Shaping AI (more) sustainably. Socio-technological perspectives on AI infrastructures

Anne Mollen and Sigrid Kannengießer

Abstract: In the field of Machine Learning, a growing body of research reveals and analyses the negative ecological effects of generative AI, especially its contribution to climate change via carbon dioxide emissions that result from generative AI training. Moreover, such analyses also consider partly how to reduce these effects. However, beyond carbon emissions, the field rarely acknowledges further ecological, economic and social consequences of the production and use of generative AI. In the social sciences and humanities, the socio-ecological-economic effects of generative AI and sustainable ways of shaping AI infrastructures thus far constitute only a minor research area. But the question of how generative AI infrastructures can be sustainably shaped demands a social science perspective. AI infrastructures include not only technological devices, such as servers, cables, data centres and consumer apparatuses on which generative AI is used. Also, all actors engaging in social practices that shape AI infrastructures must be considered. Focusing on the practices that shape AI infrastructures, therefore, can not only help to understand how these structures are currently shaped and why they cause tremendous socio-ecological-economic effects, it also has the potential to recognise attempts to shape AI infrastructures (more) sustainably and to conceptualise practices that would allow for sustainable production and use of generative AI. Therefore, using a sustainability perspective, our theoretical reflection develops a *socio-technological concept of AI infrastructures*. Firstly, it points to the socio-ecological effects of the production of AI infrastructures. Secondly, it also discusses how AI infrastructures can be shaped more sustainably. The underlying theoretical assumption is that AI infrastructures come into being through social practices that can be altered towards sustainability.

Keywords: artificial intelligence, sustainability, social practices, digital infrastructures, social sciences

1. Introduction

In the field of Machine Learning, a growing area of research reveals and analyses the negative ecological effects of generative AI, especially its contribution to climate change via carbon dioxide emissions that result from the training of the large language models (LLM) that form the basis for generative AI applications. Moreover, this research considers how these effects can be reduced.

However, the ecological, economic and social consequences of the production and use of generative AI, beyond carbon emissions, are rarely acknowledged in this field. In the social sciences and humanities, the socio-ecological-economic effects of generative AI, as well as ways of addressing these consequences and thereby shaping AI infrastructures more sustainably, thus far represent only a minor research area. But a sustainability perspective—one that understands the term in the tradition of the Brundtland report as social-ecological-economic justice (UN WCED, 1987) with a clear social dimension to it—becomes crucially important in shaping AI infrastructures. Thus, the question of how infrastructures of generative AI can be shaped in a sustainable way is one that also demands a social science perspective.

AI infrastructures include not only technological devices, such as servers, cables, data centres and consumer apparatuses on which generative AI is used, but also actors whose social practices shape these devices and AI infrastructures, in general. Therefore, focusing on the practices that shape AI infrastructures cannot only help to understand how these structures are currently shaped and why they cause tremendous socio-ecological-economic effects, it also has the potential to recognise attempts to shape AI infrastructures (more) sustainably and to conceptualise practices that would allow for producing and using generative AI sustainably. Therefore, the theoretical reflection presented here develops a **socio-technological concept of AI infrastructures** by using a sustainability perspective. Pointing to the socio-ecological effects of the production of AI infrastructures; it also discusses how AI infrastructures can be shaped in a more sustainable way. The underlying theoretical assumption is that AI infrastructures come into being through **social practices** that can be altered towards sustainability.

To develop this argument, we will first sketch the interdisciplinary research field of sustainable AI. Second, we will develop a socio-technological concept of AI infrastructures, stressing the relevance of all actors and practices shaping these structures. In doing so, we will use sociological practice theory, which has been used and further developed in media and communication studies. Third, we argue that a socio-technological perspective on AI infrastructures is necessary not only to understand generative AI, but especially so when applying a sustainability perspective to AI infrastructures. It allows an understanding of the socio-ecological-economic effects caused by the production and use of generative AI and the attempts to shape AI in a more sustainable way, as well as conceptualising practices that would allow for producing and using generative AI more sustainably.

2. The interdisciplinary research field of sustainable AI

Currently, two strands of discussion on sustainable AI can be differentiated (van Wynsberghe, 2021). One concerns the **use of automation**, especially Machine Learning technologies, to reach sustainability objectives. The other concerns the **socio-ecological-economic impacts of AI systems** themselves and the question of how to shape AI more sustainably. As part of the first discussion, researchers are, for instance, concerned with analysing the environmental benefits of applying AI systems to achieve the Sustainable Development Goals (Vinuesa et al., 2020), to save resources (Rolnick et al., 2022), to perform complex distributional tasks (Klobasa et al., 2019), as an element in environmental governance (Nishant et al., 2020), to give some examples. With a strong political tail wind (UN DESA, 2021; World Economic Forum, 2021), the discussion of the use of AI technologies for sustainability objectives seems to be much more well-established than the discussion on the sustainability impacts of AI technologies.

Nonetheless, in the field of Machine Learning, questions of sustainability are increasingly taking shape as a distinct field of inquiry (Kaack et al., 2022). However, it must be noted that environmental concerns, in particular, are addressed here. Strubell and colleagues (Strubbel et al. 2019) published a seminal analysis of the possibly immense emissions resulting from the development and training of so-called transformer LLMs, which currently form the basis for generative AI. Following this work, research interest in sustainable AI increased, focusing mainly on environmental impacts of LLMs such as BERT (Google, 2018), GPT-3 (OpenAI, 2020), LLAMA (Meta, 2023) or similar models.

Publications have emerged that attempt to understand and quantify the environmental impact of LLMs. In this regard, there have been publications on the energy usage of different LLMs (Chowdhery et al., 2022; Patterson et al., 2021), statistics related to water consumption (Li et al., 2023; Mytton, 2021), emissions calculated over the life cycle of LLMs, including in the production of hardware and inference/application (Luccioni, Viguier, et al., 2022), attempts to measure system-level impacts of AI-related emissions, especially in comparison with their potential sustainability benefits (Kaack et al., 2022) and so on.

Based on these numbers and attempts to understand the environmental impacts of AI systems, some publications have begun to address how to improve environmental impacts, for instance by choosing training times and locations based on environmental concerns (Dodge et al., 2022; Li et al., 2023) or minimising datasets to reduce computing time (Menghani, 2023). Learning about the environmental impacts of Machine Learning systems through this kind of research has led to the practical application of ecological sustainability-oriented approaches in Machine Learning development (Luccioni, Mueller et al., 2022).

Thus, sustainability of AI so far has primarily been understood based on Machine Learning heuristics. Van Wynsberghe (2021, p. 214), for instance, describes sustainable AI as ‘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’ over the life cycle of an AI.

Here, the emphasis primarily falls on technical components and production logics (e.g. computing hardware, data sets, Machine Learning algorithms, computing) and the role they play in sustainability questions. Although helpful as a structuring element, this approach has little analytical value for understanding processes and agency behind (un)sustainable AI; it thus lacks the foundations for profound, socially oriented analyses. Therefore, we argue for a **socio-technological perspective on the life cycle of generative AI**, one that acknowledges not only the technological components of the infrastructures of generative AI but also the actors and practices that shape these technologies.

3. Socio-technological perspectives on AI infrastructures

Although the relationship between AI infrastructures and sustainability has primarily been acknowledged as a technological matter within Machine Learning discourses, it is crucial to acknowledge how AI infrastructures are shaped. This is not only to understand the socio-technological-economic impacts of generative AI, but also attempts to shape AI (more) sustainably, as well as to conceptualise and call for practices that allow for more sustainable AI infrastructures.

In recent years, digital technologies and their infrastructures have become an established subject of study in communication and media research (Flensburg & Lai, 2020; Gillespie et al., 2014; Parks & Starosielski, 2015; Plantin & Punathambekar, 2019; Starosielski, 2014), engaging with perspectives of science and technologies studies on information systems, as well as information and communication technologies (Bowker et al., 2009; Star & Ruhleder, 1996) and social constructivist approaches to media technology and communicative infrastructures (Andersen, 2018; Christmann et al., 2022). Within **Human–Computer Interaction**, such socio-technical approaches have been reflected in the integration of human actors into the analysis of digital technologies.

Although definitions of digital infrastructures still stress the relevance of the backbone of the internet and understand infrastructures as a combination of consumer devices, network structures and server farms (Constantinides et al., 2018; Fox & Hao, 2017; Greenstein, 2020), defining infrastructures as a

'substrate' (i.e. something on which something else 'runs' or 'operates') has long been criticised (Star & Ruhleder, 1996, p. 112). Infrastructure is not a 'thing' that forms the basis for the internet; rather **infrastructure is a relational concept** that becomes real in and through practices (Star, 2002, p. 116).

These practices of 'infrastructuring' (Pipek & Wulf, 2009) are conducted by designers, builders, maintainers or users of information systems who shape infrastructures through their practices. A practice approach to infrastructures accordingly enables an analysis of how infrastructures come into being and what kinds of manifestations (e.g. regarding inequalities) they entail. This understanding applies also to infrastructures of generative AI that come into being through social practices.

Sociological practice theory defines social practices as:

> A routinised type of behaviour which consists of several elements, interconnected to one another: forms of bodily activities, forms of mental activities, 'things' and their use, a background knowledge in the form of understanding, know-how, states of emotion and motivational knowledge (Reckwitz, 2002, p. 249-250).

In contrast to habits, practices are patterns of actions that are based on knowledge and become routinised. Looking at AI systems, the question then is: which practices design, build and maintain AI systems? These practices can either be performed by human actors or executed by technologies, but looking at the question of who is responsible for shaping AI infrastructures more sustainably, human actors become more relevant as 'there can be no machines without humans to make them' (Jasanoff & Kim, 2015, p. 8).

In communication and media studies, practices have been subdivided into those in which actors are 'acting with media', meaning that media are used as mediators, and those in which actors 'act on media', meaning that media (as organisations, content and technologies) themselves are the focus of action (Kannengießer & Kubitschko, 2017). 'Acting on' media refers to practices in which 'people consciously and actively seek to transform [media] technologies and in doing so try to change not only the devices, but also society' (Kannengießer, 2020, p. 178). This conceptualisation, which was formally developed for media, can also be applied to other technologies, including AI, meaning that 'acting with AI' refers to those practices that use AI for whatever purpose (e.g. sustainability) and 'acting on AI' refers to those practices through which actors consciously and actively (try to) shape AI (e.g. shaping AI systems more sustainably). When examining the sustainability of AI, it is these practices of 'acting on AI' that become relevant.

4. Shaping AI infrastructures (more) sustainably

The proposed socio-technological perspective on AI infrastructures, based on a practice approach, thus allows for answering questions on how AI infrastructures can be shaped more sustainably. We can see such practices already emerging in the very different ways of researching, developing and using generative AI – partly reflecting the highly contested views that currently exist on the technology. Two fundamentally different positions are emerging in the discussions. On the one hand, there are those who perceive existential but thus far **hypothetical AI risks** as the greatest danger to humanity (**AI safety/alignment**). On the other hand, there are those who give top priority to **existing risks**, such as **bias and discrimination** (**AI ethics**), and criticise the focus on hypothetical risks as indifference to the detrimental effects AI has on groups of people who are often already marginalised (Sætra & Danaher, 2023).

Particularly with regard to these current risks and harms, we can see practices emerging that attempt to shape AI infrastructures in more sustainable ways (Stanusch et al. 2024). Although dominant generative AI players (e.g. OpenAI or Meta) align with the approach of building ever larger LLMs, other initiatives (e.g. Bloom, Eleuther AI and HuggingFace) have begun to address specific, sustainability-relevant issues: Examples include experimenting with **new modes of data management practices** as well as **output curation** to address issues of bias, discrimination and racism in AI outputs. Others try to reduce resource consumption while maintaining high model performance, as well as developing **more efficient hardware**. An important element across such attempts are matters **of openness and access**, which are intended to '**democratise**' generative AI development, as such initiatives often like to stress.

All these attempts to shape AI more sustainably, through corporations, technology experts, non-profits, policy actors and so on, have further implications relevant to matters of sustainability. Investing in more efficient hardware, for instance, might not lead to less resource consumption by generative AI systems, if these efficiency gains are again offset by LLMs that are ever-growing in number as well as in size. Furthermore, what defines non-biased datasets and outputs is equally debatable. Hence, we see negotiations, power dynamics and the normalisation of routines into practices within these attempts to create more sustainable AI systems, and thus a rich field for empirical analysis of the socio-technical emergence of AI infrastructures.

While some of the challenges regarding sustainable AI infrastructures are unique to generative AI, for example the size of data sets or the amount of compute and energy needed for creating generative AI, others have already been addressed in discourses on the sustainability of digital technologies in general. The results of research that analyse ways of shaping digital infrastructures in a more sustainable way thereby become relevant (Kannengießer, 2020), as generative AI is embedded in digital infrastructures that then integrate specific AI aspects (e.g. training with relevant data).

When looking at the actors trying to shape AI more sustainably, questions of **agency** become relevant.

Agency can be defined:

> As a temporally embedded process of social engagement, informed by the past (in its "iterational" or habitual aspect) but also oriented toward the future (as a "projective" capacity to imagine alternative possibilities) and toward the present (as a 'practical-evaluative' capacity to contextualise past habits and future projects within the contingencies of the moment) (Emirbayer & Mische, 1998).

Regarding AI and its sustainability, the question is: which actors have the capacity to shape current AI systems? This question presupposes that such actors possess knowledge about past systems and are able to imagine future possibilities, in other words that these actors have agency and have the power to either potentially shape AI systems more sustainably – or fail to do so. Reconstructing agency then helps to reveal the power structures in which AI-related actors are positioned. The question of agency directly relates to the question of practices. When applying a socio-technological perspective to the study of AI systems, it is important not only to identify actors, but also to consider the way they shape AI systems. In other words, their practices need to be an object of research. Here, we identify a research gap in the interdisciplinary academic discourse on sustainable AI.

Using practice theory for the analysis of sustainable AI helps us to move beyond understanding the sustainability of AI as an engineering problem. It allows us to integrate 'the social' into a perspective on sustainable AI. This means acknowledging the role of actors and their practices in shaping AI infrastructures – that is to say examining not only the role of AI designers, but also that of the actors involved in building and maintaining AI infrastructures, including networks, data centres, datasets, policies and, eventually, users of AI and the digital technologies that are needed for the everyday appropriation of AI in people's everyday usage.

5. Conclusion

In this article, we argue for understanding generative AI infrastructures as socio-technological phenomena that consist not only of technological aspects, but also come into being through diverse actors and their social practices. Using practice theory and investigating how actors 'act on' and thereby shape AI infrastructures allows for an understanding of the reasons underlying the socio-ecological-economic effects of generative AI. At the same time, it investigates attempts to shape AI (more) sustainably while conceptualising sustainability-oriented practices. Applying such a comprehensive concept of infrastructures makes it possible to integrate social and technological aspects of infrastructures in an empirical analysis and to analyse actors and practices involved in infrastructures in order to understand the relationship between sustainability and generative AI. At the same time, it also allows for stressing the need for shaping AI infrastructures more sustainably and identifying opportunities to do so.

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