On the study of AI metabolism, a position paper

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Abstract

This position paper explores the sustainability of ubiquitous AI through a socio-metabolic lens. We present a metabolic model, adapted from social metabolism theory, to analyze the relationships between resource flows, infrastructures, and societal needs driven by AI. The model highlights feedback loops and externalities that challenge the long-term viability of current AI. We suggest three systemic scenarios—degrowth, collapse, and controlled landing—and question the plausibility of the latter. The research goal is to determine whether sustainable AI usage exists and, if so, how it might be implemented through design or regulation. This contribution invites interdisciplinary dialogue on aligning AI development with planetary limits.

Keywords

Artificial Intelligence, Sustainability, Socio-metabolic analysis

1. Introduction

The increasing ubiquity of Artificial Intelligence (AI) technologies raises critical questions regarding their sustainability [1]. In this position paper, we propose using the analytical framework of *social metabolism*, defined as "the biophysical flows exchanged between societies and their natural environment, as well as flows occurring within and among social systems themselves."[2] to better understand its implications. This interdisciplinary framework provides a robust foundation for assessing the socio-environmental impacts of AI.

At the core of this research is the Flow-Infrastructure-Needs (FIN) model, which explores interactions between three critical dimensions: short-lived resource, energy and information **flows**, durable **infrastructure** both physical and intangible, and societal and individual **needs**. Key systemic phenomena—such as lock-in effects (or legacies), leakage (where adopting one technology increases consumption of another), and rebound effects (where implementing a supposedly resource-efficient solution results in increased overall resource use)—have been clearly highlighted by socio-metabolic research.

The application of a socio-metabolic view to AI deployment is motivated by several converging factors. First, the rapid proliferation of AI across sectors has made its use ubiquitous, creating technological dependencies and significantly reshaping both industry and everyday life. Second, AI technologies carry substantial environmental impacts—not only due to high energy consumption and resource extraction for infrastructure, but also because of their growing requirements for data, which endangers privacy. Finally, the widespread deployment of AI data centers and AI capable user devices, intensifies competition for resources[3].

While certain studies acknowledge AI's potential contributions toward specific sustainability challenges (e.g., reducing greenhouse gas emissions [4]), systematic analyses addressing the broader impacts of AI deployment remain uncommon and are predominantly focused on ethical aspects [5].

2. The FIN Model applied to AI

The proposed Flow-Infrastructure-Needs model for AI structures the analysis of ubiquitous AI into three interacting socio-technical components:

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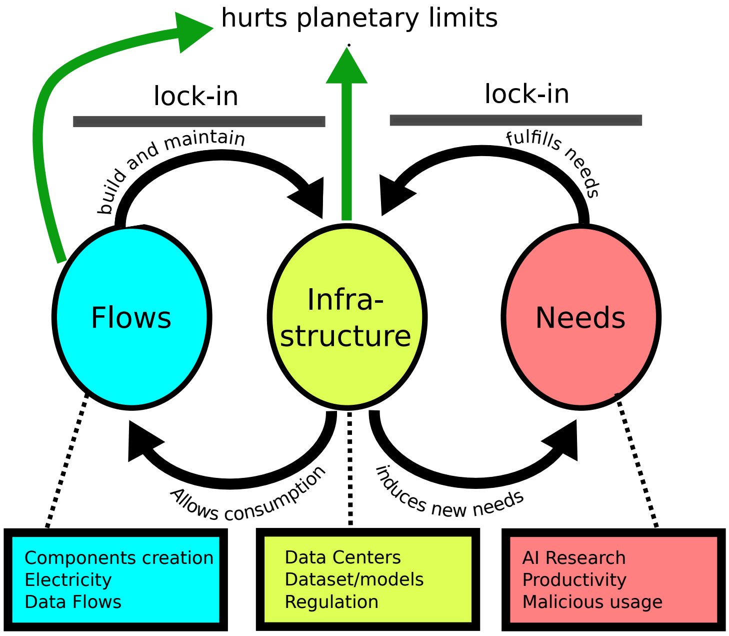

Figure 1: Integration between the component of the Flow-Infrastructure-Needs (FIN) model applied to AI. It shows the lock-ins between (Flow and Infrastructure) and (Needs and Infrastructure).

Flows are defined as the material or immaterial resources entering and leaving the system with short lifetimes, categorized into two major types: material and informational Flows. Material Flows arise from the construction and maintenance of computing hardware essential for executing AI life-cycle tasks such as data collection, preparation, feature extraction, training, testing, and inference. In centralized or shared AI models (e.g., ChatGPT, Amazon Bedrock), most infrastructure construction Flows are concentrated in data centers. Many material Flows, such as metallic minerals or rare earth elements, are non-renewable on a human time-scale, leading to gradual resource scarcity and latent negative externalities. Even renewable Flows like electricity or cooling can become effectively non-renewable when considering second-order dependencies, as their production infrastructure relies on partly renewable resources.

Informational Flows are fundamental at all stages of the AI life cycle to manage model and preserve performance. Although using public data have minimal immediate negative effects, private data usage for personalized user experience, creates privacy concerns requiring regulatory oversight, such as GDPR, to manage consent and data usage.

Infrastructures consist of durable physical, informational, and regulatory components. Physical infrastructures include data centers, energy-production facilities, and a variety of edge devices designed for capturing data and facilitating interaction with AI systems. Informational infrastructures primarily encompass datasets used for model training and inference, along with specialized hardware and software components . These AI-specific technologies typically have limited applicability beyond their intended context, differing significantly from traditional IT infrastructures [6]. Human resources form another critical component, involving both end-users who interact with AI tools and specialized professionals responsible for the design and ongoing maintenance of these systems. User participation—particularly through Reinforcement Learning from Human Feedback (RLHF)—has become central [7], leading to increasing returns to scale where AI systems progressively improve in performance with increased user interaction. Finally, regulatory infrastructures encompass AI-specific laws (such as the EU's AI Act), broader privacy frameworks (RGPD, CPRA, PIPL), and environmental regulations that influence the entire lifecycle of AI solutions. These regulations function either by enforcing mandatory constraints or providing overarching guiding principles for responsible AI deployment.

Although this infrastructure subsystem may initially appear self-regulated—with regulatory mechanisms moderating resource consumption by physical and informational components—it simultaneously stimulates the emergence of new societal needs, further driving the expansion and evolution of those unsustainable infrastructures [8].

Needs represent the individual and collective aspirations satisfied by infrastructure-based services, based on Max-Neef's framework [9] of *Need Satisfiers*. Within this framework, certain AI applications clearly function as *Synergic Satisfiers*, simultaneously addressing multiple human needs. Notable examples include AlphaFold for protein structure prediction and AI systems enabling early pathology detection, significantly contributing to scientific progress and societal well-being. Conversely, applications such as deepfake generation or cyber-attacks represent *Destroyers*, undermining rather than meeting genuine needs.

Critically important is the category of *Pseudo-Satisfiers*, which appear to fulfill needs effectively in the short term but actually compromise long-term satisfaction. Many current AI deployments may act as pseudo-satisfiers, providing immediate convenience or productivity gains while potentially exacerbating ecological impacts and undermining broader societal goals.

The FIN model highlights these intricate systemic interactions, emphasizing that AI sustainability analysis must extend beyond immediate efficiency gains to carefully consider second- and third-order effects, latent externalities, and feedback loops among Flows, infrastructures, and societal needs.

3. Exploring Alternative Scenarios

Using the FIN model and considering the lock-ins between the component, we identified three possible scenario:

- **Degrowth** : Intentional reduction of resource use, infrastructure scale-down, and reduction of purely hedonistic well-being aspirations.
- **Collapse** : Uncontrolled depletion of resources, infrastructure breakdown, forced reduction in societal needs fulfillment.
- **Controlled landing** : An intentional limitation of Flows and infrastructures to balance negative externalities against sustainable human well-being.

The viability of the controlled landing scenario remains uncertain, as its realization critically depends on physical constraints, the system's initial conditions, and society's capacity to recognize and accept usage limitations aligned with planetary boundaries. The main objective of this research line is to identify the subset of AI applications and their operational context that could provide long-term benefits for humanity while remaining within planetary limits. Should such a subset exist, the question of how to steer AI development toward it—whether through collective awareness or, more realistically, regulatory frameworks—remains open.

4. Conclusion and Future Work

This work lays the groundwork for future research by making the FIN model actionable as an analytical tool to examine the socio-metabolic dynamics of AI. Further research will aim to refine the FIN model by applying it to the design of frugal AI solutions, including those based on edge devices that may offer greater energy efficiency and enhanced privacy. While it remains uncertain whether such approaches can meet practical and societal expectations, their exploration appears necessary given the sustainability challenges posed by current AI infrastructures. It will also examine the societal transformations that underlie increasing dependence on AI, especially the socio-economic and cultural dynamics involved. Finally, it will address questions of trust and legitimacy in AI adoption, including the role of pseudo-satisfiers—solutions that appear beneficial in the short term but compromise long-term sustainability.

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