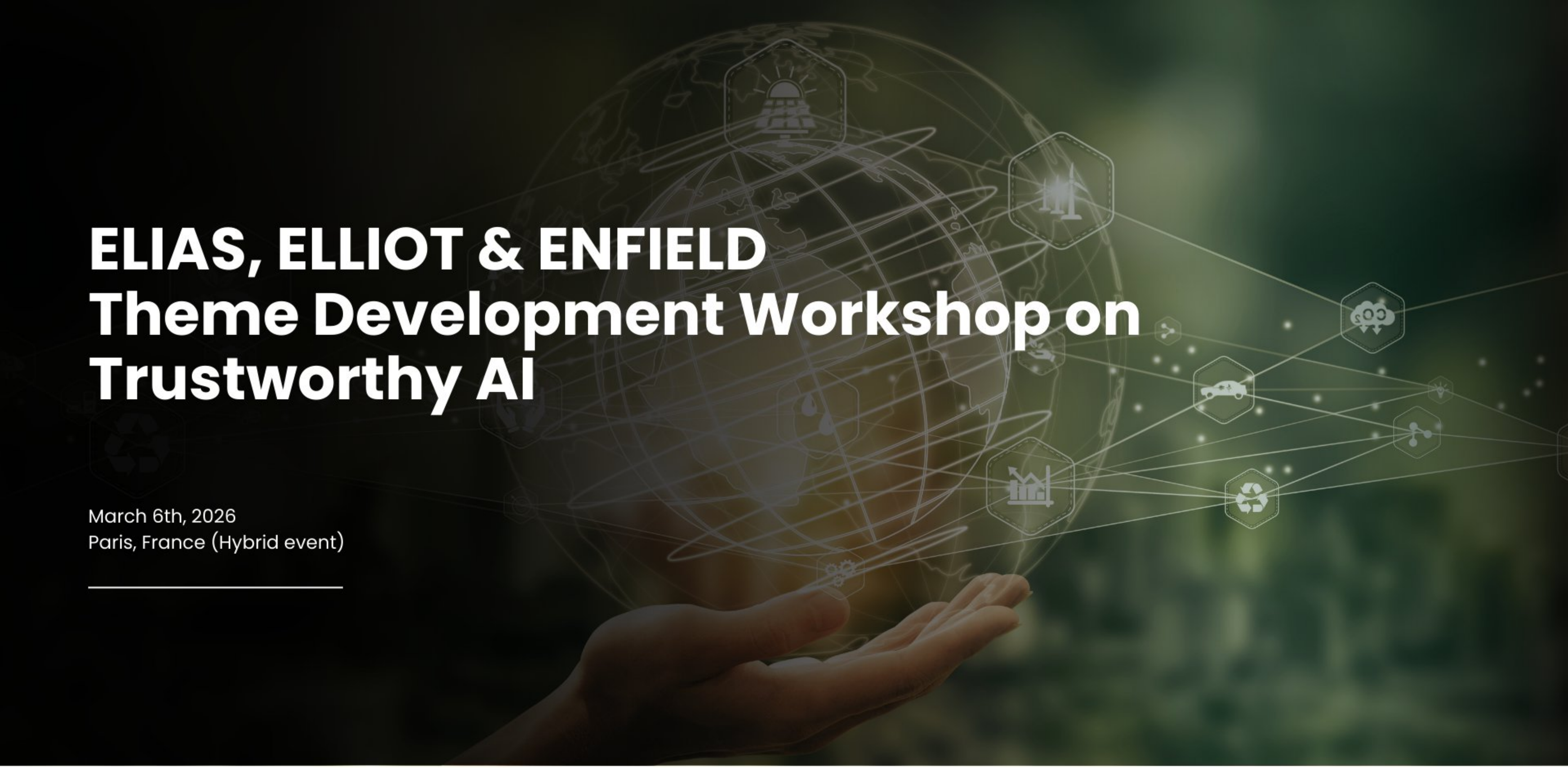


ELIAS, ELLIOT & ENFIELD Theme Development Workshop on Trustworthy AI

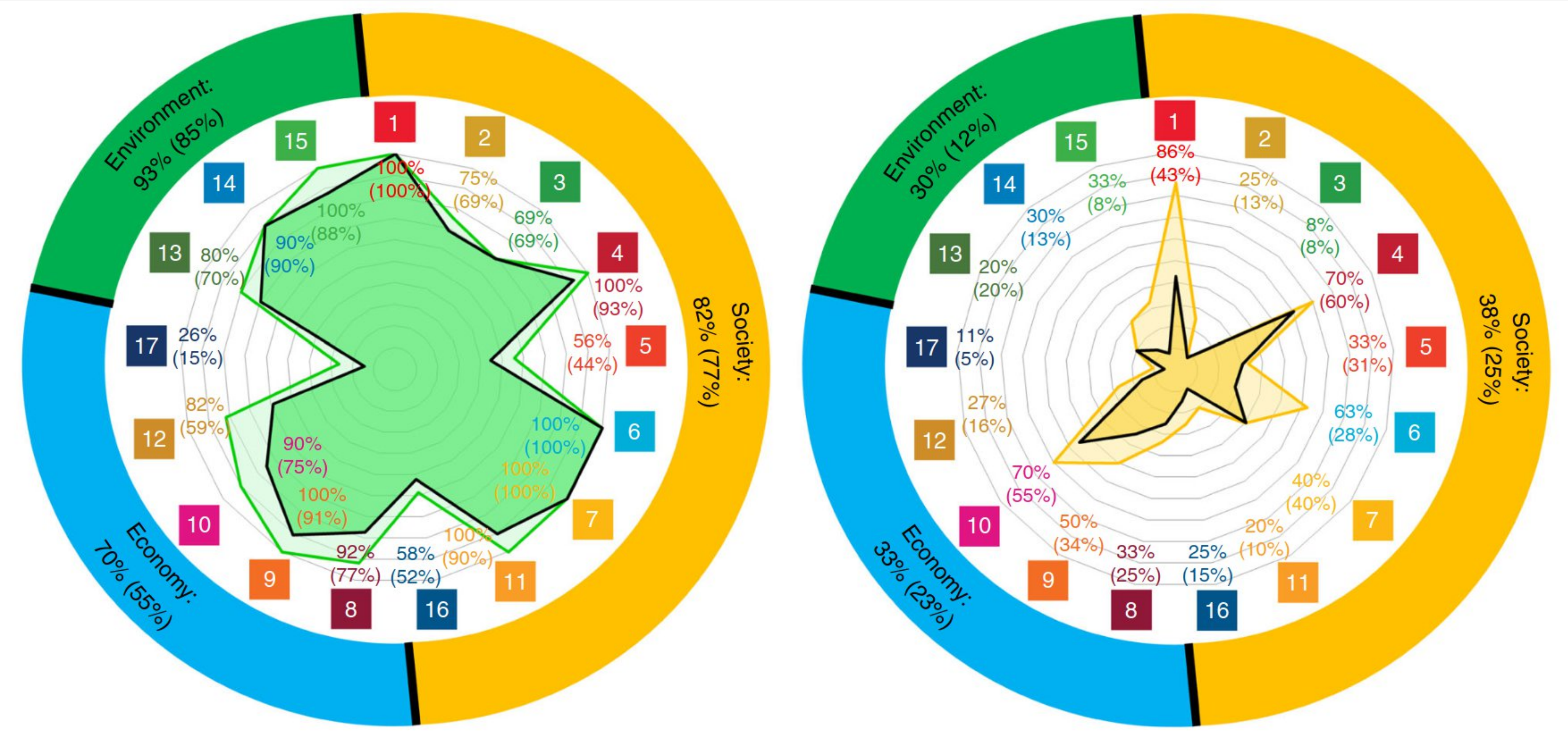
March 6th, 2026
Paris, France (Hybrid event)

Funded by
the European Union

ELIAS elliot MULTIMODAL AI MADE IN EUROPE ENFIELD

Impact of AI on Sustainable Development

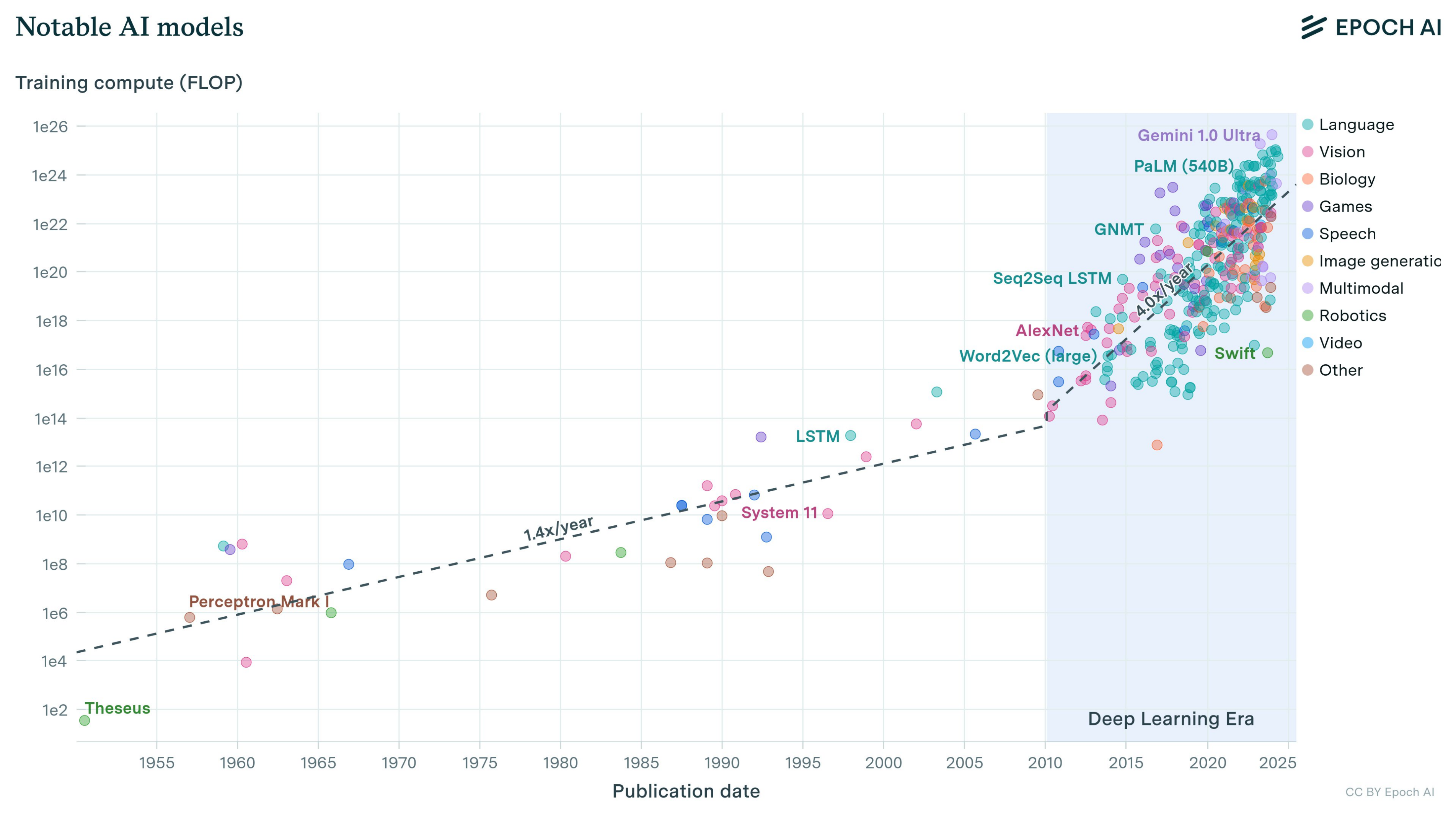
(Vinuesa, 2020)



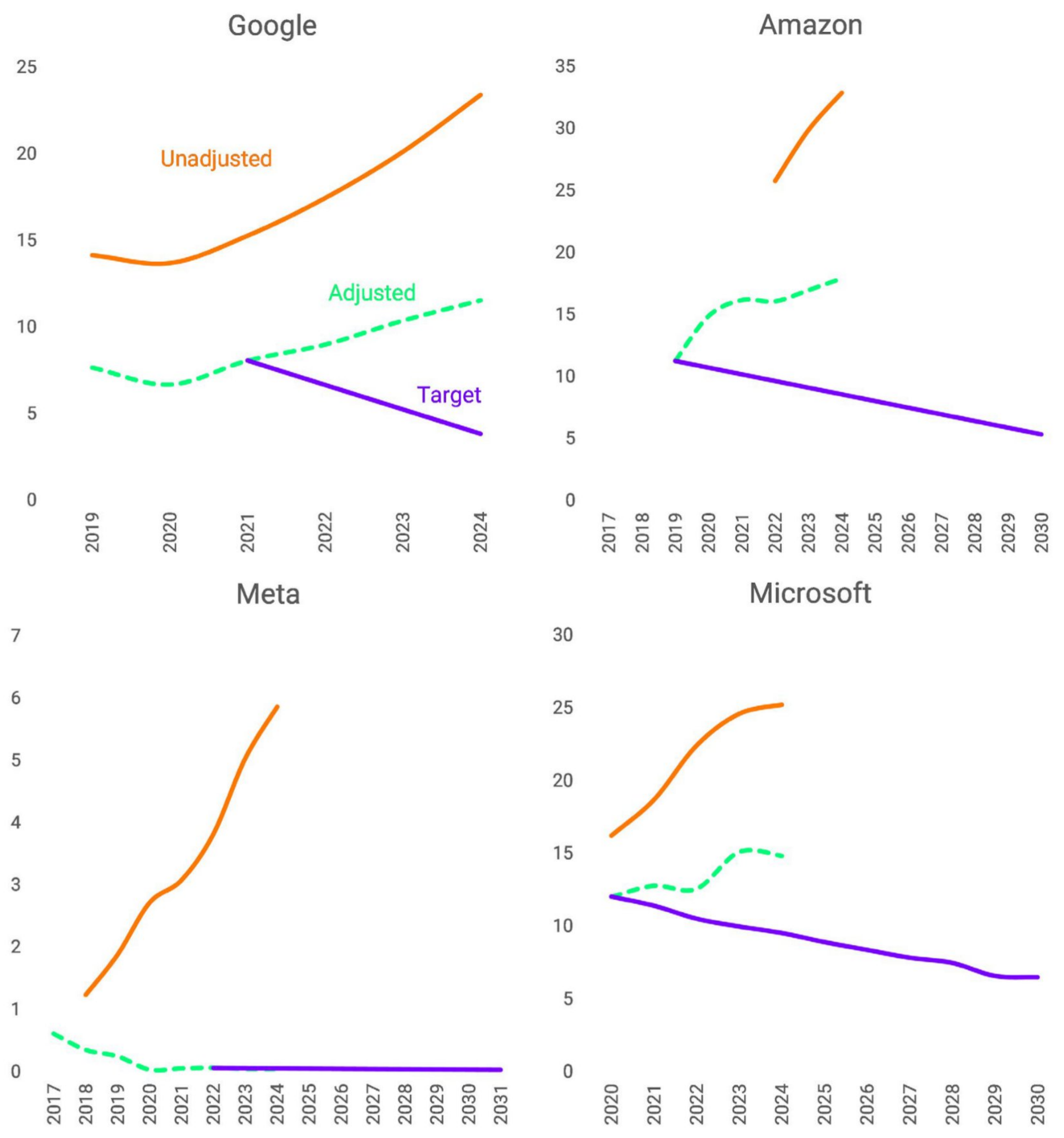
There is more evidence of AI’s positive impact than of AI’s negative impact. But...

(Negative?) Impact of AI on Sustainable Development

(Sevilla, 2022)



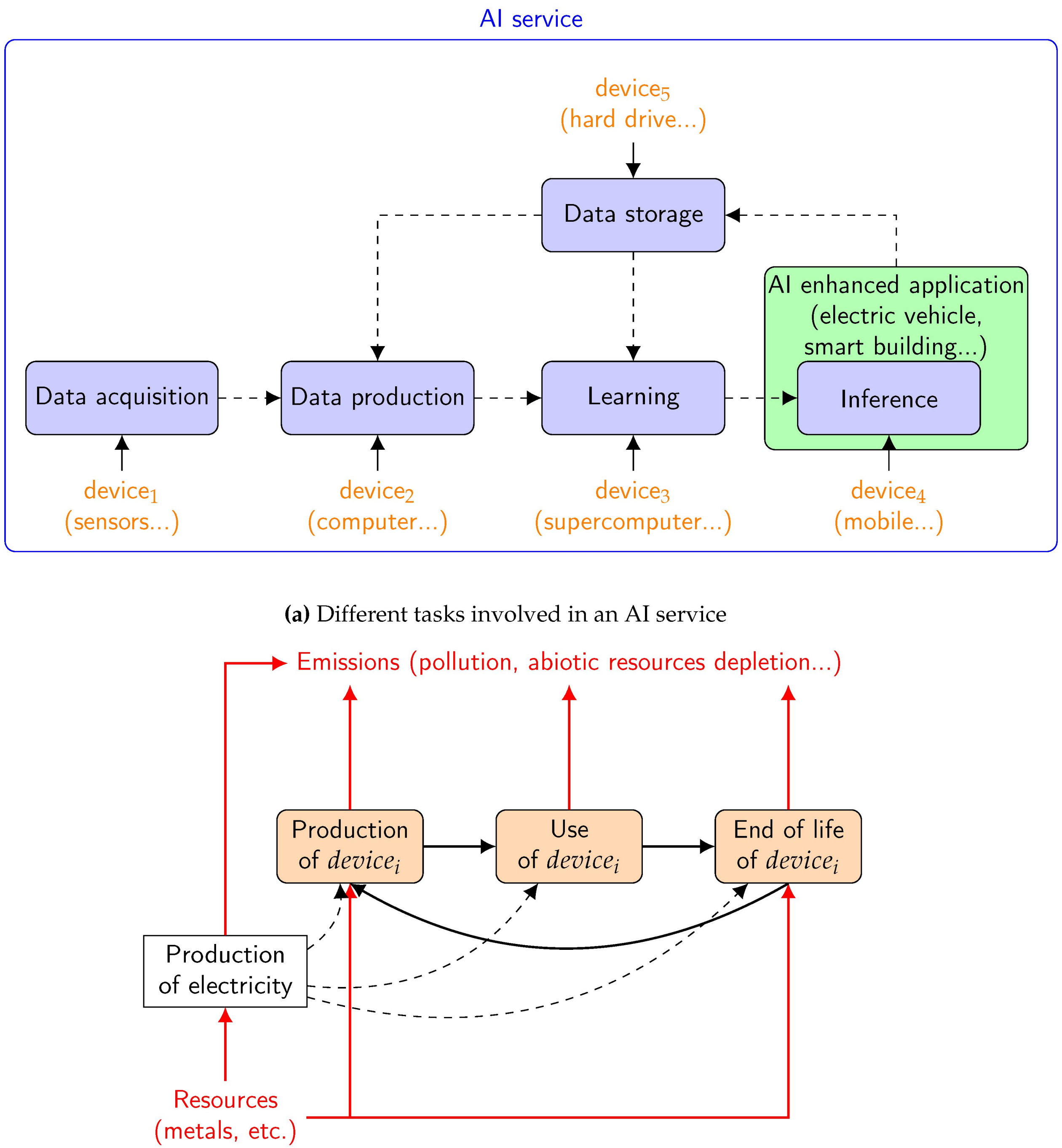
The carbon emissions of major Cloud operators increase despite net-zero targets in 2030 or 2050.



(Joshi, 2026)

Life-Cycle Analysis (LCA) assesses the net environmental impact of a product or service.

Guidelines exist for the LCA of AI services.

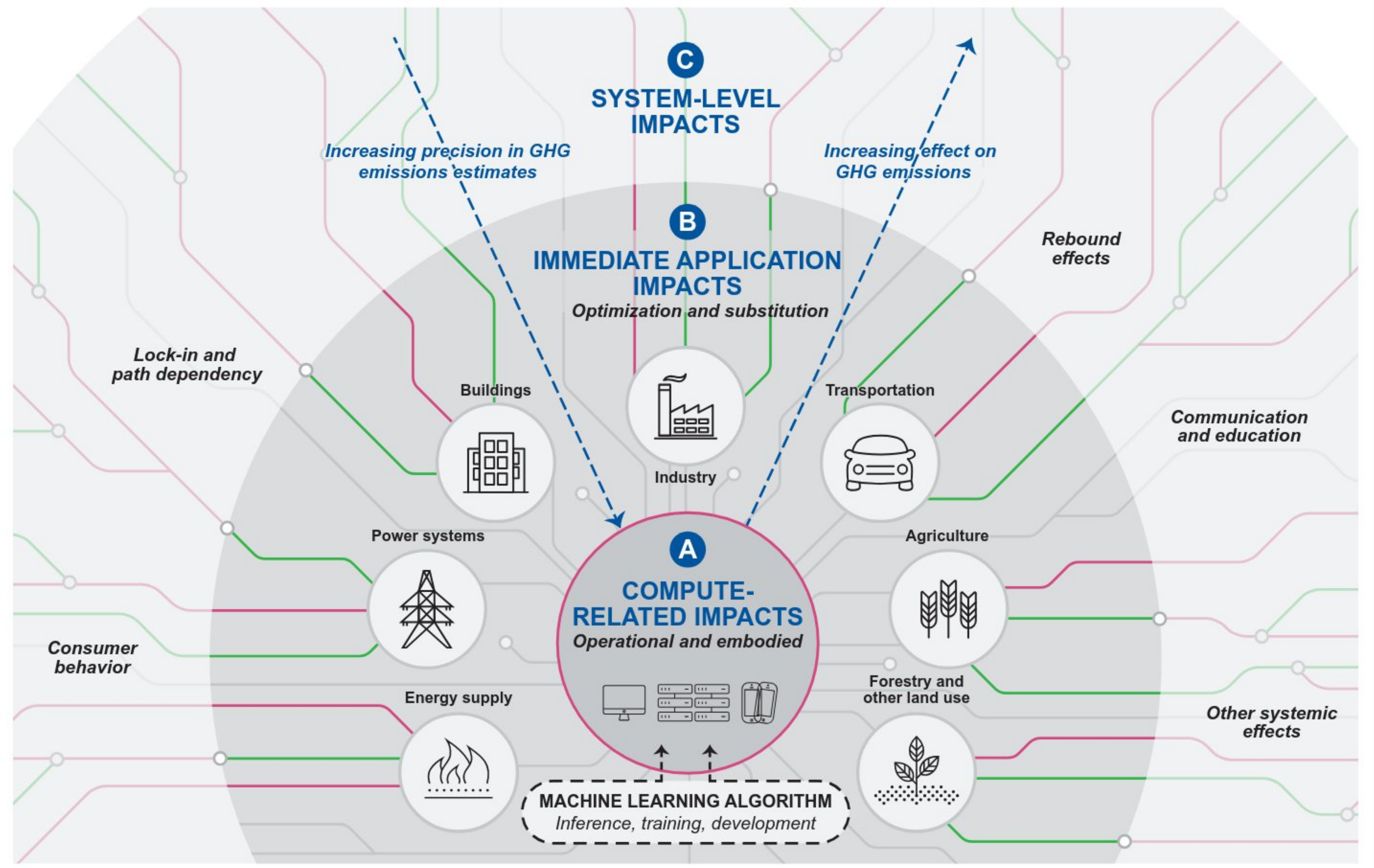


(a) Different tasks involved in an AI service

(b) Life cycle phases of each *device$_i$* used by the service

(Ligozat, 2022)

AI Services Have Higher-Order Impacts (e.g. Rebound Effects)



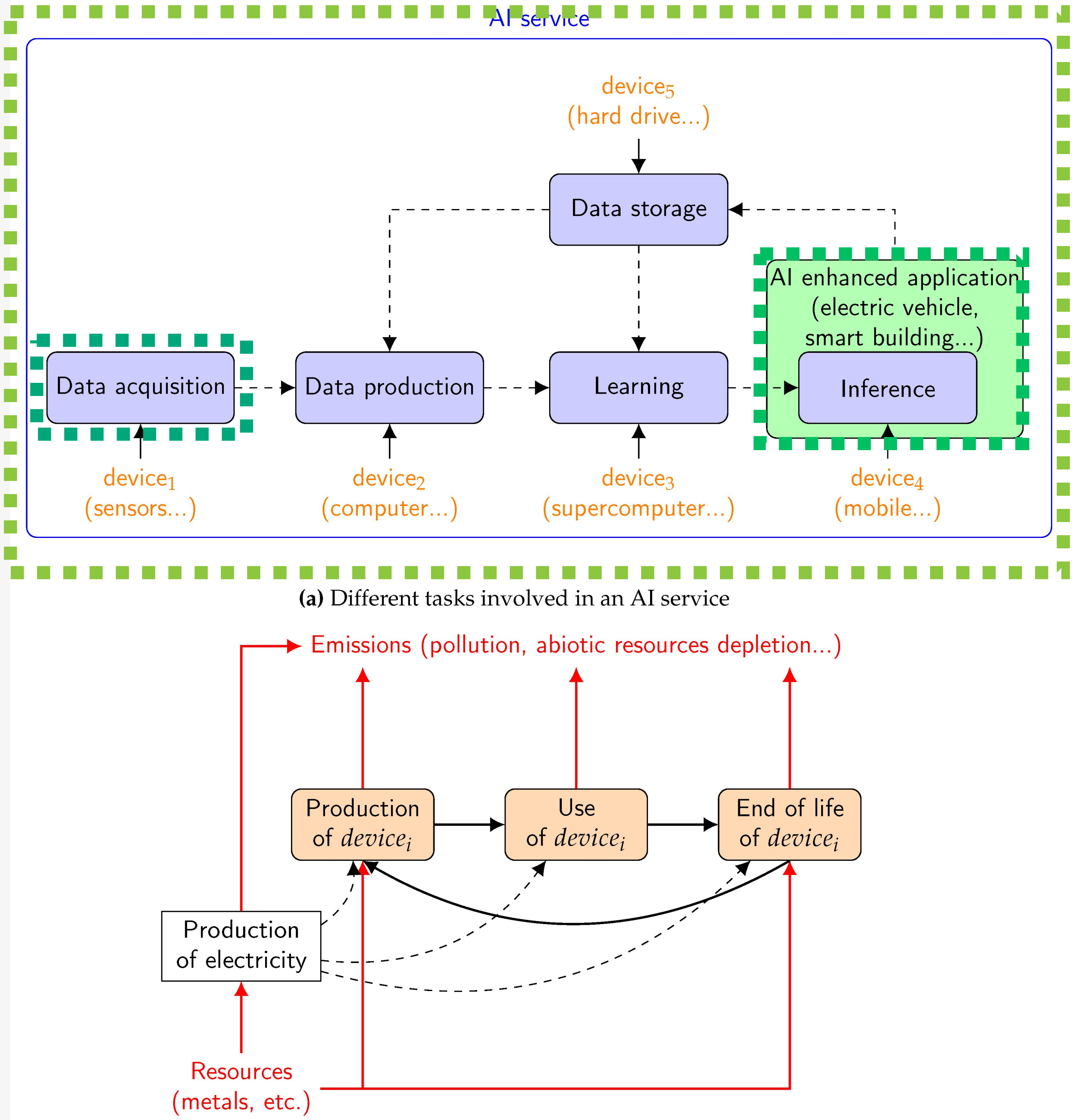
[(Kaack, 2022)](#)

Systematic Review of LCA and AI

We conducted a systematic review of papers that include both “AI” (or “ML”) and “LCA” in their text body.

We classified in four categories:

1. AI is the central LCA process (Green AI)
2. AI is in some upstream process (AI for Green)
3. AI is in some downstream process
4. AI helps LCA



(a) Different tasks involved in an AI service

(b) Life cycle phases of each *device$_i$* used by the service research

DOI:10.1145/3608473

Assessing the environmental impacts of machine learning on microcontrollers.

BY SHVETANK PRAKASH, MATTHEW STEWART, COLBY BANBURY, MARK MAZUMDER, PETE WARDEN, BRIAN PLANCHER, AND VIJAY JANAPA REDDI

Is TinyML Sustainable?

THE CONTINUED GROWTH of carbon emissions and global waste presents a great concern for our environment, increasing calls for a more sustainable future. In response, the United Nations' (UN) 2030 Agenda for Sustainable Development established a shared framework aiming toward peace and prosperity for people and the planet. At its core are 17 Sustainable Development Goals (SDGs),[48] a call to action for all countries to work toward a more environmentally, economically, and socially sustainable future.

Tiny machine learning (TinyML), which enables ML on microcontroller (MCU) devices, holds potential for addressing numerous UN Sustainable Development Goals, particularly those related to environmental sustainability (see Figure 1). While TinyML's operational benefits for sustainability are often highlighted, it is crucial to consider the entire life cycle of both applications and hardware to ensure a net carbon reduction. This article contributes by presenting case studies illustrating TinyML's sustainability benefits, examining the environmental impacts of TinyML at both MCU and system levels through a life cycle analysis (LCA), and identifying future research directions for sustainable TinyML.

TinyML is the deployment of machine learning (ML) algorithms onto low-cost, low-power, and resource-constrained MCU systems. TinyML stores neural network models directly within memory (for example, flash) and runs inference directly on the output of onboard sensors. This approach enables intelligent on-device sensor analytics unavailable with traditional Internet of Things (IoT) approaches, which instead typically rely on communication with the cloud to transmit data for external processing. Importantly, TinyML achieves this using a fraction of the compute resources needed for traditional ML systems. Table 1 compares TinyML with traditional BigML (such as cloud and mobile systems) and shows how TinyML requires orders of magnitude fewer resources across compute, memory, storage, power, and cost. Finally, while the heterogeneity and limited resources of MCU devices present new challenges for on-device training, model updating, and deployment, recent research, and the development of ML frameworks such as TensorFlow Lite for Microcontrollers[14] have increased the accessibility of TinyML.

» key insights

- **TinyML (machine learning on low-power microcontrollers) unlocks sustainable computing solutions, increasing agriculture yield and mitigating climate change, to help address many of the UN's Sustainable Development Goals**
- **Life cycle analysis (LCA) reveals a significant carbon footprint for TinyML at scale, as there are billions of MCUs deployed globally; however, TinyML can drastically reduce emissions in other sectors, offsetting its own footprint in the process**
- **The microcontroller unit (MCU) in TinyML devices has a relatively small footprint compared to the battery and sensing components; hence, TinyML devices environmental influence rests on holistic and sustainable system design.**

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ELSEVIER

Review Article

Machine learning applications in biomass pyrolysis: From biorefinery to end-of-life product management

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A R T I C L E I N F O

Keywords:
Neural network
Pyrolysis
Machine Learning
Life cycle assessment
Techno-economic analysis

A B S T R A C T

The thermochemical conversion of biomass is a promising technology due to its cost-effectiveness and feedstock flexibility, with pyrolysis being a particularly noteworthy method for its diverse product range. Despite the potential of pyrolysis, commercialization remains elusive, and there is a growing need to fully understand its dynamics to facilitate process scaling up. However, waste biomass pyrolysis is complex, time-consuming, and capital-intensive. Machine Learning (ML) has emerged as a possible means of supporting and accelerating pyrolysis research despite these challenges. This study provides a comprehensive overview of the use of ML in pyrolysis, from biorefinery to end-of-life product management. In addition, the success of ML in process optimization and control, predicting product yield, real-time monitoring, life-cycle assessment (LCA), and techno-economic analysis (TEA) during biomass pyrolysis is highlighted. Several ML methods have been utilized in a bid to study pyrolysis; the potentiality of artificial neural networks (ANNs) to learn extremely non-linear input-output correlations has led to the widespread adoption of these networks. Furthermore, the current knowledge gaps in ML research in pyrolysis and future recommendations for its application are identified. Finally, this study demonstrates the potential of ML in accelerating research and development as well as the scalability of pyrolysis of biomass.

1. Introduction

As of recent, there has been a growing focus on the commercialization and application of renewable energy sources, such as the thermochemical conversion of waste. This is greatly attributed to the depletion of fossil fuel reserves, rising fuel prices, and environmental concerns related to CO_2 emissions (Surendra et al., 2022; Yang et al., 2023). Currently, it is estimated that more than 80 percent of the world's energy needs are generated from fossil fuels, emphasizing the urgent need for alternative energy sources (Khan et al., 2023). In contrast, bio-sourced energy is a prominent renewable energy source and a promising substitute for dwindling fossil fuels (Khan et al., 2023; Ascher et al., 2022; Tran et al., 2020). Unlike other renewable energy sources such as solar and wind, which have the drawback of instability in their energy output, bioenergy is independent of meteorological conditions. This makes bioenergy a reliable and consistent source of renewable energy and has led to a current focus on developing it into a circular economy in many energy-related investigations (Ascher et al., 2022).

Abbreviations: ANFIS, Adaptive Neuro-Fuzzy Inference Systems; ANN, artificial neural network; CFD, computational fluid dynamics; DT, decision trees; EIA, environmental impact assessment; GB, gradient boosting; GREET, greenhouse gases, regulated emissions, and energy use in transportation; GRU, gated recurrent unit; GWP, global warming potential; ISO, international organization for standardization; LCA, lifecycle assessment; LCIA, life cycle inventory analysis; LSTM, long short-term memeory; MFSP, minimum fuel selling price; ML, Machine learning; MLP, multilayer perceptron; PINN, physics informed neural networks; PCA, principal component analysis; PSO, particle swarm optimization; RBF, radial basis function; RNN, recurrent neural network; RF, random forest; SVM, support vector machine; TEA, techno-economic analysis; TGA, thermogravimetric analysis.

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Spatial-Temporal Embodied Carbon Models for the Embodied Carbon Accounting of Computer Systems

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ABSTRACT

Embodied carbon is the total amount of carbon released from the processes associated with a product from cradle to gate. In many industry sectors, embodied carbon dominates the overall carbon footprint. *Embodied carbon accounting*, i.e., to estimate the embodied carbon of a product, has become an important research topic.

Existing studies derive the embodied carbon through life cycle analysis (LCA) reports. Current LCA reports only provide the carbon emission of a *product class*, e.g., 28nm CPU, yet a *product instance* can be manufactured from diverse regions and in diverse time periods, e.g., in the winter in Ireland (Intel). It is known that carbon emissions depend on the electricity generation process, which has spatial and temporal dynamics. Therefore, the embodied carbon of a specific product instance can largely differ from its product class. In this paper, we present new Spatial-Temporal Embodied Carbon (STEC) models for embodied carbon accounting. We observe significant differences between current embodied carbon models and STEC models, e.g., for 7nm CPU the difference can be 13.69%. We further examine the impact of STEC models on existing embodied carbon accounting schemes on key computer applications, such as Large Language Model (LLM) inference and LLM training. We observe that using STEC models leads to much greater differences in the embodied accounting of certain applications as compared to others (e.g., 32.26% vs. 6.35%). This is because the hardware requirements of certain applications allow for a wider range of hardware choices, while others have greater restrictions.

CCS CONCEPTS

• **Computer systems organization** → **Architectures**.

KEYWORDS

Sustainable computing, Carbon accounting, Computer architecture

ACM Reference Format:
Xiaoyang Zhang, Yijie Yang, and Dan Wang. 2024. Spatial-Temporal Embodied Carbon Models for the Embodied Carbon Accounting of Computer Systems. In *The 15th ACM International Conference on Future and Sustainable Energy Systems (E-Energy '24), June 04–07, 2024, Singapore, Singapore*. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3632775.3661939

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ACM ISBN 979-8-4007-0480-2/24/06
https://doi.org/10.1145/3632775.3661939

1 INTRODUCTION

In recent years, awareness of the importance of sustainability [10, 16, 17, 31] and carbon reduction [21–23, 38] has been growing. *Embodied carbon* is the total amount of carbon released from the processes associated with a product from cradle to gate [15]. In many industry sectors, embodied carbon dominates the overall carbon footprint of a product as compared to its *operational carbon* [4]. For example, the embodied carbon of an iPhone 11 accounts for 79% of its overall carbon footprint [14].

Embodied carbon accounting, i.e., to estimate the embodied carbon of a product, has become an important topic [6, 7, 24, 40]. There are studies on embodied carbon accounting for computer the hardware of processors, memory, and storage [14, 39]. The methodology is to leverage life cycle analysis (LCA) reports [29]. For example, in the Environmental, Social, and Governance (ESG) report of SK hynix, the embodied carbon of memory (LPDDR4) is 48 g/GB [18].

The embodied carbon of a product depends heavily on the *carbon intensity* [26, 41, 43] of the electricity used in the process of manufacturing this product. Specifically, carbon intensity is the amount of carbon emitted when generating a unit of electricity; and different energy sources (e.g., coal or solar) can lead to different carbon emissions when generating a unit of electricity. The carbon intensity of electricity has spatial and temporal dynamics. The spatial dynamics come from the energy policies of the geographic locations. For example, the electricity generated in Taiwan has a higher carbon intensity than that in Ireland, since Taiwan's energy policy is to rely on traditional energy sources due to Taiwan's lack of renewable energy sources. The temporal dynamics come from the environmental dynamics, which affect the amount of renewable energy sources when generating electricity [28, 32]. For example, the electricity generated in Ireland in the winter has less carbon intensity than that in the summer, when wind sources are abundant.

None of the existing studies on embodied carbon accounting has taken spatial and temporal dynamics into consideration. Existing LCA reports on the embodied carbon of a product represent a *product class* (e.g., 28nm CPU) with the same manufacturing process. Yet a *product instance* can be manufactured from diverse regions and in diverse time periods, e.g., in the winter in Ireland (Intel) or in the summer in Taiwan (TSMC).

In this paper, we present new embodied carbon models that can extend existing embodied carbon models to capture the spatial and temporal dynamics in different granularities.[1] Specifically, we observe that (1) energy policies have granularity at the country-level; at the treaty-zone-level of multiple countries with energy treaties, (e.g., the European Union (EU), Association of Southeast Asian Nations (ASEAN), etc.); and at the global-level and (2) environmental dynamics have granularity at a day-level, at a season-level; and at a

[1] We make our codes available: https://github.com/stuabc/STEC

Sustainable Production and Consumption 56 (2025) 37–53

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Sustainable Production and Consumption

journal homepage: www.elsevier.com/locate/spc

Review Article

Machine learning algorithms for supporting life cycle assessment studies: An analytical review

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ARTICLE INFO

Editor: Dr. Gonzalo Guillen Gosalbez

Keywords:
Life cycle assessment
Machine learning
Prediction
Analytical study
Multi criteria decision making

ABSTRACT

Nowadays, industries face increasing pressure to enhance their environmental sustainability scores, particularly in reducing carbon footprints. Life Cycle Assessment (LCA) tools are commonly used to evaluate environmental impacts across organizational levels, enabling predictions for potential improvements. But complexity and diversity of factors influencing these assessments make prediction models difficult to build and validate. Machine learning (ML) techniques present viable solutions to these challenges.

This study presents a systematic literature review (SLR) of seventy-eight peer reviewed articles, evaluating the performance of different ML models in Life Cycle Assessments applications. An analytical ranking of these models is provided based on their effectiveness for LCA predictions using the Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Results indicate that Support Vector Machine (SVM) achieve a score of 0.6412, followed by Extreme Gradient Boosting (XGB) at 0.5811 and Artificial Neural Networks (ANN) at 0.5650, and, positioning them as the most suitable models for LCA studies for prediction application. Random Forest (RF), Decision Trees (DT), and Linear Regression (LR) follow with scores of 0.5353, 0.4776, and 0.4633, respectively, while Adaptive Neuro-Fuzzy Inference System (ANFIS) and Gaussian Process Regression (GPR) rank lowest with scores of 0.4336 and 0.2791. Detailed interpretations and implications of these findings are discussed.

1. Introduction

Life Cycle Assessment (LCA) is the fundamental methodology to evaluate the environmental impacts of product(s), and/or services which assists in well-informed decisions making towards a sustainable world (Goglio et al., 2020; Joshi et al., 2022). Product Carbon Footprint (PCF) is the measurement of total quantity of greenhouse gases (GHGs) released by product during its life cycle, both directly and indirectly, and is expressed in CO_2 equivalent (Chen et al., 2020). The basic principle of these studies is to compile all the mass and energy flows that the product exchanges with the environment across its life cycle and convert this information into environmental impact assessments (Anand and Amor, 2017). These techniques are standardized procedures created to assess the ecological indicators in addition to a system's energy consumption and greenhouse gases (GHGs) emissions during every stage of its life cycle (Wong et al., 2021). The application of LCA has grown significantly in decision making for green transition and sustainable product development. Although the methods are becoming increasingly important, there are several challenges the LCA experts and stakeholders face during practical application, which compromise the accuracy and dependability of the outcomes (Anand and Amor, 2017; Costa et al., 2019). LCA studies are broad and data intensive requiring extensive data collection and rigorous analysis from both upstream and downstream processes to produce the reliable end results (Romeiko et al., 2024). Large number of input parameters and their uncertainties, unavailability, temporal and spatial differences makes LCA studies even more complicated, time consuming and resource intensive (Cabot et al., 2022; Ghoroghi et al., 2022). Sheer volume of data coming from the industries with the increasing digitalization fuels further complications to do comprehensive LCA studies (Rahman et al., 2022). Advancements in industrial digitalization, data generation, storage and analytics are driving the interest towards the application of artificial intelligence (AI),

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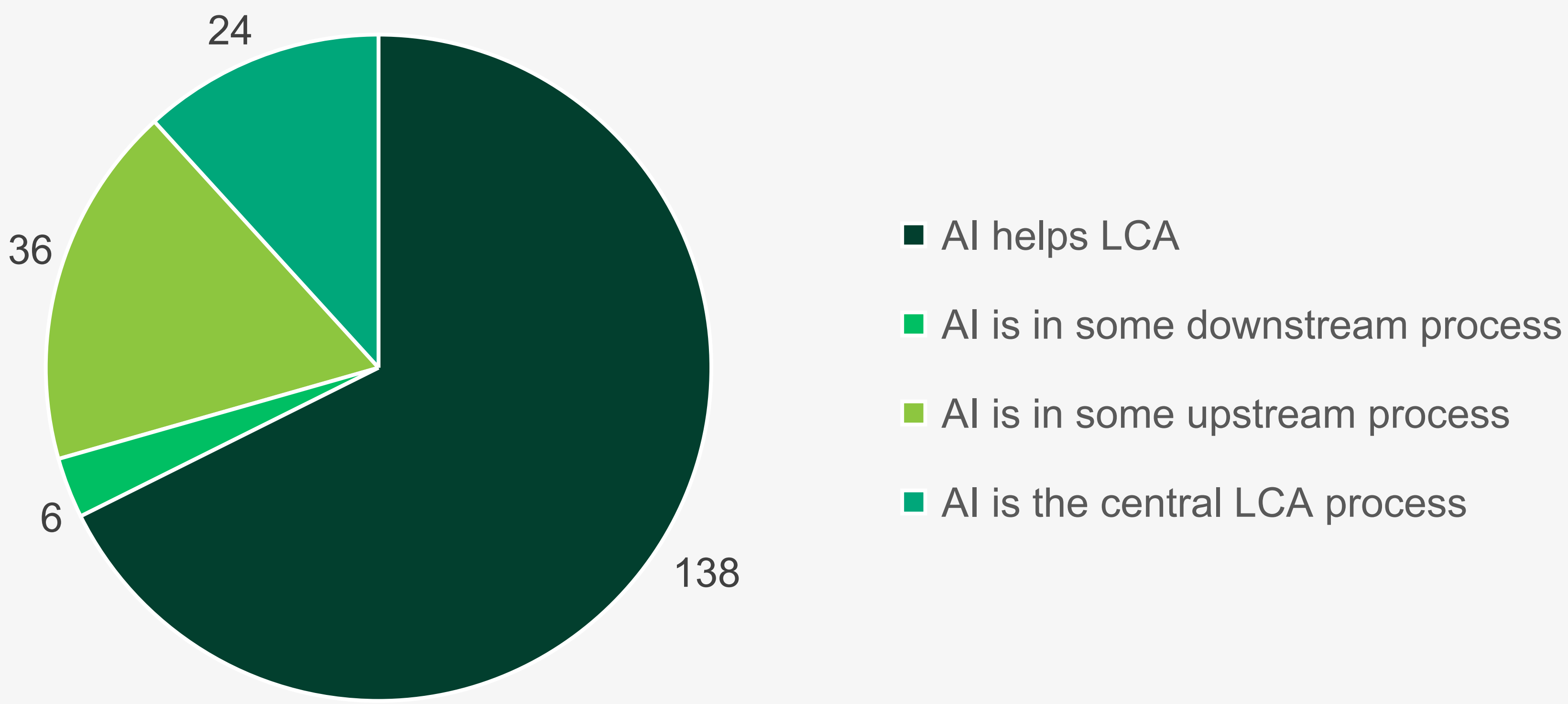
2352-5509/

Review Insights

AI is not even considered with system boundaries in 68% of the reviewed papers.

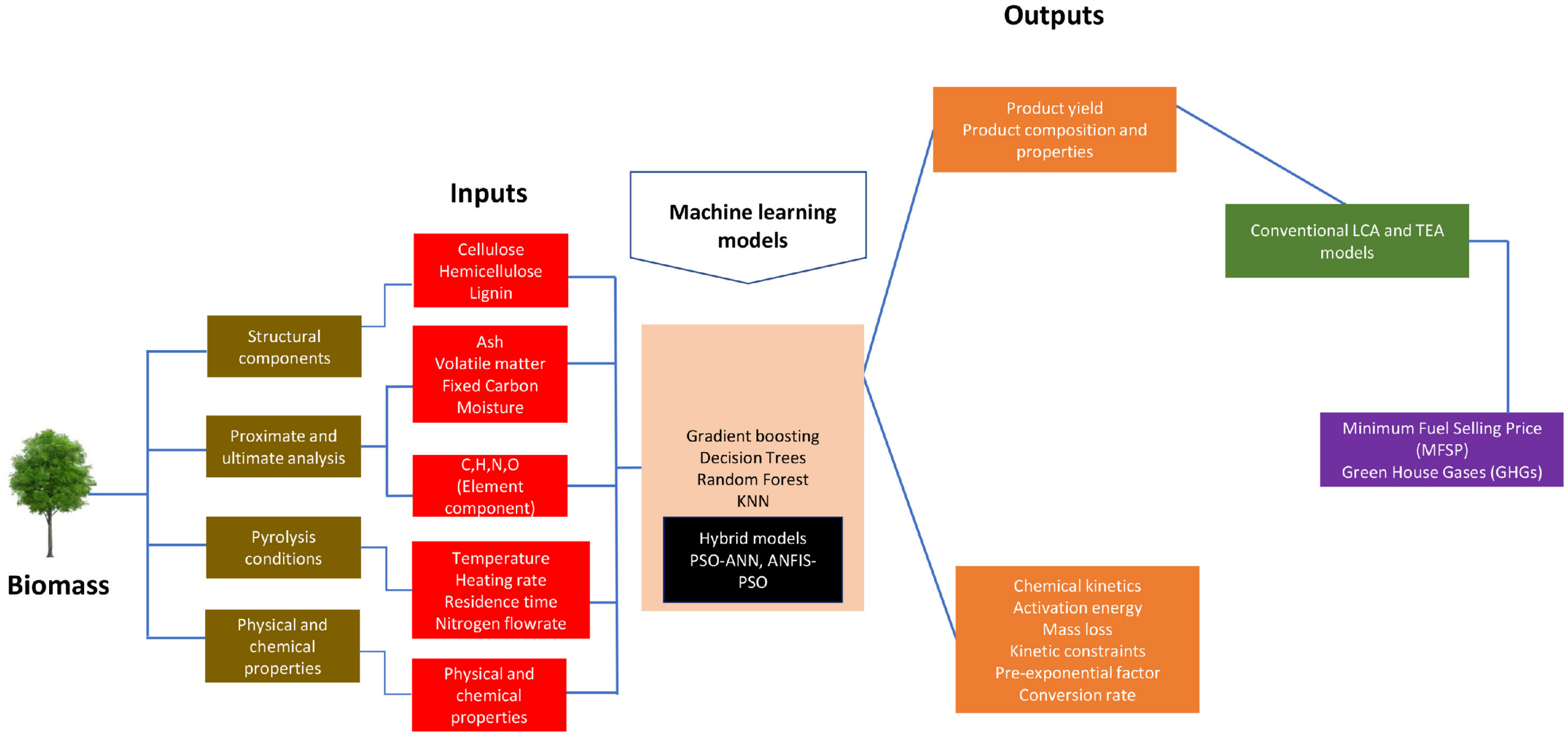


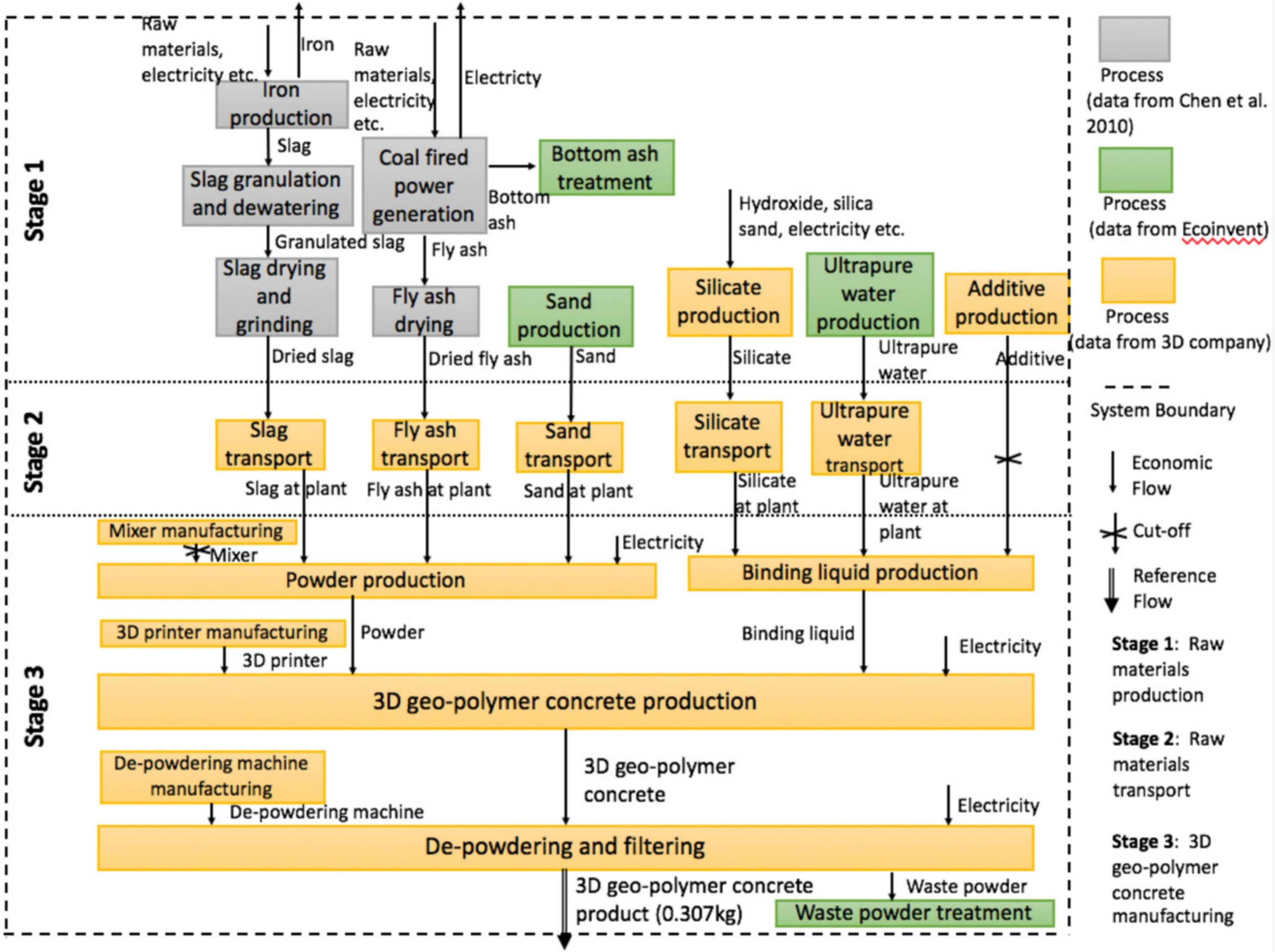
Review Insights

LCA has few application domains.

- Construction
  - Concrete manufacturing and recycling, renovation, earth moving operations
- (E-)Waste Management
  - Plastic sorting, plastic and biomass pyrolysis (biochar synthesis), bio-oil production, methanation, composting
- Carbon capture, utilization and storage
- Digital Infrastructure Management
  - Integrated circuit manufacturing, sensing, data center operations
- Miscellaneous
  - Chicken production, solar power generation, additive manufacturing

(Akinpelu, 2023)

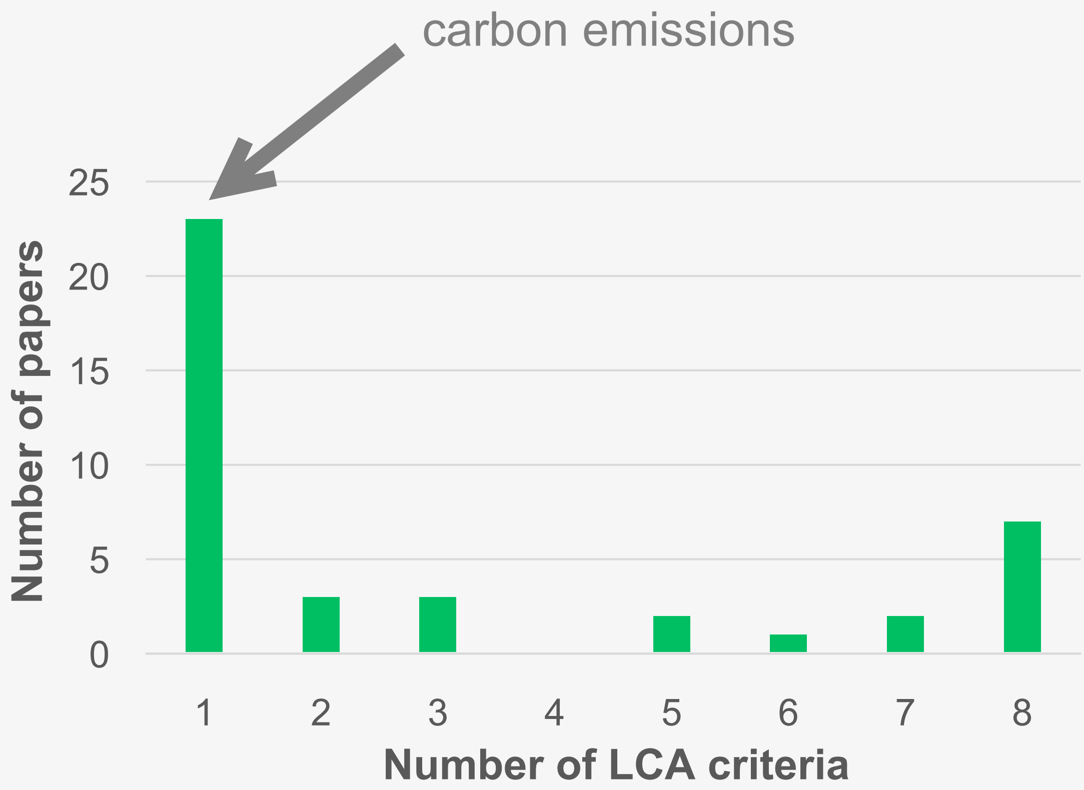


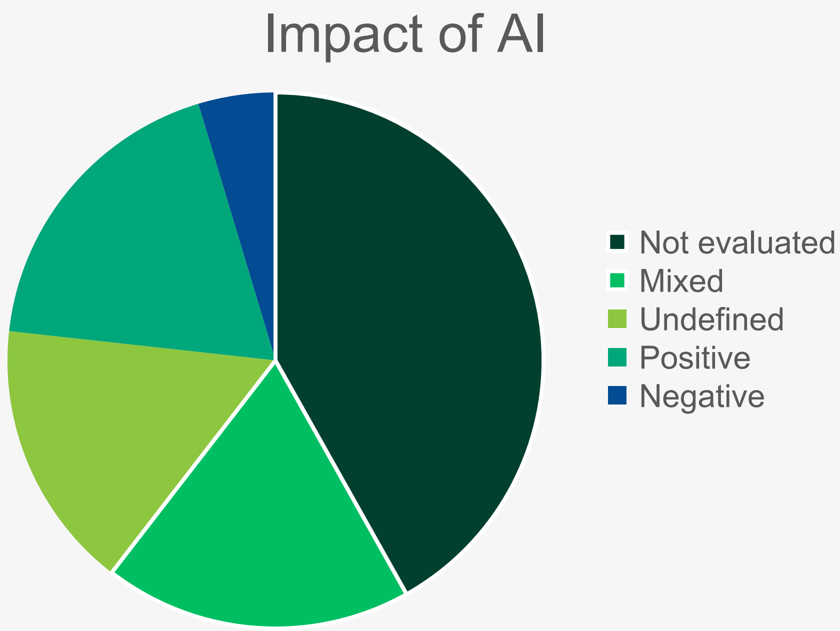


Raw materials, electricity etc.
Iron
Iron production
Slag
Slag granulation and dewatering
Granulated slag
Slag drying and grinding
Dried slag
Raw materials, electricity etc.
Electricty
Coal fired power generation
Bottom ash
Bottom ash treatment
Fly ash
Fly ash drying
Dried fly ash
Sand production
Sand
Hydroxide, silica sand, electricity etc.
Silicate production
Silicate
Ultrapure water production
Ultrapure water
Additive production
Additive
Stage 1
Stage 2
Stage 3
Slag transport
Slag at plant
Fly ash transport
Fly ash at plant
Sand transport
Sand at plant
Silicate transport
Silicate at plant
Ultrapure water transport
Ultrapure water at plant
Mixer manufacturing
Mixer
Electricity
Powder production
Binding liquid production
3D printer manufacturing
3D printer
Powder
Binding liquid
Electricity
3D geo-polymer concrete production
De-powdering machine manufacturing
De-powdering machine
3D geo-polymer concrete
Electricity
De-powdering and filtering
3D geo-polymer concrete product (0.307kg)
Waste powder
Waste powder treatment
Process (data from Chen et al. 2010)
Process (data from Ecoinvent)
Process (data from 3D company)
System Boundary
Economic Flow
Cut-off
Reference Flow
Stage 1: Raw materials production
Stage 2: Raw materials transport
Stage 3: 3D geo-polymer concrete manufacturing

(Khan, 2025)

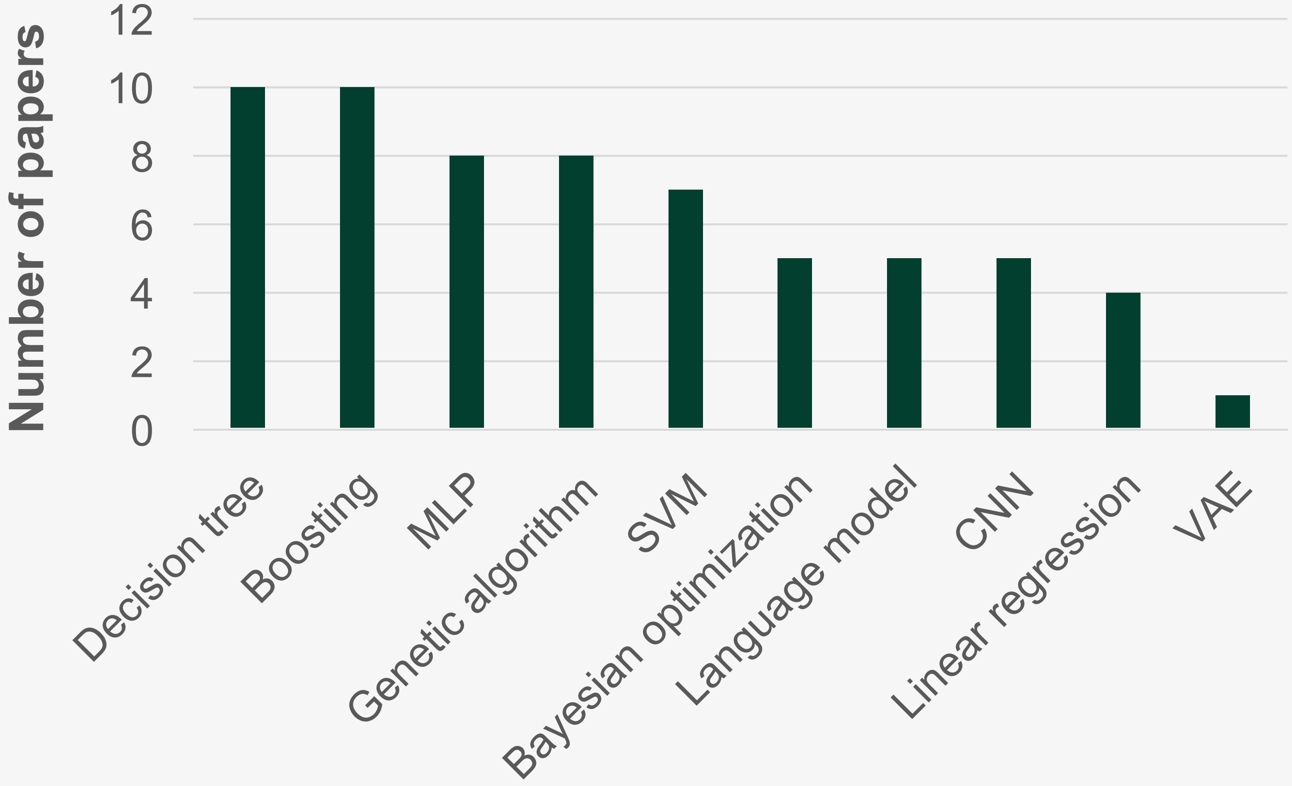
Review Insights



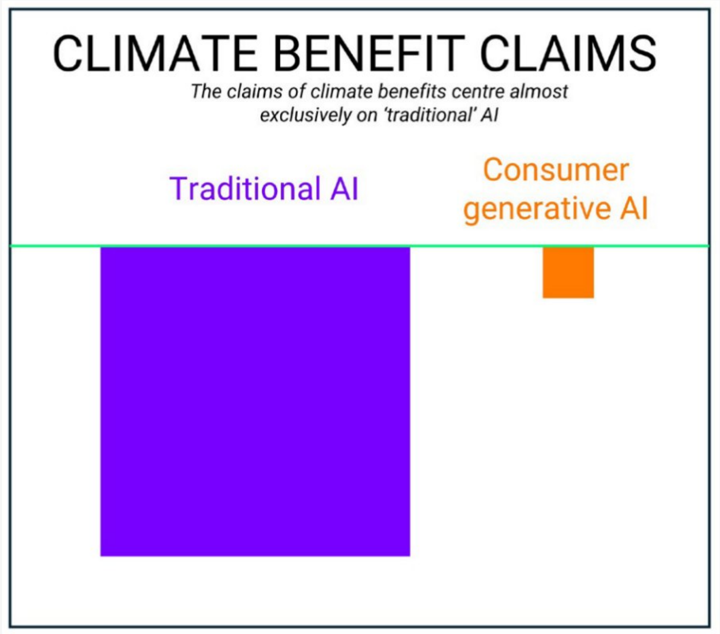


Research is biased towards carbon emissions. The impact of AI is not clearly positive, if assessed at all.

Review Insights



(Joshi, 2026)

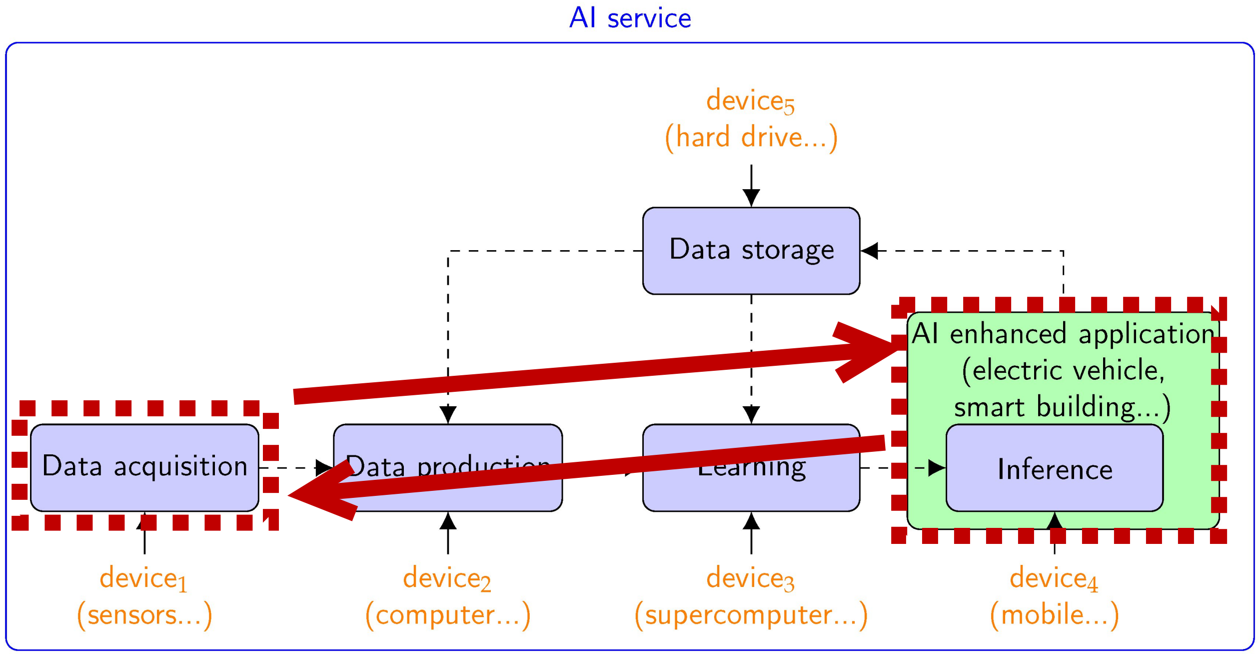


Research is biased towards "simple" AI, not generative AI whose computational cost is significantly higher.

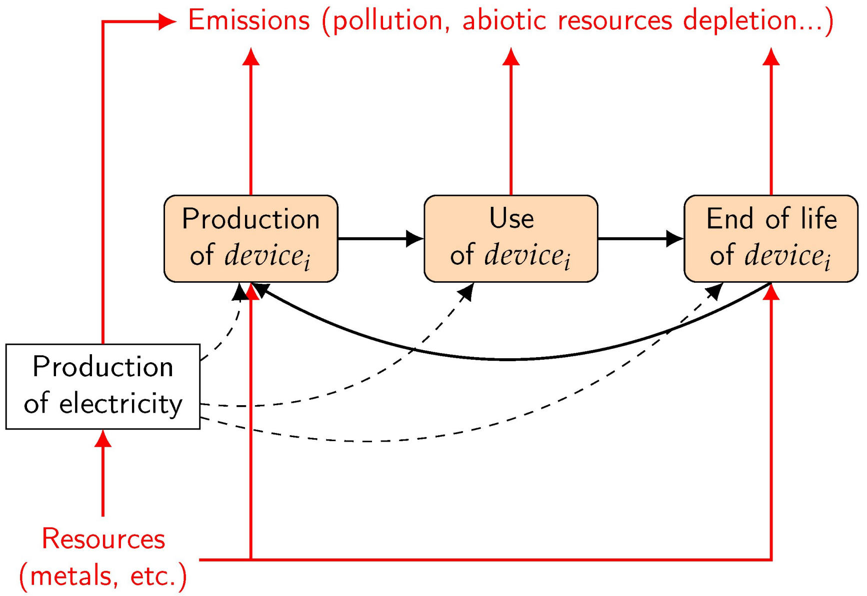
Technological Symbioses

Two technologies are in symbiosis if they reinforce each other, amplifying their mutual impact.

We found several technological symbioses in our corpus, highlighting potential higher-order impacts of AI.



(a) Different tasks involved in an AI service



(b) Life cycle phases of each $device_i$ used by the service

Accelerated Design and Deployment of Low-Carbon Concrete for Data Centers

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Figure 1: Depiction of Meta's data center in DeKalb, IL, USA where low-carbon concrete discovered by artificial intelligence methods has been tested.

ABSTRACT

Concrete is the most widely used engineered material in the world with more than 10 billion tons produced annually. Unfortunately, with that scale comes a significant burden in terms of energy, water, and release of greenhouse gases and other pollutants; indeed 8% of worldwide carbon emissions are attributed to the production

*This work was performed when the author was at the University of Illinois Urbana-Champaign.

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Artificial intelligence based e-waste management for environmental planning

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ARTICLE INFO

Keywords:
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Artificial intelligence
Environmental planning

ABSTRACT

Electronic waste is one of the world's rapidly increasing environmental issues because a wide range of toxic substances are not closely monitored that can pollute the atmosphere and affect health. This paper proposes an Artificial Intelligence Technique (AIT) for the analysis of hazardous pollutants in e-waste and their effects on the climate and human health and management policies in certain countries. Artificial Intelligence Techniques (AIT) are being developed for managing e-waste, especially based on prevailing strategies such as Life Cycle Assessment (LCA), Multi-Criteria Analysis (MCA), and Extended Producer Responsibility (EPR). In the e-waste management sector, eco-design systems must be created, e-waste properly processed, recycled, and reused content through safe methods, e-waste disposed of using appropriate techniques, used electronic devices cannot be transferred to developing countries, and the burden of e-waste should be increased. Artificial intelligence-based MCA and EPR is a reasonable approach to address the increasing problems with e-wastes.

1. Introduction to e-waste management models

Before the opening of the standardized and prevailing paradigm of electronic waste treatment, such as by funded networks and different forms of private groups, wastes have primarily focused on small social circles (Abbasi and El Hanandeh, 2016). Supervision and management are a distinctive work source of these principal social groups. Particularly, e-waste has to take more care in the present world and provide much care with financial support. Material flow theory states, in most countries before the reuse, the trend of material flow occurred (Menouer et al., 2020a).

The segregation of different waste has raised problems for this conventional treatment structure over the past few years. The reality is that few sources are available to facilitate the process if appropriate, while the percentage of e-waste treatment is increasing (Król et al., 2016). Such procedures are known as Life Cycle Assessment and Multi-Criteria Analysis as well as Extended Producer Responsibility. Several types of research by different researchers revealed that about 63% of general wastes comprise of e-waste. The longer the period as e-waste untreated technically, and the proportion of the toxic substances and pollutants begins to increase rapidly in the atmosphere (Shyam et al., 2017; Abdel-Basset et al., 2019; de Souza Melaré et al., 2017).

Waste treatment and management are related to significant social implications and can have adverse effects on the development of rich environmental culture and environmental wellbeing (Kadry, 2013). Some studies have found that waste treatment is especially susceptible to various drawbacks and that they challenge in contrast with goodness. Life with toxic pollutants has a determinantal impact on the wellbeing of the people (Sudha et al., 2016; Menouer et al., 2020b). Cross-disciplinary research in rural areas has found that e-waste is more likely toxic than different waste processing to experience consequences. Increasing the aspects of e-waste in the health, social, and cultural domains have already pushed the country's economic background. The e-waste treatment process of a country includes seeking a way to boost the safety of a nation (Qi et al., 2018; Elhoseny et al., 2017).

Previous research indicated that the maintenance of health status is one of the main factors for safety commitment and disease prevention. The LCA utilizes the unique principle of assessments to claim that such health is correlated with the reasonable, freedom of a person's material consumptions and social actions made possible under the constraints of a nation protocol (Sarc et al., 2019). For society, hazardous e-waste affects health habits like mediwaste. Sometimes it may happen in

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