CHAPTER 2

Follow the Thing: AI

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> Take an ultimate consumable item and trace back the set of inputs that culminated in this item, including prior transformations, the raw materials, the transportation mechanisms, the labour input into each of the material processes, the food inputs into the labour. (Hopkins & Wallerstein, 2016).

The Materiality that Matters: AI, Chips, and Data Centres

On January 27th, 2025, Chinese Artificial Intelligence (AI) model-makers released DeepSeek v3, a new version of a chatbot powered by Generative Artificial Intelligence (GenAI). While this may seem like just another GenAI-powered chatbot entering the AI market, DeepSeek's model shook US stock markets. To provide some numbers about the scale of the situation, while Meta's Llama 3 cost 61.6 million USD to develop, DeepSeek claimed to have reduced costs to just 6 million USD

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(The Economist, 2025). DeepSeek's breakthrough had a direct impact on the US chip designer and supplier of GPUs (graphics processing units, specialized chips for AI), NVIDIA, which saw its market value plummet by 600 billion USD on the same day. The reason is that the Chinese team demonstrated that GenAI models could supposedly achieve similar performance to competitors while using fewer chips and consuming less energy. This breakthrough challenged Sam Altman's prevailing notion that developing GenAI necessarily requires more chips, energy, and data centers (Lynn, 2024). The DeepSeek case revealed a fundamental tension: improvements in AI efficiency, and thus in sustainability, can negatively impact US stock markets and firms whose profits depend on selling more hardware resources such as chips.

This example also illustrates how technological innovation in AI efficiency exists within competing economic incentives. While there is growing interest in reducing GenAI's energy consumption to lower operational costs and environmental impact, there are simultaneously economic pressures from hardware manufacturers to maintain high resource requirements. The AI industry publicly invests in digital sustainability initiatives, yet the market's negative reaction to efficiency breakthroughs suggests complex dynamics between technological advancement, environmental concerns, and economic interests throughout the chip production supply chains, pointing out to the relevance of AI's materiality nowadays. But how we can study its materiality today?

Materiality has traditionally been understood as a relational effect, i.e., "matter that matters" (Law, 2012). As seen in DeepSeek's case, the materiality of AI—encompassing chips, data centres, and other resources essential to powering this technology—has become increasingly significant due to its political and economic influence in capital markets, reinforcing its status as "matter that matters" (Lehdonvirta, 2022; Luitse, 2024). This matter is extracted, transported and producers across the globe to make AI possible today.

Scholars from a wide range of disciplines have proposed different approaches to study the materiality of technology. For instance, STS and media scholars Kate Crawford and Vladan Joler (2018) proposed to study the anatomy of an AI system by analysing the internal structure of Amazon Echo, the device that connects users to its voice assistant, also known as Alexa. Media scholar Jussi Parikka (2021a) introduced the concept of the "Geology of Media", which explores the connections between media technologies, their materiality, hardware, energy consumption, and the geophysical environment. Parikka argues that nature both enables and bears the burden of media culture, from the extraction of metals and minerals to the accumulation of electronic waste. In fact, the making of media technologies involves manufacturing electronics and using energy to power it, which is frame in a commodity chain frame. In this vein, media scholar Sy Taffel (2021) proposed an ecological approach to examining digital media's materiality, linking media with political ecology. One important aspect of Taffel's scholarship is the stress on the relationship between media devices and environmental degradation. Taffel claims that in the current scenario of climate change it is relevant to better understand the environmental costs of the materiality media and digital technologies. Given the large and increasing number of resources needed to train GenAI products (Martin & Peskoe, 2025), scholarship has recently begun to investigate the environmental costs of GenAI by building on a traditional body of scholars analysing data infrastructure and associated environmental costs (Hogan, 2015; Velkova, 2019).

Within the recent literature on AI's environmental costs, numerous studies have examined the energy consumption associated with algorithmic training through carbon emissions. Morand et al. (2024) analysed the carbon footprint of machine learning algorithms by focusing on the energy required by graphics processing units (GPUs) for training. They found that, despite efforts to improve efficiency, AI's environmental impact has continued to rise. In a similar vein, Luccioni et al. (2023) estimated that training BLOOM, a large language model trained to be environmentally sustainable, generates a total of 50.5 tonnes of CO_2 emissions.[1]

AI also consumes vast amounts of water. During the training and development phases, water is required to cool the servers used for AI model training. Some estimations show that AI places a significant demand on water resources. For instance, Meta used 22 million litres of water to train Llama-3—an amount a Londoner would consume in just over 400 years (Valdivia, 2025). However, energy and water are also essential beyond the training phase. For example, manufacturing graphics cards requires substantial water resources (Li et al., 2023).

[1] In comparison, a flight Barcelona-London emits 0.292 CO_2 tonnes per person.

These facts illustrate the need to analyse AI's materiality and associated environmental impacts from a commodity perspective. In the context of AI, there are two types of commodities: software and hardware.[2] Data and algorithms are the software objects in the form of virtual and intangible materiality, while GPUs, memory cards, and SSD disks are hardware objects in the form of physical and tangible materiality. Within this context, part of the literature on AI's environmental costs fails to trace back the environmental impacts across both types of AI commodities (software and hardware) by connecting the various stages of the AI commodity chain, from mineral extraction to waste generation (Valdivia, 2024).

This fragmented approach prevents a comprehensive understanding of the associated environmental costs throughout the entire supply chain, including carbon emissions, water consumption, soil degradation, mass waste production, and biodiversity loss. This limitation illustrates the need to connect different stages within AI commodity chains to make visible and better estimate the balance between its environmental costs and social benefits. This chapter aims to contribute to the literature on AI and sustainability by proposing a conceptual framework that draws on critical geography and sheds light on AI commodity chains in order to defetishise its materiality (Mollen et al., 2024).

Geographies of Commodity Chains: Papayas, Mushrooms and GPUs?

Value chain, supply chain, and production network are synonymous of commodity chains, a concept that refers to a "network of labour and production processes whose end result is a finished commodity" (Hopkins & Wallerstein, 1986, p. 159). Sociologists, economists, anthropologists, historians and geographers have largely investigated commodity chains to "study patterns of development of the modem world-system" (Bair, 2014, p. 1). This method proved to be successful in advancing analytical understanding on the complexity of production networks that have become global and intrinsic within the capitalist world-economy (Tsing, 2009).

[2] I own this contribution to Dr. Valente, a colleague with whom we have had academic discussion about what does it mean to be a commodity in the digital world.

This analytical framework proposes to examine what Marx coined as "commodity fetishism" (Felluga, 2015; Marx, 1967), the idea that once commodities are purchased, the materials and human relations involved in the production of that commodity are ignored. Critical geographers such as David Harvey (1990) have drawn upon this concept asserting that "the grapes that sit upon the supermarket shelves are mute; we cannot see the fingerprints of exploitation upon them or tell immediately what part of the world they are from" (p. 423). In a similar vein, Ian Cook published in 2004 *Follow the Thing: Papaya* in which he traced the route of a papaya from a supermarket in London back to a farm in Jamaica to "unmute" commodities and explore social relations and geographies. In fact, this piece was intended as a provocation to defetishise commodity chains by connecting producers and consumers throughout different geographies, proving that it is possible to connect subjects and trace commodities across geographies. To do so, Cook proposed the *follow the thing* methodology, an approach proposed to follow the journey of commodities. This chapter builds on this scholarship to defetishise commodity chains through follow the thing analysis, focusing on the tangible commodities of AI: GPUs. First, it unveils the geographies, materialities, and social relationships involved in the production of this technology. Second, it examines and accounts for the environmental impacts, not only during the training phase of AI but across its entire commodity chain. This analysis is essential in demonstrating that the creation of AI involves not only human labour, as others have already highlighted, but also diverse geographies and significant environmental costs. Moreover, this commodity perspective challenges the prevailing "AI for sustainability" narrative and highlights persistent patterns of global distributional injustices. Examining AI through the lens of commodification does more than simply catalogue additional environmental harms along the commodity chain—it reveals how the commodification process itself actively constrains our understanding of AI technologies and their impacts. This narrowed perception obscures the full social and environmental consequences embedded in AI systems, limiting the ability to address them comprehensively.

The literature on AI commodity chains has recently emerged as a prominent field of interdisciplinary study (Brodie, 2020, 2023; Lehuedé, 2024; Parikka, 2021b; Taffel, 2023), accounting for the "organisational and geographical forces that shape the supply chains of AI" (Tubaro et al., 2025, p. 1). This includes labour tasks related to data work in AI preparation, such as low-wage data annotators (Grohmann & Fernandes Araújo, 2021; Miceli & Posada, 2022), highlighting labour injustices and the exploitation of data labellers by "powerful forces that push such companies towards limiting the actual social impact of their business model in favour of ensuring higher profit margins" (Muldoon et al., 2023, p. 1). However, AI commodity chains also extend to miners extracting minerals for GPU manufacturing, workers in factories assembling GPUs, and e-waste dismantlers (Valdivia, 2024), exposing social relationships that are neglected under the fetishism of commodities.

The defetishisation of AI commodities involves bringing attention to its key tangible materiality: its processing units. The first marketed graphic unit for personal computing was launched by NVIDIA in 1999. It was defined as "a single-chip processor with integrated transform, lighting, triangle setup/clipping, and rendering engines that is capable of processing a minimum of 10 million polygons per second" (Gaboury, 2021, p. 254). These GPUs were developed to enhance computer graphics using parallel computation but have become key components in the development of machine and deep learning algorithms. Unlike central processing units (CPUs), which are highly flexible but process calculations sequentially, GPUs are designed for parallel processing, allowing them to run multiple iterations of the same calculation simultaneously. This capability, initially developed for rendering graphics, proved highly effective for training algorithms. GPUs could process large amounts of data at once and reduce the time needed for tasks like image recognition or text generation, but at a larger computing cost (Miller, 2022). To study the materiality of AI is to study GPUs, amongst other electronics (Rella, 2024). GPUs become part of servers located in data centres that process data and train algorithms. Data centres are in turn connected to subsea and underground cables that enable data circulation across the Internet (Munn, 2021, 2022; Starosielski, 2015). As a result, they also become key infrastructure in AI materiality. Moreover, these infrastructures, GPUs, data centres, and subsea cables, are manufactured using various materials and minerals. Their extraction, as well as their production and shipment across different geographies, entails significant environmental impacts that are unveiled when defetishising these commodities.

Following the Thing AI

Raw Materials

Minerals contribute to the materiality of AI. GPUs, for example, are classified as "semiconductors" because their electrical conductivity can be controlled—they are neither superconductors nor non-conductors. The main semiconductor material used to manufacture GPUs is silicon, which is derived from high-purity quartz. While one might assume silicon is simply sand, scholar Ingrid Burrington (2024) clarifies that "the invention of silicon chips did not rely on ordinary sand but on extraordinary crystals" (p. 14). Although silicon and quartz are not considered critical raw materials due to their abundance—silicon makes up 27.7% of the Earth's crust by mass—their extraction is concentrated in specific locations where high-purity quartz is accessible. One such location is Spruce Pine, North Carolina, which holds some of the world's largest high-purity quartz deposits. The mining company Sibelco operates in Spruce Pine, and as stated on their website, "products are exported thousands of miles from North Carolina to Asia's specialist electronics" (Sibelco, 2025, Spruce Pine section).

While GPUs are primarily made of silicon, they also contain other minerals such as aluminium, copper, tin, tantalum, gold, silver, zinc, and palladium, which are used to manufacture specific components. For instance, tantalum and palladium are used in capacitors, small components within GPUs that store and release electricity when the chip requires an energy boost. Tin, gold, silver, and zinc are essential for switches and connections within the chip. Tantalum, in particular, is sourced from various locations worldwide. According to NVIDIA's *Conflict Minerals Report*, the companies that extracts this mineral are based in Brazil, France, India, China, and Japan (NVIDIA, 2022). The chemical composition of GPUs highlights the materiality of AI and its dependence on raw materials that must be extracted for chip production. Therefore, mineral extraction has significant environmental impacts.

A recent study by Owen et al. (2023) found that at least 60% of the land used for extracting minerals essential to the green transition, many of which, such as silver, copper, tin, and zinc, are also used in electronics manufacturing, belongs to Indigenous and rural geographies. The extraction of these materials requires vast amounts of energy, contributing significantly to carbon emissions. Large quantities of water are needed to purify and process the extracted minerals, leading not only to high water consumption but also to contamination of nearby water sources. Furthermore, mineral extraction is linked to biodiversity loss, as it involves deforestation and habitat destruction, disrupting local ecosystems, including insects living underground and birds affected by noise pollution. While AI as a form of commodity is promoted as a positive development, defetishing this commodity by following a chip supply chain of a mineral constituent of AI infrastructure highlights how AI is also engaged in the historical oppressive mechanisms such as land and resource extractivism.

Chip Manufacturing

Once minerals are extracted and processed, they are shipped to factories that manufacture GPUs. Manufacturing a GPU is a complex process involving several steps. First, a company must design the chip. In the AI sector, NVIDIA has become the most prominent chip designer, particularly for GPUs. This US-based company holds 80% of the market share and has surpassed major tech firms such as Meta and Amazon in market capitalisation. The primary material used, silicon, is first purified to prepare it for chip production. It is then sliced into thin wafers, onto which intricate electrical patterns are etched to form the circuits that enable the GPU to function. These wafers are then cut into individual chips, which are rigorously tested and packaged. The entire process takes place in highly controlled clean rooms to prevent contamination, as even the tiniest particle of dust could cause defects.

The main chip manufacturers of GPUs are TSMC, Samsung, and Intel. Within this context, ASML, a Dutch company, holds the monopoly of the machinery used to manufacture the chips. Contrary to popular belief, NVIDIA does not manufacture its own chips; it is a fabless company that outsources production to these manufacturers. However, NVIDIA "is a key gatekeeper in the design of chips for AI training, and three cloud infrastructure firms—Amazon Web Services, Microsoft Azure, and Google Cloud Platform—continue to dominate the provision of networked data centre services through which many access AI services today" (Myers & Vipra, 2025, p. 39).

Among the three main chips manufacturers, TSMC is the most significant, and the geopolitical tensions between the US and China are partly driven by its factories in Taiwan. During the 1970s and 1980s, the US outsourced chip manufacturing to reduce costs, as the demand for affordable chips in laptops and other devices grew. However, due to the current geopolitical climate, the US now regrets this decision and is investing in domestic chip production, including the construction of a TSMC factory in Arizona (Jolly, 2024). As Sarah Myers and Jai Vipra posit in the latest issue of Logic(s), the political economy of TSMC, which has consolidated its dominance in chip manufacturing, relies heavily on precarious labour. The workers producing GPUs in Taiwan, many of whom are migrant labourers from Southeast Asian countries such as Indonesia, Vietnam, the Philippines, and Thailand (Tay, 2023), must endure long hours and exposure to toxic chemicals that severely impact their health: "The material conditions of chipmaking, including work that requires exposure to toxic chemicals, are obscured by influential narratives that frame chips as politically valuable resources" (Myers & Vipra, 2025, p. 42). TSMC has become so economically significant to Taiwan that in 2021, the government prioritised water supply for chip manufacturing over agriculture during one of the country's worst droughts (Zhong & Chang Chien, 2021). This decision sparked anger among local farmers, who felt unfairly blamed for high water consumption, even though chip manufacturing also requires vast amounts of water.[3] This example illustrates how the commodity chain of AI reconfigures the distribution of water, and thus of environmental justice, in ways that affect other sectors in the economy, such as agriculture and farming.

But what are other environmental impacts associated to chip manufacturing? According to Roussilhe et al. (2024), who analysed the environmental impact of 16 Taiwanese electronics manufacturers, between 2015 and 2020, these companies increased greenhouse gas emissions by 7.5% annually, final energy consumption by 8.8%, electricity use by 8.9%, and water usage by 6.1%. The research highlights a direct link between production volume and environmental impact, arguing that efficiency improvements alone are insufficient to reduce the industry's overall footprint. The study warns that the rapid expansion of the electronics sector, combined with slow adoption of renewable energy, could undermine Taiwan's carbon reduction goals and sustainability efforts.

[3] According to TSMC's (2022) *Sustainability Report*, the company used 260,000 m^3 of water per day (TSMC, 2022).

Data centres

Data centres have become a crucial infrastructure in the political economy and the ongoing race for AI innovation. This is largely due to the increasing size of GenAI models. Unlike in the past, when AI models could be trained on a laptop, today's large-scale models require significant computational power, relying on multiple GPUs housed in server rooms within data centres. These facilities not only provide the necessary processing capabilities but also store the vast amounts of data used to train and fine-tune AI models.

There are various categories of data centres, but due to the growing demand for computational power and data storage, hyperscale data centres—designed to support large-scale IT infrastructure—have seen an unprecedented surge. As a result, the materiality of the "cloud" has been increasingly exposed, revealing the immense architectural structures and vast resource consumption required to sustain it. In response to this phenomenon, scholars have highlighted that data centres have emerged as "site[s] for critical inquiry into the materialities of the Internet, the cloud, and digital technologies" (Edwards et al., 2024, p. 430). Data centres form the backbone of what is commonly referred to as "the cloud" yet studying them through commodity lens reveals their role in a global network that mobilises capital and resources (Hu, 2015, p. 4). This raises critical questions: which geographies are entangled in data center operations and what resources and commodities are being extracted and transformed to sustain them?

There is a common misconception that data centres are primarily built in cold regions. Their locations are determined by political, infrastructural, and economic factors rather than climate alone. One key reason for their widespread distribution is the necessity of proximity—being closer to a data centre ensures faster data transmission. For example, a financial broker who relies on high-speed internet cannot afford even a one-second delay, as it could mean losing millions in a transaction. This growing demand for ultra-fast communication has driven the rapid expansion of data centres across the globe. However, data centres do not just emerge anywhere; they are strategically placed in regions where political actors actively encourage their deployment. During my ethnographic research in Mexico, I found that Querétaro was an ideal location for data centres because the local government explicitly welcomed and promoted their installation (Valdivia, 2024). In addition to political support, these facilities require territories with the infrastructure to meet their immense electricity and water demands. They also tend to be established in areas with high unemployment rates, often under the promise of job creation. Yet, evidence suggests that data centres do not significantly reduce unemployment in the regions where they are built (Cummins, 2024). While they employ a large number of construction workers during the building phase—requiring expertise in industrial structures, pipelines, and digital infrastructure—once operational, they require only a minimal workforce. Typically, a data centre employs only a handful of engineers to maintain the servers and a small security team to oversee the premises. The long-term economic benefits for local communities are, therefore, often overstated. On the contrast, they create and exacerbate environmental issues, such as conflicts over water (Lehuedé, 2024; Valdivia, 2024), and electricity distribution (Brodie, 2023; Libertson et al., 2021).

A 2015 study outlining the lifecycle of UK data centres (Whitehead et al., 2015) identified the various infrastructure and components required for their operation. These include IT systems (servers, storage, and networks), electrical systems (lighting, UPS losses, switchgear), mechanical systems (free cooling fans, ventilation, chillers), and public health infrastructure (water pumps). Each of these components is built from materials such as copper, PVC, concrete, polyethylene, and steel.

As the number of data centres rapidly expands across the globe, their environmental impact has become a key focus of critique. One major concern is their significant carbon emissions. Carbon emissions depend on their energy source. If the electricity grid depends on fossil fuels, data centres emit carbon emission emerging from the energy sources. However, this depends on the location and environmental regulation. For instance, data centres in the Global North used, in general, energy from renewable sources compared to those located in the Global South. These infrastructures have also faced criticism for the vast amounts of water they consume to cool their servers. In this regard, media scholar Mél Hogan was a pioneer in analysing data centre water usage in the US as early as 2015 (Hogan, 2015).

Data centres are defetishised by uncovering cloud narratives and investigating the material commodities embedded within this infrastructure. While data centres have been investigated in the literature, pre and post the GenAI era, the follow the thing analysis developed within this chapter unveils not only its materiality, but how AI chips (Khan and Mann,

2020) are magnifying the environmental impacts of data centres. But what happens to this materiality when is no longer useful?

E-Waste

Waste is the final stage within AI commodity chains, with two primary endpoints: incineration or dumping. Extracting minerals from GPU components is prohibitively expensive, making it nearly impossible to reintroduce them into the supply chain. As a result, GPUs are typically incinerated to reduce waste volume or shipped to other countries, where local communities are left to manage the electronic waste. For instance, artist and researcher Cyrus Khalatbari (2024) discovered discarded GPUs in Accra, Ghana, home to one of the world's largest e-waste dumps. Despite its environmental and social consequences, GPU waste remains largely underexplored in academic literature, with some exceptions (Velasco González, 2016; Wang et al., 2024). Greater attention should be paid to this final phase of the commodity chain, as it has serious implications for communities and ecosystems near incineration plants and e-waste dumps.

While research on GPU waste is scarce, media scholars have extensively examined electronic waste more broadly. Jennifer Gabrys studied e-waste by "mapping the sites of its multiple transformations and by examining the residue that accumulates from these transformations" (2013, p. 24). Her analysis highlights e-waste geographies in locations such as Delhi (India) and Guangdong (China), where workers dismantle electronic components, including wires and motherboards. Indeed, e-waste geographies are often concentrated in the Global South. As Taffel (2021) posits: "wealthier nations send large volumes of toxic waste to poorer countries, where they are manually treated, with few safeguards in place to protect the health and safety of workers or local environments" (p. 178).

A recent study by Wang et al. (2024) in *Nature Computational Science* analysed how Large Language Models (LLMs) and the GPUs required to train them could exacerbate the global e-waste crisis. Given that the average lifespan of a GPU is approximately five years, these components must be regularly replaced, contributing to increasing waste generation. The researchers estimated that without proper regulation or policy intervention, LLMs could increase e-waste production by a factor of 1000 by 2030. This surge in e-waste could have severe environmental and health consequences. If GPUs are incinerated, they may release toxic particles into the air, negatively affecting the health of communities living near incineration plants. Alternatively, if discarded in landfills, the hazardous materials within GPUs could contaminate the soil and groundwater, posing long-term environmental risks.

Following the thing AI until the end, when its tangible materiality is discarded, offers a critical approach to defetishise this technology. It illustrates the material side of AI and how this technology has the potential risk to increment the amount of e-waste in the future. But by following the thing AI, that is, tracing the journey back to the beginning, to mineral extraction, illustrates how AI commodities are contributing to existing social and environmental struggles across different geographies and at different points of the commodity chain. By unveiling the materialities and supply chains behind AI, we expose multidimensional conflicts that emerge at each stage: from water rights disputes at manufacturing sites to labour exploitation in mineral extraction to waste management crises.

Conclusion

Ian Cook, in his piece *Follow the Thing: Papaya* (2004), cites David Harvey's call to "get behind the veil, the fetishism of the market" (Harvey, 1990, p. 422, as cited in Cook, 2004) urging to reveal the powerful, important, and often unsettling connections between geographies, consumers and the distant producers whose contributions to their lives remain invisible, unnoticed, and largely unappreciated when a commodity is purchased. This chapter responds to that call by challenging the fetishisation of commodities of AI that obscures its materiality, as well as geographies and bodies exposed to its environmental impacts. While AI has been promoted as a sustainable technology capable of tackling climate change, its industry is advocating for the use of more resources. Consequently, the case of DeepSeek illustrated how training algorithms with (supposedly) less resources can have a negative impact in the stock market. Getting behind the veil in the age of AI involves understanding the commodities behind this technology. To do so, this chapter contributes to *AI Infrastructures and Sustainability* edited volume by *following the thing: AI*. This methodology shows the entanglements of the materiality of AI along commodity chains, and how this materiality scales up and exacerbates environmental conflicts. GPUs, made from minerals extracted in locations such as the United States and Brazil, are assembled in Taiwan to manufacture chips before being distributed to data centres worldwide. At the end of their lifecycle, these GPUs are discarded in dumping fields in Ghana or incinerated. Several geographies around the world contribute to making this technology and its material existence possible today.

One can observe that the value generated by these commodity chains is not distributed equally. As Tsing (2015) states, "supply chains make value from translating values produced in quite varied circumstances into capitalist inventory" (p. 56). In the AI commodity chains, territories in Latin America and in the periphery within the US and Europe bear the costs of extraction operations. While regions near data centres sacrifice their water and soil, their communities do not benefit from the capital accumulated by big tech companies. Similarly, farmers in Taiwan also bear the costs of TSMC factories that extract large amounts of water to manufacture GPUs, even in drought scenarios. Within these chains, one can also identify how pollution translates into profit (Tsing, 2015, p. 56): extracting minerals from the Earth, processing these minerals to manufacture chips, manufacture these chips, assembling servers into data centres, dumping electronics in landfills. All these activities observed in AI commodity chains involve the contamination of the soil and water and human bodies (Valdivia, 2024, 2025). The environmental impacts of AI commodity chains are substantial, as this chapter highlights. By following the thing, the materiality of AI is defetishised and its costs and environmental impacts revealed.

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