Henderson et al., 2020; Kaack et al., 2021; Lacoste et al., 2019; Schwartz et al., 2020) propose FPO, or FLOP (floating-point operations) as the central metric. It describes the amount of work performed by addition and multiplication calculations. This allows direct conclusions on the required energy consumption of the model. Furthermore, the key figure is independent of the hardware on which the AI model is executed, which facilitates the comparability of several models.

In addition, a variety of papers also provide tips on saving energy for training and deploying AI applications:

Energy mix: The environmental footprint of the energy mix used depends heavily on the location of the computing hardware (Anthony et al., 2020; Henderson et al., 2020; Patterson et al., 2021; Rolnick et al., 2019; Trihinas et al., 2022). Since some regions still rely heavily on fossil fuels for energy production, while others are already sourcing renewable and carbon-neutral energy, CO_2 emissions are correspondingly strongly linked to energy consumption. Depending on the contribution, the savings factors vary between the values 5-10 (Patterson et al., 2022) and 60 (Anthony et al., 2020). The high deviation is primarily due to different system boundaries of the measurement as well as different regional energy mixes considered.

Training times: In addition to location, the timing of training execution is also critical (Anthony et al., 2020), (Trihinas et al., 2022). This is due to the volatile energy supply from different sources over the course of the day, e.g., in windy and sunny hours.

Efficient algorithms: (Anthony et al., 2020; Henderson et al., 2020; Patterson et al., 2021) propose several ways such as hyperparameter tuning, optimization techniques, energy-aware training methods and others to decrease the energy consumption of a model.

Efficient hardware and hardware settings: In terms of energy consumption, the hardware used is highly important (Anthony et al., 2020; Henderson et al., 2020; Lacoste et al., 2019; Patterson et al., 2021, 2022; Trihinas et al., 2022). (Lacoste et al., 2019) summarize that CPUs (central processing unit) are 10 times more inefficient than GPUs (graphics processing unit) in computing ML models, which in turn are up to 8 times more inefficient than TPUs (tensor processing units). The efficiency is compared in FLOPs per Watt.

Model accuracy: (Henderson et al., 2020; Kaack et al., 2021; Trihinas et al., 2022) also emphasize the additional environmental and economic costs of increased model accuracy. The increase in accuracy decreases continuously as training progresses and energy is consumed. From the user's point of view, it must therefore be decided at what point gains in model accuracy exceed the additional ecological and economic costs.

Table 2: Concept matrix (Brocke et al., 2009)

Contribution	**Concepts**									
	Term			LCA				Other	Example	Keyword
	1.1	1.2	1.3	2.1	2.2	2.3	2.4			
(Anthony et al., 2020)		X						X	X	AI Carbontracker
(Arlitt et al., 2012)			X	X					X	Net-Zero DC Architecture
(Ashmore et al., 2022)		X		X						ML lifecycle
(Coroamă et al., 2020)	X			X						LCA for ICT-Service
(Farrant & Le Guern, 2012)	X			X	X	X			X	LCA for ICT-Service
(Ferreira et al., 2019)			X					X	X	ML-based carbon footprint estimation
(Flucker & Tozer, 2012)			X	X	X					LCA on DCs
(Flucker et al., 2018)			X		X					DC PUE breakdown
(García-Martín et al., 2019)		X							X	Energy estimation models
(Grimm et al., 2014)	X			X	X		X			ICT LCA report
(Gupta et al., 2022)	X		X	X	X				X	ICT/DC LCA
(Henderson et al., 2020)		X						X	X	ML Carbon tracker
(Hilty & Hercheui, 2010)	X			X	X					ICT LCA Scope
(Hischier et al., 2015)	X			X	X	X	X		X	ICT LCA
(Honée et al., 2012)			X	X	X	X	X		X	DC LCA (focus on GHG emissions)
(Kaack et al., 2021)		X			X					ML GHG Framework
(Lacoste et al., 2019)		X						X	X	ML Carbon Footprint
(Ligozat et al., 2022)		X		X	X					AI LCA
(Lykou et al., 2018)			X					X	X	DC sustainability indicator
(Malmodin et al., 2014)	X			X	X	X	X		X	ICT LCA
(Meza et al., 2010)			X		X				X	DC Resource consumption
(Mucha et al., 2022)		X			X					AI Sustainability framework
(Natarajan et al., 2022)		X		X				X		AI affordances
(Patterson et al., 2021)		X						X	X	AI Carbon Emission
(Patterson et al., 2022)		X						X	X	AI Energy Consumption
(Pohl et al., 2019)	X			X	X	X			X	Literature Review on ICT LCA
(Schödwell et al., 2012)			X		X			X		DC Green Performance Indicator
(Schödwell et al., 2013)			X		X			X		DC Green Performance Indicator
(Schwartz et al., 2020)		X						X		Green AI Indicators
(Shah et al., 2011)										DC LCA
(Shah et al., 2012)			X	X	X	X	X		X	DC LCA
(Shaikh et al., 2021)		X						X		ML Energy and CF tracking
(Steidl et al., 2023)		X		X						ML DevOps Lifecycle
(Strubell et al., 2019)		X						X	X	ML Cost Assessment (Eco and Fin)
(Trihinas et al., 2022)		X						X	X	ML Inference
(Ullrich et al., 2022)	X			X	X				X	LCA of cloud-services
(Wenninger et al., 2022)		X						X		ML Sustainability Balance Sheet
(Whitehead et al., 2014)			X	X	X					DC metrics and building LCA
(Whitehead et al., 2015a)			X	X	X					DC metrics and building LCA
(Whitehead et al., 2015b)			X	X	X	X	X		X	DC LCA
(Williams & Tang, 2012)	X				X					GHG emissions of software deployment

Contribution (Gray literature)	Concepts									
	Term			LCA				Other	Example	Keyword
	1.1	1.2	1.3	2.1	2.2	2.3	2.4			
(Farrant & Le Guern, 2012)		X						X	X	AI Carbontracker
(Aggar et al., 2012)			X	X					X	Net-Zero DC Architecture
(ETSI - European Telecommunications Standards Institute, 2015)		X		X						ML lifecycle
(ITU-T, 2014)	X			X						LCA for ICT-Service
(Laurent & Dal Maso, 2020)	X			X	X	X			X	LCA for ICT-Service
(Rohde et al., 2021)			X					X	X	ML-based carbon footprint estimation
(Schödwell et al., 2018)			X	X	X					LCA on DCs

Measurement: Of the papers cited, (Anthony et al., 2020; Henderson et al., 2020; Patterson et al., 2021; Rolnick et al., 2019; Shaikh et al., 2021) published approaches and tools to measure energy use in their papers.

Furthermore, (García-Martín et al., 2019) provide an overview of different approaches to determine the energy consumption of ML solutions and tools.

In any case, energy and resource consumption of AI is dependent on data centers. It should be noted that these do not only consume energy during operation. Significant environmental impacts also occur during their manufacture and dismantling. It is therefore highly relevant to analyze the entire life cycle of data centers.

5.4. LCA of data centers

As with AI or ML applications, there is no publicly recognized standard for performing LCA on data centers. Nevertheless, the topic has already been dealt with in greater depth in science and applied research. It is important to emphasize the strict consideration of *embodied* and *operational* emissions. The former describes environmental impacts caused by manufacturing processes of the building envelope and other built-in components, the latter the impacts caused by the operation of the data center. In the following, the literature contributions considered most relevant are classified and described in the phases of an LCA explained at the beginning.

Target definition and scope: In this phase, it is particularly questionable how the system boundary is drawn, which key components are included in the LCA and how the functional unit is defined.

(1) System boundary: Based on the literature researched, the life cycle phases of data centers are: "Material mining and processing", "Manufacturing", "Transportation", "Utilization", "Upgrades" and "End of Life"(Aggar et al., 2012; Gupta et al., 2022; Laurent & Dal Maso, 2020; A. J. Shah et al., 2012; Whitehead et al., 2015b).

In addition, (Gupta et al., 2022) links the individual life phases of a data center and the installed computing units with the emission scopes of the GHG Protocol. Scope 1 describe direct emissions caused, for example, by production processes. Scope 2 are indirect emissions caused mainly by the purchase of energy. Scope 3 are emissions upstream or downstream in the supply chain that are caused by transport or manufacturing processes.

According to (Gupta et al., 2022), Scope 2 and Scope 3 emissions should therefore be considered first and foremost in the context of the data center, which represent the environmental impact of electricity consumption during operation and the components required in the construction of the data center.

(2) Core components: The core components considered throughout the lifecycle of a data center overlap greatly across the papers. For example (Aggar et al., 2012; Laurent & Dal Maso, 2020; A. Shah et al., 2011; A. J. Shah et al., 2012) identify (1) the IT equipment, (2) the power supply infrastructure, (3) the cooling systems, and (4) the building structure as the main drivers of ecological loads in their contributions to data center LCAs.

(Whitehead et al., 2015a) are more detailed in their paper and categorize the individual system components into mechanical components, electronic components, fire protection, and public health components in addition to IT components and building structure. In summary, however, in the context of operational energy consumption over the entire life cycle, IT equipment, electronic and mechanical components, and water pumps as public health components are identified as key drivers.

(3) Functional unit: For the definition of the functional unit to perform an LCA, the literature found scatters widely. (Aggar et al., 2012) do not provide a fixed functional unit, however, provide supporting guiding questions and guidance for a custom derivation. Also (A. J. Shah et al., 2012) do not define a single functional unit, but use different functional units for each system component. (Honée et al., 2012) use one year of operation of the data center under consideration as a functional unit. More specifically, (Whitehead et al., 2015b)(Whitehead et al., 2015b) use 1 kW of IT computing power per year as the unit. They give the additional hint that the computing operations of the data center would be decisive, but the determination of this quantity entails a tremendous complexity.

Inventory analysis: The contributions also use various approaches regarding the information on which components used cause which environmental impacts.

(Honée et al., 2012) use the Ecoinvent database. In the case of physical components, weight is decisive, to which the respective proportions of the materials used are assigned. In addition, energy consumption is estimated, and the database is supported by available product information from hardware vendors.

(A. J. Shah et al., 2011) list potential data sources for the components mentioned in the paper. These are the EIO Database, data from procurement, or literature. (Whitehead et al., 2015a) provide detailed information on databases used (in prioritized order): Ecoinvent, USA Input Output Database 2002 (EIO), worldsteel, European Life Cycle Database (ELCD), Industry Data 2.0, and USLCI. In addition, GaBi database is suggested by (Flucker et al., 2018).

5.5. Other DC sustainability metrics

Since performing an LCA on data centers involves a high degree of complexity (Flucker & Tozer, 2012; Whitehead et al., 2015a), metrics for sustainability, are also increasingly considered in the literature independently of performing an LCA. Here, (Lykou et al., 2018) and especially (Björn Schödwell et al., 2018) must be mentioned, which provide an overview of the previously summarized system components in their contributions.

(Rohde et al., 2021) provide a set of indicators to determine the environmental SofAI applications across the lifecycle phases. It reflects the narrative of the rest of the literature, that above all the power consumption from (re)training in connection with model accuracy and the resource consumption of required hardware in the overall process are decisive for the environmental impact of AI.

5.6. LCA of downstream hardware

Depending on the definition of the system boundary, data center downstream products must also be considered in the life cycle assessment. However, due to the research questions raised at the beginning, these are not the focus of this research. (Malmodin et al., 2014) provide a first insight into the topic. (Grimm et al., 2014) conducted an extensive literature review on LCAs of ICT hardware. In this context (Farrant & Le Guern, 2012) provide a first summarized application example, which is also oriented towards the ADEME regulatory framework.

6. Conclusion

The paper addresses the two research questions stated in the beginning as followed:

RQ1: *What approaches exist to perform an LCA of an AI?*

This paper presents the approaches for performing an LCA on AI/ML applications through a systematic literature review. We found no generally recognized standard for LCAs specified onto AI applications. However, an important milestone is an adaptation of existing ITU-T and ETSI standards in the context of AI by (Ligozat et al., 2022). They linked different phases of the AI lifecycle with the physical devices required to create and use AI applications, including these in their LCA calculations.

RQ2: *What are the key influencing factors driving the negative environmental impact of AI that need to be considered in an LCA?*

The paper identifies several key factors that influence the negative environmental impact of AI, including the regional energy mix, the timing of model training, the efficiency of the algorithms, hardware settings, model accuracy, and data center-related impacts. It is noted that the environmental footprint of the energy mix depends heavily on the region where the computing hardware is located, as CO_2 emissions are strongly linked to energy consumption. The timing of training, choice of energy-efficient algorithms, and hardware can also significantly impact energy use. Furthermore, the importance of considering the entire lifecycle of data centers was highlighted, as these do not just consume energy during operation but also have significant environmental impacts during their manufacturing and dismantling phase.

In summary, this paper has underlined the urgent need for more standardized and universally applicable methodologies to assess the environmental impact of AI and data centers. By consolidating these findings, we hope to stimulate further research in this critical field of research.

7. Limitations

In this work, the focus was primarily on environmental sustainability. First, it must be mentioned, that this work does not claim to be a fully comprehensive examination of existing literature.

In the context of the three pillars of sustainability (Purvis et al., 2019), no attention was paid to social and financial sustainability, which can be investigated with Social LCAs, respectively Life Cycle Costing Analyses (LCCA). The social pillar is highly relevant as current topics include, among others, Explainable and Responsible AI, as well as the working conditions of people training AI in low-wage countries.

Also, not to be neglected are human, or societal, interactions, associated with the use of sustainable AI, most notably rebound effects. These were not explicitly considered in this paper. However, (Pohl et al., 2019) provide a review of current literature that addresses the measurement of such effects in the context of LCA.

The third main phase of conducting a LCA on data centers (Impact Assessment) was left out a this was not the aim of this paper.

8. Research agenda

This literature review shows that there is a strong need for research on the *SofAI.* To clearly separate future research in both fields, a more distinctive labelling and common understanding for the terms *AI for sustainability* and *sustainability of AI* is needed.

In the short term, the general awareness of the topic *SofAI* appears to be problematic. Although approaches exist for measuring individual components, such as the energy consumption of AI training or the efficiency of individual components of a data center, no holistic methods exist. Given the current developments in the research field of AI, the pace at which the technology is spreading in practice, and the simultaneous urgency of achieving sustainable transformation in society and the economy, there is a need for a generally accepted approach that regulates the measurement of the *sustainability of AI* applications over their entire life cycle.

A first overview on the existing methods and approaches was given in this paper.

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