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Analysis

The fantasy of digital immateriality: AI, ecologically unequal exchange, and appropriation of lived human time☆

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ABSTRACT

The purported immateriality of AI technologies is as illusory as the general understanding of conventional technologies as simply the application of politically neutral knowledge to nature. The materiality of technologies and their foundation in global inequalities has been illuminated by studies of ecologically unequal exchange (EUE). The aim of this article is to extend the applicability of EUE theory to digital technologies such as Artificial Intelligence (AI) by highlighting how even the data that they process have an inevitably biophysical history. AI technologies represent a novelty mainly in the sense that, in addition to exploiting extractive areas through EUE, they are based on the appropriation of data from the public. We argue for understanding the materiality of data as derived from lived human time. AI's dependence on data can thus be regarded as representing and embodying biophysical processes and asymmetric transfers implicating issues of justice.

1. Introduction

The development of automation and digital technologies such as AI is often presented as a game-changing discontinuity – a rupture said to fundamentally reconfigure our historical reliance on the material environment. The general assertion is that their focus on the management of information, rather than matter and energy, will lighten the burden of human society on nature and make it possible to decouple economic growth from material resource demands (Hussain et al., 2024). This is particularly characteristic of the so-called ecomodernist approach (Asafu-Adjaye et al., 2015) and taken to its extreme in visions of increasingly immaterial technologies (Bastani, 2019). Materiality refers to the tangible and finite nature of organic and inorganic entities existing in time and space. Dematerialisation, then, is the ambition to transcend this finiteness. In this paper, we do not intend to add to the many studies that empirically demonstrate the extent to which this expectation is built on illusions (e.g., Dourish, 2017; Crawford and Joler, 2018; Bakker and Ritts, 2018; Ensmenger, 2018; Dauvergne, 2020, 2021; Crawford, 2021; Obringer et al., 2021; Gonzalez Monserrate, 2022; De Vries, 2023; Santarius et al., 2023; Turnbull et al., 2023) but rather to problematise the very ambition to dematerialise. We argue that digital technologies like AI, in presenting themselves as somehow detached from the materiality of the biosphere, do not so much suggest a discontinuity vis-à-vis earlier technologies as a continuation of the recurrent neglect of their basis in asymmetric resource transfers.

We employ the theory of ecologically unequal exchange (EUE) to conceptualise AI technologies not primarily as strategies for *saving* energy, resources, or time but for *appropriating* them. EUE studies show that modern technologies in core regions of the world market are dependent on an unequal exchange with the periphery in terms of biophysical resources. Empirical analyses reveal that the global North imports significantly more embodied labour, resources, energy, and land than it exports, yet this trade appears as equal when gauged in purely monetary terms. This monetary perspective makes it seem as if technologies are simply local – that is, geographically confined – instances of engineering ingenuity that allow us to do more with less, although we are actually shifting our material burdens to other parts of the world. In other words, economic processes seem more dematerialised when assessed by the beneficiaries of unequal exchange.

Does the EUE narrative also account for the peculiarities of AI technologies, whose most important input is arguably not labour, resources, energy, or land, but data – an input that seems to be neither material nor even assigned a price? We believe it does. EUE theory can help us understand how the calls for more equity and more sustainability

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in AI supply chains (for instance, Crawford and Joler, 2018) are structurally linked to each other, as AI relies on the extraction of both low-cost labour and low-cost resources, but our main point is that it also entails an unequal exchange of information, which is ultimately linked to an unequal exchange of human time. While AI technologies undoubtedly increase the speed at which certain tasks are performed, their operation is also geared toward appropriating ever more of our lived time.

2. The ancient fantasy of immateriality

Philosophers and historians have observed that what Karl Jaspers, 2021 called the Axial Age (800–200 BCE) marked a watershed in intellectual history. In several parts of the world, there was a shift from what Marshall Sahlins (2022) refers to as "immanentism" to *transcendentalist* understandings of cosmic agency. Judaeo-Christian cosmology illustrates how agency was displaced from the material world to a transcendent, celestial realm. The concept "spiritual" embraced the totality of human subjectivity, including all consciousness and significantly also *knowledge*. Unlike classical Greece and medieval Europe, early modern Europe began to trust in historical progress, especially as human knowledge grew rapidly during the scientific and Industrial Revolutions. The development of new technologies in 18th- and 19th-century Europe was understood as manifestations of such progressively enhanced knowledge. The new ways of mastering matter and energy were thus closely linked to Christian ideas about spiritual growth. The human spirit would not only master the material world but also improve it (White, 1967). Given the hegemony of Descartes' mind/body distinction, technology played a pivotal but paradoxical role in these cosmological transformations (Hornborg, 2019, 2023). Although undeniably material and employed to rearrange the physical world, it has come to be perceived as essentially based on engineering knowledge – a product of mind rather than body. From the late 18th century, this perception of technology has come to serve as an ideological justification of capitalist development, obscuring the material dependence of industrial core areas on their extractive peripheries (Frank, 1998: 204). The watershed of the Industrial Revolution was the point at which technological progress was no longer contingent merely on human ingenuity but also on global discrepancies in the market prices of labour, land, energy, and materials (Marks, 2015: 210). Although fundamentally dependent on asymmetric global resource flows, modern technologies continued to be celebrated almost exclusively as triumphs of human ingenuity (as for example in Bunge, 1966; Landes, 2003; Arthur, 2011). We consider this understanding of technology as human ingenuity to be hegemonic, as it is encapsulated in the dominant political project of ecological modernisation, which promotes the idea that society's dependence on the material environment can be reduced through the ingenuity of technological innovation (Isenhour, 2016).

Developments in economic theory, particularly since the Marginalist Revolution in the 1870s, have reinforced this transcendentalist approach to technology. Industrial machinery operates through physical processes, transforming matter and energy extracted from nature, but tends to be couched in discourses on innovations in engineering, investments, and added value. Modern technologies seem to have liberated human labour from the physical resistance of soils, rocks, and rivers – but only because the technologies are geographically separated from the mines and dams that propel them. The technological artefacts seem miraculously to extend human capabilities and relieve their users of work, while the distant labour and resource extraction required to produce and reproduce those technologies remain obscured by the fetishised artefact (Pieper, 2024; Hornborg, 2023). Technological fetishism is thus a particularly perplexing instance of commodity fetishism. New digital technologies like AI do not dissolve but aggravate these conditions.

3. The challenge of connecting AI's materiality with justice issues

What we have come to understand as AI technologies is the large-scale statistical analysis of data through methods of machine learning (Katz, 2017). The promises as well as the threats of AI are numerous and often controversially discussed. AI is said to dematerialise the economy as it generates economic growth with less material input (Hussain et al., 2024). Dematerialisation promises stem not only from the observation that the much-hyped Large Language Models (LLMs) have already begun to disrupt job markets, with as much as 60% of jobs in advanced economies exposed to AI application (AI Safety Institute, 2025). Also, AI's capabilities to analyse large datasets and generate novel solutions promise to optimise production processes through more intelligent materials management, design decisions, and supply-chain management. Although there is much scientific disagreement on the actual impact of AI on the job market and industrial processes, the continuing hype of AI technologies is built on the promise of radical efficiency improvements regarding time, resources, energy, and even land requirements.

Some critical responses to these dematerialisation promises question whether AI technologies can be understood as inherently immaterial. Two kinds of critical responses shall concern us here. The first response – the value approach – reframes efficiency increases achieved by AI by highlighting how the labour inputs to AI are exploited (Fuchs, 2010). The second kind of response – the material approach – challenges AI's purported dematerialisation by highlighting the material infrastructures on which it depends (Brevini, 2023; Robbins and van Wynsberghe, 2022). In the following, we will discuss why these two critiques are difficult to reconcile unless approached from the perspective of EUE theory. While the former approach is arguably based on untenable premises, as it proposes that valuation is geared to a specific kind of material input (embodied labour), the latter gravitates toward a life-cycle assessment approach that calls for efficiency improvements while ignoring structural issues of social justice.[1] EUE theory, on the other hand, can help us bring concerns for justice and sustainability together and thus also illuminate AI's false promises of dematerialisation.

3.1. The value approach: challenging AI's dematerialisation promises by highlighting labour exploitation

We begin by considering the argument that criticises AI's purported dematerialisation successes by highlighting the exploitation of labour, a notion which largely derives from Marx's labour theory of value. This approach is generally concerned with the so-called click labour outsourced to workers under precarious conditions, often located in the global South, but also with how the users of digital services are not being properly compensated for the data they provide to corporations like Google, Facebook, or TikTok (Fuchs, 2010). Such responses call for more fairness and equity. The argument invokes the Marxist labour theory of value (LTV), which asserts that the profit of capitalist production arises from a systematic exploitation of labour. The labourers that create and clean the datasets on which AI depends are marginalised in the supply chain. Their invisibility creates the illusion that AI dematerialises production.

Christian Fuchs has argued that the LTV should be expanded to the"knowledge labour" necessary to create data (Fuchs, 2010). He holds that informational capitalism increasingly depends on "processes of cognition, communication, and cooperation" (Fuchs, 2010: 180). These

[1] Although efforts to include social aspects into life-cycle assessments do exist (Petti et al., 2018; Zarauz, Sanz-Hernández, and Rivera-Lirio, 2025) their case-by-case measurement of „social impacts"as well as the conception of „social sustainability"are not suited to analysing structural patterns of social conflict and injustice.

processes are not all located within the classical wage labour relation. They also significantly draw on unpaid labour, for example from so-called "prosumers". The prosumer consumes social media while at the same time producing user-generated data and behavioural data sold as a commodity to advertisers (Fuchs, 2013: 122). Also, the data repositories of Facebook, Instagram, or Youtube provide central sources for authentic human-produced text, images, and video (Winton, 2024). These repositories offer valuable training data for AI. In addition to the prosumer's data work, the pirated libraries of *libgen*, a file-sharing platform for making millions of academic books freely available, were used to train Meta's large language model (Knibbs, 2025). Other AI companies like OpenAI primarily use the"Common Crawl" dataset for training, which also includes large amounts of copyrighted material produced by academics, artists, and journalists (Baack and Mozilla Insights, 2024). All this training data derive from a social process of knowledge creation occurring largely outside of the wage labour relation. The results of this process are appropriated by capital with little or no compensation paid. In turning data extraction into a problem of paying a fair price, Fuchs calls for higher taxes and redistribution in the form of a guaranteed basic income for everyone (Fuchs, 2013: 193).

3.2. The material approach: challenging AI's dematerialisation promises by highlighting material infrastructures

The second kind of approaches leave the realm of economic values and focus on the material. Such approaches reduce data processing to the material infrastructure that it requires. Data centres, smartphones, computers, fibre cables – all this infrastructure requires cement, steel, silicon, rare earth minerals, as well as large amounts of energy and water. In this effort, staggering figures have been invoked: The additional global electricity demand induced through AI and cryptocurrencies has been expected to increase from 2% in 2022 to 4% in 2025 (IEA, 2024: 35). The tech industry's carbon footprint is projected to increase to 14% of all global emissions by 2040 (Belkhir and Elmeligi, 2018: 448). One of the most cited assessment of AI's energy needs holds that training a single large language model can emit as much CO_2 as five cars in their lifetimes (Hao, 2019). The data centres and gadgets needed for collecting data and processing AI algorithms will greatly increase resource extraction and e-waste, the latter of which is expected to rise from 53.6 Mt. (million metric tons) in 2019 to 74.7 Mt. by 2030 (Forti et al., 2020). These figures have been utilised by critical scholars to question the illusion of immateriality projected by proponents of data processing in AI systems (Brevini, 2023; Robbins and van Wynsberghe, 2022).

3.3. Problems with the two approaches

Starting with the value approach, which brings into view the labour exploitation of digital technologies, Fuchs' application of the LTV to knowledge labour has triggered criticism (e.g., Arvidsson and Colleoni, 2012: 142). Thatcher et al. (2016) have suggested that the production of data is best understood not as exploitation but as dispossession. They thereby put the focus less on the labour that produces the data and more on the process of privatising user data through license agreements which the users must accept if they want to use the platform. Fuchs, in focusing on the labour behind data, emphasises the material foundation of data (Fuchs, 2015: 252). However, both Fuchs and his critics are unable to conceptualise the materiality of data because they focus exclusively on monetary values. This focus on appropriated value brings into view justice issues invoking unfair remuneration but provides us with no material metric for assessing AI's most important inputs.

As Jan Overwijk (2024: 15) observes, the labour theory of value has "committed Marxism to an untenable ontology of labour that imbues human effort with unique qualities." Human labour is thought to have the unique capacity of producing more value than it costs. Capitalist profits are thought to arise from this difference between the value paid to labour and the value it produces. This conceptual pitfall of *monism* collapses the material aspects of labour time, resources, or energy with its symbolic representation through money.

Located on the flipside of what Overwijk calls the "eco-Marxist problematic" (Overwijk, 2024) are the laudable efforts of the material approach to highlight and quantify the material footprints of AI infrastructure. Avoiding the metaphysics of value found in the first approach, the sole focus of the second approach on assessing AI systems in terms of tons of raw materials and megajoules of electricity brings into view sustainability issues. At the same time, the approach does not account for the unequal structure of the global economy. Indeed, it also represents a kind of monism. Instead of collapsing the material into the symbolic, this approach collapses the symbolic into the material, as it sidelines the symbolic organisation of resources and focuses solely on their empirically measurable expenses.

In addition to our two approaches, Overwijk identifies the recurrent pitfall of monism in several orthodox and heterodox economic approaches – neoclassical environmental economics, ecological economics, orthodox Marxism, Marxist ecofeminism, and Marxist value-form theory. They all succumb to "the urge to reduce either ecology to economy or vice versa" (ibid., 17).

Constrained by the monism of both the value approach and the material approach, we can either connect AI's materiality to an overarching capitalist logic of exploitation (value approach) or highlight, on a case-by-case basis, poor labour conditions here and environmental damages there, while failing to challenge the systemic *material* injustice of these technologies (material approach). Is it possible, Overwijk asks (ibid., 33), "to develop a theory of exploitation that works across the ecology-economy boundary?" In other words, the challenge lies in devising a theory that can expose how money orchestrates material flows, but does so without conflating the symbolic monetary representation of materiality with materiality itself.

3.4. An alternative approach: challenging AI's dematerialisation promises with EUE theory

In the following, we will present EUE theory as a way to work "across the ecology-economy boundary" (Overwijk, 2024: 33). EUE theory understands the materiality of AI technologies through the global appropriation of resources by the global North. It does so by keeping physical units and their market prices distinct in their measurement but not in their causal interrelations. EUE theory can function as a foundation to challenge AI's dematerialisation promises with regard to issues of justice and issues of sustainability. To explain how, we shall first outline the theory's history as well as its basic argumentative structure.

The foundations of EUE theory can partly be attributed to Stephen Bunker and his book *Underdeveloping the Amazon* (Bunker, 1988), which problematised Emmanuel's work on the unequal exchange of labor value (Emmanuel, 1972). Other central influences include Odum's systems ecology (Odum, 1971), Ayres' and Kneese's work on uneven flows of natural resources (Ayres and Kneese, 1969), the world-system analyses developed by Wallerstein (1974), and the articulation of thermodynamics and economics pioneered by Georgescu-Roegen (1986).

EUE theory emerged from a critique of world-system theory's understanding that global inequalities result from unequal value transfers between regions. As previously observed regarding the metaphysics of the LTV, there is no valid measure to claim that monetary value is appropriated by one region from another (as this would lead to the question what the "real" value of commodity ought to be – a question that cannot be answered objectively). Measured with monetary metrics, exchanges can, by definition, only be equal. The point of EUE theory is that symmetrically exchanged monetary values obscure (while

simultaneously orchestrating) asymmetrical exchanges of biophysical resources (Schlaudt, 2023: 280). The materiality of traded commodities can be gauged in terms of the labour, land, matter, and energy that has been expended in making them available to the market. Relevant metrics are person-years, hectares, tons, and joules, respectively. Considering the physical substance of commodities reckons not only with their currently measurable contents but also with the embodied inputs of resources throughout their production histories. This understanding of embodied inputs is similar to how Odum (1988) redefined his concept of "emergy" (originally denoting "embodied energy") as *energy memory*, that is, a measure of the amount of energy that has been dissipated over the course of production. Empirical quantifications of such "embodied" resources reveal a continuous net transfer from the global South to the global North (Dorninger et al., 2021). This is a predictable consequence of the prevalence of lower wages and weaker environmental legislation in the South. As a result, greater volumes of labour and other resources are embodied in exported goods from these areas relative to their price. Put simply, a dollar can mobilise more labour hours and resources when it is spent in a country like Vietnam than it could in a country like Germany.

A common response to these circumstances is to suggest that EUE could be suppressed by enforcing environmental regulation and higher wage levels in the global South. However, we must also acknowledge that the unequal exchange between global North and global South is inextricably entwined with current conceptions of technology, progress, and modernity in the global North. In other words, to seriously attempt to curb global EUE would ultimately be to challenge the very foundation of modern civilisation and would thus be opposed by strong political interests. It follows that while the mechanism of EUE is coupled to differences in wages and environmental legislation, the continued ideological mystification and maintenance of EUE is successful in part because of the hegemony of progressivist understandings of technology, in part because of the political power of the global North. The latter is concretely expressed through diverse (and often interrelated) means such as military dominance and border protection by the North, as well as dependency on advanced technologies and foreign investment of the South (Jorgenson, 2016).

The technological capacities of high-income countries of the global North allow them to produce products that can be sold at higher prices than their incorporated upstream products from the global South. At the same time, the upstream products are more labour- and resource-intensive than the technologically refined end products. Out of this constellation emerges a general pattern in which unequal exchange relations are aggravated over time: The global North can expand its technological infrastructure and economic and military power while the global South is confined to exporting their biophysical resources (Dorninger et al., 2021, 3).

Although the global scale of supply chains maintaining advanced technologies is by no means a secret, the modern mode of thinking that separates mind from matter makes it fundamentally difficult to grasp technology as a social strategy for appropriating low-paid labour and other resources from the margins of the world-system. Due to the immense technological breakthroughs of the last 250 years, common understanding is much more aligned with the restricted view that modern technologies primarily consist of applying ever more ingenious engineering to nature (Bunge, 1966; Kline, 1995). In this sense, the fantasy of immateriality does not just arise with the advent of digital technologies such as AI (Crawford and Joler, 2018) but constitutes a core feature of the limited perspective of the global North, where technology's capacities present themselves as obvious facts, but their material burdens on other parts of the world fade into the background.

What distinguishes EUE theory from the other two approaches is that it (a) explicitly rejects the concept of value (Hornborg, 2019: 171) and thereby avoids the metaphysics of the LTV, and (b) traces the materialities of technologies, not just by counting the embodied Joules of energy and tons of resources but by considering these quantities in relation to global market exchange. Put simply, EUE theory can address issues of sustainability by focusing on measurable biophysical expenditures while simultaneously addressing issues of justice because it investigates the unequal patterns through which these biophysical expenditures flow from one region of the world to another.[2]

However, to expand EUE theory's critique of the apparent immateriality of technology to AI, we think it is important to also consider the materiality of its central input, that is, data, and the unequal patterns through which it is exchanged. This constitutes a refinement of EUE theory that thus far has been lacking from the literature.

4. Integrating data as a biophysical resource in EUE theory

Up to this point, we have discussed EUE in terms of asymmetric transfers of tangible biophysical resources such as labour, land, materials, and energy. We now turn to how the EUE approach may illuminate the global trade in data. Given the empirical evidence for global patterns of EUE and their centrality for accumulating technological infrastructure (Dorninger et al., 2021), we can expect the physical infrastructures of AI technologies to also be based in EUE. There are, however, some peculiarities about digital technologies in general, and AI in particular, that deserve reflection. Their main input is data – the digital representation of information (Oxford English Dictionary, 2024). It does seem more immaterial and ethereal than the infrastructures which they require, yet data represents a "memory" (in Odum's sense) of the organic life of the human beings from which it derives. In this regard, data is not more ethereal than the inputs of labour or energy in the production of any other commodity. It is "embodied" in a commodity as part of its history but impossible to identify through analysis of its constitution.[3]

The materiality of data cannot be entirely reduced to the materials, energy, labour, and other resources on which it is contingent. Although this is how critical approaches have generally addressed the materiality of data, and while EUE theory has so far not dealt with data itself, it is arguable that even data can be understood as a kind of embodied, biophysical resource irreducible to other resources (Baack and Mozilla Insights, 2024). No more than labour can be reduced to material resources such as energy, is data reducible to labour, energy, and materials. In other words, if we knew the exact material expenses, the electricity demand, and labour hours that go into a gigabyte of LLM training data we would still miss the fact that data also relies on the appropriation of information from the consumers (Fuchs' "prosumers") of digital technologies as well as the broader public (e.g., the books, newspaper articles etc. used to train LLMs). Of course, we could reduce this appropriated information to another form of labour. But in our view, this would stretch the meaning of labour so far that it makes more sense to simply open a new category able to grasp the peculiarities of data extraction. This is not to deny, of course, that data creation depends on low-paid click labour and an unequal exchange between global North and global South. Workers in countries such as Venezuela, Nigeria, and India clean and verify data sets under precarious conditions (Gray and Suri, 2019; Hao and Hernández). But data is not completely reducible to this.

[2] Given that exchange patterns are highly uneven, they could be normatively challenged. EUE theory does not engage directly in normatively challenging exchange patterns but clearly lays the foundations on which to do so.

[3] Admittedly, it would be very difficult to devise a method of tracing back the human time that went into creating a certain bite of data. Certainly, any general measure relating, say, 1 MB of data to X hours of human lifetime would be nonsensical. For example, 1 MB of academic text will likely be much more time intensive than 1 MB of video blog. Thus, invested human time would either have to be traced back on a case-by-case basis, or approximate averages for different types of data would have to devised (e.g., academic article, blog post, or fiction book, regarding invested time relative to text). However, similar problems arise with regard to most other biophysical resources and have been solved in empirical analysis. To determine the environmental impact of a certain quantity of extracted/produced resource, we would have to specify the kind of resource (e.g., gold, steel, sand, wheat) and its geographical origin. For a defence of EUE theory on this issue, refer to Schlaudt (2025: 39).

To see why, consider what data has in common with other biophysical resources. What the extraction of data shares with that of biophysical resources such as energy, labour, and land is that both involve a process of abstraction, in which humans and nature are reduced to a small selection of functional aspects. 'Abstract', derived from the Latin '*abstrahō*' and translating 'to pull/draw' (*trahō*) 'away' (*abs*), refers to something drawn away from a specific context (Merriam-Webster Dictionary, 2024). Therefore, 'abstraction' refers to the process of decontextualising a certain phenomenon. What makes a resource abstract? For example, one ton of oil is an abstract resource because all that matters is its energy value and it is completely substitutable with any other ton of oil (of the same type). And the written text of internet forums is an abstract resource to AI because all that matters is its information value for the training of an LLM and it is completely substitutable with another batch of data. Just as nature does not naturally present itself to us in the form of fungible resources and uniform land measurements, human life does not spontaneously appear in the form of labour or data. Along the understanding of technologies as "verified event correlations" (Schulz-Schaeffer, 2000: 223) through which the real world is simplified to only those aspects that contribute to its specific function (Luhmann, 2021: 524), we can understand the functional necessity of abstraction regarding technology. At the same time, political ecology is rife with literature that highlights how abstraction processes must also be understood as inherently violent processes of extraction (Pieper, 2026; Backhouse et al., 2025). There are significant parallels between processes of abstraction and extraction. As the complexity of the real world is reduced to fungible resources – whether steel, electricity, or data – it is made accessible for appropriation.[4]

However, there are also differences. Investigating the specifics of the abstraction and extraction processes from which data derives and is integrated into AI models reveals unique patterns of unequal exchange. These patterns are distinct from the unequal exchange in waged labour time between global North and global South. The concept of the prosumer as well as AI companies' reliance on various kinds of archives of written text, recorded images, videos, and sound highlights how much of the human time that goes into digital technology like AI is derived from outside the classical wage labour relation. Therefore, understanding data's materiality through the unpaid monetary value of labour can be misleading. Reducing data to embodied labour means that one must expand the very notion of labour by understanding the time users spend on platforms or the time it took to write the books filling a library as somehow analogous to wage labour. However, if we recognise the processing of data as a special strategy for appropriating human time, we realise how this process is distinct from wage labour.[5] Because the human time appropriated from prosumers and the larger public is unpaid, the asymmetric flows of data do not occur primarily across geographical divisions between the global North and the global South. There is no longer an incentive to seek the geographical places where it is the cheapest. Granted, different regulations pertaining to what kind of data can be accessed and stored can still contribute to geographical specifics in data extraction. Still, the primary locus of the unequal exchange of data is not global South versus global North, but public versus corporation (cf. Thatcher et al., 2016).[6]

We can better understand how this unequal exchange of data between public and corporation is constitutive of AI technologies by relating the metabolism of data – that is, the transformation of inputs into outputs – to the general metabolic patterns that EUE theory has identified for other capitalist processes (Dorninger et al., 2021). Generally, the global North tends to import low-entropy energy and raw materials from the global South in exchange for exports of more refined products and services. Their production increases entropy in the Earth system but tends to materially and economically reward the global North. This is because the global North invests less biophysical resources in the production of these refined products than it receives in exchange from the global South (Hornborg, 1998). For example, a car factory in Germany consumes low-entropy fuel and materials imported from the global South and transforms them into a car. This results in an increase of entropy but also in a product that is valued higher than its input of resources (given that production is profitable). Thus, the dissipation of energy and materials, making them unavailable for further rounds of manufacturing, is rewarded with monetary gain.

In large language models (LLMs) such as ChatGPT, Llama, or Gemini, there is a similar dynamic to the resource metabolism that EUE theory has identified regarding other modern technology. However, we are not arguing from analogy but from the claim that data is another biophysical resource that information theory suggests can be understood along thermodynamic principles. We are not merely assuming that data is unequally exchanged because EUE theory has suggested this to be the case for other biophysical resources. Instead, we shall now demonstrate that there are independent theoretical reasons, regarding the functioning principles of LLMs, that make it plausible that an unequal exchange of data is constitutive of LLMs.

LLMs extract large amounts of human-derived data from social media users, journalists, or scientists by appropriating their public output on the internet to construct the models. This is achieved through several mechanisms. In the case of social media, the platform structure incentivises users to share their own data so as to communicate with others. Users write posts, comments, and threads, or post videos that can be transcribed and utilised for training LLMs. Additionally, users generate further data traces that they have no access to (attention time, interaction frequency and patterns, etc.) and platforms are utilised to target ads or improve recommendations, thereby increasing the time people spend on platforms and the amount of data they share. Regarding the information appropriated from the larger public, this is done through different methods such as using the "Common Crawl" dataset with data from over 300 billion websites, even including copyrighted material and data behind paywalls (Reisner, 2025). Other AI companies have accessed the pirated academic book library of libgen (Knibbs, 2025) or have scanned millions of physical books before destroying them (Schaffer et al., 2026).

Information theory as established by Shannon and Weaver in *The Mathematical Theory of Communication* (Shannon and Weaver, 1998) understands information through the relation between signal and noise and thus through the degree of surprise relative to an observer: "Information as surprise can be related to Bayes theorem, as the amount of information that is gained from an observation, by comparison to the observer's prior knowledge" (Blackwell, 2023: 2117). Information is a quantifiable measure of order, its counterpart being entropy.

[4] As Mejias and Couldry have argued, the violence of data extraction on which AI depends might be different from the immediate violence implied in appropriating land for resource extraction, but continuous to exist in forms of symbolic violence (Mejias and Couldry, 2024), for example through the reproduction of racism or the reproduction of economic inequality effected by biased representation in or limited access to monopolized data.

[5] We are not implying that data *is* human time but that human time constitutes data's central material input. Thus, we are not arguing for another substantialist approach that reduces the symbolic dimension of a phenomenon to a certain material aspect. Instead, our aim is to capture the symbolically mediated process through which certain material aspects of the world are utilised to create data.

[6] The empirical challenge for understanding the geographical patterns of data flows and the unequal exchange of human lifetime would lie in estimating ratios of human lifetime embodied in different kinds of data, understanding where the data is coming from, and deciding along which proxies the AI companies to which this data flows must be located. We leave it to future research to answer these questions of operationalisation but are convinced that even crude proxies could give us an illuminating perspective on the geography of biophysical data flows connected to AI models.

Understood like this, information "is a physical quantity, directly related to mass, energy and space in the work of Heisenberg, Hawking and others" (Blackwell, 2023: 2117). Thus, to understand the "informational metabolism" of LLMs is not categorically different from understanding the metabolic flows of other biophysical resources.

The information that users derive from LLMs is invariably less rich in detail and less specific than the input data on which they are based. LLMs provide statistically likely answers, in the sense that they select the subsequent string of text with the highest probability. This leads to an information-output that is less unique, idiosyncratic, and surprising than the model's input. The informational metabolism of LLMs poses a problem for their own training: now that the Internet is flooded with AI-generated data, new training data is increasingly"contaminated" with synthetic data that is useless for further training rounds as it contains less information than human-made data (Shumailov et al., 2024; Peterson, 2025). If models are continuously trained on synthetic data this can lead to "model collapse" (Shumailov et al., 2024). "Long-tail-information" gets lost with each training round leading to narrower and increasingly unsurprising answers with little information content. In ways similar to how the technological infrastructure of the global North depends on continuous inputs of embodied low-entropy energy and other resources from the global South, AI companies rely on a continuous flow of anthropogenic information from users and the broader public to train their LLMs. AI models training themselves without human interference is thus as illusory as the early modern ambition of engineers to build perpetual motion machines (Ord-Hume, 2006) or the feasibility of an organism that survives on its own waste products. As AI models will be expected to adapt to a changing reality, they will continue to depend on new streams of human-derived data, gathered through an unequal exchange of information between the public and corporations. Given that data is tightly linked to registering the circumstances of human life, we can expect that while making some tasks faster, these new AI technologies will depend on capturing ever more of our time (Mejias and Couldry, 2024).

The big digital corporations have the technological capacity to provide us with increasingly valuable information at very low cost. The dynamics remain the same: the technological capabilities promising to provide us with more output for less effort are distortions of the fact that the owners of the technologies appropriate more resources, energy, time, land, and information than are returned to their sources. AI's time-saving promises seem illusory when we consider how these technologies depend precisely on appropriating ever more of our time as we are increasingly drawn into digital environments (Mejias and Couldry, 2024).

This is not merely a theoretical suggestion but something that can be empirically measured. Internet users have increased globally from one billion in 2005 to 5.5 billion in 2024 (Statista, 2024b). Time spent on social media (by people with internet access) increased from 90 min in 2012 to 143 min in 2024 (Statista, 2024a). Daily hours spent on digital media more than doubled in the United States between 2008 and 2018 from 2.7 h to 6.3 h, a figure that has likely seen a further increase by now (Ritchie et al., 2023). This has created and continues to create a rapidly growing fund of stored human knowledge and experience. Indeed, Campolo and Crawford (2020) have pointed out that the advances we are now seeing in AI technologies cannot be reduced to innovations in programming:

> Part of what accounts for their improved results in the present is the fact that training data is both more plentiful and that it is produced not in artificial laboratory settings but in the everyday lives of millions of people. This abundance of data affords deep learning systems a much wider range of 'real world' information on which to train and test their systems (Campolo and Crawford, 2020:7).

The idea that data accumulation and processing are based on an unequal exchange between the public and corporations is not new (Fuchs, 2010; Thatcher et al., 2016), but it has become much more widespread and elaborately analysed, as in Shoshana Zuboff's book *The Age of Surveillance Capitalism* (Zuboff, 2019). As early as 1999, entrepreneur Josh Harris characterised the business model of many future Silicon Valley companies by programmatically stating that "[e]verything is free, except the video we capture of you. That we own […] I'm going to sell you your life back" (Timoner, 2010).

The EUE perspective can add to this by pointing out that data itself, in representing embodied human time, can be seen as a kind of biophysical resource that is appropriated through unequal exchange. The spectacular economic success of contemporary digital tech corporations confirms that the appropriation, manipulation, and commercialisation of data is a highly profitable business model, drawing not only on the accumulation of the requisite technological infrastructure through conventional patterns of EUE but also on the appropriation of prosumers' and the larger public's time worldwide. A central continuity between EUE theory and the conceptualisation of prosumers is that both recognise the significance of *embodied* resource transfers, that is, appropriation understood in terms of a requisite production history (like Odum's "energy memory") rather than in terms of measurable ingredients that can be identified in the finished product. The information asymmetrically drawn from prosumers and the larger public is as invisible, yet as crucial, as the labour spent and energy/matter dissipated in production. In both digital and analogue production processes, "refinement" is based on unequal exchange and ultimately tantamount to a loss of contextual information.

Integrating data into EUE theory thus emphasises that that the materiality of AI does not end with the material infrastructure on which it runs (data centres, fibre cables, energy supply, end-user devices) but also extends to the human time embodied in the data that "flows" through this infrastructure. When challenging the sustainability of these technologies, the human time invested in the process of data creation should be considered as a central material input. What sets EUE theory apart from the LTV approach is that it keeps value and materiality separate. This gives EUE theory direct access to empirically measurable biophysical resources. Further, EUE theory sets itself apart from life-cycle-assessment-oriented approaches because it relates the materiality of AI infrastructure and data to unequal exchange relations between global North and global South as well as between corporation and the public. On this basis, issues of justice can be more clearly addressed.

5. Conclusions and implications

In this article, we have contextualised the illusory ambition of AI to dematerialise the economy and our lives. Not only does this effort implicate the problematic Cartesian mind/body dualism; the fantasy of dematerialisation is also illuminated by EUE theory. The fetishised image of technology as the weightless application of knowledge and monetary value reflects the general neglect of its global socio-material metabolism. EUE theory approaches the materiality of digital technologies without blurring the distinction between monetary value and materiality. In contrast to other critical approaches, it integrates justice issues with concerns over materiality and sustainability. Regarding AI, we have emphasised that its storing and processing of data is dependent on resources such as energy, labour, materials, and space. We have also argued that, in being based on lived human time, data itself can be seen as an embodied biophysical resource. Once we understand AI as a strategy for abstracting the world for technological manipulation, we can comprehend how AI technologies hinge not only on an ecologically unequal exchange between global North and global South but also on an unequal exchange of information between corporations and the public. In appropriating resources even from its own affluent customers, the technomass of the global North has imploded into a metaphorical cannibalism. Beyond appropriating low-wage labour time in the global South, they do not so much save or liberate time for their owners as lead them to spend ever-increasing amounts of time with digital media and AI, both at work and in leisure. As never before, capitalist profits now

hinge on persuading consumers of all ages to allow their lives to be increasingly occupied by the digital screens of their mobile phones, tablets, computers, and television sets. While the physical infrastructures for processing data are accumulated in accordance with the familiar pattern of EUE, their seemingly immaterial outputs enable capitalist corporations to derive profits from data appropriated from consumers and the broader public anywhere in the world. Digital technologies thus globally appropriate labour and other resources as well as the data they capture from lived, non-salaried human time. Given that LLMs operate through statistical pattern prediction and select for text with the highest probability, it invariably occludes less likely answers and therefore produces output that, by being less unique, idiosyncratic, and surprising, contains less information than its input data. Through this *reduction* of information, AI technologies are based on an unequal exchange of information that is structurally cognate to the unequal global exchange of embodied labour and other resources. For social theory, the aim must be to further theorise and challenge the project illuminated by the incisive question posed by Josh Harris: How to stop AI companies from selling our life and nature back to us in the form of data?

CRediT authorship contribution statement

Maximilian Mai Pieper: Writing – original draft, Conceptualization. **Alf Hornborg:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors have no conflicts of interests to declare.

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