More sustainable artificial intelligence systems through stakeholder involvement?

Artificial intelligence (AI) systems carry risks and opportunities for environmental sustainability. The use of AI systems, for instance, can result in both software-related (direct) as well as application-context-related (indirect) resource use. Stakeholders are expected to play a role in understanding and steering the environmental effects of AI systems. However, the processes and anticipated outcomes of stakeholder involvement in AI system lifecycles are not clear. We provide a non-exhaustive scoping review of six software and AI sustainability frameworks with respect to their recognition of environmental sustainability and the role of stakeholders in dealing with environmental sustainability. This serves to develop recommendations for future research on how stakeholder involvement can help firms and institutions design and use more sustainable AI systems.

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While social issues around artificial intelligence (AI) systems (such as the explainability and fairness of AI systems) have been the focus of much public debate, the environmental dimension of sustainability of AI systems has received less attention (Perucica and Andjelkovic 2022). AI development and use, for instance, require energy and cause high emissions (direct environmental effect) (Dodge et al. 2022). Moreover, the broader environmental effects of using AI systems in other fields of society (indirect environmental effect), such as increased consumption induced by AI-aided marketing, can cause substantial negative sustainability impacts. Irrespective of these risks, AI could be used for purposes beneficial for sustainability, for example, to gather and assess information about environmental issues (Nishant et al. 2020).

To counter negative and promote positive effects of AI systems, there is increasing interest in stakeholders' role to build more (environmentally) sustainable AI systems (OECD 2022, UNESCO 2022). Stakeholders in the context of AI systems may be clients who order an AI system, software firms, private users and governmental institutions who regulate AI systems, among others. The European Commission states that "the broader society, other sentient beings and the environment should be [...] considered as stakeholders throughout the AI system's lifecycle. Sustainability and ecological responsibility of AI systems should be encouraged" (HLEG AI 2019 b, p. 19). When calls for the recognition of stakeholders are made, however, it often remains unclear who stakeholders are in the context of environmental sustainability and what specific requirements environmentally sustainable AI should adhere to (Perucica and Andjelkovic 2022).

In this *Forum* article, we ask whether and how the involvement of stakeholders as one key characteristic of transdisciplinary research (Lawrence et al. 2022) is able to enhance our understanding of and dealing with AI systems' environmental effects. To discuss this question, we perform a scoping review of six software and AI sustainability frameworks. First, we analyse four sustainability frameworks for software more broadly and two sustainability frameworks for AI in particular regarding the environmental effects of software/AI they recognise and the extent to which they incorporate stakeholder involvement as a tool to identify and mitigate environmental effects in software/AI lifecycles. The analysis of both software (of which AI is part) and AI sustainability frameworks serves to increase the pool of knowledge of the environmental sustainability effects of AI and how to address them. Second, we discuss to what extent the (stronger) involvement of stakeholders could help address the weaknesses and foster the strengths of these frameworks applied to AI. Finally, we suggest future research directions regarding stakeholder involvement and multi-dimensional sustainability considerations for AI as well as software more broadly.

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Environmental effects of artificial intelligence

Artificial intelligence and environmental sustainability

The High-Level Expert Group on Artificial Intelligence set up by the European Commission defines AI systems as "software systems (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal" (HLEG AI 2019a, p. 6). Following concepts of human intelligence, typical goals for AI include understanding language, vision and problem solving. There are numerous AI techniques which build on different concepts and algorithms, such as machine learning or natural language processing. They are frequently used in search engines, image recognition software or modern robotics applications (Döbel et al. 2018).

AI systems are usually embedded in broader software systems and come with particularities that differ from "traditional" software. For the present context, the following particularities are deemed important: firstly, AI systems are more data-driven than other software. Data is fed into the system not only during its use but particularly during its initial development. Thus, experimentation with training data is at the core of AI development rather than written code (Wan et al. 2020). Secondly, AI is able to automatically evolve during the use phase, whereas other software gets updated manually. In fraud detection, for instance, a machine learning system is expected to adapt to entities that try to outplay the algorithm by reiterating the learning algorithm with the new data or train an entirely new machine learning model (Wan et al. 2020). This may lead to "unexpected" outcomes in learning processes.

Drawing from literature on software sustainability effects, we distinguish two types of environmental effects of AI: direct and indirect environmental effects (figure 1).

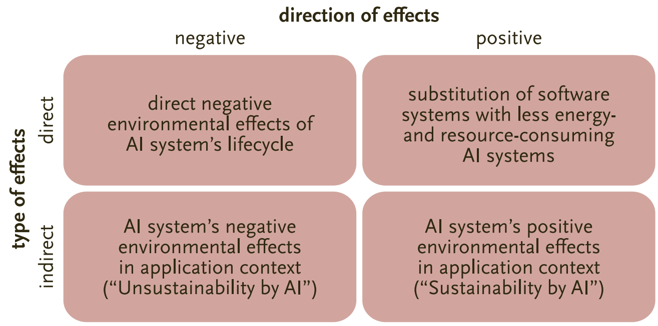

FIGURE 1: Categorisation of environmental effects of artificial intelligence (AI) systems. In this figure, the term "sustainability" refers to its environmental dimension.

Direct environmental effects

Direct environmental effects are considered all those environmental effects that occur along the lifecycle of an AI system itself, that is, environmental effects due to the production, use and disposal of physical hardware, infrastructure and software (Hilty et al. 2006, Bieser and Hilty 2018). As AI architectures differ from other algorithmic software (Gailhofer et al. 2021), AI systems' negative direct environmental effects may be larger than for other software. Patterson et al. (2021) show, for example, that emissions in training an AI system can increase more than a hundredfold depending on the architecture, processor types, data centres and power supply used. A positive direct environmental effect can arise if the AI system replaces a more energy- and resource-consuming software system (substitution effect; Börjesson Rivera et al. 2014).

Indirect environmental effects

Indirect environmental effects result from the application of systems in households, industry and agriculture, among others, which can affect the environmental sustainability of products and processes (Bieser and Hilty 2018, Börjesson Rivera et al. 2014). Increasingly automated production processes in firms, for instance, might affect their process and energy efficiency. On the one hand, AI systems entail negative indirect environmental effects. These can arise in the form of rematerialisation, induction, substitution or rebound effects, among others (Börjesson Rivera et al. 2014, Willenbacher et al. 2021) and may only become evident at the societal level and/or long term. For example, the use of individualised advertising is targeted at increasing the consumption of goods and services (induction effect) with a likely negative impact on environmental sustainability.[1] Likewise, intelligent mobility planning can make individual transport so attractive that it increases the rate of mobility and renders public transport less attractive (rebound and substitution effect, what we call "Unsustainability by AI"). With a view to positive indirect environmental effects, AI systems are supposed to contribute to sustainability in their application ("AI for sustainability" or what we call "Sustainability by AI"). For instance, AI systems are supposed to enable a flexible management of decentralised energy systems, which are confronted with fluctuations in renewable energy supply and demand (Antonopoulos et al. 2020).

Figure 1 summarises our categorisation of environmental effects (direct and indirect) and their directions (positive and negative).

Measuring environmental sustainability of artificial intelligence

An increasing body of literature deals with the question of how to measure direct and indirect environmental effects of AI (OECD 2022). For direct environmental effects of AI, different tools to measure the (direct) carbon footprint of AI are available (see table A in the online supplement[2]), but challenges in the >

1 See Gossen and Lell (2023, in this issue) for consumer policies initiatives tackling such environmental effects of digitalization.

2 See the online supplement *https://doi.org/10.14512/gaia.32.S1.10.suppl*.

measurement remain (Dodge et al. 2022). Carbon footprint is only one aspect of environmental sustainability. Measuring the entire embodied environmental footprint of the hardware used for computing, for instance, requires information on complex supply chains for electronics components regarding waste, chemicals use and biodiversity impacts, among others – but measurement of such environmental data is currently limited (Kunkel et al. 2022). For indirect effects, identifying and quantifying these effects is challenging, as questions about causality and system boundaries need to be addressed: to what extent is the use of a specific AI system causally responsible for an indirect environmental effect in society at large? What would have been the counterfactual outcome had an alternative (software) system been used? With the increasing call for stakeholder involvement in AI development, the question arises whether the involvement of stakeholders can contribute to overcoming some of these challenges and help identify, measure and mitigate direct and indirect environmental effects of AI systems. And if so, how?

Stakeholder involvement in artificial intelligence and software sustainability frameworks

To study the role of stakeholder involvement, we conducted a scoping review of a set of AI and software sustainability frameworks[3] regarding

1. which environmental effects they recognise and
2. to what extent they incorporate stakeholder involvement as a tool to identify and mitigate environmental effects in software/AI lifecycles.

Our main intention for the selection of frameworks was to cover a certain diversity of approaches. We chose AI-specific (two frameworks) and general software-related frameworks (four frameworks) which cover either several dimensions of sustainability (three frameworks) or only the environmental dimension of sustainability (three frameworks). The frameworks are provided either by industry (Microsoft principles) or found in scientific literature (all others). However, our *list of frameworks is not a representative sample* but serves to illustrate existing linkages in AI and software sustainability framework literature with stakeholder involvement. For a systematic literature review of software sustainability frameworks, for instance, see Penzenstadler et al. (2012) and Venters et al. (2018).

We extracted information on environmental effects and stakeholder involvement from the frameworks according to our two research questions. We did not use a fixed set of keywords to delineate "environmental effects" and "stakeholder involvement"; therefore, our results are our interpretations of these frameworks. We would appreciate a debate with the authors of the frameworks on our arguments. Detailed results of the analysis can be found in table B in the online supplement[2].

To summarise the analysed frameworks, two general software frameworks consider multiple dimensions of sustainability. A framework for *incorporating sustainability design in the software engineering lifecycle* is applied by Saputri and Lee (2021) to a case study. The *Sustainability Awareness Framework* (Duboc et al. 2020, Penzenstadler et al. 2020) also focuses on requirements engineering for sustainability and proposes five sustainability dimensions for software systems: social, individual, environmental, economic and technical. The framework is operationalised in the form of a workshop workbook which we analyse (Penzenstadler et al. 2020). Two of the general software-related frameworks only address the environmental dimension of sustainability. The first framework, *Kriterienkatalog nachhaltige Software* (Eng.: sustainable software criteria catalogue) (Hilty et al. 2017), focuses on resource efficiency, duration of hardware use and use autonomy. The second one by Microsoft (2022), the *Principles of Sustainable Software Engineering,* describes eight sustainability principles for improving the carbon efficiency of software, and is disseminated in the form of an online course on sustainable software development for practitioners which we analyse. Regarding AI systems, *Nachhaltigkeitskriterien für künstliche Intelligenz* (Eng.: sustainability criteria for artificial intelligence) by Rohde et al. (2021) suggest 13 sustainability criteria for AI systems for several sustainability dimensions. In their article *Aligning artificial intelligence with climate change mitigation,* Kaack et al. (2022) focus on the environmental dimension of sustainability and propose addressing the greenhouse gas emissions of AI in three categories: computational impacts, direct application impacts, and system-level impacts.

Results: Artificial intelligence, software sustainability and stakeholder involvement

Can stakeholder involvement as one characteristic of transdisciplinary research enhance our understanding, measuring and mitigation of environmental effects of AI?

First, we examined the recognition of environmental effects in software and AI sustainability frameworks. The frameworks by Hilty et al. (2017) as well Microsoft (2022) treat in varying technical detail mainly direct environmental effects along the lifecycle of software, such as the resource efficiency and carbon footprint of hardware and the environmental effects of necessary infrastructure for software. The environmental sustainability definition in the two frameworks is similar, that is, achieving a certain functionality with the lowest possible resource use. Saputri and Lee (2021), Penzenstadler et al. (2020), Rohde et al. (2022) and Kaack et al. (2022) more explicitly consider indirect (environmental) effects in their sustainability definition. Saputri and Lee (2021), however, only make a generic suggestion on "using environmental risk mitigation and having maintenance

3 We use the term "frameworks" loosely to refer to different sustainability approaches suggested in the works included in our scoping review. These approaches comprise a workshop procedure, an online course, a case study and sets of sustainability criteria stated in scientific publications.

guidelines" to address indirect environmental effects. Penzenstadler et al. (2020), in contrast, include specific questions on material and resources, soil, atmospheric and water pollution, energy, biodiversity, land use and logistics. Rohde et al. (2022) and Kaack et al. (2022) treat the positive and negative sustainability potential of AI for production and consumption and its risk of creating rebounds. While Rohde et al. (2022) consider four sustainability criteria on ecological aspects (energy, emissions, indirect resource use and sustainability potentials), Kaack et al. (2022) limit their framework to global greenhouse gas emissions and thus do not provide guidance on other environmental factors.

Secondly, we examined the extent to which the analysed frameworks incorporate stakeholder involvement. Our analysis shows that the frameworks generally recommend some sort of involvement of (non-scientific) stakeholders. Hilty et al. (2017) as well as Microsoft (2022) mention aspects of stakeholder inclusion, for example, involving "examiners" for computing sustainability or involving users to enhance the uptake of more environmentally sustainable software solutions. The Microsoft principle "demand shaping" suggests influencing user behaviour towards less energy-consuming uses of software and thereby try not only to increase resource efficiency but also to reduce demand. Moreover, several of the Microsoft principles imply that other parts of the firm and possibly stakeholders other than the programmer herself/himself would need to be involved in making software sustainability-related decisions. Rohde et al. (2022) consider the identification, classification and inclusion of stakeholders important along the entire lifecycle of AI systems and regard the number of stakeholder workshops (organised by the developing or using organisation of AI) as one important metric to measure stakeholder involvement. However, open questions remain about the design of such an involvement process and the expected outcomes with regard to environmental sustainability (e. g., how the involvement can be operationalised at the firm level throughout the entire lifecycle and how the identified environmental sustainability requirements feed back into the lifecycle). In Kaack et al. (2022), stakeholder relevance is implicitly acknowledged, for example, when stating the concern that dual use of the same technology can lead to either harmful or beneficial effects on the environment. However, the authors do not specify how more environmentally beneficial uses of technologies can be ensured.

Saputri and Lee (2021) as well as Penzenstadler et al. (2020) describe the attempt to capture trade-offs in the assessment of various sustainability levels of software development through requirements engineering. Requirements engineering is an established way to involve stakeholders in software engineering and has been explored as an approach to software sustainability (Duboc et al. 2020, Penzenstadler 2014). In Saputri and Lee (2021), a multi-criteria matrix for various sustainability aspects is established, and stakeholder requirements are captured at the beginning of the design process. Stakeholders can prioritise different sustainability dimensions, leading to priority scores for each dimension. Engineers need to weigh different stakeholders' needs and develop software requirements. However, it remains unclear by whom and how exactly environmental risks are going to be identified and mitigated in requirements engineering.

Penzenstadler et al. (2020) take a more practical approach offering a workbook for practitioners to raise awareness of sustainability effects in software engineering. They suggest a process for stakeholder workshops, where requirements engineers and stakeholders elaborate requirements for software to represent stakeholders' needs. They acknowledge, however, that the primary goal of the workshop is to raise awareness and that a "comprehensive sustainability impact analysis requires further work". Applied to AI systems, additional challenges might arise in the suggested workshop. The requirements in machine learning systems, for instance, are rather data- than code-driven and depend more on particular application contexts. In other words, different data and application contexts lead to different requirements (Wan et al. 2020). Thus, the workshop might need to be repeated for each project in a firm, which leads to questions of practicability.

Even if artificial intelligence systems are designed to minimise their negative direct environmental effects, their main goal may still be to promote unsustainable production and consumption patterns.

Discussion and research directions for stakeholder involvement for sustainable artificial intelligence systems

With a call for broader stakeholder involvement for sustainable AI systems (UNESCO 2022), the question arises if and how such involvement helps enhancing the sustainability of AI systems and how it can be put in practice. In this article, we focused on the environmental dimension of sustainability and its links with stakeholder involvement. We conclude from our scoping review of AI and software sustainability frameworks that stakeholders seem to be expected to inform specific questions on environmental effects, since no one-stop-shop approach for measuring direct and indirect environmental effects of AI/software is avail- >

able. However, while stakeholder involvement is considered important at an abstract level, we conclude that the exact processes and aims (who, how, when, why) of stakeholder involvement are not explained in sufficient detail in the analysed frameworks. Moreover, links to environmental sustainability are sometimes not made explicit. Specifically, frameworks are not clear about who stakeholders are in the context of environmental effects and what types of knowledge they could contribute to assess and mitigate environmental effects of AI/software at what stage of the AI/software lifecycle. It could be a practical challenge for developers and institutions to integrate stakeholders even if they deemed this step important. Preliminary insights into the implementation deficit of "trustworthy" AI support this concern (Beckert 2021). Even if these challenges were overcome in some firms/institutions, there would still be questions of how and why sustainability frameworks would be used at scale, that is, what the incentives and expected (economic) benefits are for firms/institutions to develop and use sustainable AI. Notwithstanding these challenges, we believe that there are several ways in which stakeholder involvement can benefit the development of sustainable AI, and ways in which research could learn more about and foster stakeholder involvement.

Stakeholder involvement to identify and assess indirect environmental effects of artificial intelligence

Our scoping review suggests that while the technical details of software and hardware optimisation may be difficult to assess by (non-technical) stakeholders, stakeholder involvement could help unveil and assess less obvious indirect environmental effects, such as rebound effects in firms using AI systems, or behaviour changes on the side of consumers. Stakeholders may be in a position to shift the debate away from a narrow focus on how to make AI systems themselves more sustainable (direct environmental effects of AI systems) to the question of what these systems are used for and which indirect environmental effects, including outside the firm's value chain, this can have ("Sustainability by AI" and "Unsustainability by AI"; figure 1). For instance, if the AI system is designed according to environmental sustainability criteria minimising its negative direct environmental effects, its main purpose could still be to trigger additional consumption by addressing customers through targeted advertisement. This negative indirect environmental effect may be larger and thus more problematic than direct environmental effects.

Stakeholder involvement to define and evaluate trade-offs between and within different dimensions of sustainability

Developers might need support and societal legitimisation in decisions over trade-offs, for example, between different environmental aspects or between environmental and social aspects of AI development. It could be helpful to involve stakeholders in identifying and evaluating trade-offs. Questions such as "If I can only reduce either the hardware requirements of my AI system or address the issue of server energy use – what should I do (first)?" or "What is the interplay between privacy and environmental concerns in my system?" could be addressed. Again, the devil lies in the details, and several procedural questions will have to be clarified. Who exactly are stakeholders for each sustainability dimension (Penzenstadler 2014)? For instance, is there one advocate in the firm who can represent environmental interests in different environmental fields, such as biodiversity or land and water use? Would it be sufficient to involve sustainability stakeholders in the requirements engineering phase, or would a continued involvement be necessary? (When) Would external stakeholders, such as environmental organisations, be needed? How could stakeholders negotiate conflicts between different sustainability dimensions?

Stakeholder involvement to align agendas of industry, politics and civil society and bring existing frameworks into use

Stakeholder involvement can also be a concrete step towards finding common ground in the agendas of industry, politics and civil society and thereby contribute to uptake of existing sustainability frameworks in firms and institutions. For instance, multi-stakeholder processes involving international organisations, governments, civil society and the private sector are suggested to address the lack of comparable measurements of environmental effects of AI (OECD 2022, UNESCO 2022). Based on standardised measurements, AI developers and users can more easily start to measure AI-related environmental effects and start discussions on priorities regarding different aspects of sustainability. If industry stakeholders are involved, the likeliness that the developed measures will be relevant and taken up in industrial application contexts may increase. Regarding the suggested sustainability principle that hardware lifetime should be extended, for instance, its implementation would need both the buy-in of firms to foster long-lived products and policies to regulate repairability, minimum support and use times of hardware. Likewise, if users are supposed to use digital technology products longer, which information channels and incentives are there to foster this behaviour?

Some open questions around operationalising stakeholder involvement for (environmental) sustainability of artificial intelligence systems

A major limitation of this scoping study is that we did not do a systematic review of sustainability frameworks, so there might be relevant work that we have overlooked which provides some answers to our questions around stakeholder involvement for sustainable AI. Notwithstanding, given the current lack of awareness of sustainable software systems in practice (Karita et al. 2019), we believe that there is still a lot to learn on how to *do* sustainable software, AI and stakeholder involvement, and we hope to encourage further work at this nexus. Specifically, we suggest that future research should

- implement case studies on "sustainable AI" in firms/institutions, using existing sustainability frameworks for sustainable software/AI (such as in Porras et al. 2021 for software),

- gather data from case studies on
  - barriers to measuring and steering environmental effects of AI,
  - which stakeholders (can) contribute at what stage of the lifecycle of AI to bring environmental and other sustainability effects to the attention of developers, managers, politicians and users,
  - how different sustainability dimensions (social, economic, individual, technical, environmental) can be weighed and trade-offs be evaluated,
- (if needed) create more detailed guidelines and decision matrices to further operationalise stakeholder involvement in sustainability frameworks for firms/institutions, and
- understand barriers to and foster the uptake of sustainability frameworks in practice.

Large bodies of knowledge regarding (software) sustainability already exist which can bring relevant insights for the assessment of sustainability effects of AI, but they are spread across different disciplines and domains. This is where (inter- and) transdisciplinary research could likely make a large impact, by bridging the gap between scientific discussion and the need for practically relevant guidelines and advice.

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