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RESEARCH

Is data material? Toward an environmental sociology of AI

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Abstract

Critical social science studies on AI often focus on its data extraction. However, this process is rarely understood as material. When scholars do look at the material extraction on which AI technologies rely, they tend to dissolve the category of data into established forms of extraction—for example of resources, energy, or labor time. Notwithstanding that they constitute a crucial part of AI's materiality, dissolving the category of data into seemingly more material ones seems unnecessarily limiting and reproduces the illusory divide between an immaterial digital and a material 'analog' realm. I argue that the concept of a dual process of abstraction and extraction, commonly evoked in literature on data extraction, can help to conceptualize the materiality of extraction as a process by which reality is narrowed to a set of functional properties, while disregarding everything else. In the case of data, this process has unique dynamics that make it distinct from, yet equally material as, resource, energy, or labor extraction. Connected to the Marxist concept of 'real abstraction', such approach is sensitive to power relations and helps to critically investigate depoliticized notions of technological functionality. The materiality of AI does not exhaust itself in the quantities of kilograms of raw material, megajoules of electricity, or labor hours. An environmental sociology of AI would instead focus on the socio-ecological processes through which people and the planet are pressed into these functional abstractions in the first place.

Keywords Artificial Intelligence · Big Data · Materiality · Real abstraction · Extraction

1 Introduction

Despite their significant and growing environmental impact, AI technologies have thus far received little attention from environmental sociologists. As of December 2024, no paper with 'AI' in its title has been published in the journal 'Environmental Sociology'. This is unfortunate. The absence of environmental sociology from critical AI scholarship appears to be indicative of a broader disinterest in theorizing AI's materiality as inherently entrenched in social conflict and inequalities. Instead of solely counting the kilograms of raw materials, megajoules of electricity, working hours, or terabytes of data that go into AI, environmental sociology has the potential to also consider the power relations and socio-ecological processes through which functional abstractions of resources, energy, labor, and data are formed in the first place. Focusing on the concept of a dual process of abstraction and extraction, frequently invoked with regard to data extractivism (Kitchin 2014, 1–2; Couldry and Mejias 2019a, 337; Sadowski 2019, 2; Pasquinelli and Joler 2021, 1277; Ricaurte 2022, 730f.), I want to offer a conceptual contribution that could help us moving toward an environmental sociology of AI and thereby also advance the wider field of critical AI and data studies.

I agree with Louise Amoore that it is misleading to claim that the form of data (or in Amoore's words: the Cloud) hides a material reality. On the contrary, data is a way of seeing. Data (processing) renders things "perceptible and actionable" (Amoore 2020, 41). So, how can a recording of things (data) be as material as the things themselves (i.e., resources, energy, labor)? My simple answer is that it is about the process not the product. The dual concepts of abstraction and extraction emphasize the processual aspect of extraction. The world does not naturally present itself to us as resources, energy, labor or data. These are ways of materially and epistemologically abstracting and simplifying the world based on certain functional properties while disregarding everything else. This process is equally material for resources, energy, labor, and data.

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With materiality I refer to the natural finiteness of (organic and inorganic) bodies existing in time and space. As a recording of human behavior, data could be considered as immaterial because it does not depend on one specific material medium. However, in reality, the process of creating data is material through and through. Rare earth minerals, microprocessors, data centers, and sensors are necessary for recording and storing data. In addition, the finite human lifetime must be bound so that some aspects of it can be captured as data (consider the screen-time spent on platforms such as TikTok or Instagram).

My focus on the way in which things and people become abstracted along certain functional properties is embedded into a Marxian framework centered around the concept of 'real abstraction'. This approach allows for a critical and productive reinterpretation of functionalist understandings of technology, such as Niklas Luhmann's concept of technology as a 'functioning simplification' (Luhmann 2021, 524; Pieper 2024)—for whom does a technology function and whose lives, landscapes, communities are functionally simplified while much of what constitutes them is neglected and destroyed? Simply put, what does it mean politically and ecologically when a technology 'functions'?

In Sect. 2, I lay out the two hurdles that seem to stand in the way of capturing AI's materiality. In Sect. 3, I discuss how the two concepts of abstraction and extraction have been used in critical data studies thus far. In Sect. 4, I present a theoretical approach to understand AI's materiality through these two concepts. In Sect. 5, I discuss the importance of an environmental sociological approach to AI. I also raise the question how this approach compares to relational-ontology approaches that understand data in its concrete entangledness with the world and in its material agency (Parikka 2014, 2015; Amoore 2020; McLean 2020). Also, I ask how we can understand the process of abstraction—of treating people and things along a limited set of functional properties—as a fruitful way to link extraction to the imposition of Western instrumental thinking through historical colonialism. In closing, I emphasize that the increasing environmental impact of AI technologies should prompt us to understand the materiality of AI not only with regard to established categories of resources, energy, or labor but to look at the new socio-ecological dynamics with regard to data itself.

2 The im/materiality of data in critical data and AI literature

Two hurdles stand in the way of capturing the full scope of AI's materiality: (1) The tendency to limit AI extractivism to data and (2) omitting the materiality of data extraction.

2.1 Limiting AI extractivism to data

A growing body of social science literature analyzes the extractive dynamics on which AI technologies are built (Couldry and Mejias 2019a; Sadowski 2019; Pasquinelli and Joler 2021; Ricaurte 2022). Maybe most prominently among them, Nick Couldry and Ulises A. Mejias have written an illuminating book on the problems and dangers of large-scale data extraction (Couldry and Mejias 2019b). These studies display a broader trend within critical AI studies: When scholars speak of extraction, they tend to focus primarily on *data* extraction. For instance, Suchman (2023), Taddeo et al. (2021), and Anshari et al. (2023) address the extractivism of AI exclusively in relation to data and statistical correlations. Morreale et al. (2023), Verdegem (2024), Mohamed et al. (2020), and Mantello and Ho (2023) do so as well albeit also mentioning more critically that this extraction of data can (in line with the Marxist labor theory of value) simultaneously be understood as an extraction of economic value from the laborer. There are also mentions of knowledge extractivism (Mohamed et al. 2020; Pasquinelli and Joler 2021), the extraction of "intimate subjective states" (Mantello and Ho 2023) and the "extraction of humanness" (Morreale et al. 2023) that are all very much adjacent to data extractivism and expand on its meaning.

Why does data extraction receive more attention than established forms of resource, energy, and labor extraction in the context of AI? One explanation could be that the term *extraction* in relation to resources, energy, and labor is strongly linked to a critical decolonial research agenda. However, when it comes to data, extraction (or mining) is often simply employed as a technical category. Thus, the concept of data extraction is more widely applicable and more prevalent.

However, this does not fully explain the limited focus on data extraction in critical AI studies. There seems to be a more important explanatory factor. Critical AI studies are strongly rooted in Big Data literature. The shift in academia from Big Data to AI follows the term's increasing popularity in the wider public. Although the term dates to the 1960s, its recent popularity can be seen as a rebranding effort. Yarden Katz argues that, in the wake of "increasing concern about the influence of major tech corporations and the data they collect" as well as increased public sensitivity for the surveillance aspect of Big Data (e.g., the NSA leaks by Edward Snowden in 2013) rebranding these practices as innovative new AI technologies "dilutes these critical looks at big data" (Katz 2017, 13). What would have been labeled as the statistical analysis of Big Data ten to fifteen years ago is now referred to as AI (Katz 2017, 2).

Social science literature has adapted and is now increasingly speaking about AI instead of Big Data.[1] Certainly, using the term of AI does not just uncritically replicate the PR of tech firms but encompasses its own potentials: Due to its breadth, the term 'AI' allows us to address not only the data collected, but also (maybe more so than 'Big Data') to capture "an idea, an infrastructure, an industry, a form of exercising power, and a way of seeing" (Crawford 2021, 18). However, the legacy of Big Data literature seems to confine these possibilities and leads to prioritizing the importance of data over the importance of resources, energy, or labor for the construction of AI.

In the following, I refer to the now common understanding of AI as large-scale statistical data analysis through neural networks. In the recent AI boom, the transformer architecture has been key, as for example in models such as ChatGPT, Dall-E, Gemini, or Llama, all of which rely on large-scale datasets. What we come to understand as 'AI' is a moving target and I do not want rule out the possibility that useful AI models based on small data sets and different architectures might also have a prominent role to play in future. In addition, data extraction processes are central not only to AI technologies, but also to more classical forms of statistical data analysis. Currently, however, AI technologies are undoubtedly a prime driver of the surge in data extraction and should thus be analyzed in close connection to it.

2.2 Omitting the materiality of data extractivism

Focusing solely on data extractivism can create a misleading imagery of AI located in "'the cloud' imply[ing] something floating and delicate within a natural, green industry" (Crawford 2021, 41). However, when addressing the materiality of data, authors tend to dissolve it into the resources used for semiconductors (Valdivia 2024), the CO_2 emissions from data centers (Hao 2019), or the outsourced click-labor in the Global South (Gray and Suri 2019).

There have been laudable efforts to emphasize the resource extraction related to AI systems (Robbins and van Wynsberghe 2022; Brevini 2023; Inclezan and Prádanos 2023; Valdivia 2024). They highlight that "AI has traditionally been understood as conceptually distinct from infrastructure" (Robbins and van Wynsberghe 2022, 2) and emphasize that AI ethics has mostly focused on "concerns of privacy, safety, and fairness" but not the environmental impact of AI (Robbins and van Wynsberghe 2022, 4). They emphasize that the data processing of AI is linked to massive quantities of energy and water (Brevini 2023; Inclezan and Prádanos 2023) and relies on data centers and end-user devices, the manufacturing of which is related to an extractive global supply chain (Brevini 2023, 28; Valdivia 2024).

Scholars also link data extractivism to labor extractivism. For example, Thatcher et al. interpret data extraction through a Marxist lens as a process by which the data producer is alienated from her own product while the company reaps the benefits of that data (Thatcher et al. 2016, 996). This works because the data is decontextualized "through a process of quantification" (Thatcher et al. 2016, 996). Due to processes of abstraction and homogenization, individual data points can be aggregated and acquire the favorable properties of Big Data (Thatcher et al. 2016, 997). Since data only becomes valuable in large quantities, only "big money and big power" can reap its benefits, leaving the actual producers of the data empty handed (Golumbia 2009; Thatcher et al. 2016, 1000). However, unlike the classical labor relation in capitalism that Marx characterized through the exploitation of the laborer, Thatcher et al. draw on David Harvey (2012) to describe data extraction as a process of capital accumulation by dispossession (Thatcher et al. 2016, 1000). This notion of reducing data extraction to problematic labor relations is also present in works that address data extractivism through phenomena such as click work, the gig economy, and 'ghost labor' (De Stefano 2015; Gray and Suri 2019; Kshetri 2021; Tirapani and Willmott 2023).

Steven Weber has also argued that geographic patterns of unequal exchange (Dorninger et al. 2021) replicate with data extractivism. The click labor involved in training, verifying, and imitating (Tubaro et al. 2020) necessary to produce valuable data sets tends to be outsourced to cheap labor in the Global South (Weber 2017). Thus, the Global South functions as a provider of cheap data labor, from which IT companies in the Global North create far more valuable products (Weber 2017)—in turn granting them even more purchasing power over cheap labor in future (cf. Hornborg 2006, 167).

It is understandable that authors try to counter the immaterial understanding of AI and its clean data processing in 'the cloud' with the material realities behind it. This shift in focus must generally be welcomed, and much valuable work has sprung from it. However, if the materiality of data extraction is only found in resource, energy, and labor extraction, then data extraction ceases to be a material phenomenon itself. Reducing data extraction to seemingly more material forms of extraction risks replicating the false dichotomy between the immaterial digital realm and the material analog realm from which one started.

It is easy to see how reducing instances of resource extraction to the labor extraction that might accompany it would be analytically limiting. Shouldn't we acknowledge the same for data extraction? Yes, different forms of extraction can accompany each other. However, each form

[1] For example, in the journal '*Big Data & Society*', between 2010 and 2016 no paper with 'artificial intelligence' in its title was published, while between 2017 and 2023 22 such papers were published. At the same time, papers with 'big data' in its title have decreased from 71 to 60.

of extraction has different material dynamics that would be lost by reducing one form of extraction to another.

3 The dual process of abstraction and extraction in critical data studies

Authors such as Couldry and Meijas (2019a) and Sadowski (2019) have put forth sound proposals for treating data as a unique analytical category. In their work and that of others in critical data studies, the dual concepts of abstraction and extraction pop up again and again, both implicitly and explicitly.[2]

Consider, for example, Rob Kitchin's influential book, *The Data Revolution* (Kitchin 2014). In the first sentence, Kitchin describes data as a "raw material produced by abstracting the world into categories, measures and other representational forms" (Kitchin 2014, 1). Kitchin then argues that the etymology of the word 'data' from the Latin *dare*, meaning 'to give', is actually confusing because data refers to "elements that are taken" and "extracted through observations, computations, experiments, and record keeping" (Borgman 2007; Kitchin 2014).

We find other mentions of the abstraction and extraction of data in Ricaurte (2022). She affirmatively cites Kitchin's assessment of data as an abstraction of the world. In the next sentence, Ricaurte describes datafication "as an extractive process [that] converts the world into a quantitative operation" (Ricaurte 2022, 730). Similarly, Sadowski understands data as "a recorded abstraction of the world" (Sadowski 2019, 2) and speaks of the data-gathering process as extraction (Sadowski 2019, 6). Amoore und Piotukh (2015) aptly capture the relationship of abstraction and extraction. They describe data analytics as a way to "focus human attention and decision on particular persons and things of interest, while annulling or discarding much of the material context from which they are extracted" (Amoore and Piotukh 2015, 341).

Nick Couldry and Ulises A. Mejias argue that the massive extraction of (personal) data can be understood as 'data colonialism' (Couldry and Mejias 2019b). They describe data colonialism as "an emerging order for the appropriation of human life so that data can be continuously extracted from it for profit" (Couldry and Mejias 2019b, xiii). Hereby, "[d]ata colonialism combines the predatory extractive practices of historical colonialism with the abstract quantification methods of computing" (Couldry and Mejias 2019a, 337). "[D]ata abstracts life by converting it into information that can be stored and processed by computers and appropriates life by converting it into value for a third party" (Couldry and Mejias 2019b, xiii).

One could argue with John Holloway that this constitutes a general aspect of systems of domination (Holloway 2002). Complex interrelationships must be decontextualized into discrete objects because only then can these objects be turned into property and ruled over (Holloway 2002; Graeber 2006, 70–71). This should be understood as a form of colonialism because not only are physical resources appropriated, but also the very resources with which we make sense of the world. Thus, both economic and cognitive power are involved. Therefore, the extraction of data cannot be understood solely in terms of the logic of capitalism, but also in terms of the logic of colonialism (Couldry and Mejias 2019b, xii).

In contrast to Marxist approaches to data extraction that attempt to explain the phenomenon in terms of labor relations (Thatcher et al. 2016), Couldry and Meijas propose that data extraction is a phenomenon unto itself, based on the concept of 'abstraction'. They propose an approach similar to Moishe Postone's (Postone 1996). Postone argues that, for Marx, the foundational social form of capitalism is not the labor relation, but the underlying commodification of daily life (Postone 1996). In line with this, Couldry and Mejias argue that the centrality of data should not to be primarily understood through the labor relations *behind* it (Couldry and Mejias 2019b, 30f.). Although click work, the gig economy, or ghost labor are essential to maintaining digital infrastructure (De Stefano 2015; Gray and Suri 2019; Kshetri 2021; Lohmann 2022; Tirapani and Willmott 2023) Couldry and Mejias emphasize that data extraction is not reducible to labor relations, but rather, it arises out of the more foundational logic of commodification (Couldry and Mejias 2019b, 31). They write that "just as industrial capitalism, according to Marx, changed society by transforming the universal human activity of work into a social form with an abstract dimension (via the commodification of labor), so capitalism today, in the expansionary phase we call data colonialism, is transforming human nature (that is, preexisting streams of human life in all its diversity) into a newly abstracted social form (data) that is also ripe for commodification" (Couldry and Mejias 2019b, 32).

[2] I originally stumbled across both terms in Kate Crawford's book *Atlas of AI* (2021). In the introduction, she writes that AI systems depend "on the twin moves of abstraction and extraction: abstracting away the material conditions of their making while extracting more information and resources from those least able to resist" (Crawford 2021, 18). She cites Michael Hardt's and Antonio Negri's 2017 book *Assembly* (Hardt and Negri 2017) as a reference. However, Hardt and Negri are interested in this double operation not with regard to the resource and data extractivism of AI but more generally with regard to the role of finance capital for extracting value "from wealth that resides elsewhere, both the wealth of the earth and the wealth that results from social cooperation and interaction" (Hardt and Negri 2017, 164). Besides Crawford's citation of Hardt and Negri (Crawford 2021, 217), most authors that employ both terms with regard to data do not seem to be aware of their work.

Sadowski compellingly argues that data should be understood as a form of capital rather than a commodity (Sadowski 2019). Data collection is "not a way of producing and obtaining commodities that are somehow converted into monetary value" (Sadowski 2019, 2). Rather, the datafication of the economy is "driven by the logic of perpetual [.] accumulation and circulation" of data (Sadowski 2019, 2), often without clear, direct monetization of data in sight (Sadowski 2019, 4–5). As a case in point, he cites the AI researcher Andrew Ng, who has worked at Google and Baidu. Ng states that they sometimes "launch products not for the revenue, but for the data. We actually do that quite often … and we monetize the data through a different product" (Stanford Graduate School of Business 2017). This grants data the status of "a form of capital that is distinct from, but has its roots in, economic capital" (Sadowski 2019, 4).

4 Theorizing abstraction and extraction

The dual concepts of abstraction and extraction appear to be significant to all the aforementioned authors. They emphasize that extraction is not merely a process of collecting a preexisting substance; rather, data are a particular way of abstracting the world. Bringing these two concepts together allows the authors to understand data in terms of its processual characteristics. Thus, the specific political economy of data gathering and processing comes to the fore—not as something hidden behind the form of data, but as something implicated in it.

Data are valued as a commodity or form of capital because it enables certain technical functions that are often interlinked and generate economic value: These functions include profiling and targeting people (e.g., for advertisement), optimizing systems (e.g., large-language models), and modeling probabilities (e.g., for predictive policing) (cf. Sadowski 2019, 5). In all these functions, data is the essential component of AI technologies. To understand the materiality of data alongside (but not reducible to) resources, energy, or labor we should examine these functional categories more closely and how they relate to the dual concepts of abstraction and extraction.

In short, I will argue that these categories all point to distinct processes of reducing—and thereby abstracting—a more-than-functional reality to certain functional abstractions that can be integrated into technologies. The violence this process entail is evident in the long history of colonialism and its extractive legacies in the present.

4.1 Real abstraction

Let me first focus on 'abstraction'. The English word 'abstract' comes from the Latin '*abstrahō*' which literally translates as 'to pull/draw' (*trahō*) 'away' (*abs*). The different meanings of the adjective 'abstract' all have in common that they mark a difference to something specific, empirical, contextualized and comprehensive (Wiktionary 2024). For the purposes of this discussion, I will use the meaning of 'abstract' as "disassociated from any specific instance" (Merriam-Webster Dictionary 2024a)—something that is pulled or drawn away from context.

In empiricist as well as rationalist philosophical traditions, abstraction refers to an operation of the mind in which abstract thought emerges either from direct sensual experience or from reason. However, this does not seem to be the how critical data scholars such as Couldry and Mejias (2019b), Sadowski (2019), and Kitchin (2014) use the term when they describe data as a "social form with an abstract dimension" (Couldry and Mejias 2019b, 32), a "recorded abstraction" (Sadowski 2019, 2), or "a material produced by abstracting the world into categories" (Kitchin 2014, 1). In these descriptions, data is abstract not in thought but in its very existence as a simplification of the world based on certain functional properties.

This understanding of abstraction does not neatly align with established distinctions between the mind and matter, the 'object of knowledge' and the 'real object' (Althusser 1996, 186) or the idea of abstract thought and concrete reality. The way in which data resists these distinctions might be best captured by the Marxian category of 'real abstraction' (Toscano 2008). Marx himself did not use this term, and obviously he also did not write about data. Social philosopher Alfred Sohn-Rethel (1978) coined the term through his exegesis of Marx's analysis of the commodity in *Capital* (Marx 1992) and from the Introduction to *A contribution to the critique of political economy* (Marx 1970).

What is special about Marx's thinking is that, instead of considering an abstraction to be thought content, he understood abstraction as a social relation (Morris 1998, 45). According to Sohn-Rethel's interpretation of Marx, the commodity form does not merely represent a real object in thought. The exchange value that we attribute to, say, an apple or linen, does not simply manifest because the minds of the exchanging subjects think about it. After all, during an exchange, both parties are more likely to consider the apple's or linen's concrete use-value. However, by equating the apple and the linen to each other through exchange, and thus through their action, they treat both apple and linen as commodities with an abstract exchange value. For Sohn-Rethel, this means that the commodity exists as a real abstraction, because it manifests itself through the subjects' actions and relations to each other rather than in their thoughts (Sohn-Rethel 1978, 28). Ultimately, Sohn-Rethel's overarching point is that our abstract scientific thinking is based not on thought abstractions, but on abstract social relations.

Regarding data, the philosopher Lorenzo Cillario argues that the concept of 'real abstraction' takes on a new significance in today's capitalism, which increasingly relies on data and information processes (Toscano 2008, 284; Cillario 1996). In 'cognitive capitalism' the real abstraction exists not only in commodity exchange but also in all computer based processes of calculation and measurement (Cillario 1996, 165). Instead of merely manifesting in exchange, abstraction becomes part of the materiality of the production processes themselves (Toscano 2008, 284).

4.2 Functional simplification as abstraction

There appears to be an immediate intuition about data as abstract to which one can connect here. While we tend to concretize abstractions such as 'resources', 'energy' and 'labor' by reifying them into pieces of metal, power plants, or offices, most of us remain unaware of data's infrastructure. "Servers are hidden in nondescript data centers, and their polluting qualities are far less visible than the billowing smokestacks of coal-fired power stations" (Crawford 2021, 41).

Because we lack imagery and sensory experience of data, it may be easier for us to understand it as abstract. However, just as data is a functional abstraction, so are resources, energy, and labor. Natural resources are created by decontextualizing certain material and chemical properties of nature, not with regard to their role in the ecosystem, but rather, with regard to how they can be reintegrated into a technical function. Energy is created by identifying and making use of 'potentialities' in nature, where one puts in less energy than one gets out. Human labor is created by distinguishing it from leisure and play and by setting up institutions (such as Kindergartens, schools, elderly homes) that 'free' people from all other obligations, enabling them to exist as pure labor power for certain periods of the day.

Reducing the world to a few functional properties is central to every technology. The sociologist Niklas Luhmann defines technology broadly as a functioning simplification (Luhmann 2021, 524). He views technologies as strategies of societies to handle complexity. Through technologies, society is able to exclude the "world-at-large" ("die Welt-im-übrigen") (Luhmann 2021, 524) and to focus only on the "cause-and-effect chains" (Marton 2009, 144) that make a technology function. This exclusion can be observed as succesful if a technology functions repeatably and reliably, without unwanted forces of the world-at-large interferring (Luhmann 2021, 525).

The point is to instantiate "verified event correlations" ("gesicherte Ereigniszusammenhänge") (Schulz-Schaeffer 2000, 223). Everything else can be ignored as long as it does not impede (directly) on the functioning of a technology. For example, one need not know the extent to which running a large-language model contributes to global CO_2 emissions or whether the click worker in India who aligns the model slept well or fought with her husband. As long as the technology functions smoothly, everything else becomes irrelevant and can be disregarded.

In the context of increasing datafication, one might argue that the principle of simplification is no longer valid. Ever more details of our lives get sucked into our interaction with technology in the form of data (Campolo and Crawford 2020, 7). Indeed, the immense increase in computing power makes it possible to handle staggering amounts of data. However, no matter how plentiful the data, it must always remain an abstraction of what it attempts to record. Take profiling as an example: TikTok might collect data based on how long you watch certain kinds of videos and creates a profile of you. However, this profile will only ever be an abstraction of the infinitely complex you. The technological functionality of the TikTok algorithm does not depend on how accurately it captures your real self. All that matters is successfully integrating your abstract profile into the technological function. For TikTok, all that matters is that you spend more time on the platform. Similar for the optimization of large-language models: The cultural context of words, sentences, articles, and books is simplified into matrices of vectors, which are used to fine-tune the model so that it gives increasingly plausible responses. Another example is probability modelling in predictive policing, where the complex cultural composition of neighborhoods, their histories, and contingent development are simplified to the statistical likelihood of crime in order to allocate police officers most efficiently.

Of course, there are multiple problems with such depoliticized, functionalist definition of technology. If technology is a functioning simplification, then we should ask: Functioning for whom? Simplifying for whom? Alongside the concept of 'real abstraction', I propose that we can critically and productively re-read Luhmann to better understand of the abstraction process that constitutes data, resources, energy, and labor. The key to doing so is understanding simplification as a form of abstraction and, in turn, understanding abstraction as a social relation. 'Simplify' means reducing something to its basic elements (Merriam-Webster Dictionary 2024c). In the case of technology, this means reducing something to its basic functional elements and properties. What is functionally simplified is thereby withdrawn from its more-than-functional context and in this sense abstract.

One might counter that understanding technology as functioning simplification is much too broad and generalizing. It seems to fail completely in capturing the specific historical context, social structures, environmental factors, and actors' goals to which specific technologies relate. Why bother with Luhmann's generalized conception of technology when one could instead revert to *interpretive flexibility* and examine the contextual particularities of specific technologies (Pinch and Bijker 1984)? Similarly, why bother conceptualizing data extractivism at large when this does not capture in detail how different AIs extract different forms of data for their function? It is problematic to frame this as an either/or question. Both approaches are by no means exclusionary. On their own, both generalizing and contextual approaches provide only a partial image. Luhmann's generalizing concept of functional simplification does not capture how specific technologies are distinct from each other, but interpretive flexibility risks omitting what unifies different technologies (Kallinikos 2005, 9). If each technology was completely determined by its immediate context, one might wonder why we need the concept of 'technology' to begin with.

Not only does Luhmann provide us with an overarching operational principle of technology that takes on different forms in different contexts, his concept captures particularly well that AI and data extractivism are, by default, abstract phenomena. If functioning simplification appears as a rather depoliticized operational principle of technology, it is because the very form of technology—based on abstract relations between people and things—lends itself to be depoliticized and fetishized. What the concept of real abstraction emphasizes is that by being acted out these abstract social relations become an objective social reality: people at large act as if they relate only functionally to other beings and objects. They act as if data arise naturally and that its computation is the normal way of interacting with the world. They act as if there is no possibility to politically renegotiate and change all of this. And because people act as if this were the case, it actually becomes the case in social reality.

4.3 Extraction and more-than-functionality

Understanding how this depoliticizing process of simplification and abstraction is itself political leads us to the concept of extraction. The definition of extraction is strikingly similar to that of abstraction. The English word 'extract' shares a similar Latin root with abstract, translating as 'to pull/draw' (*trahō*) 'out of' (*ex*) (Wiktionary 2024). As a verb, it can mean "to draw something forth (as by research)" or "to pull or take out forcibly" as well as "to obtain by much effort from someone unwilling" (Merriam-Webster Dictionary 2024b). The similarity between 'abstract' and 'extract' is also reflected in their entangled history, during which both terms were once used interchangeably (Merriam-Webster Dictionary 2024b).

However, extraction also encapsulates an act of violence that the concept of abstraction does not immediately invoke. In the "narrow and literal sense of extraction" the violence of extraction "refers to the forced removal of raw materials and life forms from the earth's surface, depths, and biosphere" (Mezzadra and Neilson 2017, 1). In an expanded sense, extraction also encompasses all acts through which "patterns of human cooperation and social activity" enter the realm of capitalist property relations (Mezzadra and Neilson 2017, 10).

When people and things are commodified they become abstracted from their context in an epistemological sense (by being comparable on a global market) and in a political-economic sense (by being buyable and controllable by others). To grasp the reality and violence of extraction fully, we must understand energy, resources, labor, and data not as fixed things waiting to be collected, but as processes in which abstraction and extraction converge. This also emphasizes their complete material character. What's implicated in extraction is always more than an abstract designation such as 'data' can suggest. Here, the environmental humanities' formulation of 'more-than-human'—introduced to overcome the anthropocentric view of nature (O'Gorman and Gaynor 2020)—might be usefully appropriated. In our case, we can use the 'more-than' formulation to overcome functional abstractions and recognize that the process of extraction involves 'more-than-data', more-than-resources', 'more-than-energy', and 'more-than-labor'.

The way an ecosystem becomes abstracted into a resource, or an energy source, the way in which human life becomes abstracted into labor and data are examples of how an infinitely complex, more-than-functional world is made functional. To understand the consequences of this, we can counterfactually ask ourselves what would have existed anyway had it not been extracted and integrated into the technological function of AI. While the data itself would not have existed outside of the technological context, the time it took to create the data by keeping someone in front of a screen would have. While the lithium used for the smartphone batteries would not have existed as a purified resource, there would have been an intact ecosystem and clean drinking water. While energy would not have existed, there would have been unobstructed rivers and clean air. While labor would not have existed, there would have been more time to spend with friends or family.

We quickly forget that technologies consist not only of nuts, bolts, cogs, circuits, processors and microchips, but also of social relations. Functional abstractions, such as resources, energy, labor, and data, create the impression of a relation between objects. This gives way to a fetishized perception of technologies that seem to function universally and apolitically, and that are exempt from the violence of extractivism (Pieper 2024, 23). While the functioning of any given technology proves that the coupling of its physical natural elements is legitimate, this does not mean that the social relations that comprise a technology are equally 'legitimate'. Here, "we are confronted with simplifications, historically specific sociopolitical arrangements of human interaction that do not obey absolute laws but could just as well be made different" (Pieper 2024, 23).

The political battles occurring in processes of abstraction and extraction—such as indigenous people fighting against the water consumption of data centers in México, Querétaro (Valdivia 2024); Serbians protesting a lithium mine (The Guardian 2024); and content moderators in Nairobi suing Facebook (Foxglove 2024)—make clear that AI technology is not merely a neutral thing with seemingly animate properties. Rather, it embodies hierarchical social relations. Technologies, along with the resources, energy, labor, and data that constitute them, reflect a world reduced to functional use. This functionality isn't merely a product of abstract engineering and programming knowledge; it is a real abstraction—a social relation materialized in technical form.

The political battles surrounding abstraction and extraction also highlight that there is no pure form of human mastery over our surroundings. Nature, things, and humans can and do resist being abstracted to energy, resources, labor, and data. One reason for this is political agency on the part of humans. However, as relational ontologic approaches have emphasized in recent decades, the material character of infrastructures, ecosystems, and artifacts also plays a role in resisting extraction (Latour 2000; Bennett 2010; LeCain 2015). For instance, protest movements benefit from public spaces in which to gather; ecosystems may be so inaccessible as to prevent easy resource extraction; and VPN-equipped devices may complicate data extraction. However, the material character of things can also *facilitate* extraction. For instance, public infrastructure can hinder gatherings, easily accessible resource depots can enable cheap extraction, and we can be incentivized to shift more aspects of our lives to digital environments (Mejias and Couldry 2024 refer to them as 'data territories') in which more of our behavior can be captured in the form of data.

In this sense, the process of socially instantiating abstract functional relationships between people and the Earth is hindered and enabled by various socio-material factors. In this context, 'data' represents distinct strategies for abstracting and extracting a narrow set of functional properties from the Earth and from human lifetimes rife with social conflict and inequality. Consider the billions of hours spent each day worldwide in front of devices, from which valuable knowledge and information about human emotions, interactions, recognition, and attention are extracted. Consider also the monitoring of wildlife, aquatic systems, the atmosphere, forests and rivers (Turnbull et al. 2023) via sensors, cameras and drones, as well as the data-driven management of ecosystems that stems from this monitoring. Consider what is lost in these processes of abstraction and extraction: the time that could have been spent differently or the toxic chemicals whose ecological damage escapes digital representation yet continues to harm ecosystems and human health. Everything about these data extraction processes is material. However, the specific social conflicts and inequalities they entail are inadequately captured when broken down into established categories of 'resources', 'energy', or 'labor'.

5 How an environmental sociological approach to AI relates to relational ontologies and decolonial scholarship

How is this related to environmental sociology? And why would we need an environmental sociology of AI?

AI (and cryptocurrencies) will increase global data center electricity consumption from 2% in 2022 to 4% in 2025 (IEA 2024, 35). This will also increase the carbon footprint of the tech industry to 14% of all global emissions by 2040 (Belkhir and Elmeligi 2018, 448). The manufacturing and disposal of materials necessary for building data centers, as well as technological artifacts for data collection and running AI algorithms (e.g., computers, cameras, smartphones, and sensors) are expected to increase resource extraction and e-waste. The latter is projected to rise from 53.6-million metric ton in 2019 to 74.7-million metric ton by 2030 (Forti et al. 2020).

Given the increasing environmental impact of AI technologies, it is peculiar that environmental sociology has displayed little interest in AI thus far. This is unfortunate because environmental sociology has the theoretical toolkit to look beyond a narrow set of functional properties and restorative pleas for more efficient, fair, or ethical AI. Instead, it focuses on social structures and processes to problematize the functioning of AI itself (Adams 2021; Munn 2023). Without wanting to limit interdisciplinary critical AI and data scholarship to the confines of one discipline, I believe environmental sociology could contribute to a critical understanding of the materiality of data and AI. The discipline's self-understanding aligns with my approach in this paper, which is to understand environmental destruction, impacts and changes always in relation to societal dynamics.

In this paper, I have emphasized substituting the problematic distinction between immaterial data opposed to material resources, energy, and labor with the better distinction between abstract data, resources, energy, and labor opposed to a concrete more-than-functional reality. This places my approach in some way open to, yet also opposed to approaches to data influenced by relational ontologies such as actor-network-theory, posthumanism, and new materialism[3] (Parikka 2014, 2015; Amoore 2020; McLean 2020).

[3] Of course, there are differences between these approaches as well as large overlaps. I am bundling them here under the term 'relational ontologies' with regard to their common emphasis on the agency of nonhuman actors.

These approaches try to decenter human agency by emphasizing data as a concrete, material phenomenon that actively influences physical infrastructure, ecosystems, and human actors. Granting agency to data could be seen as a critical project insofar as this agency is understood as socially constituted. Relational ontologies, such as Karen Barad's agential realism, explicitly oppose essentializing matter and highlight the processes through which agency arises (Barad 2003, 822).

A critical Marxist approach centered on the concept of real abstraction could contribute to this aim while overcoming the often lamented reluctance of relational ontologies to address social conflict (Bessire and Bond 2014; Hornborg 2014; Martin 2014; Kipnis 2015). Amoore is correct in stating that the form of data does not conceal a material reality that must be uncovered. Data is a material reality in itself that we must take seriously (Amoore 2020, 41). What needs to be uncovered is that we collectively shape this materiality and that it is not concrete, but inherently abstract. To trace the social processes and structures through which we make data would enable us to connect its materiality to social conflict: How does the form of data—meaning its reduction of the world to a stream of bytes stored and processed in nondescript data centers—both *enable* abstract social relations prone to inequality and conflict and *is enabled* by them?

The theoretical scope of this paper has forced me to address extraction rather unspecifically. It is important to note that that the extractivism of AI should not only be understood theoretically as the violent or forceful removal of something from its context. The process by which people's lifetime is extracted and integrated into the capitalist market as data not only resembles colonial patterns and strategies of extraction, but in many ways continues historical colonialism (Adams 2021, 179). After all, the technical infrastructure that enables large-scale extraction and analysis of data is predominantly controlled by companies in countries of the Global North, that have historically benefited from and built their wealth on colonialism (Mejias and Couldry 2024, 50f.). Data extraction perpetuates colonial strategies of expropriation to establish capitalist markets. As scholars like Nancy Fraser or Jason W. Moore have emphasized, market-based capitalism can only exist in and through colonialist expropriation (Fraser 2017; Moore 2018). In order to exploit labor and take advantage of cheap resources, energy and land, these things must first be introduced into legal property relations. This occurs when certain functional aspects are singled out and commodified for ownership. Meanwhile, the more-than-functional conditions that make their continued extraction possible in the first place are left uncommodified. Ecofeminists refer to this with regard to the care work in the private sphere and the reproductive work of nature (Biesecker and Hofmeister 2010; Barca 2020). In the case of data extraction, behavioral patterns and knowledge become commodified as data, while their foundational more-than-functional conditions (e.g., the upbringing and socialization of children) remain outside of the market. This separation of a marketized sphere of capitalist rationality from its wider enabling conditions is closely related to how the colonial project controlled populations by establishing certain forms of knowledge, such as the statistical enumeration of land and people (Appadurai 2013), and the management the human body in the image of the machine (Fiori 2020) while rejecting other forms of knowledge, such as indigenous knowledge (Smith 1999).

Therefore, Catriona Gray has rightly argued that the AI's extractivism tends to be embedded in historical colonial forms of extraction (Gray 2023). AI's extractivism does not merely reflect or resemble historical colonial forms of extraction; it has its "very foundations in colonial orders of knowledge and value" (Gray 2023, 2). However, contrary to Gray's broader argument, it can be analytically useful to abstract from the historical specifics of colonial extractivism and reduce it to its underlying logic. In this case, it becomes clear that data does not fit neatly into the historical extractive dynamics of an ecologically unequal exchange between Global North and Global South. The largest cross-border data exchanges are between countries in the Global North (McKinsey Global Institute 2016). The vast majority of the data that IT giants use to develop their algorithms is generated by users and companies in the Global North. This does not mean that the precarious click labor in the Global South is not an indispensable part of making large data sets useful (Tubaro et al. 2020) nor does it mean that there are no continuities with historical colonialism. Rather, it means that the process of data extraction challenges us to consider new dynamics that diverge from historical forms of colonialism, such as the enormous screen time and the unfolding mental health crisis among U.S. teenagers (Haidt 2024).

Regarding the epistemological dimensions, "the colonial orders of knowledge and value" (Gray 2023, 2), which decolonial scholars have emphasized in relation to data (Kwet 2019; Ricaurte 2019; Lohmann 2022), as well as science and technology in general (Mignolo 2011), my theorization of abstraction and extraction processes, based on the Marxian concept of real abstraction and Luhmann's notion of functioning simplification may offer valuable connections points. Rather than accepting a Western instrumentalist understanding of functionality, my approach offers useful tools to deconstruct the apparent objectivity and apolitical character of technologies like AI.

6 Conclusion

I started this paper with the problem that, on the one hand, the extractivism of AI is primarily discussed in relation to data, yet data is rarely considered a material category in its own right. This fosters a problematic divide between an immaterial digital realm and material 'analog' one. Treating data and the digital realm as immaterial hinders the development of an environmental sociology of AI that can capture the specific material dynamics of data extraction. I have suggested that the dual concepts of abstraction and extraction from critical data studies could solve this problem. Through the concept of 'real abstraction', I have emphasized that the abstraction of data must be understood with regard to social relations. By examining the violent extractive processes through which the concrete lives of people and the concrete complexity of ecosystems are reduced to a narrow set of functional properties to be integrated into a technology, we can deconstruct the seemingly objective and neutral functioning of AI technologies. In this process of abstraction and extraction, data can be understood as a material category, distinct from, yet on par with resources, energy, and labor.

The potential of an environmental sociology of AI lies in its capacity to look beyond harmless pleas for more efficient, ethical, or fair AI and problematize the social structures that make AI function in the first place. Counting the kilograms of raw material, the megajoules of electricity, or the working hours that go into making AI is not enough. Getting absorbed with the content from which AI is made will be a senseless undertaking if we do not also investigate the social form of AI itself.

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Declarations

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