Renewable and Sustainable Energy Reviews 234 (2026) 116861

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

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

Reviewing the socio-technical dynamics of AI, data centers and digitalization on energy and the environment☆

Jinsoo Kim [a,*], Jihyo Kim [b], Benjamin K. Sovacool [c,d,e,**], Steve Griffiths [f], Morgan Bazilian [g], Felix Creutzig [c,h], Dylan D. Furszyfer Del Rio [i], Matthew Agrawala [c], Minki Choi [a], Ramit Debnath [j]

[a] Department of Earth Resources and Environmental Engineering, Hanyang University, Seoul, Republic of Korea
[b] Graduate School of Green Growth & Sustainability, Korea Advanced Institute of Science and Technology, Daejeon, Republic of Korea
[c] Bennett Institute for Innovation and Policy Acceleration, University of Sussex Business School, United Kingdom
[d] Institute for Global Sustainability, Boston University, Massachusetts, USA
[e] Department of Business Technology and Development, Aarhus University, Denmark
[f] American University of Sharjah, Sharjah, United Arab Emirates
[g] Colorado School of Mines, Colorado, USA
[h] Potsdam Institute for Climate Impact Research, Potsdam and Berlin, Germany
[i] Iniciativa Climática de México, Mexico
[j] University of Cambridge, United Kingdom

ARTICLE INFO

Keywords:
| artificial intelligence
Digitalization
Data center
Energy and environment
Low-carbon innovations
Socio-technical dynamics

ABSTRACT

|The recent and rapid expansion of artificial intelligence (AI), data centers, and other digitalization technologies has accelerated global electricity consumption, creating a new paradigm in energy and growth. Still, no comprehensive framework exists to evaluate the role of low-carbon innovations across AI's complex socio-technical ecosystem. This review addresses three questions: What low- and zero-carbon technologies can help mitigate the energy and carbon footprint of AI and digitalization? What barriers prevent their adoption? Which policy interventions can overcome these barriers? Using a sociotechnical systems approach, we conducted a systematic literature search and screened 364 articles published from 2000 to 2025 to analyze impacts and opportunities across four critical dimensions of AI, data centers, and digitalization provisioning: natural resources, facilities and components, applications, and users and institutions. We identify over 70 mitigation technologies, with reported energy reductions ranging from 13% to 94% across individual studies, alongside projections in high-growth scenarios where data center electricity demand could grow by 13–15% per year to 2030. Three barrier categories emerged: technological constraints, institutional and political limitations, and behavioral resistance. Policy measures such as carbon pricing and mandatory energy reporting, and operational strategies, such as geographic load balancing, are frequently highlighted as high-leverage options for overcoming these barriers. This holistic STS framework provides a foundation for future interdisciplinary research and policy development, identifying critical research gaps including demand forecasting, Global South equity, and organizational change.

1. Introduction

Artificial intelligence (AI) is already driving a transformation in employment, knowledge generation, and lifestyles, permeating nearly all aspects of daily life and economic structure. The computing hardware and infrastructure required for widespread digitalization, particularly through the use of artificial intelligence tools to extract value from digital data and cryptocurrency mining, are a significant source of

☆ Given their role as Associate Editor, Steven Griffiths had no involvement in the peer-review of this article and has no access to information regarding its peer-review. Full responsibility for the editorial process for this article was delegated to another journal editor.

* Corresponding author. Department of Earth Resources and Environmental Engineering, Hanyang University, Republic of Korea
** Corresponding author. Bennett Institute for Innovation and Policy Acceleration, University of Sussex Business School, United Kingdom.
E-mail addresses: jinsookim@hanyang.ac.kr (J. Kim), benjaminso@hih.au.dk (B.K. Sovacool).

https://doi.org/10.1016/j.rser.2026.116861
Received 9 July 2025; Received in revised form 3 February 2026; Accepted 24 February 2026
Available online 12 March 2026
1364-0321/

electricity demand. In the face of climate change, the urgent need for sustainable, low-carbon energy innovations to meet this growing demand has become more apparent. The intersection of these critical areas—sustainable energy and digitalization—presents unprecedented opportunities and significant challenges.

A systematic categorization of the interface between digitalization and carbon emissions identifies diverse and challenging issues, such as direct and indirect carbon and energy footprints, technological innovations for climate solutions, and a broader range of systemic impacts across the natural environment and society [1]. Here we focus on the first component, energy and environmental footprint of AI-driven digitalization, while acknowledging the potentially much larger impacts of the two other categories (see Creutzig et al. [2]). Our focus also allows us to distinguish four important domains that are relevant for assessing AI, data centers, and digitalization's climate impact: natural resources, facilities and components, applications, and users and institutions. This allows an integrated view and subsequent policy development to make digitalization provisioning environmentally less harmful.

Digitalization is a transformative process that involves the integration of digital technologies and data into various domains of society and business, leading to the creation of new value-creation opportunities, the optimization of processes, and the restructuring of sociotechnical systems (STS) [3]. As Bockshecker et al. [4] noted, the terms digitization, digitalization, and digital transformation are often used interchangeably, but this is inaccurate as they refer to distinct concepts. Digitization primarily focuses on technical aspects, while digitalization encompasses both technical and social components within a STS. Meanwhile, digital transformation describes the broader change process driven by ICT innovations, integrating both social and technical dimensions. Consequently, this study, which examines the socio-technical dynamics of energy demand and environmental impact, can be regarded as addressing the subject of digitalization. This review places particular emphasis on the subjects of AI-driven digitalization, cryptocurrency, and data centers including cloud computing.

Recent discussions on the relationship between energy and broader social trends such as AI and cryptocurrency have highlighted a complex, bi-directional interaction. On the one hand, AI and digital services are beginning to be harnessed to optimize energy systems, improve efficiency, and accelerate the transition to renewable sources. On the other hand, the growing energy demands of AI systems and cryptocurrency transactions are raising concerns about their environmental impacts, carbon footprint and sustainability (Fig. 1).

The left side of the balance scale illustrates "AI's Growing Energy Appetite," depicting the significant environmental and infrastructural burdens the technology imposes. This weight begins with device manufacturing, which involves the energy-intensive production of specialized chips and AI-enabled hardware. It extends to the operational phase with the rapid expansion of data centers, requiring massive amounts of power for processing and cooling, which drives overall energy demand. These factors collectively create substantial infrastructure challenges, pressing existing electrical grids to upgrade and expand to support the skyrocketing power loads required for AI growth.

Conversely, the right side presents "AI as a Sustainable Energy Solution," highlighting how the technology acts as a counterweight by driving efficiency and decarbonization. This includes smart energy management systems that optimize electricity use in real-time and process optimization that streamlines industrial operations to minimize waste. On the supply side, AI-enhanced renewables improve the

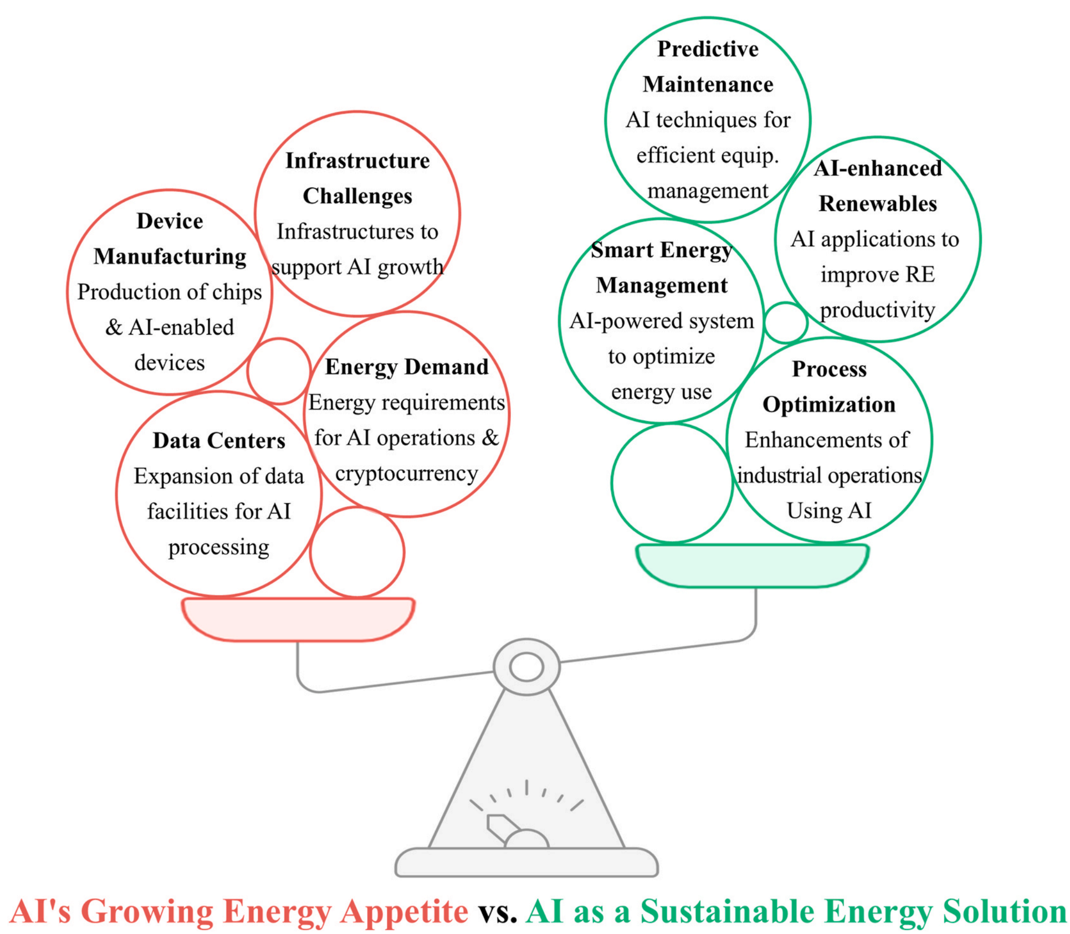

Fig. 1. Sustainability tradeoffs between AI and energy use.
Source: Authors.

productivity of wind and solar assets through better forecasting and grid integration. Additionally, predictive maintenance utilizes AI techniques to manage equipment efficiently, preventing energy waste from mechanical failures and extending the lifespan of critical infrastructure.

The potential of AI to transform the energy sector is substantial. Machine learning algorithms are being employed to enhance weather forecasting for renewable energy generation, optimize grid management, and improve the efficiency of energy storage systems. These applications can support integration and utilization of variable renewables and efficiency improvements, contributions that align with international targets to triple renewable energy capacity and double the rate of energy-efficiency improvement by 2030 [5], while simultaneously reducing the energy footprint of AI.

However, the energy consumption of AI systems and data centers, especially those involving machine learning and large language models as well as cryptocurrency mining, is growing faster than AI efficiency gains can deliver. The computing power required for AI has been doubling approximately every 100 days, with a single generative AI query consuming nearly ten times more electricity than a traditional Internet search [6,7]. IEA projects thatelectricity consumption from AI and data centers may double by 2026 to over 1000 TWh, roughly matching Japan's total electricity demand and driven by AI workloads and crypto mining [8]. This surge in energy demand puts pressure on electrical grids and potentially offsets some of the environmental benefits AI aims to deliver in other sectors [9].

The dynamics linking energy and digitalization across AI, cryptocurrencies, data centers, and cloud computing extend beyond mere technological considerations; they encompass a complex sociotechnical system that involves policymaking, economic factors, and societal implications. For instance, the Jevons' Paradox suggests that AI-driven improvements in energy efficiency need to be combined with demand-side interventions to reduce rebound effects. Similarly, the development of AI-driven smart grids not only requires technological innovation but also requires changes in energy policies, market structures, and consumer behavior [10]. Initiatives such as the World Economic Forum's Artificial Intelligence Governance Alliance are working to apply a cross-industry lens to understand how AI can be leveraged to drive impact on innovation, sustainability, and growth [9].

Navigating this complex landscape requires a system-level approach to fully understand the dynamic relationships between digitalization and sustainable energy futures. The approach must consider not only the technological aspects but also the economic, social, and environmental dimensions of this interaction. In this review, we aim to provide the following research contributions.

- What low- and zero-carbon technologies can help mitigate AI, data centers, and digitalization's climate impacts? —A comprehensive mapping of low- and zero-carbon innovations for digitalization across four sociotechnical domains: natural resources, facilities and components, applications, and users and institutions;
- What barriers prevent their adoption? Which policy interventions can overcome these barriers?—A systematic analysis of barriers (policy, technological, institutional, and behavioral) that prevent the adoption of sustainable AI-driven digital innovations, with corresponding policy interventions;
- Development of a novel sociotechnical framework that integrates energy and AI systems to guide future policy and research;
- Identification of critical research gaps to advance the sustainable development of digitalization, particularly AI technologies.

While previous studies have examined either digitalization's energy consumption or sustainable computing solutions in isolation, this review makes three novel contributions: (1) it applies a comprehensive sociotechnical systems lens that captures the full ecosystem of digitalization sustainability; (2) it systematically maps innovations across all four STS domains rather than focusing on single technical fixes; and (3) it directly links barriers to specific policy interventions, providing actionable guidance for policymakers. The paper is organized as follows: Section 2 provides background for energy demand and AI-driven digitalization, research design, and a STS framework for this review. Section 3 examines promising decarbonization innovations for each STS. Section 4 and 5 describe barriers and policy instruments to overcome the barriers. Lastly, Section 6 concludes with research gaps and future agenda.

2. Background, conceptual approach and research design

2.1. Energy demand and implications of AI-driven digitalization, data centers and cryptocurrency

AI-driven digitalization has significantly increased energy demand, primarily because data centers serve as the physical infrastructure underpinning digital services. In this sense, data centers constitute the main channel through which the energy demand implications of AI-driven digitalization materialize. Previous studies have shown that, despite exponential growth in data center workloads, corresponding increases in electricity demand were largely mitigated over the past decade through efficiency improvements and a shift toward large-scale cloud-based service provision [11,12]. However, this decoupling trend has recently weakened, as shown in Fig. 2. The rapid development of AI hardware and the expansion of data center services into computation-intensive applications, such as, large-scale AI model training and cryptocurrency mining, have substantially increased computational resource requirements, leading to a renewed acceleration in electricity demand growth [13,14]. Recent evidence suggests that electricity demand from data centers now accounts for a non-negligible and rapidly growing share of global electricity consumption, and that recent demand growth has outpaced historical efficiency gains [12,15,16]. These trends underscore that the interaction between digitalization and energy consumption is critical in determining whether AI-driven digitalization ultimately supports environmental sustainability [17].

The current trend of rising energy demand associated with AI-driven digitalization is expected to continue and may even accelerate [19]. AI-driven digitalization influences energy demand—particularly electricity demand—through multiple channels (see Fig. 3). Accordingly, recent discussions have increasingly shifted their focus from digitalization, in general, to the energy and emissions impacts of specific technologies that underpin AI-driven digitalization, most notably, AI systems and data centers [1,20]. This perspective is consistent with earlier debates on how ICT-driven innovations affect energy consumption [21–26]. Building on this literature, the energy demand implications of AI-driven digitalization can be categorized into three broad channels (see Fig. 3). While clean electricity sourcing and contractual arrangements play an important role in reducing the emissions associated with AI-driven digitalization, they do not directly affect the level of electricity demand. Accordingly, this section focuses on demand-side mechanisms—particularly energy efficiency and direct electricity use—while issues related to clean energy procurement are addressed in later sections. First, direct impacts arise from the production, operation, and disposal of AI-related technologies. Second, indirect impacts operate through efficiency improvements in the energy system enabled by AI applications. Third, tertiary impacts encompass broader feedback effects, including increased energy demand driven by AI-induced economic growth, as well as ripple effects associated with structural changes in industry triggered by AI-driven digitalization. The overall impact of AI-driven digitalization on energy demand ultimately depends on which of these channels becomes dominant over time.

In the context of AI-driven digitalization, electricity consumption arising from both the production and operation of digital infrastructure, most notably the manufacturing of AI-related hardware and the operation of data centers hosting AI workloads and related computational services, as documented by the IEA and LBNL [15,16,18], falls under the category of direct impacts. As data center services increasingly support

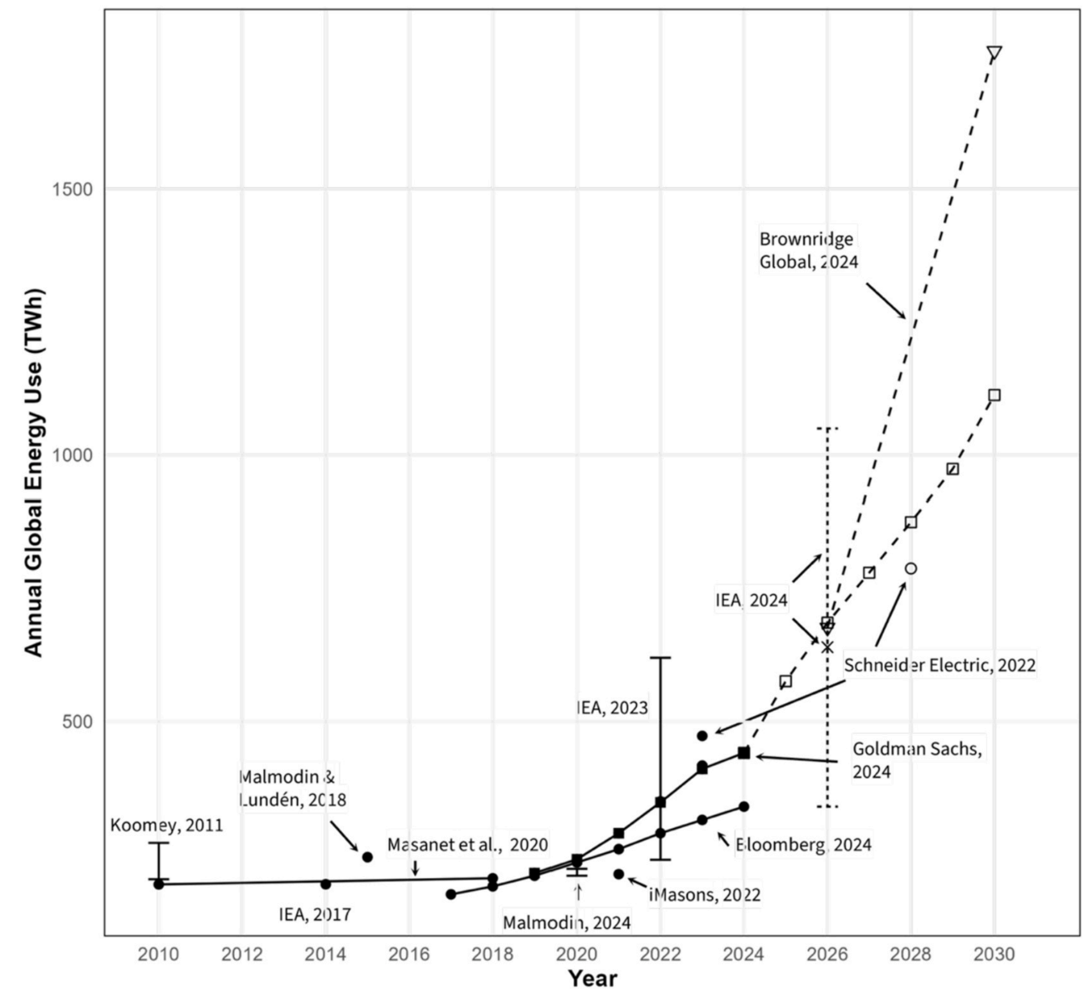

Fig. 2. Academic and industry historical estimates of global data center energy use.
Source: LBNL [18].

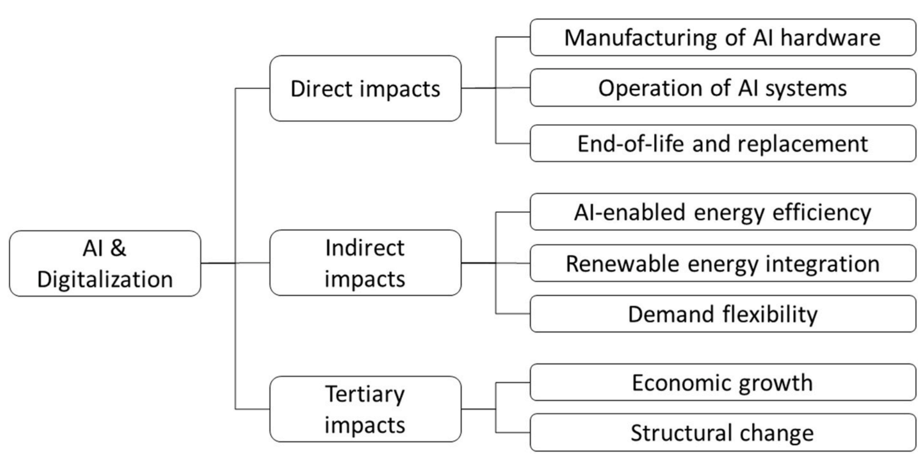

Fig. 3. Channels of AI-related energy impacts.
Source: Authors.

computation-intensive workloads, such as large-scale AI model training and cryptocurrency mining, electricity demand at the infrastructure level is expected to rise accordingly. Indirect impacts arise from the application of AI to improve the performance of the energy system. In particular, AI is anticipated to play an increasingly important role in optimizing the balance between electricity supply and demand, as well as in facilitating the integration of renewable energy sources into power systems [10,27–29]. Existing applications include renewable energy forecasting, which supports higher penetration of variable renewables and improved grid integration, thereby reducing reliance on fossil fuel generation [30,31]. AI-based tools can also enhance the accuracy of electricity supply and demand forecasting [32], optimize energy use

[33], and increase demand flexibility through the expansion of demand responses [27]. By contrast, the direction and magnitude of tertiary impacts remain difficult to predict or generalize [1,34].

AI-driven digitalization influences macroeconomic factors, such as employment, labor productivity, industrial structure, and economic growth [35], all of which can affect energy demand in complex and context-dependent ways [34]. Taken together, these considerations suggest that assessing the energy demand implications of AI-driven digitalization requires particular attention to the interplay between direct and indirect impacts. While tertiary effects may shape long-run outcomes, the balance between infrastructure-level electricity demand growth and AI-enabled efficiency improvements is likely to be central to determining the net impact of digitalization on energy demand [36].

As AI-driven digitalization continues to advance, electricity demand associated with data centers is widely expected to grow rapidly. While existing studies differ in their assumptions and methodologies, they consistently project a substantial increase in electricity consumption from data centers over the coming decade, underscoring the significance of direct impacts of power systems [12,14,19,37]. Importantly, these direct impacts are not evenly distributed across regions but are geographically concentrated in countries hosting large clusters of data centers, such as the United States, parts of Europe, and China [15,16,18,38–40], as shown in Fig. 4. From an energy and sustainability perspective, the implications of this concentration depend not only on the scale of electricity consumption, but more critically on the carbon intensity of local electricity supply and region-specific cooling requirements, both of which vary substantially across regions [41]. As a result, similar growth in AI-driven electricity demand can translate into very different outcomes in terms of emissions, grid stress, and system sustainability. This spatial and technological heterogeneity complicates any straightforward assessment of the overall energy implications of AI-driven digitalization.

What is the net impact of AI-driven digitalization on energy demand through the aforementioned channels? Quantitative predictions that directly address this question remain scarce. Nevertheless, insights can be drawn from earlier empirical studies that examine relationship between ICT development and energy demand at an aggregate level using historical data. In the absence of targeted mitigation efforts, this historical relationship is likely to provide a useful benchmark for understanding the potential net effects of AI and digital services. Existing evidence, however, does not point to a clear consensus. Some studies suggest that ICT development has contributed to rising energy demand, (e.g., Lange et al. [17]), while others find offsetting effects through efficiency improvements (e.g., Ishida [42]). Schulte, Welsch [23] found that ICT is associated with a decline in non-electric energy demand, but a significant increase in electricity demand. Simiarly, Wang and Lee [22] noted that the construction of ICT-related infrastructure—such as manufacturing of ICT equipment—can raise energy demand, whereas improving ICT access driven by software development may enhance efficiency and reduce energy use. Taken together, these findings suggest that AI-driven digitalization may increase or reduce energy demand through different channels, highlighting the importance of coordinated technological and policy efforts to steer AI-driven digitalization toward a more sustainable trajectory [43].

To mitigate the rising energy demand associated with AI-driven digitalization, reducing its direct impacts is a critical first step. Without curbing these effects, neither clean energy sourcing nor indirect efficiency gains can meaningfully reduce the net energy implications of AI-driven digitalization. Accordingly, two approaches are central to mitigation efforts: improving digital infrastructure and software efficiency and increasing the use of clean electricity. Efficiency improvements operate across multiple layers of the digital stack. At the infrastructure and system-operation levels, they include advances in chip technologies, the adoption of sustainable computing practices related to workload management and system operation, optimization of power usage effectiveness (PUE), and innovations in cooling systems [16,44,45]. At the software and algorithmic levels, improvements in AI code and algorithmic efficiency can substantially reduce energy

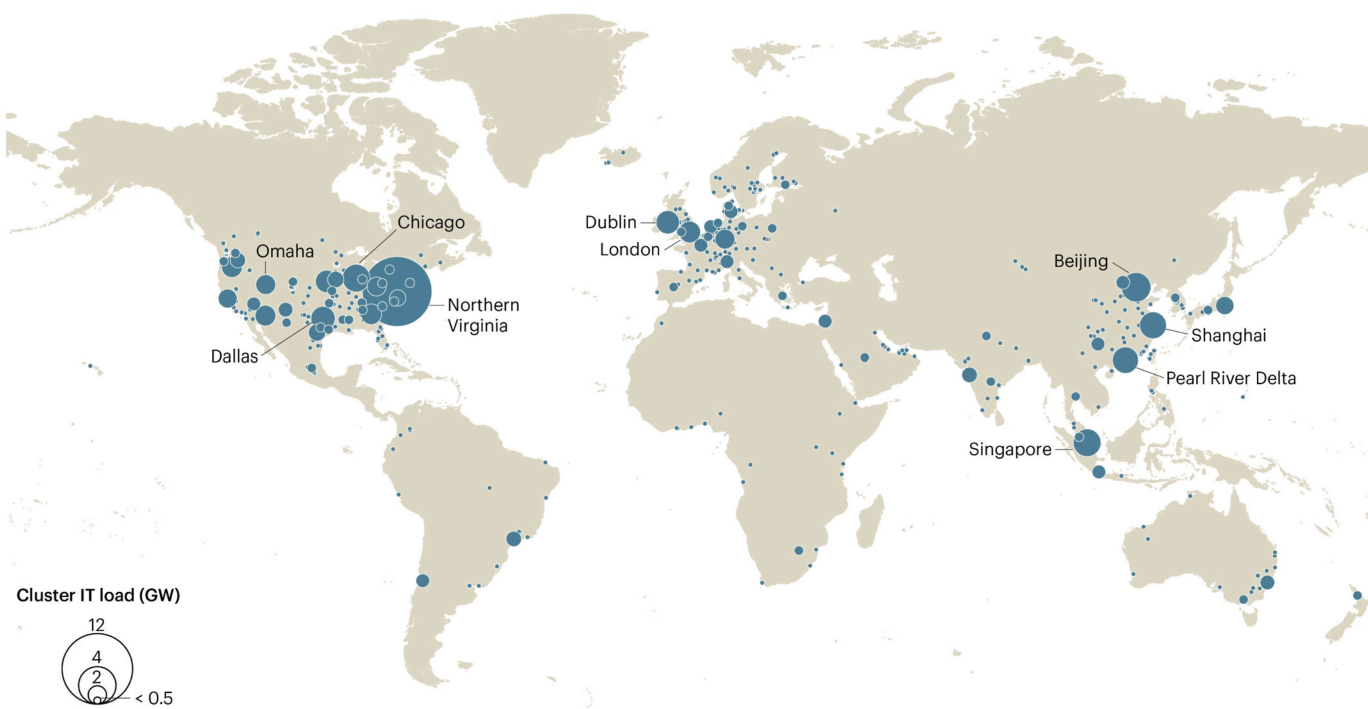

Fig. 4. Global placement of data center **clusters and its corresponding electricity load (in GW).**
Notes: GW = gigawatt. We define a data center cluster as a group of data centers located within 100 km of each other. The ten largest clusters have been named. The Pearl River Delta encompasses the combined capacity of Guangzhou, Shenzhen and Hong Kong (China).
Source: IEA [19].

requirements by lowering computational complexity and avoiding redundant calculations [46,47]. Meanwhile, expanding the use of clean electricity can substantially reduce Scope 1 and Scope 2 emissions, even though it does not directly lower electricity demand. At the same time, it should be acknowledged that this process might address potential side effects, such as increased competition for low-cost clean electricity, grid congestion, and the concentration of clean energy access among large technology companies, which may distort resource allocation and reduce consumer surplus [48–50]. Together, these approaches address both efficiency and sustainability challenges inherent to the digital transformation.

While energy efficiency improvements across multiple layers of the digital stack, including infrastructure, system operation, software, and algorithms, can partially offset the rising energy demand from AI-driven digitalization, they do not fully resolve the structural sources of energy intensity of AI workloads. A key driver of high energy use is the energy cost of data movement between computation and memory, which dominates consumption in data-intensive AI systems and reflects the limitations of the traditional von Neumann architecture [51,52]. Addressing these structural constraints would require numerous fundamental changes in chip architectures. Accordingly, AI hardware designers have explored opportunities to redesign computer chips for improved energy performance, including approaches such as in-memory computing, which reduce energy use by collocating memory and computation and shortening data transfer distances [53,54]. However, such deep chip-level modifications remain largely experimental and face significant barriers to widespread adoption, including the need for major architectural shifts, new materials and manufacturing processes, and long development timelines across the semiconductor ecosystem. As a result, chip-level architectural innovation should be viewed as a long-term, system-wide strategy, rather than a near-term solution to the energy demand challenges posed by AI-driven digitalization.

At the same time, indirect impacts of AI-driven digitalization can play a complementary role in moderating its overall energy implications. By improving the efficiency, flexibility, and integration of energy systems, AI applications can help accommodate higher shares of renewable energy and reduce emissions associated with rising electricity demand. However, these indirect benefits are contingent on appropriate policy and system design and are unlikely to offset rapid growth in electricity demand on their own. Accordingly, indirect impacts should be understood as supportive mechanisms that enhance, rather than replace, efforts to curb the direct energy demand associated with AI-driven digitalization.

2.2. Sociotechnical systems for sustainable energy and digitalization

The concept of STS originates from integrating social and technical subsystems within societies. Sociotechnical theory emphasizes the interdependence between social systems (e.g., human behaviors, organizational culture, and relationships) and technical systems (e.g., tools, processes, and technologies) to achieve optimized outcomes as well as political systems (regulations, governance) and economic systems (markets, price signals, firm behavior) [55,56]. Initially developed in the 1950s, this theory underscores the importance of designing systems that balance technical efficiency with human and organizational needs [57]. STS theory in essence posits that changes in one subsystem inevitably affect the other.

Digitalization is a complex concept that has evolved over time, with various definitions across various applications. While there is no single universally accepted definition, digitalization refers to the process of leveraging digital technologies and data to transform various aspects of society, business, and daily life. It goes beyond the mere conversion of analog information to digital format, so-called "digitization" [58]. Digitalization is a transformative process that involves the integration of digital technologies and data into various domains of society and business, leading to the creation of new value-creation opportunities, the optimization of processes, and the restructuring of STS [3].

Because AI and digital services create fundamental changes in organizational operations, structures, and value creation, they are inherently sociotechnical, requiring the alignment of technological advances with organizational culture, human capital, and strategic goals. Winby and Mohrman [59] considered traditional sociotechnical systems and strategic organization design frameworks and proposed a new digital sociotechnical systems design paradigm. Compared to traditional STS, which emphasized mechanical technologies, organizational optimization, and internal processes, digital STS focuses on ecosystems, artificial intelligence, and agile responses to uncertainty. Traditional STS concentrated on optimizing the fit between social and technical work systems within organizational boundaries, whereas digital STS expands this scope to include external networks, stakeholder motivations, and customer journeys. Moreover, digital STS adopts a continuous, data-driven design approach utilizing automated feedback and iterative learning, contrasting with the traditional STS method of implementing projects sequentially with discrete assessment phases [59] (See Appendix Table A1).

As mentioned in the introduction, the aim of this study is to review the dynamics between energy and digitalization and to discuss the low- or zero-carbon options for a sustainable digital economy from an STS perspective. However, not only digitalization, but also the energy value chain is becoming increasingly complex. Therefore, for a clearer and more in-depth examination, we have focused on the following digitalization technology considerations:

- Inclusion of ata storage and processing via AI, cloud computing as well as blockchain applications, particularly cryptocurrency mining;
- Inclusion of perations, hardware manufacturing, and non-data center sites that run mining rigs (for blockchain technologies);
- Exclusion of end-use sectors that will be continually increasing data output (smart homes, connected/autonomous vehicles, manufacturing plants with digital twins, etc.), but with consideration of the increasing demands caused by those sectors.

For industrial decarbonization technologies, a series of studies identified key STS for energy-intensive industries like iron and steel [60], chemicals [61], oil refining [62], and cement and concrete [63]. These studies have developed an analytical framework that examines energy and material flows across the technology value chain from a sociotechnical perspective. The framework incorporates value chain analysis while considering institutional and end-user stakeholders' inputs, structures, and drivers. Building on the approaches to designing a search protocol and the STS lens used in these studies, we developed a new STS framework to examine the dynamics of AI, data centers and digitalization on energy and environment. Considering the coverage of AI, cryptocurrency, and energy technologies in this study, we framed the STS of this review with four categories: natural resources, facilities and components, applications, and users and institutions (Fig. 5).

The four domains in Fig. 5 are well-justified from a STS perspective because they collectively encompass the full sociotechnical landscape required to understand digitalization's environmental impact. The first domain, natural resources, serves as the foundational layer of the system, encompassing the physical inputs required to build and sustain modern energy and digital infrastructure. It includes the extraction of raw materials such as critical minerals, silicon, and uranium, which are essential for manufacturing batteries and semiconductors. It also involves the logistical networks of terrestrial and rail transport needed to move these materials, as well as the industrial processes of concentration and smelting. Crucially, this sector highlights the importance of water resources, which are indispensable for both processing raw materials, manufacturing semiconductors, and cooling energy and digital facilities.

The facilities and components domain represents the hardware infrastructure that bridges the gap between raw inputs and useable services. On the energy side, this includes power generators like solar

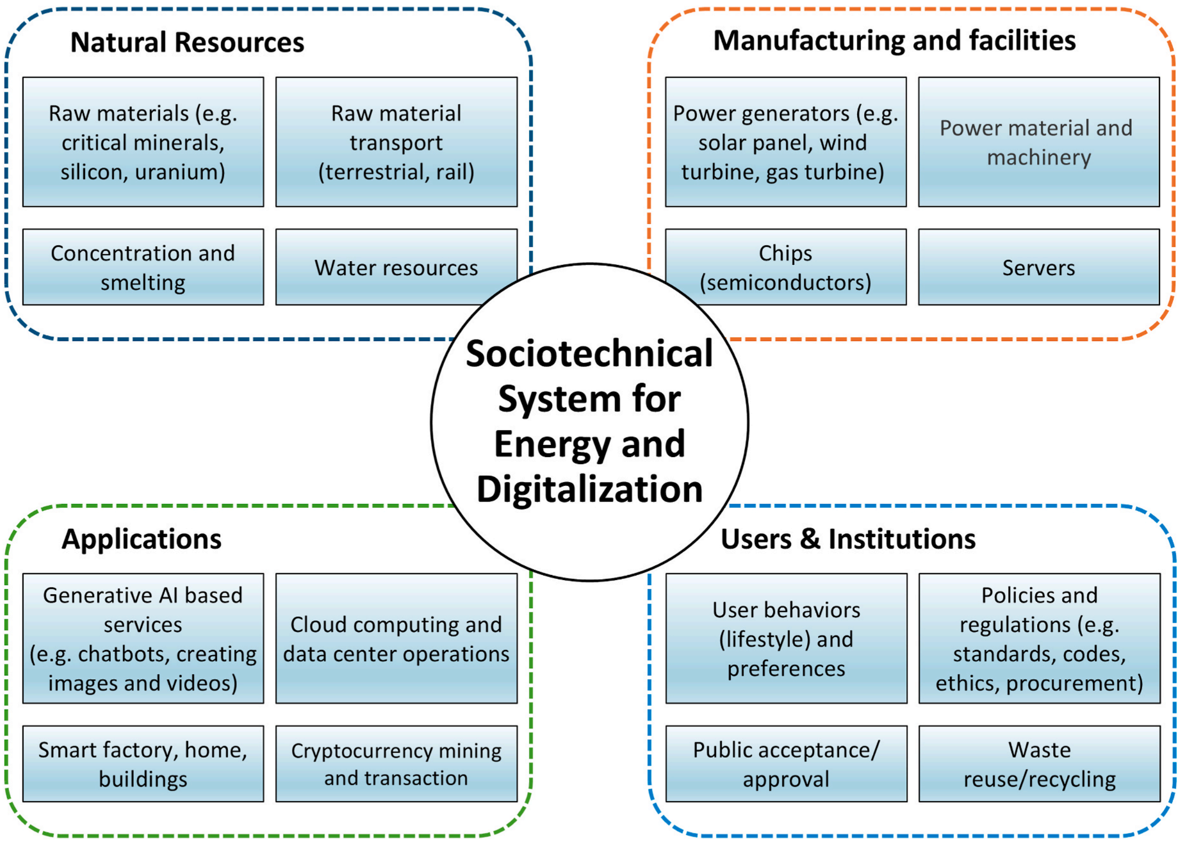

Fig. 5. An integrated sociotechnical system for sustainable energy and digitalization.
Source: Authors.

panels, wind turbines, and gas turbines, alongside the power grids and machinery required for transmission. On the digital side, it encompasses the physical brains and bodies of the system: the chips, servers, and data centers that process and store information. It also illustrates the deep physical integration of energy and digitization, as data centers and digital components are increasingly significant consumers of the power generated by these facilities.

The applications domain details the functional outputs and services, representing the businesses' demand side of the STS. It includes high-computational tasks such as generative AI services (chatbots, image creation), cloud computing, and data center operations. It also covers energy-intensive activities like cryptocurrency mining and blockchain transactions. This section underscores how advanced digital services act as the primary drivers for upstream development, creating the demand that necessitates the expansion of both energy generation and hardware manufacturing.

Finally, the users and institutions domain reflects the co-shaping of technology by social norms, governance, and behavioral patterns, essential to STS analysis. This includes user behaviors and lifestyle preferences that dictate energy and data consumption patterns. It also encompasses the regulatory frameworks—policies, standards, ethics, and procurement rules—that define the boundaries of operation. Additionally, this domain addresses critical social factors such as public acceptance of new technologies and the management of end-of-life issues like E-waste reuse and recycling, ensuring the system remains socially sustainable and politically viable. This framing enables a multi-scalar, relational understanding of AI-driven digitalization as both a technical artifact and a product of sociopolitical systems, thus offering a comprehensive approach to environmental analysis.

2.3. Research design

To explore the relations between digitalization and energy use through a sociotechnical lens, we conducted a structured literature review based on a systematic search and transparent screening protocol. The first category focused on the overarching theme of energy consumption and carbon emissions, the second on digitalization, and the third on the specific topic of interest, such as efficiency, reduction, or mitigation. As shown in Fig. 6, we detail the search terms and parameters used for the systematic review. By combining search terms from these three categories, we generated 45 unique search strings. However, because terms like “energy,” “data center,” and “efficiency” are commonly used, the initial search through academic databases, such as ScienceDirect, SpringerLink, JSTOR, Taylor & Francis Online, Wiley Online Library, and Sage Journals yielded millions of results. To refine the selection, for each search string and database we screened the titles and abstracts of the first 100 results returned when sorted by the database's default relevance ranking. We then de-duplicated records across databases before applying the second-round screening criteria described below. In total, the abstracts of 4500 articles were reviewed to capture critical insights and the latest scholarly research on sustainable energy options for digitalization.

From the initial screening of 4500 articles, we applied 3 s-round screening protocols to select a final corpus of 364 studies for in-depth review. These protocols were: recency (published after 2000), relevance (focused on mitigation options and demand-side mechanisms for digitalization), and originality (de-duplication across databases). Review papers were retained for background synthesis but excluded from the core mitigation-evidence dataset. Considering the rapid development of AI, data centers, cloud computing, and cryptocurrencies as recent phenomena, literature published after 2000 was deemed sufficient. Accordingly, findings should be read as a structured snapshot of

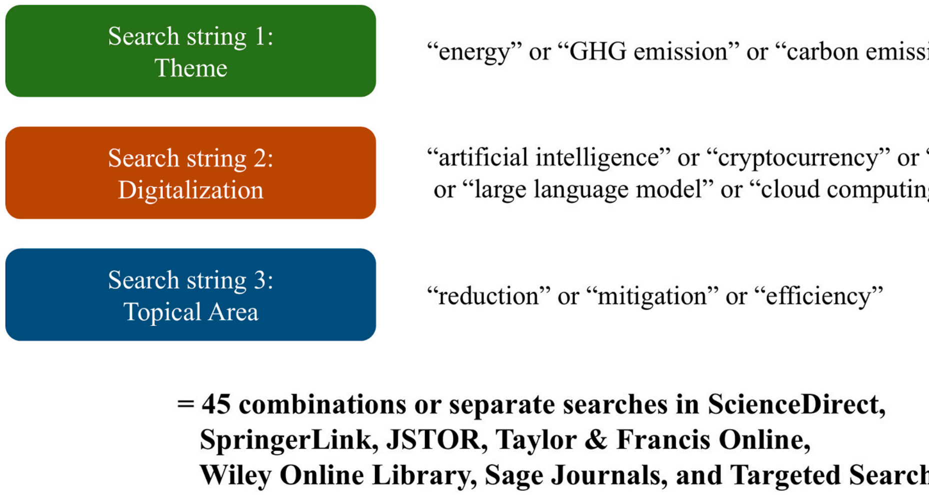

Fig. 6. Summary of systematic review search terms and parameters.
Source: Authors.

scholarship through 2025 and periodic updates are needed as technologies and deployments change and the growth of digital technologies continues to evolve. Further, this review is intentionally grounded in the peer-reviewed scholarly literature captured by our search and screening process. We recognize that a rapidly expanding grey-literature ecosystem (e.g., industry reports, NGO assessments, technical standards, and policy white papers) may address implementation details and near-term practices earlier than peer-reviewed publication. Accordingly, where we identify gaps or pose research questions, these should be interpreted primarily as gaps in peer-reviewed evidence, scholarly synthesis, and reproducible evaluation, rather than an absence of activity or insight in grey sources.

Following the in-depth review, we categorized the identified options using the STS framework, including natural resources, facilities and components, applications, and users and institutions. Fig. 7 shows a significant increase in energy, carbon, and efficiency research in AI, cryptocurrency, data centers, and cloud computing since 2000. The predominant forms of these publications are journal articles and peer-reviewed conference papers.

3. Innovations for the sustainable energy future of AI

Adopting a sociotechnical lens, this section discusses four types of innovations and technologies for AI across the categories of natural resources, facilities and components, applications, and users and institutions. It ends with a subsection looking at crosscutting innovations across multiple domains of the STS.

3.1. Innovations for natural resources

Despite natural resources being a significant component of the sociotechnical system in terms of energy and digitalization life cycles and supply chains, the search protocol set for this study yielded little relevant literature on the topic. This suggests that discussions about decarbonizing AI and digitalization have not sufficiently addressed the natural resources domain. Rare earth elements and other mineral resources embedded in server hardware, the water required for cooling, the energy and electricity needed for system operation, and the waste heat generated during computation collectively constitute the material basis and infrastructure that sustain data centers [64].

As demonstrated by sociotechnical studies on innovations in

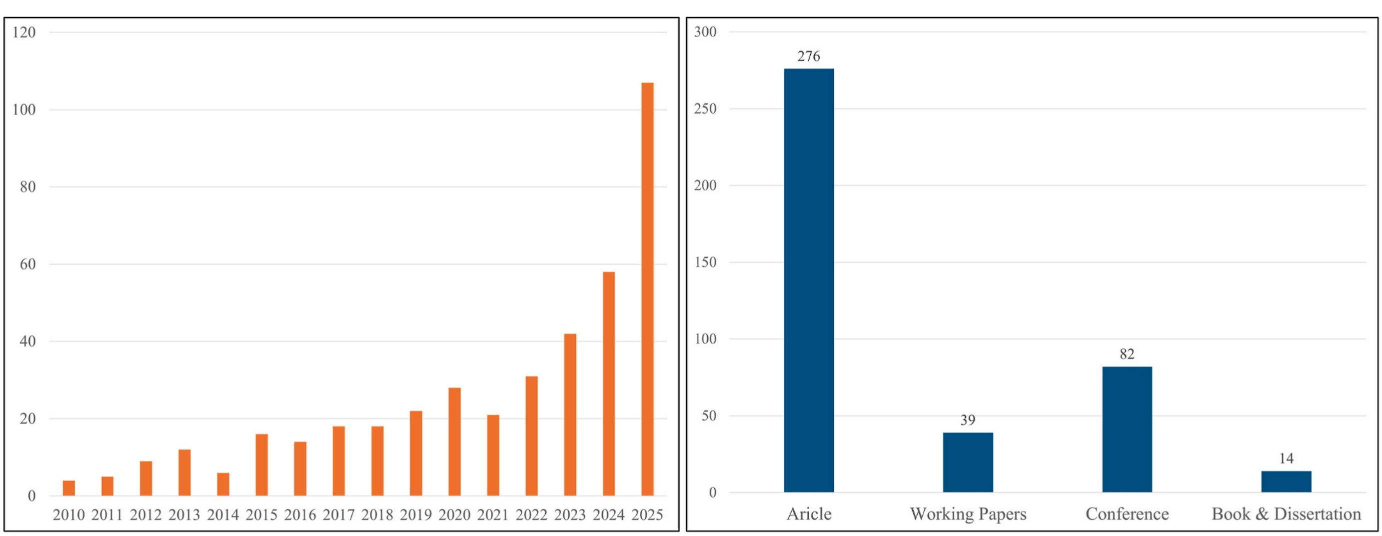

Fig. 7. Results per year for publication period (2000-2025) reviewed in this systematic search (left) and results classified by type of document (right).
Source: Authors.

industrial decarbonization, general approaches exist for decarbonizing mining, mineral transportation, refining, smelting, and water supply. These approaches include the electrification of heavy haulage [65], the use of renewable energy microgrids and storage systems [66], bioleaching, green refining and processing technologies [67], sustainable logistics and transportation, material efficiency [68], and water stewardship in data center supply chains [69]. Although these methods are not easily found through searches using keywords such as AI, data centers, and cryptocurrency, we expect research on the natural resources domain to increase as one of the key STS areas for AI, data centers, and cryptocurrency, given the growing interest in Scope 3 emissions.

AI is also accelerating the development of higher-performing materials for energy innovation. For instance, researchers from a U.S. government laboratory and Microsoft recently used AI to screen 32.5 million solid electrolyte candidates, identifying 23 promising new electrolytes for lithium-based batteries, while scientists in Sweden screened 45 million battery cathode materials, discovering around 4600 potential high-performance candidates [70] (Table 1).

3.2. Innovations for facilities and components

Renewables and green technologies in manufacturing: Renewable energy is also crucial for a sustainable future of energy infrastructure for AI, as well as for the other STS of energy and AI. As we reviewed in the Natural Resources section, a number of articles supported the role of renewable electricity for energy infrastructure and AI applications. Energy migration refers to redistributing energy demand due to geopolitical or regulatory changes, as seen in the cryptocurrency mining sector. For instance, regulatory shifts in China displaced significant energy demand, prompting redistribution to regions like Central Asia and the U.S., potentially impacting global carbon emissions based on regional energy mixes. Such migrations underscore the importance of energy management policies tailored to specific geographic and geopolitical contexts [71]. Green IoT involves sustainable practices in IoT technology, including energy-efficient RFID systems and wireless sensor networks (WSNs). Green RFID systems harvest ambient energy, eliminating battery dependence and waste [72]. Similarly, Green WSNs employ methods like the GREEN routing scheme, enhancing energy efficiency through optimized node selection based on residual energy and geographical positioning, significantly reducing the environmental footprint of IoT deployments [73].

Eco-friendly manufacturing: As AI and data center growth drives demand for high-performance, low-power chips, manufacturing optimization becomes critical for energy efficiency and embodied carbon reduction. At the front end, reinforcement learning (RL) and deep RL (DRL)–based scheduling improves overall equipment effectiveness and cuts energy losses, while deep learning predictive maintenance reduces downtime and material scrap. Post-production, AI–IoT–blockchain tracking and computer vision–based e-waste sorting boost material recovery and lower virgin-input emissions—gains amplified by advanced nodes and chemical-gas abatement [74]. In semiconductor manufacturing, abatement systems capture high-GWP gases such as NF_3 from etching and deposition, converting them via combustion, plasma, or catalytic methods before scrubbing and monitoring to minimize atmospheric release. This directly reduces embodied carbon at the fabrication stage, which is significant given IC manufacturing's large share of hardware emissions [75].

Table 1
Low- or zero-carbon energy innovations for natural resources.

Innovations	Target	References
Renewable energy	All; generative AI, data centers, cloud computing, and cryptocurrency	[66]
Electrification of heavy haulage		[65]
Green refining and processing		[67]
Material efficiency		[68]
Water stewardship		[69]
Higher-performing materials		[70]

Source: Authors.

Industry 4.0 integrates Internet of Things (IOT), data analytics, AI, and automation across manufacturing and facility operations, enabling real-time monitoring and control. Sensor-based data collection and AI-driven decisions allow precise management of energy, equipment, and resources. Advances like data locality optimization and low-precision computation offer potential multi-order-of-magnitude efficiency gains at system and computational levels [76]. Those advances are particularly relevant in the semiconductor and advanced manufacturing industries, where integrating IoT and AI enables precise monitoring and reduction of chemical and greenhouse gas emissions produced during the manufacturing process [77]. Building on Industry 4.0, Industry 5.0 moves beyond efficiency-driven automation to emphasize human–machine collaboration, resilience, and sustainability. By integrating human judgment into advanced production systems, Industry 5.0 aims to ensure long-term environmental and social sustainability [76].

Advanced energy infrastructure: MVMS-GDC (Monitoring, Visualization, and Management System for Green Data Centers) is an automation platform for maximizing energy efficiency and decarbonization in green data centers. It monitors and visualizes renewable microgrids, weather, workloads, and hardware health, while a policy module automatically controls node power states. By aligning computing resources with renewable energy availability, MVMS-GDC minimizes unnecessary consumption and maximizes low-carbon electricity use [78]. DCIES (Data Center Integrated Energy System) cooperative optimization jointly plans computing workloads (L2) with energy supply and cooling infrastructure (L1) to maximize efficiency and decarbonization. Scheduling delay-tolerant tasks around renewable availability and integrating storage increases low-carbon electricity use, while hybrid cooling recovers waste heat to cut cooling demand. This yields roughly 28% CO_2 reduction, over 23% lower operating costs, and reduced curtailment and storage requirements [79]. Shared energy infrastructure integrates AI data centers and crypto mining into a unified system, jointly optimizing renewable generation, storage, and load management. Co-locating solar, wind, battery, and green hydrogen assets increases renewable utilization while load shifting reduces grid dependence. This lowers curtailment and capacity expansion needs, enabling large-scale emissions reductions and net-zero operation without additional system costs [80].

Advanced electricity grid: Load flexibility reshapes Large Language Model (LLM) inference and fine-tuning power profiles in response to grid signals, improving grid efficiency and decarbonization. It exploits energy-performance decoupling combined with coordinated scheduling, idle GPU reassignment, and minute-level dynamic frequency scaling [81]. Supply and demand optimization aligns data-center workloads with real-time grid signals to boost efficiency and cut emissions. Demand response shaves peaks, while spatio-temporal shifting moves computation to times and locations with abundant renewables. Combined with AI scheduling and energy storage that captures surplus renewables for peak discharge, this offers substantial decarbonization potential [82]. A smart grid applies digital technologies to connect all actors, such as generators, markets, providers, consumers, enabling real-time two-way communication between utilities and users. It integrates physical energy flow with information processing to monitor and control variable renewables, enhancing flexibility, stability, and resilience. Within this framework, cloud computing extends beyond IT provisioning to improve grid efficiency, control, and resource allocation for greenhouse-gas mitigation [83]. Lastly, microgrid-enabled crypto mining couples mining devices directly with renewables, using surplus electricity that would otherwise be curtailed or sold cheaply, reducing fossil reliance. System efficiency improves further through waste heat recovery for heating or CHP integration. Mining's rapid load adjustability also enables demand response, supporting grid stability while decarbonizing digital operations [84] (Table 2).

3.3. Innovations for applications

Heuristic algorithms: The CarbonMin algorithm reduces carbon emissions during generative AI inference by intelligently routing user requests to data centers located in regions with lower carbon intensity. It continuously monitors real-time carbon intensity data from power grids to optimize request routing, balancing carbon reduction and user experience by minimizing latency. Studies project that CarbonMin can reduce carbon emissions by 35% under current conditions, with potential reductions up to 71% by 2035 when leveraging idle data center capacities [86]. The Cuckoo Search (CS) algorithm draws inspiration from cuckoo bird behaviors to optimize task scheduling and energy efficiency [95]. By randomly placing 'eggs' (tasks) into 'nests' (resources) and iteratively selecting high-quality solutions [96], CS efficiently balances computational resources. Comparative analyses highlight its superior computational efficiency and energy reduction—up to 121 times less energy consumption compared to conventional methods [46]. Eco-aware scheduling also minimizes energy consumption and CO_2 emissions in cloud computing by employing metrics such as resource availability and energy use. It systematically optimizes the infrastructure's environmental impact and energy efficiency, aligning computational tasks with periods and locations offering lower carbon intensity [97].

Efficient task scheduling algorithms like Heterogeneous Earliest Finish Time (HEFT), Compromised Time-Cost (CTC), and Min-Min/Max-Min strategically balance task completion times, execution costs, and energy consumption [98,99]. They optimize resource utilization, significantly reducing energy demands and CO_2 emissions by integrating smaller and larger tasks appropriately, ensuring cost-effective operations and minimized environmental impact [100]. Hybrid algorithms combine different optimization methods—such as Ant Colony Optimization (ACO) and Cuckoo Search—to tackle cloud computing's scheduling and energy consumption challenges. By integrating the strengths of individual algorithms, these hybrids optimize task completion time and reduce energy consumption more effectively [101].

Virtualization and cloud computing applications: Dynamic structural pruning streamlines Generative Diffusion Models (GDM) by eliminating redundant neurons and connection weights [102]. This optimization significantly reduces computational costs, energy consumption, and carbon emissions, particularly beneficial in resource-intensive applications like autonomous driving and cloud computing [103,104]. Dynamic load management adjusts resource allocation based on real-time server utilization. Servers are classified into overloaded, underloaded, or optimal states, facilitating dynamic and efficient energy management strategies within cloud data centers [105]. Server virtualization consolidates multiple virtual machines onto fewer physical servers, maximizing resource efficiency. This strategy reduces energy usage through dynamic VM migrations and efficient deployment, maintaining system performance while significantly cutting power consumption [106]. The Software-as-a-Service (SaaS) model also optimizes software resource utilization by centralizing software hosting, reducing redundant storage, and enhancing energy efficiency [107]. Compared to traditional setups, SaaS applications achieve energy savings between 15% and 27% [108].

Multitenancy enables multiple user groups (tenants) to share a single software instance, significantly reducing resource duplication and improving energy efficiency. This architectural approach is crucial in cloud environments, allowing optimized resource allocation, customization per tenant, and substantial energy savings [109]. Nano Data Centers decentralizes computing resources by distributing smaller data centers throughout a network, significantly lowering energy consumption compared to centralized architectures. This decentralized approach offers approximately 30% energy savings, particularly effective for content delivery services [110]. Infrastructure-as-a-Service (IaaS) delivers computing resources on-demand, eliminating the need for physical infrastructure maintenance [108]. It dramatically reduces energy use and carbon emissions, providing scalable, efficient, and cost-effective cloud solutions with potential energy reductions of up to 87% when migrating traditional IT infrastructures to cloud-based platforms [111,112]. Lastly, Virtual Network Function (VNF) transforms hardware-based network functionalities into software, offering greater flexibility, efficiency, and substantial energy savings. Coupled with network function virtualization, VNF optimizes network operations, significantly reducing carbon emissions in data centers [113].

The CBWO algorithm is a unique hybrid that builds on the promising Beluga Whale Optimization (BWO) metaheuristic search method. CBWO combines chaotic behavior to achieve a balance between exploration and exploitation, solving the poor convergence rate problem of the underlying BWO algorithm [114]. Energy-efficient load balancing (EELB) uses Markov decision processes to dynamically distribute loads among virtual machines based on real-time resource utilization and energy consumption. The model reduces energy use, minimizes service level violations, and enhances scalability, offering a sustainable, energy-aware, and performance-optimized solution for modern cloud infrastructures [115].

Optimization techniques: Autoscaling dynamically adjusts cloud resources to match workloads, minimizing idle resources and power consumption. This technique includes horizontal scaling (adding/removing virtual machines) and vertical scaling (adjusting resources within a virtual machine) [116], effectively enhancing server utilization and energy efficiency [110,117]. Dynamic Voltage and Frequency Scaling (DVFS) dynamically adjusts processor frequency and voltage, significantly reducing power consumption in computing systems, particularly beneficial for memory-bound workloads. It is a pivotal energy-saving technology in both mobile and enterprise environments [118]. Dynamic provisioning allocates computing resources in real-time according to demand, significantly reducing unnecessary resource usage [119]. This approach ensures optimal operational efficiency and minimizes energy consumption within data centers [120]. Task consolidation optimizes resource use by grouping tasks onto fewer, highly utilized servers, substantially reducing overall energy consumption by minimizing idle and under-utilized resources [121]. Techniques like Energy-Conscious Task Consolidation and MaxUtil achieve energy savings ranging from 13% to 18% [122]. Workload Consolidation: Workload consolidation maximizes server utilization and reduces total server

Table 2
Low- or zero-carbon energy innovations for facilities and components.

Category	Technology	Target	References
Renewables and green technologies	Renewable electricity	Generative AI	[85–88]
	Energy migration	Data Center	[89]
	Green IoT	Cloud computing	[90,91]
		Artificial Intelligence	[92]
Eco-friendly manufacturing	Industry 4.0 & 5.0 Abatement process Process optimization	All; generative AI, data centers, cloud computing, and cryptocurrency	[74–77]
Advanced energy infrastructure	Monitoring, Visualization, and Management System for Green Data Centers (MVMS-GDC) Data Center Integrated Energy System (DCIES) Shared energy infrastructure	Data Center All; generative AI, data centers, cloud computing, and cryptocurrency	[78,79] [80].
Advanced electricity grid	Load flexibility	Large Language Model	[81]
	Supply and demand optimization	Data Center	[82]
	Smart grid	Cloud computing	[83,93]
	Microgrid	Cryptocurrency	[84,94]

Source: Authors.

count by efficiently clustering tasks, using virtualization and container technologies. This method significantly improves data center energy efficiency by streamlining workloads and minimizing resource wastage [123–125]. Geographical Load Balancing (GLB) optimizes energy consumption across distributed data centers by dynamically reallocating computing workloads to regions with favorable energy conditions, such as lower costs or higher renewable energy availability [126].

Technologies for generative AI and deep learning: BigScience Large Open-science Open-access Multilingual Language Model(BLOOM) significantly reduces greenhouse gas emissions relative to comparable models like GPT-3 by optimizing energy use during training. With its 176-billion-parameter architecture, BLOOM consumes significantly less electricity, highlighting its role in sustainable AI development [127, 128]. Deep Neural Networks (DNNs) effectively model complex, nonlinear relationships and hierarchical data structures. By optimizing computational split points between cloud and edge devices, DNN-based systems can drastically reduce energy consumption—up to 94.7%—in mobile and distributed computing environments [129]. LLaMA, developed by MetaAI, is a highly energy-efficient autoregressive LLM. It achieves superior task performance with substantially lower energy consumption (approximately 24 times less than GPT-3), further optimized through precision reductions and efficient algorithmic practices [75,130]. Green AI prioritizes reducing AI's environmental impact through energy-efficient algorithms, optimized hardware, and systematic energy monitoring [131]. Initiatives in Green AI [132], such as NVIDIA's green GPU platform, have achieved up to 50% power reduction, significantly curbing greenhouse gas emissions [133]. Green Code integrates sustainable coding practices that emphasize energy-efficient algorithms and software design patterns [47]. DeepSeek's case suggests that energy efficiency can be easily improved by wide margins (Box 1) – though scale effects (Jevon's paradoxon) are likely to overcompensate for these wins. By minimizing energy consumption and carbon emissions, Green Code contributes significantly to sustainability efforts in large-scale computing and cloud environments [134].

Energy Efficiency: Data centers significantly impact global energy consumption, primarily through cooling requirements. Between 2000 and 2010, data center power consumption more than doubled, reaching approximately 2% of U.S. electricity usage [136]. Most energy consumed by data centers converts directly to heat, necessitating effective cooling methods, which represent around 50% of total energy use [137,138]. Notably, cooling power remains high even when servers operate at low capacity, requiring between 60% and 100% of maximum power [139]. Immersion cooling technologies, despite potential environmental risks with certain coolants, offer substantial improvements in energy efficiency [140]. Additionally, recycling the heat generated by data centers provides opportunities for further energy conservation [139]. Microwave Power Transfer (MPT) technology enables wireless power transmission primarily developed for high-power, point-to-point applications. This method addresses energy management challenges in battery-dependent devices, including mobile and IoT devices [141]. Advances in MPT have led to Wireless Information and Power Simultaneous Transmission (SWIPT), integrating energy harvesting with wireless communications technologies such as MIMO, OFDMA, and relay transmissions [142]. SWIPT systems efficiently harvest energy from wireless signals, thus reducing dependency on frequent battery replacements and improving overall energy efficiency in local and cloud computing environments [141]. Edge computing facilitates processing data closer to the source, significantly benefiting applications requiring real-time processing [143]. The paradigm involves distributed networks of moderately capable devices—smartphones, wearable devices, single-board computers, and local network infrastructure—handling data preprocessing and initial analytics at the network's edge. This model complements traditional cloud computing by reducing latency and bandwidth requirements [144]. By shifting computational tasks to devices at the edge, data transfer over the internet decreases, resulting in faster response times, reduced energy consumption, and optimized network performance [145].

High performance computing: Google's Tensor Processing Unit (TPU) significantly accelerates artificial intelligence and deep learning tasks, optimized particularly for use with frameworks like TensorFlow. Due to its low power requirements and high computational efficiency, TPU technology suits small-scale edge computing devices, enhancing AI applications' energy efficiency at the network edge [146]. Attojoule optoelectronics integrate optical and electronic nanostructures to minimize energy use drastically, reaching efficiency levels measured in attojoules (10^{-18} J). This technology presents significant opportunities for reducing power consumption in data transmission and processing, providing a sustainable solution for growing computational demands [147].

Blockchain technologies: Originally, blockchain networks operated using the energy-intensive Proof of Work (PoW) consensus, relying heavily on computational power [148]. In contrast, Proof of Stake (PoS) dramatically reduces energy usage by relying on stakeholder validation rather than computational tasks. Validators are selected based on their stake (economic share), removing the competition that characterizes PoW. This change substantially reduces energy consumption, as PoS systems avoid resource-intensive mining processes, making it a viable and sustainable alternative for blockchain networks [149]. The Stellar Consensus Protocol (SCP) is a Byzantine fault-tolerant family consensus mechanism that does not compete for computation like PoW. Distributed consensus is possible without energy-intensive operations such as PoW [150]. Permissioned blockchain is optimized for low-power nodes

Box 1
Efficiency Innovations and DeepSeek's Approach:

With concerns mounting about AI's energy appetite, researchers and companies have been pursuing strategies to improve efficiency. Techniques like model compression, optimized algorithms, and low-precision arithmetic have shown promise in curbing energy use per computation. A notable example is DeepSeek – a recent large-model architecture that explicitly aims to *reduce* resource consumption while maintaining performance. DeepSeek's architecture and training approach represent a potential breakthrough in energy efficiency for AI model development. First, DeepSeek-V3 introduces *Multi-Head Latent Attention (MLA)*, a technique that compresses the model's memory footprint during inference by using low-rank representations for attention keys/values. This substantially cuts memory usage and *"greatly reduces inference costs"* (i.e. less energy per query) without degrading model accuracy. Second, DeepSeek employs *Multi-Token Prediction (MTP)* to generate multiple words in parallel rather than one-by-one, which improves inference throughput and efficiency. Finally, on the training side, DeepSeek adopted low-precision FP8 training – using 8-bit floats instead of the typical 16 or 32-bit. This can dramatically lower the computational work and memory traffic, translating to energy savings. DeepSeek's engineers implemented clever techniques (e.g. fine-grained quantization and mixed-precision accumulation) to preserve accuracy with 8-bit values. These optimizations allow DeepSeek to reach similar capabilities as other GPT-class models while using fewer computational resources. Indeed, reports indicate that DeepSeek was able to train a leading model for only about \$6 million in costs – a fraction of the >\$100 million reportedly spent on GPT-4's training – suggesting a much lower energy expenditure as well [135]. In summary, DeepSeek's architecture demonstrates that *scaling up AI does not have to strictly mean scaling up energy usage.*

and fundamentally minimizes the computational, communication, and storage energy consumption of blockchain-based services at the application stage by applying lightweight consensus and transaction designs to the chain [151].

Renewables and green technologies for application service providers: A number of articles [75,76,84,90,152–173] show that switching to renewable energy is necessary to reach a low- or zero-carbon future for AI operations. Using renewable electricity sources for all natural resources in the STS can significantly reduce the carbon footprint associated with AI, cloud computing, and cryptocurrency mining. Battery storage systems are integral to managing intermittent renewable energy supplies because they store excess electricity for later use. Minimizing the use of fossil fuels and enhancing the efficiency of battery storage, particularly in cloud computing infrastructure, can substantially decrease energy costs and environmental impact, thus promoting the sustainability of AI-driven data centers and cloud services [174]. Improving the energy mix involves integrating more renewable energy sources into existing energy systems that are traditionally dominated by fossil fuels [81]. For cryptocurrency mining in particular, optimizing the energy mix by incorporating higher proportions of renewables can reduce greenhouse gas emissions and dependency on carbon-intensive energy sources [71]. Green hydrogen, which is generated by electrolyzing water using renewable energy, is a promising zero-carbon alternative for energy storage and supply. Using green hydrogen can significantly reduce environmental impact by enabling the decarbonization of energy-intensive cryptocurrency mining processes [168]. Small modular reactors (SMRs) can be deployed near data centers to provide round-the-clock, zero-carbon baseload power for AI and LLM operations, replacing fossil-based electricity and reducing greenhouse gas emissions. Utilizing waste heat for cogeneration (CHP) and cooling, as well as complementing intermittent renewables, further enhances the energy efficiency and accelerates the decarbonization of AI infrastructure [175].

Other innovations: Brown-out enhances application robustness by selectively disabling non-critical functionalities during resource shortages [176]. This technique effectively manages short-term capacity constraints, reducing overall energy consumption and ensuring sustained operational reliability [177]. SPROUT framework sustainably manages large language model inference by minimizing unnecessary token generation, resulting in up to 40% lower carbon emissions. This framework incorporates real-time data on GPU consumption and grid carbon intensity, promoting continual optimization in energy use and emissions management [178] (Table 3).

3.4. Innovations for users and institutions

The 6R framework—Research, Reduce, Reuse, Recycle, Rescue, and Revive—guides businesses toward integrating environmental sustainability comprehensively into management practices [245]. The 6R model emphasizes incorporating environmental considerations into corporate decision-making and policy research (Research), implementing innovative technologies and methods to minimize waste and emissions (Reduce), promoting the use of eco-friendly materials by repurposing existing resources (Reuse), facilitating waste recycling processes to enhance resource efficiency (Recycle), engaging in environmental initiatives to promote corporate social responsibility and environmental awareness (Rescue), and continually improving organizational sustainability practices (Revive). These principles collectively offer a systematic approach to managing environmental impacts across sectors, particularly relevant in cloud computing and data-intensive AI services.

Transparency from AI developers regarding energy consumption and carbon emissions is crucial for sustainability. This policy encourages AI companies to disclose detailed data on user bases, hardware specifications—including GPU and cloud service usage—and regional energy consumption patterns. Transparency facilitates informed assessments of

Table 3
Low- or zero-carbon energy innovations for applications.

Category	Technology	Target	References
Heuristic algorithm	CarbonMin algorithms Cuckoo Search (CS) Eco-aware scheduling Task scheduling Hybrid algorithms	Generative AI Data Center Cloud computing	[86] [46,100] [46,179]
Virtualization and cloud computing applications	Dynamic structured pruning Dynamic load Server virtualization Software-as-a-Service (SaaS) Multitenancy Nano Data Centers (NaDa) Infrastructure-as-a-Service (IaaS) Virtual Network Function (VNF) Chaotic Beluga Whale Optimization (CBWO) Energy-Efficient Load Balancing (EELB)	Generative AI Data Center Cloud computing	[103] [113,180,181] [115,182–194]
Optimization	Autoscaling Dynamic voltage and frequency scaling (DVFS) Dynamic provisioning Dynamic load Task consolidation Workload consolidation Geographical Load Balancing (GLB)	Generative AI Data Center Cloud computing	[81] [79,122,126,195–197] [105,119,198,199]
Technologies for generative AI and deep learning	BLOOM training Deep Neural Networks (DNN) LLaMA Green AI Green Code	Generative AI Data Center Cloud computing Artificial Intelligence Cryptocurrency	[127,133,134] [200,201] [93,202,203] [204–206] [207]
Energy efficiency	Hardware optimization, efficiency Power efficiency Cooling system Microwave Power Transfer (MPT) Edge network, edge computing	All resources Generative AI Data Center Cloud computing	[208–211] [212–215] [216–224] [141,225–229]
Renewables, energy mix improvement, and green technologies	Renewable energy Holistic framework Green hydrogen Nuclear power (small modular reactors) Higher-performing materials	All; generative AI, data centers, cloud computing, and cryptocurrency Large Language Model Cryptocurrency	[70,80,157,167,169,170,172,175,230] [81] [168]
High performance computing	Tensor Processing Unit (TPU) Attojoule Optoelectronics	Data Center	[147,231]
Blockchain technologies	Proof of Stake (PoS) Stellar Consensus Protocol (SCP)	Cryptocurrency	[20,94,154,158,165,173,232–237]

(continued on next page)

Table 3 (*continued*)

Category	Technology	Target	References
Others	Permissioned blockchain	Generative AI	[178]
	Brown-out SPROUT framework	Cloud computing	[151,177, 238–244]

Source: Authors.

AI's environmental impacts, especially significant given the variable carbon intensity of regional energy mixes. Enhanced transparency practices directly support broader environmental accountability in the generative AI sector [246].

Low-carbon investments direct capital toward technologies that mitigate climate impacts, shifting from carbon-intensive practices to renewable energy and efficient technologies. Despite initial financial and technical barriers, such investments are essential for the sustainable transition of energy-intensive sectors like cryptocurrency [247]. Incorporating carbon allowances, particularly EU allowances (EUAs), into cryptocurrency portfolios enables them to serve as hedging instruments or partial safe havens against major cryptocurrencies. This mitigates losses during periods of sharp market downturns or high volatility by diversifying the portfolio and taking advantage of inter-market heterogeneity. However, given the weak preference for low-carbon investment in cryptocurrency markets, broader diffusion requires government intervention, including the internalization of external environmental costs through environmental taxation and adjusting allowance supply or emission caps to restrain increases in mining activity and emissions during periods of rising cryptocurrency prices (see Table 6 in Section 5). Enhancing the attractiveness of low-carbon investments through government incentives, risk mitigation measures, and financial innovations can significantly accelerate adoption rates within AI-driven sectors [248].

OptionGLB employs option pricing mechanisms to procure energy strategically during peak market prices, significantly reducing operational costs and fossil fuel dependency. OptionGLB is not just a spatial tool that shifts workloads toward regions with lower-carbon electricity. Rather, it is an integrated energy management mechanism that combines financial, physical, and temporal dimensions. Empirical studies indicate that Option GLB can yield up to 69% cost reductions compared to traditional energy optimization strategies, promoting sustainability through intelligent operational management [174].

The development of *evaluation metrics* and the use of (tradable) *certificates* are also effective innovations for changing the behaviour of users and institutions. *Green Power Usage Effectiveness* (GPUE) complements the traditional Power Usage Effectiveness metric by evaluating not just energy efficiency but also the environmental sustainability of energy sources powering data centers [249]. While PUE measures total power relative to IT equipment power, GPUE accounts explicitly for whether the energy derives from renewable or fossil-based sources. By incorporating source-specific environmental impacts, GPUE enables more nuanced comparisons between data centers, incentivizing increased adoption of renewable energy [250].

Guarantees of Origin (GOs) are tradeable certificates that verify energy is produced from renewable or low-carbon sources. Initially implemented within the EU through directives such as RED (Renewable Energy Directive) I and RED II, GOs allow consumers and businesses to substantiate their renewable energy usage claims legally [251]. Each GO represents 1 MW-hour (MWh) of renewable energy generated, traded internationally across European countries [252]. Demand for GOs has surged, reflecting increased corporate and governmental commitments to renewable energy [253]. This market-driven mechanism promotes the adoption of renewable energy within industries that heavily depend on energy-intensive technologies, including cryptocurrency mining and data centers.

Given cryptocurrency mining's substantial environmental impact, there is a critical need for systematic measurement tools. The *Index of Cryptocurrency Environmental Attention* (ICEA) quantifies public and media attention to cryptocurrencies' environmental impacts, providing empirical insights into how environmental concerns affect financial markets [254]. This index helps policymakers understand public perception and prioritizes regulatory responses, highlighting a policy tool to guide more effective environmental governance of digital assets [255,256]. Certifications such as LEED [257] and BREEAM [258] have been expanded to include data centers, guiding industry practices toward comprehensive energy efficiency and sustainable construction practices. These certifications establish measurable benchmarks for energy use, water management, and carbon emissions, directly supporting sector-wide decarbonization (Table 4).

The implementation of the 6R framework can fundamentally alters user behavior by shifting management mindsets from linear consumption to circular responsibility, forcing businesses to integrate environmental impact directly into their decision-making mindset. This strategic reorientation is operationalized through enhanced transparency and advanced evaluation metrics above (GPUE and ICEA). By disclosing detailed data on hardware specifications and regional energy mixes, AI developers eliminate the information asymmetry that often obscures carbon footprints, while metrics like GPUE incentivize behavior change by benchmarking not just energy efficiency, but the specific sustainability of the energy source. Complementing this strategic shift, technological innovations and market-based mechanisms like GLB and GOs drive behavioral change through automation and economic incentivization. GLB can change operational behavior by dynamically routing workloads to regions with lower costs or higher renewable availability, thereby aligning financial interest with environmental sustainability. Likewise, GOs and comprehensive certifications monetizes sustainable practices, allowing investors and corporations to validate their renewable claims and reduce the risk associated with carbon-intensive assets.

3.5. Cross-cutting innovations across the STS

Many of the innovations required for the decarbonization of AI and digitalization that we examined above are so-called “cross-cutting” solutions that can be applied across multiple domains, not just one STS domain (Fig. 8).

Energy efficiency and renewable energy drive GHG reductions primarily by decarbonizing the energy supply and curbing demand across the physical infrastructure. For natural resources, shifting mining and smelting operations to renewable power sources cuts the intense Scope 1 and 2 emissions associated with raw material extraction. In the realm of facilities, higher-efficiency power delivery and low-carbon electricity procurement can substantially reduce the operational emissions of energy-intensive data centers, although residual embodied emissions

Table 4
Low- or zero-carbon energy innovations for users and institutions.

Technology	Target	References
6R (Research, Reduce, Reuse, Recycle, Rescue, and Revive) framework	Cloud Computing	[245]
Developer transparency (Green AI)	Generative AI	[246]
Low-carbon investment	Cryptocurrency	[248]
Geographical load balancing	Cloud Computing	[174]
Performance assessment and certificates		
- Green power usage effectiveness	Cloud Computing	[250]
- Guarantees of origin	Cryptocurrency	[155]
- Index of cryptocurrency environmental attention	Cryptocurrency	[254]
- Green data center certificates	Data center	[258]

Source: Authors

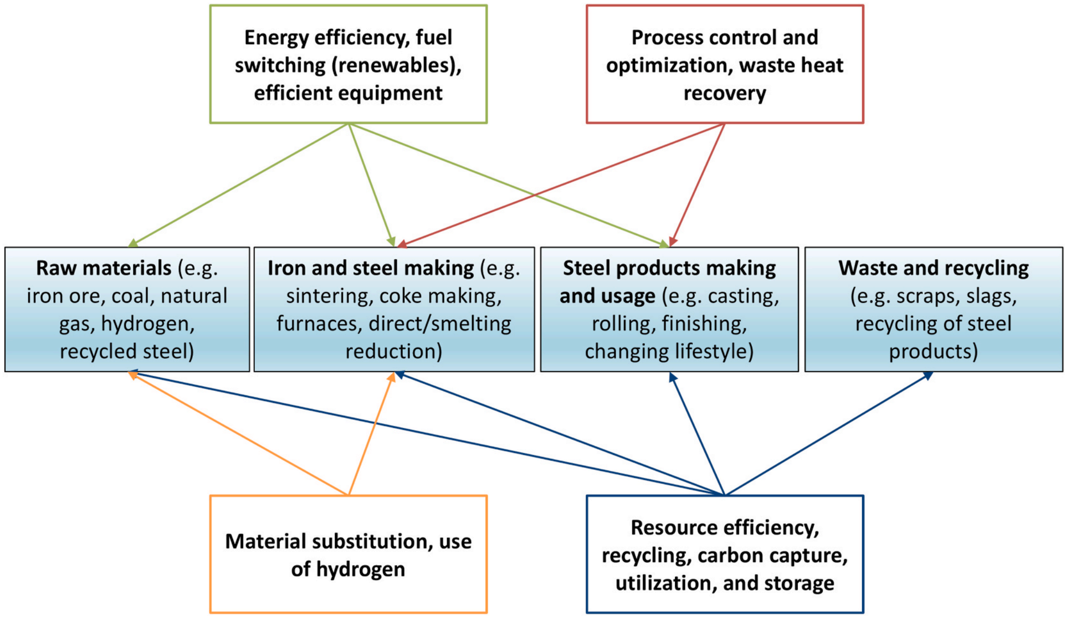

Fig. 8. Cross-cutting innovations for sustainable energy and digitalization.
Source: Authors

and backup generation can remain. Simultaneously, for applications, green coding practices reduce the computational cycles required for tasks, lowering the aggregate electricity demand placed on the hardware by end-users.

AI-Based optimization, advanced cooling, and heat recovery target operational excellence to manage the heat and complexity of computing. AI models enhance resource extraction by predicting deposits with higher precision, reducing the energy wasted on low-yield mining. For facilities, technologies like liquid immersion cooling drastically lower PUE, while waste heat recovery systems turn data center thermal exhaust into a heating resource for nearby communities. Furthermore, AI enables dynamic workload allocation for applications, shifting processing tasks in real-time to servers that are running cooler or are situated in regions with currently available zero-carbon energy.

Blockchain technologies act as a transparency and coordination layer to enforce efficiency and verify claims. A critical shift in applications is the move from energy-intensive PoW to PoS consensus mechanisms, which can reduce operational electricity use by orders of magnitude for networks that adopt PoS. However, PoW networks remain electricity-intensive where they persist. For users and institutions, blockchain provides immutable digital product passports, ensuring regulatory compliance and empowering consumers to make purchasing decisions based on verified carbon footprint data.

Lastly, resource efficiency, recycling, and higher-performing materials focus on reducing embodied carbon through a circular economy approach. Instead of new extraction, urban mining recovers critical minerals from e-waste, significantly lowering the energy intensity required to obtain natural resources. Facilities benefit from advanced materials, which handle power conversion with minimal heat loss. By enforcing Right to Repair policies and recycling mandates, institutions drive a behavioral shift among users away from disposable tech, extending the lifespan of devices and reducing the manufacturing emissions associated with hardware replacement.

4. Barriers to innovations for AI, data centers, and cryptocurrency mining

Despite the promising innovations that are available, as we presented in Section 3, several barriers and challenges prevent the widespread adoption of low- or zero-carbon technologies for AI, data centers, and cryptocurrency. As also evident under an STS approach, these barriers span technical, institutional, political, and economic, and behavioral domains.

4.1. Technological barriers

The previous section introduced a number of innovative low-carbon technologies for digitalization in STS, but many technical challenges remain before these innovations are realized. A significant challenge lies in navigating the inherent dilemma between the economic viability of supplying large-scale, stable power and the imperative of clean energy. As outlined in the Energy Demand of AI and Data Centers section, the use of AI and cryptocurrency is projected to demand substantial electricity, a challenge that is further compounded by the intermittent nature of renewable energy sources such as PV and wind power. For example, a regulatory crackdown in China in 2021 shifted mining to other regions and paradoxically increased the carbon intensity of the network, resulting in an estimated 65 $MtCO_2$ annual carbon footprint for Bitcoin mining, comparable to the emissions of an entire country like Greece [162]. In addition, many existing power grids lack the infrastructure required to support large-scale renewable energy integration, especially in regions with less developed energy systems and even in large developed countries such as the United States and very digitally advanced countries like South Korea. While energy storage technologies are essential for managing the variability of renewable energy, they are still under rapid development and are often too expensive for large-scale deployment [75].

Thermal management and cooling efficiency pose another critical challenge in digital infrastructure operations, as cooling systems remain a major energy consumer. Traditional air-cooling systems often struggle to handle the increasing power density of modern servers, particularly those optimized for AI and cryptocurrency workloads. Advanced cooling technologies, such as liquid cooling, offer promising innovations but need substantial upfront investments. In addition, the effectiveness of cooling solutions varies greatly depending on local climate conditions, complicating efforts to standardize cooling practices [259,260]. Developing and deploying efficient cooling technologies that can keep pace with those advancements while minimizing energy consumption remains an ongoing and critical focus for digital infrastructure operators. Finally, water consumption for meeting cooling demands is a significant issue, particularly in water scarce locations where data centers and cryptocurrency mining operations are being established [261].

In addition, a major obstacle to AI energy efficiency is the inefficiency of current hardware architectures, particularly the energy-hungry process of moving large datasets between separate memory and computation units, a characteristic of the Von Neumann design [262]. This problem requires significant breakthroughs and industry-wide efforts to overcome.

We also recognize that continued progress cannot be guaranteed. Diminishing returns in hardware efficiency and the emergence of power-hungry applications such as AI could erode the gains. As Masanet et al. [263] emphasized, sustained innovation and the implementation of policies such as incentivizing best practices and efficient hardware are required to avoid a rebound in energy use. To meet both the low-carbon sustainability goal and the energy needs of high performance computing centers and AI supercomputing facilities, a holistic approach—improving hardware efficiency, deploying innovative cooling and waste heat reuse, and redesigning the power infrastructure to source renewable energy and manage electrical loads—is essential [264].

4.2. Institutional, political and economic barriers

The main institutional barriers to implementing low- or zero-carbon innovations for digitalization are fragmented jurisdictions and high compliance costs with slow-moving standards [265,266]. AI, digital services, and cryptocurrencies operate in a complex and highly variable regulatory landscape across regions and jurisdictions. The rapid evolution of green technology standards, particularly for energy efficiency and carbon emissions, means that companies must continually adapt to new regulations. This results in significant compliance costs, especially when updates differ across regions. Freitag et al. [267] note that current ICT-related climate regulations are lagging and piecemeal, requiring companies to navigate a regulatory critique and adjust to shifting goalposts. Moreover, different jurisdictions impose a patchwork of regulations, creating complexity for global operators. Laws and standards vary widely between local, national, and international levels, making it hard to implement uniform low-carbon practices across data centers and digital operations. As UN CODES stressed [266], greater international coordination is needed to align the intent of key digital regulations across geographies. The lack of global metrics is also impeding the transition to a zero-carbon digital infrastructure. Currently, there is no internationally recognized benchmark for what constitutes low-carbon or energy-efficient operations in data centers, AI training, or blockchain mining. As a result, effective regulation is hampered by insufficient data on energy use and emissions in these sectors.

Cryptocurrency regulations also vary significantly across jurisdictions due to differences in legal frameworks, government attitudes, and the maturity of the crypto industry in each country [268]. For example, even within a single country, the United States, federal and state authorities take different approaches [269]: The Securities and Exchange Commission (SEC) regulates cryptocurrencies as securities, where applicable, with a focus on investor protection; the Commodity Futures Trading Commission (CFTC) treats certain cryptocurrencies as commodities, linking derivative markets; and the Internal Revenue Service (IRS) classifies cryptocurrencies as property for tax purposes. Therefore, as with AI, there are bound to be policy difficulties in achieving low-carbon innovations for cryptocurrencies.

Infrastructure constraints caused by existing power and digital infrastructure are also critical institutional barriers. In many regions, there is insufficient electricity transmission capacity to meet the high electricity demand projected for AI-intensive data centers. Very slow electricity infrastructure permitting processes can make the timeline for new power generation and transmission capacity much longer than the timeline for building new data centers and cryptocurrency mining operations. In the U.S., for example, data centers can be developed and connected to the grid in less than two years, while new power generation and transmission can take four years or more [270]. Legacy IT systems and aging infrastructure are also often incompatible with newer, more energy-efficient technologies. Retrofitting existing facilities with sustainable energy technologies can be costly and may not be the optimal solution from an economic decision point of view, given the long lifespan of power and digital infrastructure [271].

Market dynamics can also complicate the adoption of sustainable energy options. Volatile energy prices and inconsistent availability make it difficult for data centers and computing resources to secure stable, long-term contracts for low- or zero-carbon electricity [272]. Even in a country with a regulated electricity market system, such as South Korea, renewable and clean energy may not be economically feasible [273]. Meanwhile, the competitive nature of the tech industry often prioritizes rapid growth and cost reduction over long-term sustainability investments [274]. The lack of standardized sustainability reporting and transparency also hinders the ability of consumers and investors to make proper decisions, reducing accountability for environmental impact.

Skills gaps are another critical barrier to implementing advanced low- or zero-carbon innovations. Integrating sustainable energy practices into data center operations requires significant expertise. Professionals with deep knowledge of advanced digital technologies and sustainable energy solutions are scarce. While policymakers are growing concerned about the energy and water demands of large-scale AI models and cryptocurrency, the topic remains highly technical and poorly understood outside of specialist circles [275]. The rapid development of AI, data centers, cryptocurrency, and clean energy technologies requires continuous learning, yet many universities and educational institutions struggle to adapt their curricula quickly enough to meet industry needs.

4.3. Behavioral barriers

A classic behavioral barrier, known as “resistance to change,” is one of the key hurdles in the energy and AI space in terms that both AI software developers and data center managers are unlikely to change their practices without significant incentives. In an OECD survey [276], about half of companies cited high costs and lack of skills as barriers, but a significant proportion also said they were “not convinced by the technology.” Managers remain skeptical about the value of AI or unsure how it fits into their business model, reflecting a lack of understanding of AI's potential role in energy efficiency and economic benefits. Such skepticism and internal misalignment of incentives can stifle adoption. De Freitas et al. [277] categorized the perceived problems with AI in following categories: opacity (AI is a “black box” and not understandable), emotionlessness (AI lacks moral judgment), rigidity (AI is seen as inflexible), autonomy (fear of AI making decisions independent of human control), and group membership (people view AI as an out-group agent). Improving the usability and transparency of AI applications is therefore critical to building positive attitudes.

Other human factors, such as a lack of executive prioritization, misaligned staff incentives, and siloed IT and facilities teams, could act as critical barriers to low-carbon options for AI. If only upper management cares about energy, for instance, improvements will stall because IT and facilities personnel have no direct incentives to act [278]. The complex ecosystem surrounding AI, cryptocurrency, and data center operations involves a wide range of stakeholders, including hardware manufacturers, software developers, energy providers, and end users. Achieving stakeholder alignment is thus another major barrier to advancing sustainability. The diverse priorities of technical teams, management, and external partners often lead to conflicts when implementing low- or zero-carbon innovations [279]. Overcoming these barriers requires education, best practices (well-designed demonstration projects), and clear communication of the tangible benefits that sustainable energy technologies can bring. The barriers in the three aforementioned areas can be summarized as shown in Table 5.

Table 5
Barriers to innovations for AI, data centers and cryptocurrency mining.

Category	Barrier	Subjects	References
Technological	Clean power vs. reliable large-scale supply dilemma	Electricity demands	[162]
	Grid readiness for renewables	Grid infrastructure and storages	[75]
	Cooling/thermal management constraints	Cooling system	[259,260]
	Water use for cooling	Cooling system	[261]
	Hardware-architecture inefficiency	Computing hardware	[262]
	Risk of stalled efficiency gains/ rebound	Electricity (energy) use	[263]
Institutional, political and economic	Fragmented jurisdictions and costly compliance	Standards, codes and regulations	[265,266]
	Lagging & piecemeal ICT climate regulation	Standards, codes and regulations	[267]
	Patchwork rules; lack of global metrics	Standards, codes and regulations (local/ international rules)	[266,268, 269]
	Electricity infrastructure constraints and slow permitting	Grid infrastructure	[270]
	Legacy systems and retrofit economics	Digital infrastructure	[271]
	Volatile prices and inconsistent availability	Market	[272]
	Uneconomic clean energy (in certain economies)	Market	[273]
	Skills gaps & slow curriculum adaptation	Education (learning)	[275]
Behavioral	"Resistance to change" and skepticism	Developers and managers	[276]
	Perceived AI problems (trust/ acceptance)	Public	[277]
	Misaligned incentives and organizational silos	Policy makers, IT/ facilities teams	[278]
	Stakeholder misalignment across the ecosystem	Stakeholders	[279]

Source: Authors.

5. Policy options for more sustainable AI, data centers and digitalization

Addressing the barriers to implementing low- or zero-carbon innovations for AI and data centers requires a multifaceted approach that includes strategic initiatives and policy interventions. Policy interventions can be categorized as those that apply directly to key digital applications and infrastructure. For example, AI algorithms and data centers, as well as those that simply support the adoption of clean energy for data center power consumption, such as broad GHG emissions targets and related policies and regulations. General decarbonization policies such as carbon taxes, offsets, credits, and emissions trading schemes, as well as unique options for AI, cryptocurrencies, and data centers are also effective in overcoming technological, institutional, and behavioral barriers. Table 6 presents the classification results that align the policy options using the categories proposed by the IEA 4E TCP (Technology Collaboration Programme on Energy Efficient End-use Equipment) [285] and the four barriers outlined in the previous section.

Table 6
Policy options to overcome the barriers to more sustainable AI use.

Policy categories	Effective to			
	Policy barriers	Technological barriers	Institutional barriers	Behavioral barriers
Government permitting schemes - Power Usage Effectiveness metric - Green Permits (Singapore) etc.	✔✔	✔✔	✔✔	✔
Minimum energy/ carbon performance standards - Energy standards (China) - Energy Efficiency Law (Germany) - Data center energy benchmark (Japan) - Voluntary best practice guideline (India) etc.	✔	✔✔		✔✔
Public sector procurement - Federal data center optimization initiative (US) - Green public procurement guidelines (EU) - Cloud First initiative (Singapore) etc.			✔✔	✔✔
Incentive Schemes - Carbon taxes, offset, and credit [280,281] - Carbon pricing (emission trade system) - Green taxonomy and Corporate Sustainability Reporting Directive (EU) - Tax exemption (France) - Incentives for renewable-powered crypto mining (Uzbekistan) - Utility rebates and grants (US) etc.		✔✔		✔✔
Voluntary Agreements - Code of Conduct for data centers (EU) - Crypto Climate Accord [282] etc.			✔✔	✔✔
Energy Reporting Obligations - Energy efficiency labels for data centers [283] - Sustainability risk assessment under AI Act [284]	✔✔		✔✔	✔✔

(continued on next page)

Table 6 (*continued*)

Policy categories	Effective to			
	Policy barriers	Technological barriers	Institutional barriers	Behavioral barriers
- Mandatory data center energy reports (EU) etc.				

Note: One ✔ refers to "sometimes," two checks ✔✔ refers to "usually."
Source: Authors.

Government permitting schemes require AI industries and data centers to meet specific energy efficiency and carbon reduction standards as part of the approval process. By tying permits to energy or carbon criteria, these policies address policy and institutional barriers (ensuring robust oversight where none existed) and technological barriers (forcing adoption of efficient designs). They could also influence behavior, as companies must plan greener projects to secure permits. By requiring best practices upfront, permitting schemes overcome inertia and "lock-in" low-carbon performance for decades. However, they require strong governance capacity and may slow expansion if set too strictly.

Minimum energy/carbon performance standards set mandatory efficiency thresholds or improvement targets that AI industries and data centers must meet, often by law. They directly tackle technological barriers (by phasing out inefficient equipment and practices) and behavioral barriers (forcing organizations to prioritize energy efficiency). They could also fill policy gaps by establishing baseline requirements for industry.

Public sector procurement policies leverage government buying power to demand energy-efficient, low-carbon digital infrastructure. By requiring green criteria in the data centers and cloud services that governments use, these policies overcome institutional barriers (e.g. fragmented efforts across agencies) and drive market change, sending a clear signal to industry. They also address behavioral barriers by leading by example: when the public sector insists on efficiency, it normalizes the behavior for other customers and providers. Procurement rules can cover government-owned facilities as well as contracts with private data center service providers.

Incentive schemes use financial carrots to encourage low- or zero-carbon innovations. These include tax credits, rebates, grants, favorable tariffs, or conversely carbon fees and charges. Such policy measures directly tackle economic and behavioral barriers: they improve the profitability of efficiency or renewable investments and nudge companies that might otherwise focus on short-term costs. Incentives also help overcome technological barriers by offsetting the higher upfront cost of innovative solutions. Implementing a carbon tax specifically for cryptocurrency and AI activities would require new tax frameworks. This could increase national revenues while promoting the transition to renewable energy and mitigating environmental burdens on the public [286], but at the same time, the policymakers should be careful about double taxation, as carbon taxes typically apply to electricity generation. A practical design implication is that demand-side taxes on data-center or mining loads should either be integrated with upstream power-sector carbon pricing (crediting the upstream price) or structured as performance-based fees (e.g., tied to verified load flexibility, emissions intensity, or heat-reuse) to avoid duplicative pricing of the same emissions. Carbon credits specifically stimulate emissions reductions, often based on blockchain technology [287], derived from ecosystem restoration projects, renewable energy deployment, or advanced carbon capture technologies.

Voluntary agreements involve industry stakeholders committing to certain targets or best practices without direct legal mandates. They address behavioral and institutional barriers by fostering collaboration, information sharing, and peer pressure to improve. While not enforced by law, they often arise in response to the threat of regulation or public concern, and they can pave the way for future standards. For AI, data centers, and digital services, voluntary initiatives create a platform to tackle issues such as efficiency standards, renewable energy adoption, and research & development, in a more flexible way.

Energy reporting obligations require AI industries, data center operators, and crypto miners to measure and disclose their energy use and efficiency metrics. This type of policy addresses a fundamental informational barrier. The lack of data on energy performance has made it difficult to manage or improve efficiency. By requiring reporting, these policies also address behavioral barriers: simply having to report can incentivize companies to improve in order to avoid looking bad publicly. In addition, transparency creates accountability and enables institutional learning, leading to better policies in the future.

6. Conclusions and research frontiers

This comprehensive review reveals a fundamental insight: achieving sustainable digitalization requires simultaneous interventions across all four sociotechnical domains. No single solution, whether related to energy supply, energy efficiency, policy or other types of interventions covered, will suffice in isolation. Instead, coordinated action spanning natural resource management, manufacturing processes, infrastructure design, and institutional frameworks is essential. Our analysis of barriers further demonstrates that technological innovations alone cannot drive this transition; they must be coupled with policy innovations that address fragmented governance, market failures, and behavioral resistance.

The intersection of digitalization—including AI, cloud computing, data centers and cryptocurrencies—and sustainable energy presents a complex and dynamic sociotechnical system that requires careful consideration and strategic action. In this paper, we have explored the multifaceted relationship between them and identified the STS of sustainable energy solutions for digitalization. We have also examined the barriers to the implementation of innovations for sustainable growth in digitalization and proposed a set of policy options to overcome these barriers (Fig. 9).

The rapid advancement of AI technologies offers unprecedented opportunities to optimize energy systems, improve efficiency, and accelerate the transition to renewable and zero-carbon energy sources. From enhancing weather forecasting for renewable energy generation to optimizing grid management and improving energy storage systems, AI has the potential to address key challenges in integrating intermittent renewable energy sources into existing power grids. These applications can support efforts to triple renewable energy capacity and double energy efficiency by 2030, as outlined in the international climate agreements of COP28 [5].

The STS of the energy and digitalization nexus encompasses technological, economic, environmental, social, and policy dimensions. Each of these dimensions plays a crucial role in shaping the dynamics of energy consumption and digital transformation. To address the surging energy demands of AI, data centers and other digitalization technologies, particularly cryptocurrencies, a range of low- and zero-carbon solutions and innovations have been proposed and implemented. These include the use of nuclear energy, integration of renewable energy sources, AI-driven energy optimization, advanced cooling technologies, and efficient infrastructure.

Despite the investigation of sustainable energy solutions for digitalization using a newly developed sociotechnical lens, there is still significant potential for further research. In light of this review, we have proposed the following nine-point research agenda.

1. *Future demand growth and scalability*: While this review has examined the energy demand associated with the expansion of AI, data centers, and cryptocurrencies, there is still a great deal of uncertainty in the outlook for future electricity demand. In addition, the emergence of large-scale reinforcement learning without supervised fine-tuningmakes forecasting energy demand difficult. Therefore, more

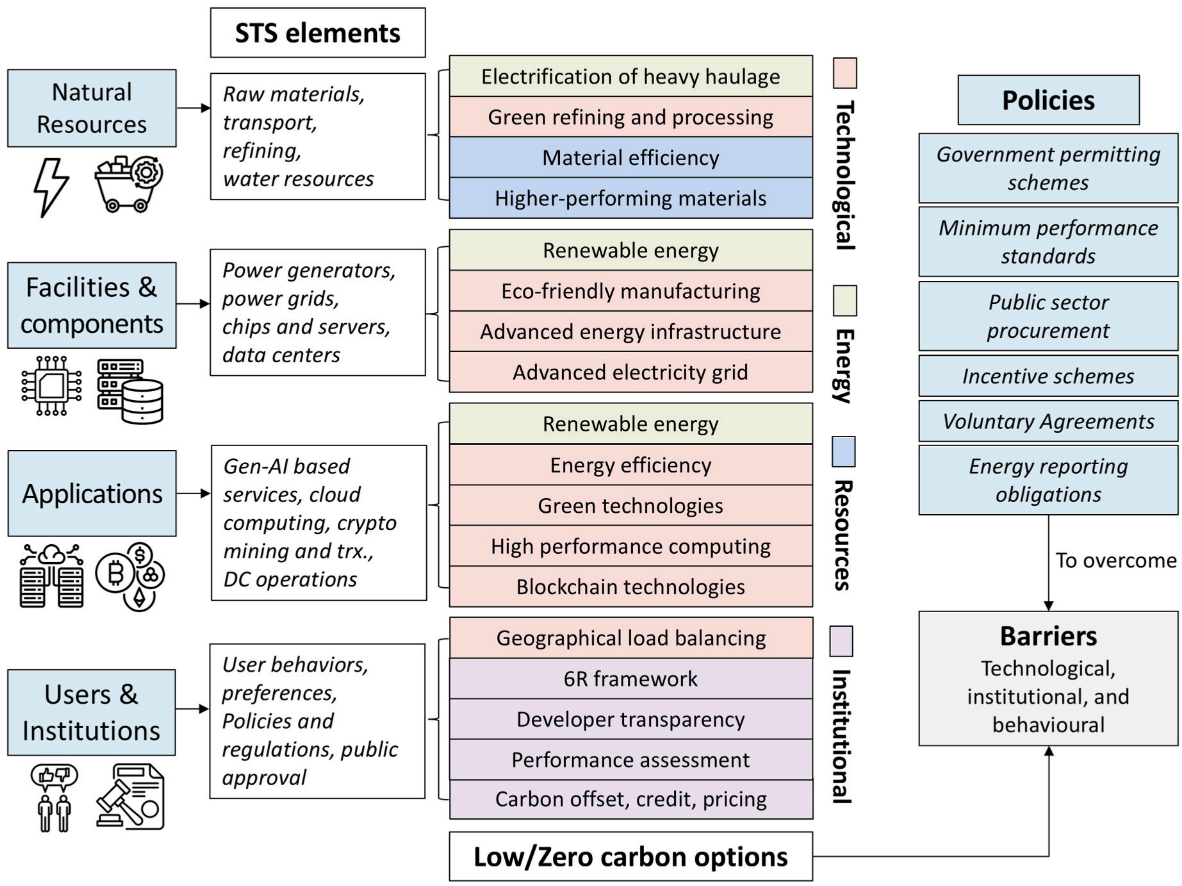

Fig. 9. Sociotechnical system of energy and digitalization, and low-carbon innovations.
Source: Authors.

research is needed on the outlook for electricity consumption. Investigations should differentiate between energy requirements of various AI applications, including generative AI, real-time analytics, and autonomous systems, as well as diverse cryptocurrency protocols. In addition, assessing genuine long-term growth from temporary "hype cycles" are essential to inform policymakers and infrastructure planners.

2. *Global distribution of data centers*: Equitably engaging the Global South in data center infrastructure growth necessitates examination of implications such as grid reliability challenges and limited renewable energy availability. The Global North functions as the epicenter of AI development to date. By hosting cutting-edge computing resources, these countries can impose regulations on AI training processes and shape the types of AI systems that enter global markets. In contrast, the Global South serves as a hub for AI deployment, where governments can control which AI applications are implemented locally, but have limited influence over development. As AI becomes a tool of economic, military, and cultural power, countries compete to secure and control these infrastructures [288]. Future studies should investigate the opportunities and barriers to expanding data center operations in developing regions, including renewable energy resource availability, regulatory frameworks, infrastructure deficits, and workforce development. Research should also focus on enhancing international collaboration and investments to address energy and infrastructure gaps, promoting global digital equity.
3. *Technological and operational efficiency*: Innovations in cooling technologies, energy-efficient processors, and advanced energy storage systems warrant focused research to substantially decrease the energy footprint of AI and cryptocurrency operations. Moreover, leveraging AI and blockchain technologies themselves for operational optimization and energy minimization is a promising research frontier. Adaptive load management strategies aligning data center operations with renewable energy availability should also be rigorously examined. In addition, as we have discussed in this paper, they all focus on infrastructure efficiency rather than IT hardware efficiency. This highlights a gap, namely that current standards largely ignore IT efficiency, which is a missed opportunity. Thus, future research and policy may need to target efficiency and utilization, particularly in data centers for AI, more directly. Advancing the design of hardware and computing infrastructure to dramatically improve energy efficiency for AI workloads could be another critical area.
4. *Community and environmental impacts*: Research should closely assess the social and environmental impacts of data center siting, particularly in communities experiencing water scarcity or limited land availability. Developing frameworks for community engagement by data center operators to ensure equitable outcomes and minimize disruptions is essential. In addition, research on evaluating trade-offs between economic benefits—such as job creation and infrastructure development—and resource consumption within host communities will inform sustainable development practices. Lifecycle assessment of the environmental footprint of AI could be another powerful research topic. Previous work reminds us that AI's environmental impact is multidimensional, encompassing hardware manufacturing, supply chains, and end-of-life disposal, not just electricity consumption. To ensure that we are truly moving toward a low- and zero-carbon digital infrastructure, research must fill gaps in understanding these indirect impacts.

5. *Equity and justice considerations*: Future research must analyze how energy-intensive data centers either exacerbate or alleviate local energy inequities. Policy studies should identify mechanisms to prevent adverse effects on energy affordability for communities hosting data centers. Aligning data center development with energy justice principles, especially in energy-constrained regions, requires deeper exploration to provide policymakers with actionable insights.
6. *Cryptocurrency-specific challenges*: Exploring alternative consensus mechanisms such as Proof of Stake and Proof of Space to replace energy-intensive Proof of Work models presents a significant research opportunity. Integrating comprehensive energy and environmental cost assessments into cryptocurrency valuation frameworks is also critical. Additionally, evaluating the potential energy implications of decentralized finance (DeFi) applications under widespread adoption scenarios will offer valuable foresight.
7. *Policy and regulation*: The review highlights various policy measures to overcome barriers to implementing sustainable energy options for AI, data centers, and cryptocurrencies. However, as we can see from the review results, most of the measures are still in the early stages and there are many areas that need to be refined in the future. Researchers should further explore mechanisms ensuring fair distribution of costs between data centers and local utilities regarding grid upgrades and renewable energy initiatives. Furthermore, the development and enforcement of international standards for data center energy efficiency and sustainability represent critical policy research avenues. In addition to the metrics presented in this report, there is a need to develop transparent, robust methods for measuring and reporting the energy and environmental footprint of AI systems. Building on calls from previous work, researchers should establish standards for reporting computational energy, carbon emissions, and training times for AI models.
8. *Cross-sector interactions*: Investigating the potential of AI infrastructure and data centers as "prosumers," capable of generating renewable energy and providing grid services such as demand response and backup power, should be prioritized. Understanding how data centers can support electrification initiatives in adjacent sectors, including transportation and manufacturing, through synergistic grid interactions is also essential. Lastly, research on partnerships between tech companies, utilities, and governments to accelerate grid modernization to accommodate rising data center demands will be instrumental in ensuring future energy security.
9. *Organizational and behavioral change in AI practice*: Lastly, future research must address the institutional and behavioral dimensions of adopting green AI solutions and innovations, such as how to change mindsets, cultures, and incentives within organizations that develop or deploy AI. As explored in this study, there are many institutional and behavioral barriers to the sustainable energy future of digitalization. Studies of data centers and AI infrastructure show that operators may be reluctant to adopt energy-saving measures due to fears of compromising reliability, siloed organizational structures, or simply a lack of awareness and training. To overcome these, we need research on how to effectively embed sustainability into the decision-making and culture of AI-focused organizations.

We note that a number of topics included in this research agenda are actively discussed in grey literature sources and hence our contribution is to synthesize and map what is supported in the peer-reviewed scholarly literature and to highlight where validation and comparative analysis remain limited. The latter is particularly important for supporting the evidence-based policymaking that should be foundational in steering the future growth of AI, data centers, cryptocurrencies and related digital technologies and infrastructure.

The window for action is narrowing. With AI-driven electricity demand growing rapidly and global climate commitments requiring immediate emissions reductions, the luxury of incremental progress no longer exists. This review demonstrates that sustainable digitalization is technically feasible and the innovations exist across all four sociotechnical domains. What remains is the challenge of implementation with particular emphasis on aligning technological innovation with policy frameworks, overcoming institutional inertia, and transforming organizational cultures. The sociotechnical framework presented here offers insights, but success will ultimately depend on unprecedented coordination between technologists, policymakers, industry leaders, and civil society. The research agenda we propose is not merely academic but rather a call for the interdisciplinary collaboration necessary to ensure that the most powerful digital technologies support, rather than undermine, our collective future.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: RSER-D-25-00646 Given my role as Associate Editor of the journal, Steven Griffiths had no involvement in the peer review of this article and had no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor.

Appendix

Table A1
Comparison of traditional and digital STS.

Dimension	Traditional STS	Digital STS
Era and time	Industrial and Computer: 1950-2010	Digital Era: 2011–current–future
Technology	Mechanical and computer technologies	Digital, machine learning/AI
What leads to high performance	The organization's social and technical work system optimization and fit. Absorption of uncertainty.	Social (stakeholder motivations), Technical (work processes), digital technology, and information optimization and fit. Agility the in face of uncertainty and variation.
Unit of analysis for design	The organization and its work units	Ecosystem
Technical system	Internal focus, linear, routine, production/office processes	Internal and external focus, network of activity, nonlinear, uncertain, e.g., customer user journey
Social system	Workers, work processes, and management	Ecosystem/network
Work system	Work units—jobs, roles, teams, and workflow regulation. Interpersonal deliberations and iterations.	Operating model—Smart teams with digital system central to coordination, integration, and learning. Work systems that cut across organizations and include stakeholders and members of the relevant ecosystem

(*continued on next page*)

Table A1 (*continued*)

Dimension	Traditional STS	Digital STS
Cybernetic system	Self-regulation	Artificial intelligence, decision criteria and support built into digital system, continuous learning system
Approach to design	Design project by project: Implementation, assessment and iteration	Continuous design: research, accelerated design and build, measure, learn, and iterate. Automated data and feedback providing ongoing sensing of problems and opportunities and trigger redesign.

Source: [59].

Data availability

No data was used for the research described in the article.

References

[1] Kaack LH, Donti PL, Strubell E, Kamiya G, Creutzig F, Rolnick D. Aligning artificial intelligence with climate change mitigation. Nat Clim Change 2022;12:518–27.
[2] Creutzig F, Acemoglu D, Bai X, Edwards PN, Hintz MJ, Kaack LH, et al. Digitalization and the anthropocene. Annu Rev Environ Resour 2022;47:479–509.
[3] Gradillas M, Thomas LDW. Distinguishing digitization and digitalization: a systematic review and conceptual framework. J Prod Innovat Manag 2025;42:112–43.
[4] Bockshecker A, Hackstein S, Baumöl U. Systematization of the term digital transformation and its phenomena from a socio-technical perspective–A literature review. 26th European conference on information systems (ECIS). United Kingdom: Portsmouth; 2018.
[5] UNFCCC. COP28: global renewables and energy efficiency pledge. UAE: UNFCCC; 2023.
[6] Ammanath B. How to manage AI's energy demand — today, tomorrow and in the future. Switzerland: World Economic Forum; 2024.
[7] Luccioni S, Gamazaychikov B, Hooker S, Pierrard R, Strubell E, Jernite Y, et al. Light bulbs have energy ratings—so why can't AI chatbots? Nature 2024;632:736–8.
[8] IEA. Data centres and data transmission networks. International Energy Agency; 2025.
[9] Kemene E, Valkhof B, Tladi T. AI and energy: will AI help reduce emissions or increase demand? here's what to know. Switzerland: World Economic Forum; 2024.
[10] Benes KJ, Porterfield JE, Yang C. AI for energy: opportunities for a modern grid and clean energy economy. Washington D.C.: U.S. Department of Energy; 2024.
[11] Shehabi A, Smith SJ, Masanet E, Koomey J. Data center growth in the United States: decoupling the demand for services from electricity use. Environ Res Lett 2018;13:124030.
[12] Sachs G. AI is poised to drive 160% increase in data center power demand. Goldman Sachs; 2024.
[13] Chow AR. How AI is fueling a boom in data centers and energy demand. Time; 2024.
[14] Ramachandran KSD, Hardin K, Crossan G. As generative AI asks for more power, data centers seek more reliable. Cleaner energy solutions. Deloitte; 2024.
[15] IEA. Electricity 2024. Analysis and forecast to 2026. Paris: International Energy Agencey; 2024.
[16] IEA. World energy outlook 2024. Paris: International Energy Agency; 2024.
[17] Lange S, Pohl J, Santarius T. Digitalization and energy consumption. Does ICT reduce energy demand? Ecol Econ 2020;176:106760.
[18] Arman Shehabi SJS, Hubbard Alex, Newkirk Alex, Lei Nuoa, Abu Md, Bakar Siddik BH, Koomey Jonathan, Masanet Eric, Sartor Dale. 2024 United States data center energy usage report. Lawrence Berkeley National Laboratory; 2024.
[19] IEA. Energy and AI. World energy outlook special report. Paris: International Energy Agency; 2025.
[20] Zhang D, Chen XH, Lau CKM, Xu B. Implications of cryptocurrency energy usage on climate change. Technol Forecast Soc Change 2023;187:122219.
[21] Faucheux S, Nicolaï I. IT for green and green IT: a proposed typology of eco-innovation. Ecol Econ 2011;70:2020–7.
[22] Wang E-Z, Lee C-C. The impact of information communication technology on energy demand: some international evidence. Int Rev Econ Finance 2022;81:128–46.
[23] Schulte P, Welsch H, Rexhäuser S. ICT and the demand for energy: evidence from OECD countries. Environ Resour Econ 2016;63:119–46.
[24] Li X, Lepour D, Heymann F, Maréchal F. Electrification and digitalization effects on sectoral energy demand and consumption: a prospective study towards 2050. Energy 2023;279:127992.
[25] Morley J, Widdicks K, Hazas M. Digitalisation, energy and data demand: the impact of internet traffic on overall and peak electricity consumption. Energy Res Social Sci 2018;38:128–37.
[26] Berkhout F, Hertin J. De-materialising and re-materialising: digital technologies and the environment. Futures 2004;36:903–20.
[27] Antonopoulos I, Robu V, Couraud B, Kirli D, Norbu S, Kiprakis A, et al. Artificial intelligence and machine learning approaches to energy demand-side response: a systematic review. Renew Sustain Energy Rev 2020;130:109899.
[28] Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, et al. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. J Clean Prod 2021;289:125834.
[29] Rozite Vm J, Oh S. Why AI and energy are the new power couple. International Energy Agency; 2023.
[30] Abisoye BO, Sun Y, Zenghui W. A survey of artificial intelligence methods for renewable energy forecasting: methodologies and insights. Renew Energy Focus 2024;48:100529.
[31] Jha SK, Bilalovic J, Jha A, Patel N, Zhang H. Renewable energy: present research and future scope of artificial intelligence. Renew Sustain Energy Rev 2017;77:297–317.
[32] Aderibigbe AO, Ani EC, Ohenhen PE, Ohalete NC, Daraojimba DO. Enhancing energy efficiency with ai: a review of machine learning models in electricity demand forecasting. Eng. Sci. Technol. J. 2023;4:341–56.
[33] Mousavi S, Villarreal-Marroquín MG, Hajiaghaei-Keshteli M, Smith NR. Data-driven prediction and optimization toward net-zero and positive-energy buildings: a systematic review. Build Environ 2023;242:110578.
[34] Greening LA, Greene DL, Difiglio C. Energy efficiency and consumption—the rebound effect—a survey. Energy Policy 2000;28:389–401.
[35] Chinoracky R, Kurotova J, Janoskova P. Measuring the impact of digital technologies on transport industry–macroeconomic perspective. Transp Res Procedia 2021;55:434–41.
[36] Dhar P. The carbon impact of artificial intelligence. Nat Mach Intell 2020;2:423–5.
[37] Rouch MDA, Hanbury P, Renno P, Gray E. AI's power surge: the looming data center energy challenge. Bain & Company; 2024.
[38] Howland E. Trump plans to use emergency powers to fast-track generation co-located with AI, https://www.utilitydive.com/news/trump-emergency-co-located-power-plants-ai-data-center-davos/738209/; 2025 [accessed 11 June 2025].
[39] Granskog AvS S, Diaz DH, Noffsinger J, Moavero L, Schdeva P, Bhan A. The role of power in unlocking the European AI revolution. McKinsey & Company; 2024.
[40] Gang C. In: Energy-guzzling AI industry threatens China's green transition; 2024. Think China.
[41] de Vries-Gao A. The carbon and water footprints of data centers and what this could mean for artificial intelligence. Patterns 2025:101430.
[42] Ishida H. The effect of ICT development on economic growth and energy consumption in Japan. Telematics Inf 2015;32:79–88.
[43] Greene-Dawasmes GTT. AI's energy dilemma: challenges, opportunities, and a path forward. World Economic Forum; 2025.
[44] Liu Y, Wei X, Xiao J, Liu Z, Xu Y, Tian Y. Energy consumption and emission mitigation prediction based on data center traffic and PUE for global data centers. Glob. Energy Interconnect. 2020;3:272–82.
[45] Zakarya M, Khan AA, Qazani MRC, Ali H, Al-Bahri M, Khan AUR, et al. Sustainable computing across datacenters: a review of enabling models and techniques. Comput Sci Rev 2024;52:100620.
[46] Yakhchi M, Ghafari SM, Yakhchi S, Fazeli M, Patooghy A. Proposing a load balancing method based on Cuckoo optimization algorithm for energy management in cloud computing infrastructures. In: 2015 6th international conference on modeling, simulation, and applied optimization (ICMSAO). IEEE; 2015. p. 1–5.
[47] Manimegalai R, Sandhanam S, Nandhini A, Pandia P. Energy efficient coding practices for sustainable software development. In: Proceedings of the first international conference on science, engineering and technology practices for sustainable development. ICSETPSD; 2023. 17th-18th November 2023, Coimbatore, Tamilnadu, India2024.
[48] Castro V, Georgiou M, Jackson T, Hodgkinson IR, Jackson L, Lockwood S. Digital data demand and renewable energy limits: forecasting the impacts on global electricity supply and sustainability. Energy Policy 2024;195:114404.
[49] Howland E. FERC rejects interconnection pact for talen-amazon data center deal at nuclear plant, https://www.utilitydive.com/news/ferc-interconnection-isa-talen-amazon-data-center-susquehanna-exelon/731841/; 2024 [accessed 13 June 2025].
[50] Martucci B. Meta seeks up to 4 GW of new nuclear power to help meet AI, sustainability objectives, https://www.utilitydive.com/news/meta-seeks-up-to-4-gw-of-new-nuclear-power-to-help-meet-ai-sustainability/734599/; 2024 [accessed 22 June 2025].
[51] Vega A, Bose P, Buyuktosunoglu A. Rugged embedded systems: computing in harsh environments. Cambridge, MA: Elsevier; 2017.

[52] Tian K., Qiao L., Liu B., Jiang G., Li D. A survey on memory-efficient large-scale model training in AI for science. arXiv preprint arXiv:250111847 2025.https://doi.org/10.48550/arXiv.2501.11847.
[53] Bourzac K. Fixing AI's energy crisis. Nature outlook. Springer Nature; 2024.
[54] Hellenbrand M, Bakhit B, Dou H, Xiao M, Hill MO, Sun Z, et al. Thin film design of amorphous hafnium oxide nanocomposites enabling strong interfacial resistive switching uniformity. Sci Adv 2023;9.
[55] Geels FW, Sovacool BK, Schwanen T, Sorrell S. The socio-technical dynamics of low-carbon transitions. Joule 2017;1:463–79.
[56] Sovacool BK, Baum CM, Low S. Reviewing the sociotechnical dynamics of carbon removal. Joule 2023;7:57–82.
[57] Imran F, Shahzad K, Butt A, Kantola J. Digital transformation of industrial organizations: toward an integrated framework. J Change Manag 2021;21:451–79.
[58] Reis J, Amorim M, Melão N, Cohen Y, Rodrigues M. Digitalization: a literature review and research agenda. In: Proceedings on 25th international joint conference on industrial engineering and operations Management–IJCIEOM: the next generation of production and service systems 25. Springer; 2020. p. 443–56.
[59] Winby S, Mohrman SA. Digital sociotechnical system design. J Appl Behav Sci 2018;54:399–423.
[60] Kim J, Sovacool BK, Bazilian M, Griffiths S, Lee J, Yang M, et al. Decarbonizing the iron and steel industry: a systematic review of sociotechnical systems, technological innovations, and policy options. Energy Res Social Sci 2022;89:102565.
[61] Chung C, Kim J, Sovacool BK, Griffiths S, Bazilian M, Yang M. Decarbonizing the chemical industry: a systematic review of sociotechnical systems, technological innovations, and policy options. Energy Res Social Sci 2023;96:102955.
[62] Griffiths S, Sovacool BK, Kim J, Bazilian M, Uratani JM. Decarbonizing the oil refining industry: a systematic review of sociotechnical systems, technological innovations, and policy options. Energy Res Social Sci 2022;89:102542.
[63] Griffiths S, Sovacool BK, Del Rio DDF, Foley AM, Bazilian MD, Kim J, et al. Decarbonizing the cement and concrete industry: a systematic review of socio-technical systems, technological innovations, and policy options. Renew Sustain Energy Rev 2023;180:113291.
[64] Edwards D, Cooper ZGT, Hogan M. The making of critical data center studies. Convergence 2025;31:429–46.
[65] Bao H, Knights P, Kizil M, Nehring M. Electrification alternatives for open pit mine haulage. Mining 2023;3:1–25.
[66] Chamanara S, Ghaffarizadeh SA, Madani K. The environmental footprint of bitcoin mining across the globe: call for urgent action. Earths Future 2023;11.
[67] Byeon M, Park J, Kim J-H, Kyung S, Lee MW, Kim J, et al. Decarbonization strategies in semiconductor manufacturing: reducing greenhouse gas emission and energy consumption in the CVD process. Int J Precis Eng Manuf Green Technol 2025. https://doi.org/10.1007/s40684-025-00783-4.
[68] Kim J, Sovacool BK, Bazilian M, Griffiths S, Yang M. Energy, material, and resource efficiency for industrial decarbonization: a systematic review of sociotechnical systems, technological innovations, and policy options. Energy Res Social Sci 2024;112:103521.
[69] George AS. Data centers and water crisis in India: why digital infrastructure could drain our Wells dry by 2030, vol. 3. Partners Universal Innovative Research Publication; 2025. p. 1–36.
[70] IEA. How will artificial intelligence transform energy innovation? Paris: International Energy Agency; 2024.
[71] Sang X, Leng X, Xue L, Ran X. Based on the time-spatial power-based cryptocurrency miner driving force model, establish a global CO2 emission prediction framework after China bans cryptocurrency. Sustainability 2022;14:5332.
[72] Lektomiller JM. Energy harvesting RFID circuit, energy harvesting RFID tag, and associated methods. Google Patents; 2019.
[73] Ge Y, Yin Q, Tan SK, Yao Q, Yeo BS, Seah W. GREEN: a grid-based energy efficient probabilistic routing in wireless sensor networks. In: 2005 IEEE 61st vehicular technology conference. IEEE; 2005. p. 2597–600.
[74] Vijay Kumar V, Shahin K. Artificial intelligence and machine learning for sustainable manufacturing: current trends and future prospects. Intell Sustain Manuf 2025;2:10002.
[75] Wu C-J, Acun B, Raghavendra R, Hazelwood K. Beyond efficiency: scaling AI sustainably. IEEE Micro; 2024.
[76] Jiang P, Sonne C, Li W, You F, You S. Preventing the immense increase in the life-cycle energy and carbon footprints of LLM-powered intelligent chatbots. Engineering 2024;40:202–10.
[77] Wang P, Zhang L-Y, Tzachor A, Chen W-Q. E-waste challenges of generative artificial intelligence. Nat Comput Sci 2024;4:818–23.
[78] Hojati E, Sill A, Mengel S, Sayedi SMB, Bilbao A, Schmitt K. A comprehensive monitoring, visualization, and management system for green data centers. IEEE Syst J 2025;19(1):119–29.
[79] Han J, Han K, Han T, Wang Y, Han Y, Lin J. Data-driven distributionally robust optimization of low-carbon data center energy systems considering multi-task response and renewable energy uncertainty. J Build Eng 2025;102:111937.
[80] Lal A, You F. Climate sustainability through AI-Crypto synergies and energy transition in the digital landscape to cut 0.7 GtCO2e by 2030. Environ Sci Technol 2025;59:6061–73.
[81] Wang Y, Guo Q, Chen M. Providing load flexibility by reshaping power profiles of large language model workloads. Adv Appl Energy 2025:100232.
[82] Chountalas PT, Chrysikopoulos SK, Agoraki KK, Chatzifoti N. Modeling critical success factors for green energy integration in data centers. Sustainability 2025;17:3543.
[83] Markovic DS, Zivkovic D, Branovic I, Popovic R, Cvetkovic D. Smart power grid and cloud computing. Renew Sustain Energy Rev 2013;24:566–77.
[84] Hajipour E, Khavari F, Hajiaghapour-Moghimi M, Hosseini KA, Vakilian M. An economic evaluation framework for cryptocurrency mining operation in microgrids. Int J Electr Power Energy Syst 2022;142:108329.
[85] Dodge J, Prewitt T, Tachet des Combes R, Odmark E, Schwartz R, Strubell E, et al. Measuring the carbon intensity of ai in cloud instances. In: Proceedings of the 2022 ACM conference on fairness, accountability, and transparency; 2022. p. 1877–94.
[86] Chien AA, Lin L, Nguyen H, Rao V, Sharma T, Wijayawardana R. Reducing the carbon impact of generative AI inference (today and in 2035). In: Proceedings of the 2nd workshop on sustainable computer systems; 2023. p. 1–7.
[87] Berthelot A, Caron E, Jay M, Lefèvre L. Estimating the environmental impact of Generative-AI services using an LCA-based methodology. Proced CIRP 2024;122:707–12.
[88] Gupta U, Jiang D, Balandat M, Wu C-J. Towards green, accurate, and efficient ai models through multi-objective optimization. Vienna, Austria: ICLR; 2023.
[89] Zhu C, Leung VC, Shu L, Ngai EC-H. Green internet of things for smart world. IEEE Access 2015;3:2151–62.
[90] Yu X, Hu Y, Zhou D, Wang Q, Sang X, Huang K. Carbon emission reduction analysis for cloud computing industry: can carbon emissions trading and technology innovation help? Energy Econ 2023;125:106804.
[91] Patel UA, Patel S, Nanavati J. Towards a greener future: harnessing green computing to reduce ICT carbon emissions. 2024 7th international conference on circuit power and computing technologies (ICCPCT). IEEE; 2024. p. 960–9.
[92] Rojek I, Mikołajewski D, Mroziński A, Macko M, Bednarek T, Tyburek K. Internet of things applications for energy management in buildings using artificial intelligence—A case study. Energies 2025;18:1706.
[93] Mohammed Z, Mohammed NUM, Mohammed A, Gunda SKR, Ansari MAA. AI-Powered energy efficient and sustainable cloud networking. J Cognit Comput Cyber Innovat 2025;1:31–6.
[94] Kohli V, Chakravarty S, Chamola V, Sangwan KS, Zeadally S. An analysis of energy consumption and carbon footprints of cryptocurrencies and possible solutions. Digit Commun Netw 2023;9:79–89.
[95] Yang X, Deb S. Cuckoo search via lévy flights proceedings of the World Congress on Nature and biologically inspired Computing. NABIC'09); December 2009. Coimbatore. India210–214.10.
[96] Yang X-S, Deb S. Cuckoo search: recent advances and applications. Neural Comput Appl 2014;24:169–74.
[97] Wajid U, Cappiello C, Plebani P, Pernici B, Mehandjiev N, Vitali M, et al. On achieving energy efficiency and reducing CO 2 footprint in cloud computing. IEEE Trans Cloud Comput 2015;4:138–51.
[98] Singh P, Dutta M, Aggarwal N. A review of task scheduling based on meta-heuristics approach in cloud computing. Knowl Inf Syst 2017;52:1–51.
[99] Arunarani A, Manjula D, Sugumaran V. Task scheduling techniques in cloud computing: a literature survey. Future Gener Comput Syst 2019;91:407–15.
[100] Soltani N, Soleimani B, Barekatain B. Heuristic algorithms for task scheduling in cloud computing: a survey. Int J Comput Netw Inf Secur 2017;11:16.
[101] Mezmaz M, Melab N, Kessaci Y, Lee YC, Talbi E-G, Zomaya AY, et al. A parallel bi-objective hybrid metaheuristic for energy-aware scheduling for cloud computing systems. J Parallel Distr Comput 2011;71:1497–508.
[102] Du H, Li Z, Niyato D, Kang J, Xiong Z, Huang H, et al. Diffusion-based reinforcement learning for edge-enabled AI-generated content services. IEEE Trans Mobile Comput 2024;23(9):8902–18.
[103] Wen J, Kang J, Niyato D, Zhang Y, Mao S. Sustainable diffusion-based incentive mechanism for generative AI-driven digital twins in industrial cyber-physical systems. IEEE Trans Ind Cyber-Phys Syst 2024;3:139–49.
[104] Su W, Li Z, Xu M, Kang J, Niyato D, Xie S. Compressing deep reinforcement learning networks with a dynamic structured pruning method for autonomous driving. IEEE Trans Veh Technol 2024;73(12):18017–30.
[105] Chaabouni T, Khemakhem M. Energy management strategy in cloud computing: a perspective study. J Supercomput 2018;74:6569–97.
[106] Khalid U, Ahmad SG, Chang B, Nisar MW, Cha J, Munir EU. Energy optimization in cloud computing environmentthrough virtual machine consolidation. 2023.
[107] Katal A, Dahiya S, Choudhury T. Energy efficiency in cloud computing data centers: a survey on software technologies, vol. 26. Cluster Computing; 2023. p. 1845–75.
[108] Park J, Han K, Lee B. Green cloud? An empirical analysis of cloud computing and energy efficiency. Manag Sci 2023;69:1639–64.
[109] Krebs R, Momm C, Kounev S. Architectural concerns in multi-tenant saas applications. Closer 2012;12:426–31.
[110] Bindhu V, Joe M. Green cloud computing solution for operational cost efficiency and environmental impact reduction. J ISMAC 2019;1:120–8.
[111] Manvi SS, Shyam GK. Resource management for infrastructure as a service (IaaS) in cloud computing: a survey. J Netw Comput Appl 2014;41:424–40.
[112] Masanet E. The energy efficiency potential of cloud-based software: a US case study. 2013.
[113] Bari MF, Chowdhury SR, Ahmed R, Boutaba R. On orchestrating virtual network functions. In: 2015 11th international conference on network and service management (CNSM). IEEE; 2015. p. 50–6.
[114] Bhardwaj S, Saxena S, Kamboj VK, Malik O. A sophisticated solution to numerical and engineering optimization problems using Chaotic Beluga Whale Optimizer. Soft Comput 2024;28:9803–43.
[115] Kotteswari K, Dhanaraj RK, Balusamy B, Nayyar A, Sharma AK. EELB: an energy-efficient load balancing model for cloud environment using Markov decision process. Computing 2025;107:1–41.

[116] Jannapureddy R, Vien Q-T, Shah P, Trestian R. An auto-scaling framework for analyzing big data in the cloud environment. Appl Sci 2019;9:1417.
[117] Heidari S, Buyya R. A cost-efficient auto-scaling algorithm for large-scale graph processing in cloud environments with heterogeneous resources. IEEE Trans Software Eng 2019;47:1729–41.
[118] Le Sueur E, Heiser G. Dynamic voltage and frequency scaling: the laws of diminishing returns. In: Proceedings of the 2010 international conference on power aware computing and systems; 2010. p. 1–8.
[119] Wibowo S, Wells M. Green cloud computing and economics of the cloud: moving towards sustainable future. GSTF J Comput 2016;5.
[120] Buyya R., Beloglazov A., Abawajy J. Energy-efficient management of data center resources for cloud computing: a vision, architectural elements, and open challenges. arXiv preprint arXiv:10060308 2010. https://doi.org/10.48550/arXiv.1006.0308.
[121] Hsu C-H, Slagter KD, Chen S-C, Chung Y-C. Optimizing energy consumption with task consolidation in clouds. Inf Sci 2014;258:452–62.
[122] Lee YC, Zomaya AY. Energy efficient utilization of resources in cloud computing systems. J Supercomput 2012;60:268–80.
[123] Hindman B, Konwinski A, Zaharia M, Ghodsi A, Joseph AD, Katz R, et al. Mesos: A platform for {Fine-Grained} resource sharing in the data center. In: 8th USENIX symposium on networked systems design and implementation (NSDI 11); 2011.
[124] Schwarzkopf M, Konwinski A, Abd-El-Malek M, Wilkes J. Omega: flexible, scalable schedulers for large compute clusters. In: Proceedings of the 8th ACM european conference on computer systems; 2013. p. 351–64.
[125] Vogels W. Beyond server consolidation: Server consolidation helps companies improve resource utilization, but virtualization can help in other ways, too. ACM Queue 2008;6:20–6.
[126] Ahmad I, Khalil MIK, Shah SAA. Optimization-based workload distribution in geographically distributed data centers: a survey. Int J Commun Syst 2020;33: e4453.
[127] Luccioni AS, Viguier S, Ligozat A-L. Estimating the carbon footprint of bloom, a 176b parameter language model. J Mach Learn Res 2023;24:1–15.
[128] Scao TL, Fan A, Akiki C, Pavlick E, Ilić S, Hesslow D, et al. BLOOM: a 176B-Parameter open-access multilingual language model. 2023.
[129] Kang Y, Hauswald J, Gao C, Rovinski A, Mudge T, Mars J, et al. Neurosurgeon: collaborative intelligence between the cloud and mobile edge. ACM SIGARCH Comput Architect News 2017;45:615–29.
[130] Touvron H., Lavril T., Izacard G., Martinet X., Lachaux M.-A., Lacroix T., et al. Llama: open and efficient foundation language models. arXiv preprint arXiv: 230213971. 2023. https://doi.org/10.48550/arXiv.2302.13971.
[131] Clemm C, Stobbe L, Wimalawarne K, Druschke J. Towards Green AI: current status and future research. In: 2024 electronics goes green 2024+(EGG). IEEE; 2024. p. 1–11.
[132] Schwartz R, Dodge J, Smith NA, Etzioni O. Green ai. Commun ACM 2020;63: 54–63.
[133] Alzoubi YI, Mishra A. Green artificial intelligence initiatives: potentials and challenges. J Clean Prod 2024:143090.
[134] Sikand S, Mehra R, Sharma VS, Kaulgud V, Podder S, Burden AP. Do generative AI tools ensure green code? An investigative study. In: Proceedings of the 2nd international workshop on responsible AI engineering; 2024. p. 52–5.
[135] Drax. The Government's AI plans will supercharge electricity demand. Electric insights. Selby: Drax; 2024.
[136] Koomey J. Growth in data center electricity use 2005 to 2010. Rep Anal Press, Completed New York Times 2011;9:161.
[137] Van Heddeghem W, Lambert S, Lannoo B, Colle D, Pickavet M, Demeester P. Trends in worldwide ICT electricity consumption from 2007 to 2012. Comput Commun 2014;50:64–76.
[138] Group I-TR. Top 10 energy-saving tips for a greener data center, vol. 11. Operate & Optimize Info-Tech Advisor Premium-operate; 2007.
[139] Ebrahimi K, Jones GF, Fleischer AS. A review of data center cooling technology, operating conditions and the corresponding low-grade waste heat recovery opportunities. Renew Sustain Energy Rev 2014;31:622–38.
[140] Zhang Q, Meng Z, Hong X, Zhan Y, Liu J, Dong J, et al. A survey on data center cooling systems: technology, power consumption modeling and control strategy optimization. J Syst Architect 2021;119:102253.
[141] You C, Huang K, Chae H. Energy efficient mobile cloud computing powered by wireless energy transfer. IEEE J Sel Area Commun 2016;34:1757–71.
[142] Huang K, Zhou X. Cutting the last wires for mobile communications by microwave power transfer. IEEE Commun Mag 2015;53:86–93.
[143] Shi W, Cao J, Zhang Q, Li Y, Xu L. Edge computing: vision and challenges. IEEE Internet Things J 2016;3:637–46.
[144] Mansouri Y, Babar MA. A review of edge computing: features and resource virtualization. J Parallel Distr Comput 2021;150:155–83.
[145] Satyanarayanan M. The emergence of edge computing. Computer 2017;50:30–9.
[146] Carrión D.S., Prohaska V. Exploration of TPUs for AI applications. arXiv preprint arXiv:230908918. 2023. https://doi.org/10.48550/arXiv.2309.08918.
[147] Miller DA. Attojoule optoelectronics for low-energy information processing and communications. J Lightwave Technol 2017;35:346–96.
[148] Nair PR, Dorai DR. Evaluation of performance and security of proof of work and proof of stake using blockchain. In: 2021 third international conference on intelligent communication technologies and virtual Mobile networks (ICICV). IEEE; 2021. p. 279–83.
[149] Lin S. Proof of work vs. proof of stake in cryptocurrency. Highlights in Science. Eng Technol 2023;39:953–61.
[150] Laimon M, Almadadha R, Goh S. Energy consumption of crypto mining: consequences and sustainable solutions using systems thinking and system dynamics analysis. Sustainability 2025;17:3522.
[151] Fernández-Blanco G, Froiz-Míguez I, Fraga-Lamas P, Fernández-Caramés TM. Design, implementation and practical energy-efficiency evaluation of a blockchain based academic credential verification system for low-power nodes. Appl Sci 2025;15:6596.
[152] Zhang T, Pota H, Chu C-C, Gadh R. Real-time renewable energy incentive system for electric vehicles using prioritization and cryptocurrency. Appl Energy 2018; 226:582–94.
[153] Náñez Alonso SL, Jorge-Vázquez J, Echarte Fernández MÁ, Reier Forradellas RF. Cryptocurrency mining from an economic and environmental perspective. Analysis of the most and least sustainable countries. Energies 2021;14:4254.
[154] Howson P, de Vries A. Preying on the poor? Opportunities and challenges for tackling the social and environmental threats of cryptocurrencies for vulnerable and low-income communities. Energy Res Social Sci 2022;84:102394.
[155] Castellanos JAF, Coll-Mayor D, Notholt JA. Cryptocurrency as guarantees of origin: simulating a green certificate market with the Ethereum Blockchain. In: 2017 IEEE international conference on smart energy grid engineering (SEGE). Ieee; 2017. p. 367–72.
[156] Bitir-Istrate I, Gheorghiu C, Gheorghiu M. The transition towards an environmental sustainability for Cryptocurrency mining. In: E3S web of conferences. EDP Sciences; 2021, 03004.
[157] Yan L, Mirza N, Umar M. The cryptocurrency uncertainties and investment transitions: evidence from high and low carbon energy funds in China. Technol Forecast Soc Change 2022;175:121326.
[158] Miśkiewicz R, Matan K, Karnowski J. The role of crypto trading in the economy, renewable energy consumption and ecological degradation. Energies 2022;15: 3805.
[159] Zheng M, Feng G-F, Zhao X, Chang C-P. The transaction behavior of cryptocurrency and electricity consumption. Financ Innov 2023;9:44.
[160] Andrae AS, Edler T. On global electricity usage of communication technology: trends to 2030. Challenges 2015;6:117–57.
[161] Belkhir L, Elmeligi A. Assessing ICT global emissions footprint: trends to 2040 & recommendations. J Clean Prod 2018;177:448–63.
[162] De Vries A, Gallersdörfer U, Klaaßen L, Stoll C. Revisiting Bitcoin's carbon footprint. Joule 2022;6:498–502.
[163] Fagundes Isolani L, Ribeiro Brasil D. The control of greenhouse gas emissions generated by the use of cryptocurrencies. Law Digit Technol 2023;3:18–25.
[164] Mustafa F, Mordi C, Elamer AA. Green gold or carbon beast? Assessing the environmental implications of cryptocurrency trading on clean water management and carbon emission SDGs. J Environ Manag 2024;367:122059.
[165] Bajra UQ, Rogova E, Avdiaj S. Cryptocurrency blockchain and its carbon footprint: anticipating future challenges. Technol Soc 2024;77:102571.
[166] Goodkind AL, Jones BA, Berrens RP. Cryptodamages: monetary value estimates of the air pollution and human health impacts of cryptocurrency mining. Energy Res Social Sci 2020;59:101281.
[167] Lu E. The environmental implications of cryptocurrencies. J High School Sci 2023;7.
[168] Lal A, You F. Climate sustainability through a dynamic duo: green hydrogen and crypto driving energy transition and decarbonization. Proc Natl Acad Sci 2024; 121:e2313911121.
[169] Packard L, Singh AK, Oguntoye O. Crypto has an emissions challenge: here's what leaders can do about it. Future Technol 2022;1:6–13.
[170] Strubell E, Ganesh A, McCallum A. Energy and policy considerations for modern deep learning research. In: Proceedings of the AAAI conference on artificial intelligence; 2020. p. 13693–6.
[171] Jain A, Mishra M, Peddoju SK, Jain N. Energy efficient computing-green cloud computing. In: 2013 international conference on energy efficient technologies for sustainability. IEEE; 2013. p. 978–82.
[172] Radu L-D. Green cloud computing: a literature survey. Symmetry 2017;9:295.
[173] Xiao Z, Cui S, Xiang L, Liu PJ, Zhang H. The environmental cost of cryptocurrency: assessing carbon emissions from bitcoin mining in China. J Digit Econ 2023;2:119–36.
[174] Khalil MIK, Ahmad I, Shah SAA, Jan S, Khan FQ. Energy cost minimization for sustainable cloud computing using option pricing. Sustain Cities Soc 2020;63: 102440.
[175] Cha S. The potential role of small modular reactors (SMRs) in addressing the increasing power demand of the artificial intelligence industry: a scenario-based analysis. Nucl Eng Technol 2025;57:103314.
[176] Klein C, Maggio M, Årzén K-E, Hernández-Rodriguez F. Brownout: building more robust cloud applications. In: Proceedings of the 36th international conference on software engineering; 2014. p. 700–11.
[177] Xu M, Toosi AN, Buyya R. A self-adaptive approach for managing applications and harnessing renewable energy for sustainable cloud computing. IEEE Trans Sustain Comput 2020;6:544–58.
[178] Li B, Jiang Y, Gadepally V, Tiwari D. Sprout: green generative AI with carbon-efficient LLM inference. In: Proceedings of the 2024 conference on empirical methods in natural language processing; 2024. p. 21799–813.
[179] Moganarangan N, Babukarthik R, Bhuvaneswari S, Basha MS, Dhavachelvan P. A novel algorithm for reducing energy-consumption in cloud computing environment: web service computing approach. J King Saud Univ-Comput Inf Sci 2016;28:55–67.
[180] Swain SR, Parashar A, Singh AK, Lee CN. An intelligent virtual machine allocation optimization model for energy-efficient and reliable cloud environment. J Supercomput 2025;81:237.

[181] Wang N, Guo Y, Huang C, Tian B, Shao S. Multi-scale collaborative modeling and deep learning-based thermal prediction for air-cooled data centers: an innovative insight for thermal management. Appl Energy 2025;377:124568.
[182] Abd SK, Al-Haddad SAR, Hashim F, Abdullah AB, Yussof S. An effective approach for managing power consumption in cloud computing infrastructure. J Comput Sci 2017;21:349–60.
[183] Kaur T, Chana I. Energy efficiency techniques in cloud computing: a survey and taxonomy. ACM Comput Surv 2015;48:1–46.
[184] AlIsmail SM, Kurdi HA. Green algorithm to reduce the energy consumption in cloud computing data centres. In: 2016 SAI computing conference (SAI). IEEE; 2016. p. 557–61.
[185] Bui D-M, Yoon Y, Huh E-N, Jun S, Lee S. Energy efficiency for cloud computing system based on predictive optimization. J Parallel Distr Comput 2017;102: 103–14.
[186] Bharany S, Sharma S, Khalaf OI, Abdulsahib GM, Al Humaimeedy AS, Aldhyani TH, et al. A systematic survey on energy-efficient techniques in sustainable cloud computing. Sustainability 2022;14:6256.
[187] Baliga J, Ayre RW, Hinton K, Tucker RS. Green cloud computing: balancing energy in processing, storage, and transport. Proc IEEE 2010;99:149–67.
[188] Yadav R, Zhang W, Kaiwartya O, Singh PR, Elgendy IA, Tian Y-C. Adaptive energy-aware algorithms for minimizing energy consumption and SLA violation in cloud computing. IEEE Access 2018;6:55923–36.
[189] Achar S. Cloud computing: toward sustainable processes and better environmental impact. J Comput Hardware Eng (JCHE). 2022;1.
[190] Rao PH, Rajakumar P, Geetha S. Energy efficiency task Re-scheduling in virtualized cloud computing. Scalable Comput Pract Exp 2025;26:1165–79.
[191] Rawat PS, Gaur S, Barthwal V, Gupta P, Ghosh D, Gupta D, et al. Efficient virtual machine placement in cloud computing environment using BSO-ANN based hybrid technique. Alex Eng J 2025;110:145–52.
[192] Han X, Wang J, Wu J, Song J. Energy-efficient cloud systems: virtual machine consolidation with Γ-robustness optimization. iScience 2025;28.
[193] Yu X, Mi J, Tang L, Long L, Qin X. Dynamic multi objective task scheduling in cloud computing using reinforcement learning for energy and cost optimization. Sci Rep 2025;15:45387.
[194] Hayyolalam V, Özkasap Ö. CBWO: a novel multi-objective load balancing technique for cloud computing. Future Gener Comput Syst 2025;164:107561.
[195] Cao Z, Wang R, Zhou X, Tan R, Wen Y, Yan Y, et al. Adaptive capacity provisioning for carbon-aware data centers: a digital twin-based approach. IEEE Trans Sustain Comput 2025;10(4):730–43.
[196] Ji E, Wang Y, Xing S, Jin J. Hierarchical reinforcement learning for energy-efficient API traffic optimization in large-scale advertising systems. IEEE Access 2025;13:142493–516.
[197] Fan J, Yan R, He Y, Zhang J, Zhao W, Liu M, et al. Stochastic optimization of combined energy and computation task scheduling strategies of hybrid system with multi-energy storage system and data center. Renew Energy 2025;242: 122466.
[198] Chen Y, Xie G, Li R. Reducing energy consumption with cost budget using available budget preassignment in heterogeneous cloud computing systems. IEEE Access 2018;6:20572–83.
[199] Dayarathna M, Wen Y, Fan R. Data center energy consumption modeling: a survey. IEEE Commun Surv Tutor 2015;18:732–94.
[200] Karuppasamy M, Balakannan S. Energy saving from cloud resources for a sustainable green cloud computing environment. J Cyber Secur Mobil 2018: 95–108.
[201] Karamchand G. Sustainable cybersecurity: green AI models for securing data center infrastructure. Int J Hospit Inf Technol 2025;7:6–16.
[202] Sanjalawe Y, Fraihat S, Al-E'mari S, Abualhaj M, Makhadmeh S, Alzubi E. Smart load balancing in cloud computing: integrating feature selection with advanced deep learning models. PLoS One 2025;20:e0329765.
[203] Qasim M, Sajid M, Lapina M, Shahid M. COBGA: MCDM-assisted improved genetic algorithm for scheduling industrial-internet-of-things jobs in cloud computing. Clust Comput 2025;28:944.
[204] Lv Z, Zhao J. Resource-efficient artificial intelligence for battery capacity estimation using convolutional FlashAttention fusion networks. eTransportation 2025;23:100383.
[205] Dash S. Green ai: enhancing sustainability and energy efficiency in ai-integrated enterprise systems. IEEE Access 2025; 13:21216-21228.
[206] Ahmed SR, Baghdadi R, Bernadskiy M, Bowman N, Braid R, Carr J, et al. Universal photonic artificial intelligence acceleration. Nature 2025;640:368–74.
[207] Valko D, Kudenko D. Increasing energy efficiency of bitcoin infrastructure with reinforcement learning and one-shot path planning for the lightning network. Neural Comput Appl 2025;37:18811–21.
[208] Hazelwood K, Bird S, Brooks D, Chintala S, Diril U, Dzhulgakov D, et al. Applied machine learning at Facebook: a datacenter infrastructure perspective. In: 2018 IEEE international symposium on high performance computer architecture (HPCA). IEEE; 2018. p. 620–9.
[209] Uchechukwu A, Li K, Shen Y. Improving cloud computing energy efficiency. In: 2012 IEEE Asia Pacific cloud computing congress (APCloudCC). IEEE; 2012. p. 53–8.
[210] Uchechukwu A, Li K, Shen Y. Energy consumption in cloud computing data centers. Int J Cloud Comput Serv Sci 2014;3:31–48.
[211] Mastelic T, Oleksiak A, Claussen H, Brandic I, Pierson J-M, Vasilakos AV. Cloud computing: survey on energy efficiency, vol. 47. Acm computing surveys (csur); 2014. p. 1–36.
[212] Xu M, Du H, Niyato D, Kang J, Xiong Z, Mao S, et al. Unleashing the power of edge-cloud generative ai in mobile networks: a survey of aigc services. IEEE Commun Surv Tutor 2024;26(2):1127–70.
[213] Na M, Lee J. Generative AI-Enabled energy-efficient Mobile augmented reality in multi-access edge computing. Appl Sci 2024;14:8419.
[214] Zhang Y, Zhang J, Yue S, Lu W, Ren J, Shen X. Mobile generative ai: opportunities and challenges. IEEE Wireless Commun 2024;31:58–64.
[215] Kusumaraju SH, Suneesh A, Rana A, Bodicherla S, Tyagi B. EcoGen: fusing generative AI and edge intelligence for sustainable scalability. Memory.24:64GB.
[216] Stoll T, Young D, Bandhauer T. Data center sustainability: the role of flexible fuel CCHP in mitigating grid emissions and power constraints. Energy Convers Manag 2025;326:119455.
[217] Zhao C, Jing Y, Xie X, Jiang Y. Application and simulation of IEC water chillers for summer free cooling in data centers. Appl Therm Eng 2025;260:124915.
[218] Mao R, Wu H, Li C, Zhang Z, Liang X, Zhou J, et al. Experimental investigation on the application of cold-mist direct evaporative cooling in data centers. Int J Therm Sci 2025;208:109500.
[219] Huang Y, Liu C, Zhong Y, Zhang C. Experimental study on jet-enhanced immersion liquid cooling for energy-efficient data centers. Energy 2025:137584.
[220] Zhang Y, Han H, Zhang Y, Li J, Liu C, Liu Y, et al. Experimental study on the performance of a novel data center air conditioner combining air cooling and evaporative cooling. Int J Refrig 2025;170:98–112.
[221] Singh N, Permana I, Agharid AP, Wang F-J. Innovative retrofits for enhanced thermal performance in data centers using independent row-based cooling systems. Therm Sci Eng Prog 2025;57:103101.
[222] Wu X, Yang J, Liu Y, Zhuang Y, Luo S, Yan Y, et al. Investigations on heat dissipation performance and overall characteristics of two-phase liquid immersion cooling systems for data center. Int J Heat Mass Tran 2025;239: 126575.
[223] Alkasmoul FS, Almogbel AM, Shahzad MW, Al-damook AJ. Thermal performance and optimum concentration of different nanofluids in immersion cooling in data center servers. Results Eng 2025;25:103699.
[224] Mahmud A, Kamal KS, Reza AW. Greener and energy-efficient data center for blockchain-based cryptocurrency mining. Procedia Comput Sci 2025;252: 192–201.
[225] Premsankar G, Di Francesco M, Taleb T. Edge computing for the internet of things: a case study. IEEE Internet Things J 2018;5:1275–84.
[226] Alsharif MH, Jahid A, Kannadasan R, Singla MK, Gupta J, Nisar KS, et al. Survey of energy-efficient fog computing: techniques and recent advances. Energy Rep 2025;13:1739–63.
[227] Ali A, Ullah I, Singh SK, Sharafian A, Jiang W, Sherazi HI, et al. Energy-efficient resource allocation for urban traffic flow prediction in edge-cloud computing. Int J Intell Syst 2025;2025:1863025.
[228] Hasan RA, Yasin K, Kareem PR, Salih AM, Jasim H, Ameedudeen MA, et al. Energy-efficient task offloading and resource allocation in mobile cloud computing using edge-AI and network virtualization. Khwarizmia 2025;2025: 42–9.
[229] Chen H, Liu J, Zhu Z. A dynamic energy-efficient scheduling method for periodic workflows based on collaboration of edge-cloud computing resources. Concurrency Comput Pract Ex 2025;37:e8362.
[230] Zhang Y, Tang H, Li H, Wang S. Unlocking the flexibilities of data centers for smart grid services: optimal dispatch and design of energy storage systems under progressive loading. Energy 2025;316:134511.
[231] Jouppi NP, Young C, Patil N, Patterson D, Agrawal G, Bajwa R, et al. In-datacenter performance analysis of a tensor processing unit. In: Proceedings of the 44th annual international symposium on computer architecture; 2017. p. 1–12.
[232] Fan S, Gyllensvärd E, Farkas E, Schutzner J. Intervention for cryptocurrency emissions: a China case study. 2022.
[233] Erdogan S, Ahmed MY, Sarkodie SA. Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability. Environ Sci Pollut Control Ser 2022;29:31723–33.
[234] De Vries A. Cryptocurrencies on the road to sustainability: ethereum paving the way for Bitcoin. Patterns 2023;4.
[235] Sedlmeir J, Buhl HU, Fridgen G, Keller R. The energy consumption of blockchain technology: beyond myth. Bus Inf Syst Eng 2020;62:599–608.
[236] Gundaboina L, Badotra S, Tanwar S. Reducing resource and energy consumption in cryptocurrency mining by using both proof-of-stake algorithm and renewable energy. In: 2022 international Mobile and embedded technology conference (MECON). IEEE; 2022. p. 605–10.
[237] Li J, Li N, Peng J, Cui H, Wu Z. Energy consumption of cryptocurrency mining: a study of electricity consumption in mining cryptocurrencies. Energy 2019;168: 160–8.
[238] Liu B, Prodromou T, Suardi S, Xu C. Ethereum's merge: market liquidity, efficiency and volatility in the proof of stake era. Econ Lett 2025;247:112202.
[239] Hasyim F, Hapsari AN, Sukardi B, Waluyo W, Anggorowati LS. Exploring sustainability in cryptocurrency protocols: environmental insights from PoW to PoS. BIS Econ Bus 2025;2. V225015-V.
[240] Zhou X, Guo X, Ji J. Exploring the impact of cryptocurrency and energy markets on global carbon emissions: a wavelet quantile analysis. Environ Dev Sustain 2025:1–26.
[241] Wolfson A, Khaladjan G, Lurie Y, Mark S. The greater sustainability of stablecoins relative to other cryptocurrencies. J Risk Financ Manag 2025;18:161.
[242] Sereti Z, Mavrikos E, Cholevas C, Tsekouras GE. Green NFTs: technologies related to energy-efficient non-fungible tokens. Information 2025;16:305.
[243] Alabi AT, Ishola AO. Revisiting the carbon footprint of cryptocurrency trading: a granger causality approach. Sustain Futures 2025:100995.

[244] Haodic G, Xing Z. Stake-based block generation and its impact on Ethereum transaction efficiency. J Curr Res Blockchain 2025;2:216–27.
[245] Liang D-H, Liang D-S, Chang C-P. Cloud computing and green management. In: 2012 second international conference on intelligent system design and engineering application. IEEE; 2012. p. 639–42.
[246] Utz V, DiPaola S. Climate implications of diffusion-based generative visual ai systems and their mass adoption. In: Proceedings of the 14th international conference on computational creativity; 2023.
[247] Schmidt TS. Low-carbon investment risks and de-risking. Nat Clim Change 2014; 4:237–9.
[248] Yang L, Hamori S. The role of the carbon market in relation to the cryptocurrency market: only diversification or more? Int Rev Financ Anal 2021;77:101864.
[249] Belady C, Rawson A, Pfleuger J, Cader T. Green grid data center power efficiency metrics: PUE and DCIE. The green grid 2008;1.
[250] Chowdhury CR, Chatterjee A, Sardar A, Agarwal S, Nath A. A comprehensive study on cloud green computing: to reduce carbon footprints using clouds. Int J Adv Comput Res 2013;3:78–85.
[251] Abad AV, Dodds PE. Green hydrogen characterisation initiatives: definitions, standards, guarantees of origin, and challenges. Energy Policy 2020;138:111300.
[252] Hamburger Á. Is guarantee of origin really an effective energy policy tool in Europe? A critical approach. Soc Econ 2019;41:487–507.
[253] Holzapfel PK, Bánk J, Bach V, Finkbeiner M. Relevance of guarantees of origin for Europe's renewable energy targets. Renew Sustain Energy Rev 2024;205:114850.
[254] Wang Y, Lucey B, Vigne SA, Yarovaya L. An index of cryptocurrency environmental attention (ICEA). China Finance Rev Int 2022;12:378–414.
[255] Krause MJ, Tolaymat T. Quantification of energy and carbon costs for mining cryptocurrencies. Nat Sustain 2018;1:711–8.
[256] Stoll C, Klaaßen L, Gallersdörfer U. The carbon footprint of bitcoin. Joule 2019;3: 1647–61.
[257] Moud HI, Hariharan J, Hakim H, Kibert C, flood I. Sustainability assessment of data centers beyond LEED. In: 2020 IEEE green technologies conference (GreenTech); 2020. p. 62–4.
[258] Cai S, Gou Z. A comprehensive analysis of green building rating systems for data centers. Energy Build 2023;284:112874.
[259] Khalaj AH, Halgamuge SK. A review on efficient thermal management of air-and liquid-cooled data centers: from chip to the cooling system. Appl Energy 2017; 205:1165–88.
[260] Alkrush AA, Salem MS, Abdelrehim O, Hegazi AA. Data centers cooling: a critical review of techniques, challenges, and energy saving solutions. Int J Refrig 2024; 160:246–62.
[261] Li P., Yang J., Islam M.A., Ren S. Making AI less "Thirsty": uncovering and addressing the secret water footprint of AI models. arXiv preprint arXiv: 230403271 2023.https://doi.org/10.48550/arXiv.2304.03271.
[262] Muralidhar R, Borovica-Gajic R, Buyya R. Energy efficient computing systems: architectures, abstractions and modeling to techniques and standards. ACM Comput Surv 2022;54:236.
[263] Masanet E, Shehabi A, Lei N, Smith S, Koomey J. Recalibrating global data center energy-use estimates. Science 2020;367:984–6.
[264] Silva CA, Vilaça R, Pereira A, Bessa RJ. A review on the decarbonization of high-performance computing centers. Renew Sustain Energy Rev 2024;189:114019.
[265] OECD. Going digital: shaping policies, improving lives. Paris: Organisation for Economic Co-operation and Development; 2019.
[266] CODES. Action plan for a sustainable planet in the digital age. New York: UN Coalition for Digital Environmental Sustainability; 2022.
[267] Freitag C, Berners-Lee M, Widdicks K, Knowles B, Blair GS, Friday A. The real climate and transformative impact of ICT: a critique of estimates, trends, and regulations. Patterns 2021;2.
[268] Xiong X, Luo J. Global trends in cryptocurrency regulation: an overview. In: Leonardos S, Alfieri E, Knottenbelt WJ, Pardalos P, editors. Mathematical research for blockchain economy. Cham: Springer Nature Switzerland; 2024. p. 71–92.
[269] Emmert F. The regulation of cryptocurrencies in the United States of America. Eur J Law Reform 2023;25:1–2.
[270] Aljbour J, Wilson T, Patel P. Powering intelligence: analyzing artificial intelligence and data center energy consumption. EPRI White Paper no 3002028905; 2024.
[271] Liu Z, Sun Y, Xing C, Liu J, He Y, Zhou Y, et al. Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: challenges and future perspectives. Energy AI 2022;10:100195.
[272] Fridgen G, Körner M-F, Walters S, Weibelzahl M. Not all doom and gloom: how energy-intensive and temporally flexible data center applications may actually promote renewable energy sources. Bus Inf Syst Eng 2021;63:243–56.
[273] Cho S, Kim J, Lim D. Optimal design of renewable energy certificate multipliers using an LCOE-integrated AHP model: a case study of South Korea. Renew Energy 2024;226:120386.
[274] Ahmad A, Khan RA, Khan SU, Alwageed HS, Al-Atawi AA, Lee Y. Green cloud computing adoption challenges and practices: a client's perspective-based empirical investigation. Cognit Technol Work 2023;25:427–46.
[275] OECD. Measuring the environmental impacts of AI compute and applications: the AI footprint. Paris: Organization for Economic Cooperation and Development; 2022.
[276] Lane M, Williams M, Broecke S. The impact of AI on the workplace: main findings from the OECD AI surveys of employers and workers. OECD social, employment and migration working papers no 288. Paris: Organisation for Economic Co-operation and Development; 2023.
[277] De Freitas J, Agarwal S, Schmitt B, Haslam N. Psychological factors underlying attitudes toward AI tools. Nat Hum Behav 2023;7:1845–54.
[278] Hanus N, Newkirk A, Stratton H. Organizational and psychological measures for data center energy efficiency: barriers and mitigation strategies. Energy Effic 2023;16:1.
[279] Nishant R, Kennedy M, Corbett J. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int J Inf Manag 2020;53: 102104.
[280] ITI. ITI's Sustainable Technology Policy Guide. Understanding ai's role in the energy transition. Washington D.C.: The Information Technology Industry Council; 2024.
[281] Esram NW, Elliott N. Turning data centers into grid and regional assets: considerations and recommendations for the federal government, state policymakers, and utility regulators. ACEEE Policy Brief. Washington D.C.: ACEEE; 2024.
[282] CCA. Crypto Climate Accord. Crypto Clim Accord, https://cryptoclimate.org/ ; 2025 [accessed 22 June 2025].
[283] IEA. Data centre energy efficiency labels. Paris: International Energy Agency; 2024.
[284] Ebert K., Alder N., Herbrich R., Hacker P. AI, climate, and regulation: from data centers to the AI act. arXiv preprint arXiv:241006681 2024.https://doi.org/10.48550/arXiv.2410.06681.
[285] IEA. Policy development on energy efficiency of data centres. Paris: International Energy Agency; 2024.
[286] Truby J. Decarbonizing Bitcoin: Law and policy choices for reducing the energy consumption of blockchain technologies and digital currencies. Energy Res Social Sci 2018;44:399–410.
[287] Swinkels L. Trading carbon credit tokens on the blockchain. Int Rev Econ Finance 2024;91:720–33.
[288] Lehdonvirta V, Wú B, Hawkins Z. Compute north vs. compute south: the uneven possibilities of compute-based AI governance around the globe. In: Proceedings of the AAAI/ACM conference on AI, ethics, and society; 2024. p. 828–38.