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Assessing the carbon footprint of artificial intelligence in higher education: a bibliometric and institutional analysis

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Abstract

The rapid integration of artificial intelligence (AI) across higher education has transformed research, teaching, and institutional operations. Yet its environmental implications remain poorly understood at the institutional level. While a growing literature examines the energy consumption and carbon footprint of AI systems, little is known about how these concerns are recognised or addressed within universities. This study addresses this gap by combining a bibliometric analysis of 461 peer-reviewed publications indexed in Scopus (2014–2025) with a multiple-case study analysis of selected research-intensive universities. The bibliometric analysis reveals a rapidly expanding research landscape dominated by themes such as machine learning, energy consumption, optimisation, and sustainability, alongside a comparatively limited focus on higher education as an institutional context. The case studies, based on sustainability reports, climate action plans, and environmental disclosures, focus on a set of research-intensive universities with substantial AI-related infrastructure. They show a consistent pattern: despite the centrality of high-performance computing (HPC) and cloud-based platforms, institutional reporting of energy and carbon emissions remains aggregated, rarely examining AI-specific impacts. This reveals a governance gap between the expanding scientific understanding of AI's environmental footprint and the maturity of sustainability practices in academia. The novelty of this study lies in the integration of bibliometric analysis with institutional case study evidence to systematically examine how AI-related energy use and carbon emissions are addressed in higher education. By bridging these two analytical dimensions, the study provides new insight into the disconnect between research advances and institutional practice and highlights the need for dedicated frameworks to account for AI-related energy use and emissions. The study also aligns with the United Nations Sustainable Development Goals (SDGs), particularly Affordable and Clean Energy (SDG 7), Climate Action (SDG 13), and Quality Education (SDG 4), contributing to the ongoing debate on responsible and sustainable AI in higher education.

Keywords Artificial intelligence, Carbon footprint, Higher education, Sustainability, Energy efficiency, Institutional governance

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Introduction

Sustainable development has become the defining framework for addressing the interconnected challenges of environmental degradation, urbanisation, and technological transformation, within broader global policy discussions on sustainable digital transformation. Studies have emphasised the interdependence of economic development, social inclusion, and environmental protection as core pillars of sustainable progress. Renewable energy plays a central role in this transition by reducing greenhouse gas emissions and supporting key Sustainable Development Goals, particularly SDG 7 and SDG 13 [1]. Consequently, urban sustainability and long-term spatial planning have emerged as key mechanisms for reducing carbon emissions, optimising resource use, and promoting climate resilience in both cities [2, 25] and institutions alike [24, 28]. Recent evidence shows that sustainable urban development has become increasingly central to both academic research and policy agendas, reflecting growing recognition of the interdependence between urban planning, environmental governance, and digital transformation [2].

Within this context, insights from urban sustainability research provide a useful analytical lens for understanding how complex, infrastructure-intensive systems manage energy demand and technological change. Universities share several of these characteristics: they operate as dense, multifunctional environments with significant energy requirements, advanced digital infrastructure, and complex governance arrangements. In this sense, universities can be understood as "micro-scale" analogues of urban systems, where questions of energy use, digital transformation, and sustainability governance intersect [27]. The growing integration of artificial intelligence (AI) within higher education intensifies these dynamics. Universities are not only users of AI technologies in teaching, administration, and operations, but also key developers and producers of AI research and innovation. Recent research further shows that AI plays a critical role in enhancing energy efficiency, supporting carbon reduction, and enabling data-driven energy management within university campuses, while also highlighting the importance of institutional readiness and adoption dynamics [5].

This dual role implies both direct energy consumption, associated with the operation of AI systems and high-performance computing (HPC) infrastructure, and indirect impacts linked to the development and dissemination of AI technologies. While this distinction is conceptually important, existing institutional reporting practices rarely differentiate between these dimensions, and AI-related energy use typically remains embedded within broader categories of digital or Information and Communication Technology (ICT)-related consumption in institutional reporting [28, 29]. Unlike many other large public institutions, universities combine large-scale operational infrastructures with decentralised research activity and a strong normative commitment to sustainability leadership. This unique configuration creates specific challenges for monitoring energy use, aligning technological innovation with environmental goals, and translating sustainability commitments into measurable governance practices. Understanding how universities engage with the environmental implications of AI is therefore critical for advancing both institutional sustainability and broader debates on responsible digital transformation.

At the same time, the environmental implications of AI are increasingly raising questions that extend beyond technical efficiency to issues of institutional governance. Advances in AI—particularly the rapid diffusion of large-scale machine-learning models, foundation models, and cloud-based computational platforms—are driving unprecedented growth in energy demand associated with new data centres and HPC infrastructure.

There are three main reasons for this trend:

i) *The exponentially increasing scale of the models:* The defining theme of modern AI is the scaling theory—that larger (and therefore more representative) models trained on more data with more compute achieve drastically enhanced performance [14]. Core models like GPT-4, Gemini, and Claude have scaled from billions to trillions of parameters. The process of training one large language model can consume terawatt-hours of electricity, equivalent to the annual energy consumption of thousands of homes. That "compute-bounded" race only further pushes energy demand upward.
ii) *The shift to ubiquitous inference (not just training):* While training a model is a massive, concentrated energy expenditure, the operational phase (inference) is where the real scaling challenge lies. Every query to ChatGPT, every image generated by DALL-E, every real-time translation, and every AI feature embedded in millions of apps requires computational power. As these models are integrated into global services used by billions, the cumulative energy cost of inference vastly outstrips the one-time training cost, creating a persistent and growing load [38].
iii) *The concentration in hyperscale data centres:* AI workloads do not consume ordinary server space; they need specific, dense computational infrastructure such as specialised hardware. These, in turn, depend on clusters of tens of thousands of power-hungry Graphics Processing Units (GPU) and AI

accelerators (like NVIDIA's H100s and Google's c), which have power densities orders of magnitude greater than traditional Central Processing Units (CPU) [17]. There are also co-location needs, since these clusters need large, interconnected data centres, and sophisticated cooling systems (frequently liquid cooling) to keep them from overheating. This creates a concentration of extraordinary power demand into particular geographic locations, with local grids and infrastructure strained.

In this transformation, universities occupy a paradoxical position. On the one hand, they are among the world's leading producers of AI research and expertise; on the other hand, they simultaneously emerge as intensive organisational users of energy- and carbon-intensive digital infrastructure. Notably, despite their historical role as leaders in climate and sustainability, universities rarely treat AI as a distinct object of environmental reporting. Instead, AI-related energy use and emissions tend to remain embedded (and largely hidden) within aggregated institutional reporting categories, obscuring environmental impacts. This disconnect suggests not an isolated reporting oversight but a structural governance gap, in which well-established scientific knowledge on the energy and carbon intensity of AI is not systematically translated into institutional sustainability practices. This paper contributes to the literature by identifying and empirically substantiating this governance gap through the integration of bibliometric evidence and cross-regional institutional case studies. Given the global scale of higher education and its growing reliance on AI in research, teaching, and administration, closing this gap is integral to the credibility, accountability, and practical efficacy of sustainability governance in academia.

This article synthesises existing research to identify key themes, highlight current limitations, and delineate the research gap addressed in this study. Existing literature has made significant progress in examining the environmental impact of artificial intelligence, particularly through frameworks that analyse its energy consumption and carbon emissions across computational, application, and system levels [19]. In parallel, recent studies emphasize the growing role of AI in supporting climate change mitigation and sustainability efforts, while also highlighting challenges related to energy use, environmental impact, and governance [26]. However, despite these advances, the literature remains largely focused on technical systems and broader sectoral analyses, with comparatively limited attention to higher education institutions as organisational and governance contexts. Moreover, prior research rarely integrates these dimensions within the specific context of university campuses, where institutional dynamics and decision-making processes can differ significantly [5]. This study addresses this limitation by asking three interrelated research questions:

(RQ1) how has the scientific literature framed and represented the relationship between AI, energy consumption, and carbon emissions;

(RQ2) to what extent are these concerns acknowledged, reported, or governed within higher education institutions; and

(RQ3) what patterns of misalignment can be identified between research trends and institutional practice.

Given the exploratory and integrative nature of the study, the analysis is not structured around formal hypothesis testing but instead aims to identify patterns, relationships, and gaps within and between the scientific literature and institutional practice.

To address the research questions, the paper adopts an integrative approach combining a large-scale bibliometric analysis with institution-level case studies, moving beyond abstract discussions of AI sustainability to examine its operationalisation in real-world academic environments. Through this approach, the study offers original empirical insight into the current limits of AI-related energy and carbon reporting in higher education and highlights governance challenges relevant to the responsible and sustainable deployment of AI in universities.

The remainder of the paper is structured as follows. Sect. "Literature review" presents a short literary context for the study. Sect. "Methods" outlines the methodological approach, including the bibliometric analysis and case study design. Sect. "Results and Discussion" presents the results, combining insights from bibliometric analyses with findings from institutional case studies. Sect. "Conclusions" concludes the paper by summarising the main findings, discussing their implications, and outlining directions for future research.

Literature review

The environmental impact of AI has become an emerging area of research, particularly in relation to energy consumption and carbon emissions. Existing studies show that AI systems rely heavily on computational processes and digital infrastructure, which contribute to increasing energy demand. For instance, data centres, which underpin AI operations, consume substantial amounts of electricity and contribute to global carbon emissions [18]. However, more recent evidence suggests that improvements in efficiency have partially mitigated energy growth despite increasing computational demand [29]. To better understand these dynamics, Kaack et al. [19] propose a comprehensive framework categorising AI's environmental impact into compute-related, application-level, and system-level effects. This highlights that AI is not only a source of emissions due to its energy-intensive computation but also a potential solution through its applications in optimising energy systems and improving efficiency. Within the context of higher education, universities represent complex and energy-intensive environments where AI can play a critical role. Studies show that campus energy systems exhibit dynamic and non-linear consumption patterns, making them suitable for AI-based optimisation [3]. Empirical research further demonstrates that machine learning models can significantly improve energy forecasting and reduce energy consumption in university buildings [32, 50]. Similarly, large-scale campus studies confirm that integrating environmental, technical, and behavioural data enhances prediction accuracy and supports more efficient energy management [8]. At the same time, AI is increasingly recognised as a tool for supporting climate action and sustainability goals. It enables advanced data analysis, climate modelling, and decision-making processes, although concerns remain regarding its own energy consumption and carbon footprint [26]. In addition, digital infrastructures within universities, such as websites and online systems, also contribute to measurable carbon emissions, highlighting the broader scope of digital environmental impact [22].

Beyond technical capabilities, recent research emphasises that the adoption of AI in universities is influenced by institutional and behavioural factors. Evidence shows that perceived benefits, awareness of AI applications, and technological readiness significantly drive adoption, while financial constraints act as key barriers [5]. This indicates that the effectiveness of AI in improving sustainability is not solely dependent on technology, but also on organisational readiness and decision-making processes. Despite these advances, the existing literature remains fragmented. Most studies focus either on the technical efficiency of AI, its environmental implications, or its adoption drivers, without integrating these dimensions within the specific context of higher education institutions. In particular, limited attention has been given to how universities simultaneously experience, manage, and govern the carbon footprint of AI while adopting it for sustainability purposes. Therefore, this study addresses this gap by providing an integrated analysis of AI's carbon footprint in higher education, combining bibliometric insights with institutional evidence to bridge the divide between technical knowledge, environmental impact, and organisational practice.

Methods

The increasing adoption of AI in higher education has raised growing concerns about its environmental implications, particularly regarding energy consumption and carbon emissions. Despite the expanding role of AI across research, administration, and learning environments, the extent to which academic research has examined its carbon footprint within university settings remains unclear. To address this gap, this study adopts a two-stage methodological approach. It first conducts a bibliometric analysis to systematically map the academic literature on the carbon footprint of AI in higher education, followed by a multiple-case study investigation to explore how the insights from this body of research are reflected and translated into institutional practice. It is important to note that the bibliometric component of this study is intended to map research trends and thematic structures rather than to provide an in-depth conceptual or qualitative analysis of individual studies. As such, the findings should be interpreted as indicative of dominant patterns within the literature. The identification of misalignments between research and institutional practice is therefore based on a comparative interpretation between aggregated bibliometric insights and case study evidence, rather than on direct content analysis of individual publications.

Bibliometric analysis

This study employed a bibliometric analysis to examine research trends related to the carbon footprint and energy consumption of AI within educational contexts, with a particular focus on higher education. Bibliometric analysis is widely used to quantitatively map the structure, development, and thematic focus of scientific literature, especially in emerging and interdisciplinary research areas [4]. All bibliographic data were retrieved from the Scopus database, selected for its comprehensive coverage of peer-reviewed literature across the domains of AI, sustainability, and education. The search encompassed publications indexed in Scopus between 2014 and 2025, reflecting the most recent complete data available at the time of data collection. To retrieve the dataset, a structured search strategy was developed using Boolean operators to capture studies addressing three interconnected dimensions: AI or machine learning, environmental indicators such as carbon footprint or energy consumption, and educational or university contexts. The search string was intentionally designed to prioritise precision by focusing on studies that explicitly connect these three dimensions. While the inclusion of additional terms, such as specific AI technologies (e.g., large language models) or alternative institutional descriptors (e.g., college, faculty, or school), could have expanded the dataset, it would also have increased the likelihood of retrieving studies in which these elements are not directly linked. This reflects an inherent methodological trade-off between precision and recall, whereby greater specificity reduces irrelevant results at the risk of omitting relevant studies. As a result, the search strategy may not capture all relevant studies, particularly those using emerging terminology or broader institutional labels, which is acknowledged as a limitation of the bibliometric approach. At the same time, the use of broad core terms yields a dataset encompassing diverse perspectives on the relationship between AI and energy. In particular, the corpus encompasses both studies examining the energy consumption and carbon footprint of AI systems themselves, as well as studies investigating the application of AI for energy optimisation, including within campus environments. This dual inclusion reflects the broader research landscape, in which AI is simultaneously framed as both a contributor to environmental impact and a tool for sustainability.

The exact search query used was: TITLE-ABS-KEY ("AI" OR "machine learning" OR "artificial intelligence") AND ("carbon footprint" OR "energy consumption") AND ("education" OR university) AND PUBYEAR > 2013 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "cr") OR LIMIT-TO (DOCTYPE, "re") OR LIMIT-TO (DOCTYPE, "ch")).

The search yielded a total of 461 documents, all of which were included in the bibliometric analysis. Consistent with standard bibliometric research practices, no manual screening or quality-based exclusion criteria were applied, as the objective was to map the full scope of published research rather than assess the methodological quality of individual studies [12]. Bibliographic records, including authorship information, publication year, keywords, citations, and source details, were exported from Scopus in CSV format for analysis. Data analysis was conducted using Bibliometrix (Biblioshiny for Rstudio, Version 2024), VOSviewer (Version 1.6.20) and Tableau (Version 2024). Bibliometrix was used to compute descriptive bibliometric analysis, such as annual scientific production and keyword frequencies, as well as to analyse thematic evolution over time [4]. VOSviewer was employed to visualise scientific networks, including keyword co-occurrence and co-citation structures, which facilitated the identification of thematic clusters and collaboration patterns within the literature [49]. Tableau was used as an additional visualisation tool to generate graphical representations of publication trends and geographical distributions of research output [36]. The methodological approach therefore provided not only a quantitative overview of the field but also a clearer understanding of the intellectual structure and evolving interests within this domain.

Case study selection

The case study component of this research adopted a multiple-case study design following a holistic Type 1 approach [51], in which each university constitutes a single unit of analysis. This design is well suited to examining institutional-level practices, governance arrangements, and reporting structures related to AI and environmental sustainability, rather than evaluating specific technologies or systems. The case studies complement the bibliometric analysis by translating dominant themes in the scientific literature into observable institutional contexts within higher education.

The analytical focus of the case studies was derived directly from the bibliometric results, which revealed strong concentrations around AI computational intensity, energy consumption, sustainability, and carbon footprint, alongside a comparatively weaker but emerging focus on education-related contexts. These themes informed both the selection of case study institutions and the analytical dimensions examined. Specifically, universities were selected based on evidence of AI-intensive infrastructure and the availability of publicly accessible documentation on energy use and sustainability practices, allowing alignment with the dominant themes identified in the literature. The bibliometric findings also guided the dimensions analysed in each case, including: the presence of AI-related infrastructure; the reporting of energy consumption associated with digital or computing systems; the treatment of carbon footprint and emissions; and the existence of mitigation or governance strategies related to AI or digital infrastructure. In this way, the case study analysis operationalises the thematic patterns identified in the bibliometric stage, enabling a structured comparison between research trends and institutional practice.

The selection of case studies followed a purposive and evidence-driven logic, designed to include research-intensive universities with identifiable AI-related infrastructure and publicly available sustainability or environmental reporting. Specifically, universities were included where publicly available documentation allowed the assessment of AI-related activity and provided at least partial insight into energy use or sustainability practices, ensuring alignment with the analytical dimensions derived from the bibliometric analysis. An initial pool of institutions was screened based on these criteria, from which a final set of 13 universities was selected for detailed analysis based on data availability and relevance to the study objectives. While not intended to be statistically representative, the selected institutions reflect cross-regional global coverage and variation in institutional contexts, thereby enabling insightful comparative perspectives on how AI-related energy use and carbon emissions are addressed in practice.

It should be noted that the institutional documents analysed span different reporting years (ranging approximately from 2020 to 2025), reflecting the most recent publicly available disclosures for each university at the time of data collection. While this introduces a degree of temporal heterogeneity, the analysis focuses on structural patterns of reporting and governance rather than year-specific performance, thereby limiting the impact of such variation on the overall findings.

Further, the reliance on publicly available sources means that the analysis reflects institutional reporting rather than necessarily capturing internal practices, operational data, or ongoing initiatives that are not disclosed. As such, variation in institutional transparency may result in some practices remaining undocumented. Scientific articles were not used to describe individual universities directly. Instead, peer-reviewed literature was used to inform the analytical interpretation of institutional practices, particularly with respect to the established energy intensity of AI and machine learning, the carbon implications of large-scale computation, and the methodological challenges of attributing emissions to specific digital activities [15, 23, 34, 39]. This separation between institutional evidence and scientific interpretation ensures analytical rigour and avoids over-claiming.

Results and discussion

The bibliometric results provide a structured overview of the evolving scientific discourse on AI, energy consumption, and carbon footprint, while simultaneously revealing a notable gap in institution-focused analyses. Although the existing literature increasingly explores the environmental implications of AI from technical, engineering, and sustainability perspectives, higher education institutions are typically treated as abstract contexts rather than as concrete organisational units of analysis. This gap underscores the need to move beyond descriptive bibliometric mapping toward a deeper understanding of institutional engagement with sustainability issues. Consequently, the subsequent case study investigation shifts the analytical lens from research trends to institutional practice. It examines how universities with significant AI-related activity acknowledge, report, and govern their energy use and carbon emissions, thereby providing an empirical perspective on how scientific insights are translated into sustainability frameworks within higher education. The following subsection provides an overview of the bibliometric dataset, outlining its composition, scope, and key descriptive characteristics that form the basis for the subsequent analysis.

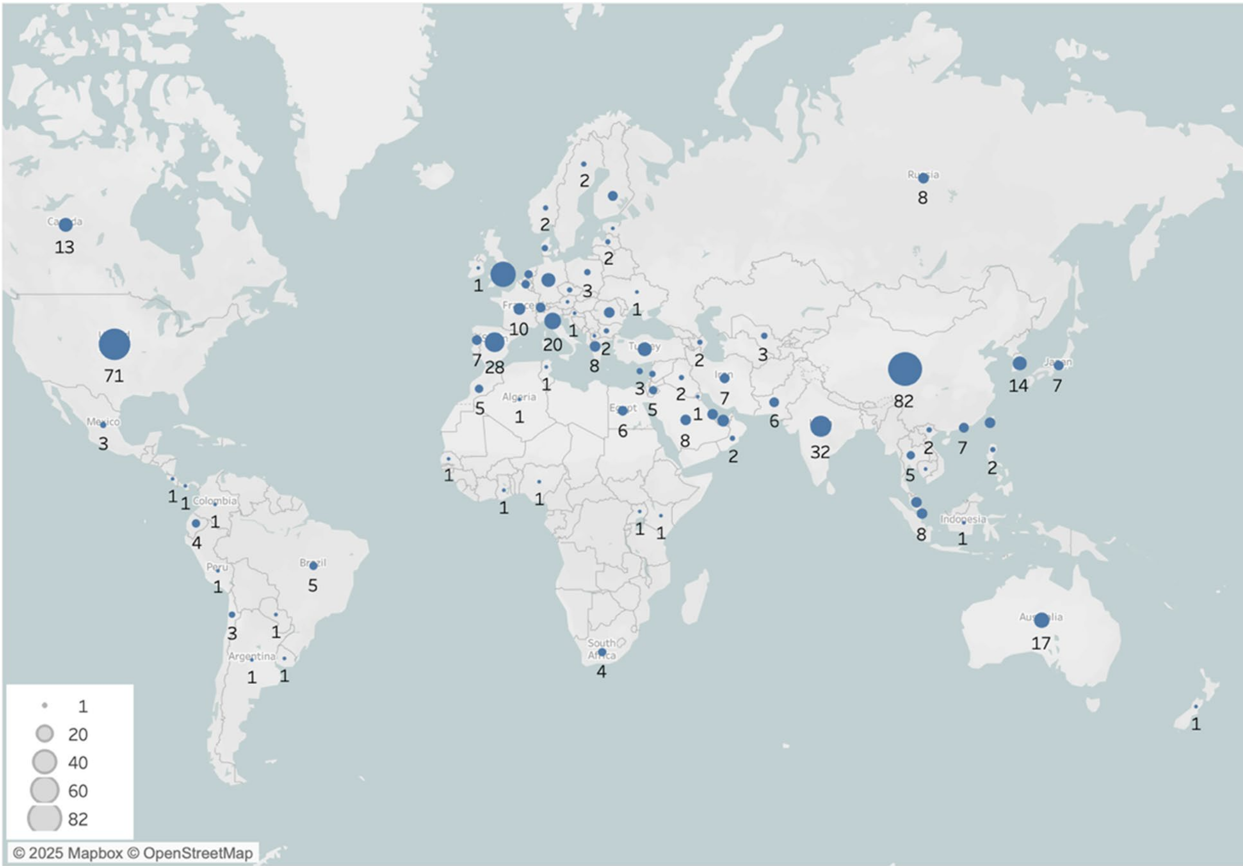
Bibliometric analysis of the research landscape

This section provides a descriptive overview of the bibliometric dataset used in this study. A total of 461 peer-reviewed publications were retrieved using the predefined Scopus search query targeting the intersection of AI, energy consumption, carbon footprint, and educational contexts. All retrieved documents were included in the analysis to preserve the integrity and comprehensiveness of the bibliometric approach.

Figure 1 illustrates the geographical distribution of publications addressing the environmental impacts of AI within educational contexts. The results reveal a markedly uneven global research landscape, with academic output concentrated primarily in East Asia, North America, and Western Europe. These regions account for the largest shares of publications, reflecting their strong research capacity in AI and sustainability-related fields. In contrast, research output from regions including Africa, South America, and parts of the Middle East remains comparatively limited, with only a small number of publications originating from these areas. Overall, the distribution highlights a concentration of research activity in technologically advanced and research-intensive regions and research systems, indicating that academic engagement with the carbon footprint and energy implications of AI in education is geographically uneven.

Transitioning from spatial patterns to temporal trends, Fig. 2 illustrates the temporal evolution of publications on AI, carbon footprint, and energy consumption within educational contexts over the period 2014–2026. The results reveal a pronounced upward trajectory, indicating rapidly accelerating academic interest in the environmental implications of AI in education. In the early years (2014–2017), research output remained minimal, with fewer than ten publications annually, reflecting the nascent stage of this interdisciplinary field. A gradual increase emerged between 2018 and 2020, coinciding with growing global attention to AI ethics, digital sustainability, and environmental accountability. A substantial surge is observed from 2021 onward, culminating in sharp peaks during 2023 and 2024 (65 and 87 publications, respectively). The notable rise in 2025 (122 publications) indicates an expanding research frontier driven by broader adoption of AI technologies in higher education and heightened awareness of their ecological footprint. Overall, the temporal trend demonstrates that this topic has transitioned from a marginal research niche into a rapidly maturing domain, highlighting increasing global recognition of the need to evaluate AI's sustainability implications within educational systems.

To better understand the intellectual structure behind this growth, the keyword co-occurrence network presented in Fig. 3 reveals the conceptual landscape of



Map based on Longitude (generated) and Latitude (generated). Size shows sum of Document. Details are shown for Country.

Fig. 1 Global distribution of publications (2014–2025). Circle size represents the total number of publications per country (raw counts) obtained from Scopus. The numbers displayed next to each circle indicate the exact publication count

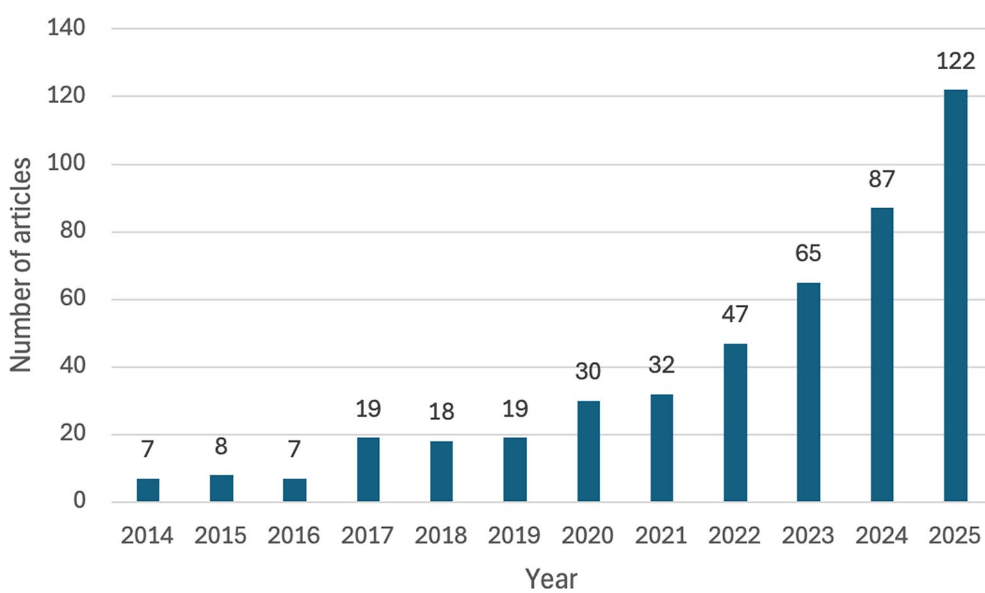


Fig. 2 Annual publication trend (2014–2025)

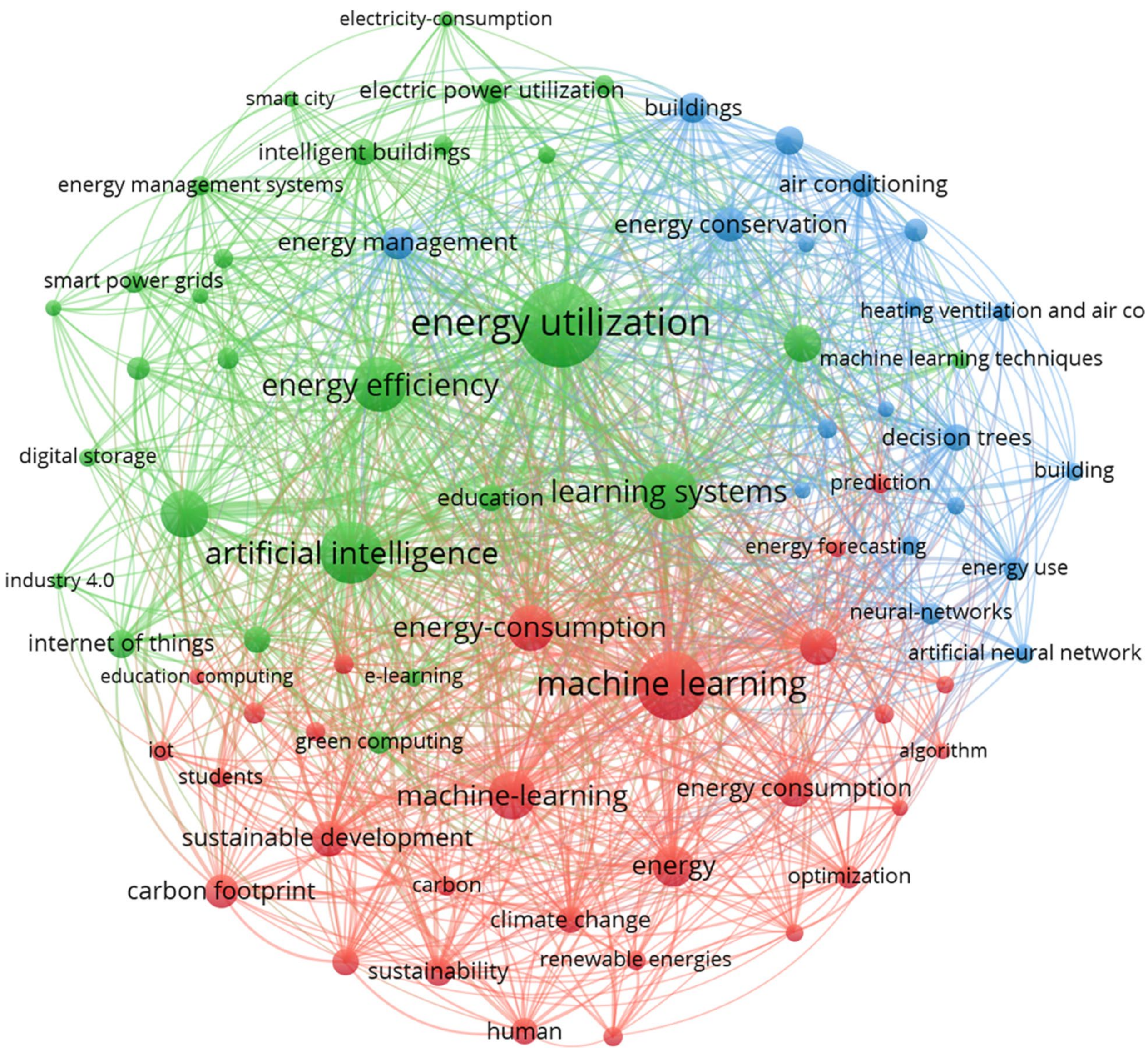


Fig. 3 Keyword co-occurrence network

research examining the environmental impact of AI within educational contexts. The network shows three interconnected clusters, each contributing to understanding how AI adoption in higher education relates to energy consumption and carbon emissions. The red cluster centres on AI and machine learning in relation to environmental sustainability, linking keywords such as machine learning, AI, carbon footprint, energy consumption, sustainability, education, students, and e-learning. The co-occurrence of education-related terms with environmental impact keywords indicates that a substantial body of literature explicitly addresses the energy and carbon implications of AI-driven educational technologies. The green cluster focuses on energy management and infrastructure-related themes, including energy efficiency, energy utilisation, intelligent buildings, energy management systems, and smart grids. This cluster highlights research that connects AI applications with energy optimisation and sustainability practices within institutional and campus-level environments. The blue cluster comprises methodological and technical keywords such as learning systems, prediction, neural networks, and energy forecasting. These terms reflect the use of AI-based modelling and predictive techniques to analyze and manage energy consumption associated with digital and educational systems. Overall, the network demonstrates that research on AI-related environmental impacts in education spans educational applications, sustainability-oriented infrastructure, and technical energy modelling.

A complementary perspective emerges from the temporal overlay visualisation of keyword evolution (Fig. 4), which illustrates how research themes connecting AI, energy consumption, and environmental sustainability have developed, particularly within higher education. The color gradient, from dark blue (older terms, ~ 2020) to yellow (recent terms, ~ 2023), reveals a clear shift in academic focus. Early studies (2020–2021) concentrated on technological and engineering topics such as energy efficiency, intelligent buildings, smart grids, and energy management, reflecting a technical orientation with limited attention to education. Between 2021 and 2022, research transitioned toward AI, learning systems, and machine learning, signaling efforts to link computational processes with energy-related outcomes. The most recent period (2022–2023), highlighted in yellow, marks growing interest in carbon footprint, energy consumption, sustainability, and education-related terms such as students, e-learning, and educational computing. This late but rapid emergence suggests that concerns about the carbon emissions and energy intensity of AI-driven

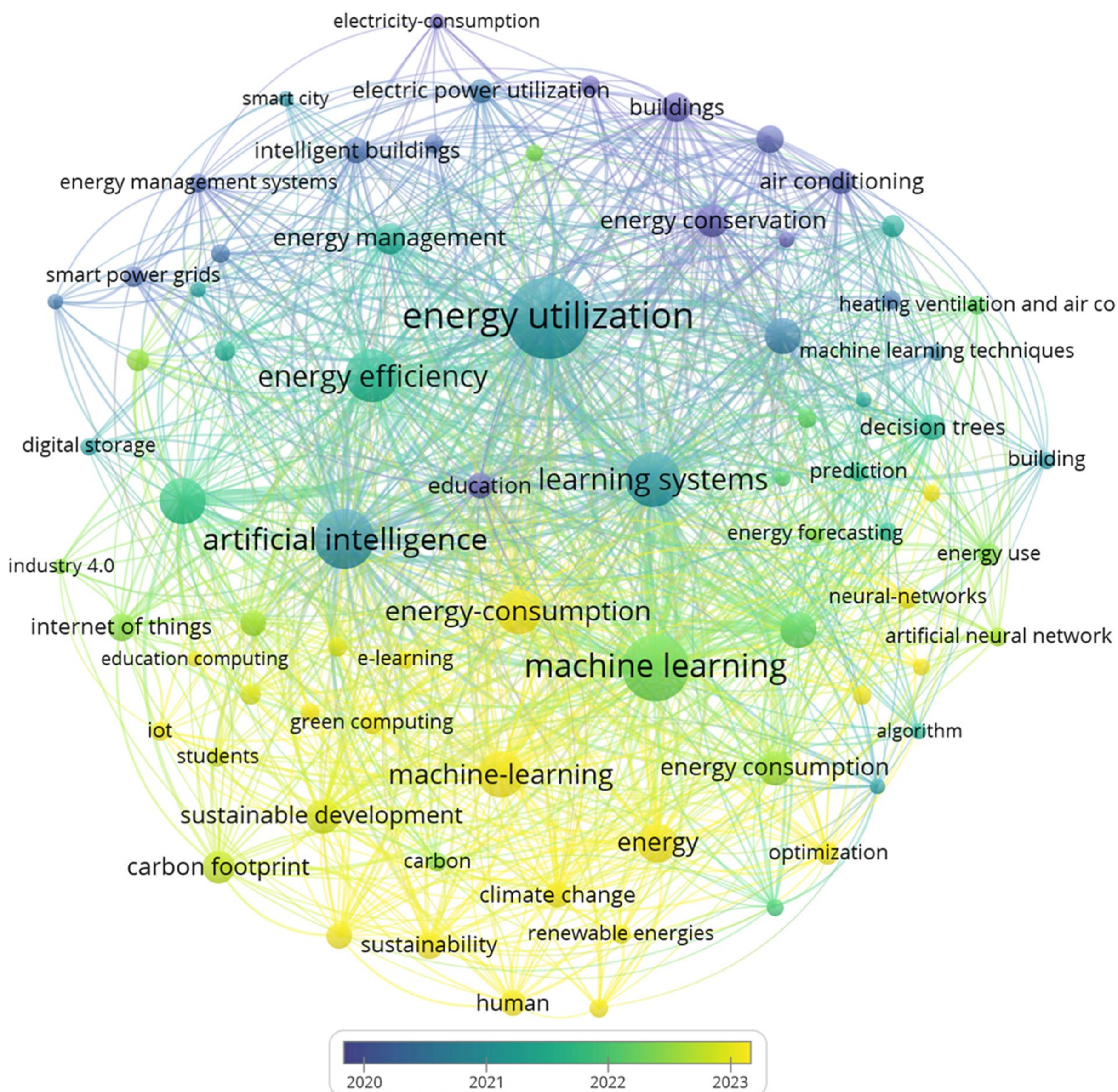


Fig. 4 Overlay visualisation of keyword co-occurrence

educational technologies, cloud-based learning, and data infrastructures are relatively new. Overall, the overlay visualisation illustrates a clear evolution of research themes, from early technical optimisation of energy systems, through the integration of AI and machine learning, to a recent focus on educational sustainability and the carbon footprint of AI-driven learning technologies.

Further refinement comes from the frequency treemap in Fig. 5, which visualises the most frequently occurring terms within the dataset and illustrates dominant research themes at the intersection of AI, energy consumption, and sustainability in educational contexts. The asymmetrical structure of the treemap reflects the unequal distribution of keyword frequencies within the dataset, where a small number of dominant themes—such as energy utilisation, machine learning, and AI, occupy a disproportionately large share of the literature. This asymmetry is therefore not a visualisation artefact but a substantive feature of the research landscape. Prominent terms such as energy consumption, energy efficiency, and energy management highlight a strong focus on quantifying and mitigating the environmental impacts of AI operations. These keywords emphasise growing recognition that AI's carbon footprint stems not only from model training but also from continuous deployment across sectors, including education. Importantly, the treemap also displays education-related terms, including education, engineering education, learning systems, and deep learning, although with comparatively smaller representation. Their presence suggests that while most studies analyse AI's environmental impact from a technical perspective, a smaller but emerging body of work is beginning to explore its relevance to higher education. The inclusion of carbon footprint further reinforces that sustainability concerns are increasingly entering academic discussions on AI adoption. Overall, the asymmetry of the treemap reflects a concentration of research attention on technical and energy-related dimensions, with comparatively limited focus on institutional contexts, thereby underscoring the significance of the present study.

Building on the bibliometric results presented in Figs. 1, 2, 3, 4 and 5, the following discussion interprets the observed publication patterns, thematic structures, and temporal trends to provide deeper insights into how AI, carbon footprint, energy consumption, and environmental sustainability intersect within higher education

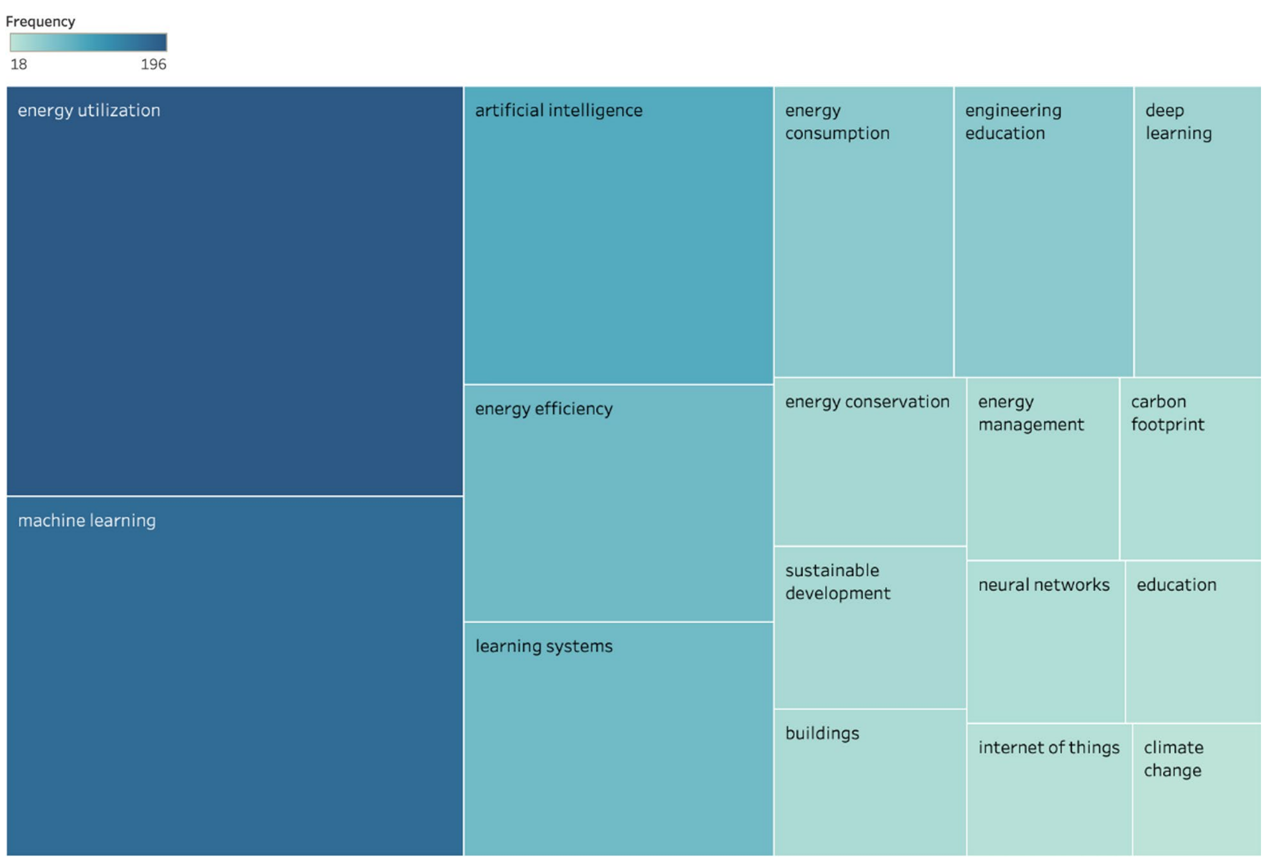


Fig. 5 Treemap visualisation of the most frequent keywords in the dataset

contexts. The pronounced growth in publication output observed after 2020 reflects a broader shift in academic attention toward the environmental consequences of data-intensive digital technologies. This trend aligns with increasing concerns regarding the computational demands of advanced AI systems, particularly large-scale machine learning and foundation models, whose training and deployment are associated with substantial energy use and carbon emissions [19, 23]. At the same time, AI is increasingly recognized as a potential tool for promoting sustainability and supporting climate mitigation strategies [26].

One of the most salient findings emerging from the bibliometric patterns is the transition from early research focused primarily on technical AI foundations and energy optimisation toward more sustainability-oriented investigations [50]. The increasing prominence of keywords related to energy consumption, carbon footprint, and climate change [29] suggests that environmental responsibility has become a central component of AI-related research. This evolution mirrors broader developments in the literature on sustainable and responsible AI, which emphasize the need to assess not only efficiency and performance, but also the environmental externalities associated with AI systems [19, 23, 28].

Within this expanding body of research, higher education emerges as a distinct yet still underexamined context [28]. Although education-related keywords appear less frequently than technical or energy-focused terms, their increasing visibility in recent years reflects growing recognition of universities as significant sites of AI deployment [50]. Higher education institutions act simultaneously as developers, adopters, and large-scale users of AI technologies, integrating AI into research computing, learning management systems, digital assessment, and campus-wide digital infrastructure, all of which depend on energy-intensive systems and data-centre operations [8, 35, 18]. These activities rely heavily on cloud services and HPC facilities, contributing to institutional energy consumption and associated carbon emissions [29]. Beyond computational workloads, recent evidence indicates that universities' broader digital infrastructures also generate measurable carbon emissions, as energy-intensive digital assets, data transfer volumes, and hosting configurations contribute to the environmental footprint of academic digital services [22, 28].

Recent campus-scale research demonstrates that AI-based predictive and optimisation models, particularly those employing advanced machine-learning algorithms such as XGBoost, are increasingly applied to manage energy demand and reduce CO_2 emissions across university buildings, highlighting both the scale and complexity of energy systems in higher education [3, 32]. Such applications highlight the growing role of AI-driven energy forecasting in shaping electricity demand and emissions trajectories across higher education campuses [50]. Machine-learning-driven forecasting systems have also shown substantial potential to enhance energy efficiency and reduce peak demand in campus operations, underscoring the operational scale and energy intensity of AI-supported infrastructure [50]. Empirical evidence further demonstrates that AI-based energy forecasting and management systems implemented in university campuses can significantly influence electricity demand patterns, reinforcing the role of AI-driven infrastructure in shaping institutional energy use [8]. Despite these developments, prior research on sustainability in higher education has largely focused on physical infrastructure and operational emissions, with comparatively limited attention paid to the environmental impacts of digital and AI-driven systems [26, 28].

The bibliometric findings further reveal a gap between technical research on AI energy efficiency and institution-level assessments of carbon emissions within universities. While a substantial portion of the literature addresses algorithmic optimisation, energy-aware computing, and predictive modelling, relatively few studies explicitly quantify or report the carbon footprint of AI adoption in higher education settings. This observation is consistent with earlier studies highlighting the absence of standardized metrics and reporting frameworks for digital emissions in universities [22, 28, 29]. As a result, organisational, governance, and policy-related dimensions of AI sustainability in higher education remain insufficiently explored [26].

Furthermore, the concentration of research output in technologically advanced regions raises important questions regarding the global representativeness of current knowledge. The dominance of publications from North America, Europe, and East Asia indicates that empirical insights into AI's environmental impact are shaped primarily by contexts with strong computational infrastructure and research capacity. This geographical imbalance may limit the applicability of existing findings to institutions operating in resource-constrained environments, where energy availability, digital infrastructure, and sustainability priorities may differ substantially.

Overall, the bibliometric analysis positions the carbon footprint AI in higher education as an emerging yet increasingly significant area of inquiry. The observed trends highlight the need for research that moves beyond technical optimisation toward integrated assessments combining computational, environmental, and institutional perspectives. By situating universities within the broader discourse on sustainable AI, this study contributes to ongoing efforts to understand how higher education institutions can reconcile technological innovation with environmental responsibility. Future research should also address the methodological standardisation of carbon accounting for AI-related activities in academia. Building on these bibliometric insights, the next subsection bridges the gap between scientific evidence and institutional practice by examining how universities engage with the sustainability implications of AI.

Linking institutional practice with scientific evidence

This subsection connects the findings of the bibliometric analysis with empirical evidence from institutional practice. It examines how universities with substantial AI-related research and innovation activities acknowledge, monitor, and govern their energy use and carbon emissions. The case studies in Table 1 reveal a consistent and cross-cutting pattern. Universities are rapidly expanding AI-related research and digital infrastructure, yet the environmental implications of this expansion are rarely articulated as a distinct analytical category. All institutions examined demonstrate substantial engagement with AI through HPC facilities, specialised research centres, or cloud-based computational platforms. This finding is fully consistent with the bibliometric results, which reflect a strong and growing research focus on machine learning, AI, and computational optimisation. As shown in Fig. 6, the case studies span North America, Europe, Asia, Africa, South America, and Australia, illustrating the global cross-regional distribution of institutions included in the analysis and supporting the comparative assessment of AI-related energy use and reporting practices across different institutional and geographical contexts.

The findings reported in Table 1 reflect patterns of institutional reporting and governance rather than quantified measurements of AI-specific energy consumption or carbon emissions. These references are not part of the bibliometric dataset but are used solely to support the interpretation of institutional practices. The column "Scientific literature informing analysis" provides a conceptual and analytical reference point used to interpret institutional practices in light of established scientific knowledge on the energy intensity and carbon implications of AI and machine learning. It includes both general scientific references and, where applicable, institution-specific sources underpinning the case evidence. These references are therefore not presented as prescriptive guidance for universities, but as a means of situating observed institutional practices within the broader research literature. Despite the expansion of AI-related infrastructure across the cases, energy reporting remains largely aggregated. Universities typically disclose total campus energy use or data-centre electricity consumption, but these figures are not disaggregated to reflect AI workloads specifically. From an analytical perspective, this aligns with the scientific literature, which has shown that AI-related energy consumption is often embedded within broader computational activity and is therefore difficult to isolate without dedicated monitoring frameworks [15]. The absence of AI-specific energy metrics should therefore be interpreted not as an institutional anomaly, but as a systemic limitation reflecting the current state of energy use reporting practice.

Carbon footprint reporting exhibits a similar pattern. Most universities publish institutional carbon inventories, frequently structured around Scope 1 (direct emissions), Scope 2 (indirect emissions from purchased energy), and occasionally Scope 3 (other indirect emissions) [6, 31], as illustrated in Fig. 7. However, none of the cases examined explicitly attribute emissions to AI systems, machine learning training, or algorithmic workloads. This absence is particularly notable given the growing body of scientific evidence demonstrating that large-scale AI models can have substantial carbon footprints [26], especially when trained on energy-intensive infrastructure or powered by carbon-intensive electricity grids [23, 39]. From a practical perspective, the scope-based framework illustrated in Fig. 7 provides a useful basis for developing AI-specific reporting approaches in higher education. AI-related emissions may be distributed across Scope 1, Scope 2, and Scope 3 categories depending on how computational activities are hosted and powered. For example, on-campus data centres and institution-owned HPC systems may contribute to Scope 1 emissions where direct fuel use is involved, e.g., backup generators, and to Scope 2 emissions through electricity consumption required to operate Graphics Processing Units (GPU) clusters and cooling systems. Similarly, AI workloads executed on university-owned GPU infrastructure are typically reflected in Scope 2 emissions through purchased electricity use. In contrast, AI services delivered via external cloud providers, e.g., large-scale model training or inference conducted off-site, fall under Scope 3, as indirect emissions associated with third-party digital services. Additional Scope 3 contributions may arise from the embodied emissions of AI hardware, including GPUs and specialised computing equipment within supply chains. Applying this framework with such distinctions can support more transparent and operationally meaningful reporting of AI-related environmental impacts, enabling institutions to better identify, monitor, and manage emissions associated with digital infrastructure.

The discussion also highlights a governance gap. While the literature increasingly calls for "Green AI" approaches that prioritise energy efficiency, transparency, and

Table 1 Institutional evidence on AI-related energy use and carbon reporting in selected higher education institutions

University [data year]	Country	AI-related infrastructure	Energy-related reporting	Carbon footprint treatment	Scientific and institutional sources informing analysis
University of Cambridge [44]	United Kingdom	HPC facilities supporting AI and data-intensive research	Aggregate campus and data-centre energy use reported	Institutional carbon footprint reported without AI disaggregation	HPC and large-scale machine learning training are recognised as energy intensive and carbon significant [15, 39]
Stanford University [2024]	United States	Dedicated AI research centres and extensive cloud-based AI use	Energy efficiency discussed in data-centre context	Scope-based emissions reported at institutional level	Cloud-based AI and large models contribute substantially to energy demand [23, 34, 37]
Eidgenössische Technische Hochschule Zürich [13]	Switzerland	National-scale research computing and AI laboratories	Computing infrastructure energy discussed	Carbon neutrality targets articulated	Optimisation and efficiency are key mitigation pathways for AI-related emissions (ETH Zürich, 2020; [34])
National University of Singapore [30]	Singapore	AI research hubs and smart-campus systems	Energy management systems reported	Institutional emissions disclosed	Smart systems and AI-driven optimisation can reduce energy use but increase computational load [15],NUS, 2024)
University of California, Berkeley [2023]	United States	AI-intensive research and shared computing platforms	Campus and ICT energy reporting	Climate action plans include ICT emissions	Computational research is a growing contributor to institutional carbon footprints [23, 43]
University of Oxford [2023]	United Kingdom	AI institutes and research computing services	Campus-level energy data reported	Institutional carbon accounting	Digitalisation in higher education embeds AI impacts within broader ICT emissions [15, 47]
University of New South Wales (UNSW Sydney) [46]	Australia	High-performance computational cluster (CPU/GPU nodes, cores, storage)	Reporting includes energy and water efficiency, onsite solar and gas	Institutional carbon reporting at whole-of-university level (no routine AI disaggregation)	Compute-intensive AI and HPC are increasingly recognised as energy- and carbon-significant within institutional footprints ([15, 34, 48], UNSW, n.d.)
University of Cape Town (UCT) [45]	South Africa	HPC environment positioned to support deep learning	Attention to efficiency (e.g., cooling/power considerations)	Carbon footprint report produced at institutional level (AI-specific attribution not foregrounded)	AI-scale computation can be carbon significant, even when not separately attributed in institutional reporting ([7, 15, 39], University of Cape Town, n.d.)
King Abdullah University of Science and Technology (KAUST) 2024[20, 21]	Saudi Arabia	Supercomputing capability (Shaheen) for AI-relevant workloads	Energy-intensive digital infrastructure sits within institutional footprint	Greenhouse-gas reporting presented institutionally by scopes without AI-specific partitioning	Large-scale AI data-centre operations entail substantial carbon and water footprints [11, 34, 20, 21]
Indian Institute of Technology (IIT), Madras [16]	India	Dedicated AI/data science centre/s embedded in major research university	Institutional report (fuel, energy, water and waste) publicly available; AI is not separately metered	Carbon footprint captured within institutional accounting (AI-specific attribution not required and not assumed)	Attributing emissions to specific digital activities is challenging, making whole-of-institution reporting a pragmatic proxy [15], IIT, n.d.; [23]
Universidade Federal de Santa Catarina (UFSC) [42]	Brazil	University-linked AI laboratory with advanced computing and DGX-class infrastructure	Public GHG emissions inventory for institutional-level energy/emissions accounting	Carbon footprint accounting via institutional inventory; AI-specific disaggregation not presumed	AI computing can materially affect institutional energy use, so GHG inventories offer a baseline for assessment ([23, 39], UFSC, 2024, 2025)

Table 1 (continued)

University [data year]	Country	AI-related infrastructure	Energy-related reporting	Carbon footprint treatment	Scientific and institutional sources informing analysis
Universidad de los Andes [40]	Colombia	Center for Research and Formation in Artificial Intelligence (CINFONIA)	Sustainability report on accounting meets "public documentation" criterion	Carbon footprint treated at organisational level; AI-specific attribution not required	Green AI emphasises linking institutional AI capability to transparent emissions reporting [9, 23, 34, 40]
Tecnológico de Monterrey [2023]	Mexico	Institution-wide AI capacity with cloud-oriented AI (useful contrast to campus-owned HPC models)	Sustainability reporting (Ruta Azul) provides public-facing institutional data on energy/emissions	Carbon/impact in institutional sustainability reporting (no AI-specific attribution)	Carbon-aware measurement frameworks can help make AI-linked impacts visible in institutional sustainability reporting [10, 11, 15, 33]

The final column includes both general scientific references and institution-specific sources used to contextualise and interpret the case evidence

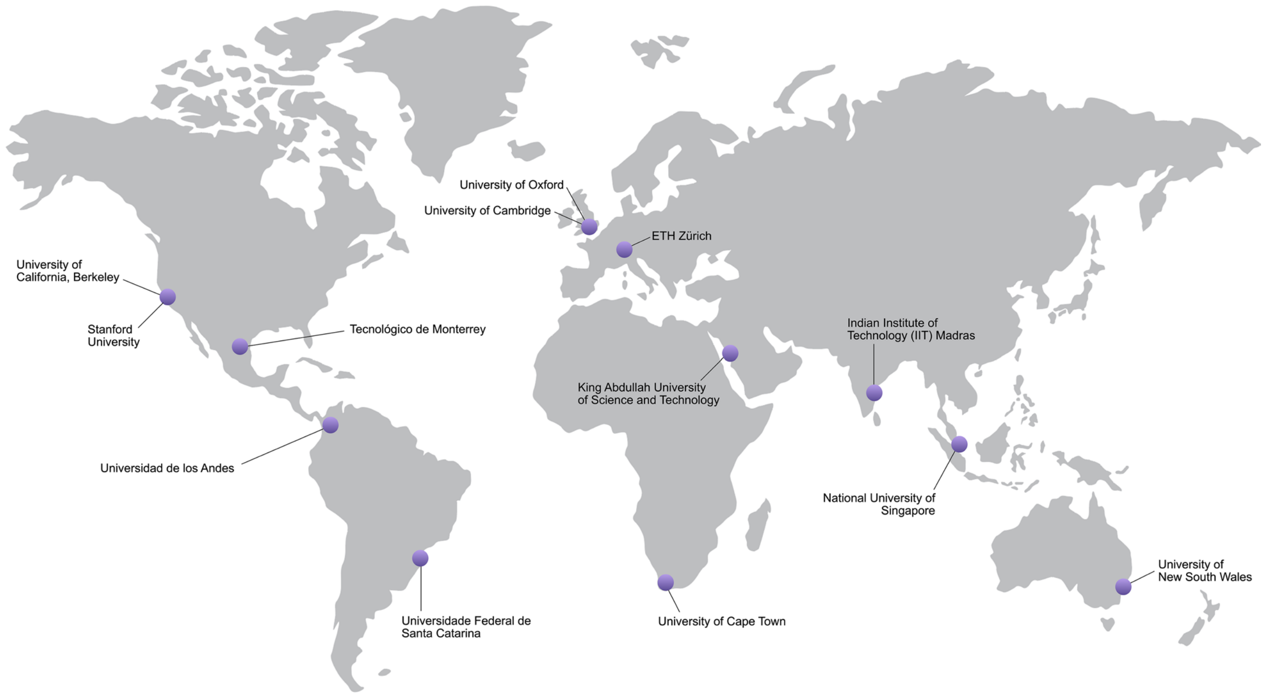


Fig. 6 Global distribution of the university case studies included in Table 1**.** Points indicate institutional locations for the selected case-study universities; labels identify each institution. The map is a compilation by the authors based on publicly available institutional case-study evidence presented in Table 1 (source: figure by authors)

responsible deployment [34], universities rarely translate these principles into formal sustainability reporting or AI governance frameworks. Where mitigation strategies are mentioned, such as energy-efficient data centres or renewable energy procurement, they are generally framed as institution-wide sustainability measures rather than responses to AI-specific risks. This reinforces the bibliometric observation that education-related considerations remain secondary within the broader AI–energy discourse. The consistent absence of AI-specific energy reporting across the case studies may be explained by several interrelated factors. First, technical constraints make it difficult to isolate AI workloads within shared computing environments, particularly in HPC infrastructures where multiple processes run concurrently. Second, institutional reporting practices typically aggregate energy consumption across digital and ICT systems, reflecting established accounting conventions rather than deliberate exclusion of AI-related impacts. Third, current sustainability reporting frameworks do not require AI-specific disaggregation, reducing incentives for universities to develop more granular monitoring systems. Taken together, these factors suggest that the absence of AI-specific reporting reflects a combination of technical, institutional, and regulatory limitations rather than a single underlying cause.

The case studies In Table 1 demonstrate that the environmental implications of AI in higher education are largely implicit rather than explicit. The lack of AI-specific energy and carbon metrics is not simply a data gap but a structural characteristic of current institutional practice. By situating this finding within a well-established scientific literature on AI energy consumption and carbon footprint, the study provides robust evidence that universities have yet to operationalise emerging research insights into transparent and standardised sustainability governance. This misalignment represents a critical challenge for higher education institutions seeking to balance rapid digital transformation with environmental responsibility.

Conclusions

This study set out to examine how the environmental implications of AI are addressed within higher education, focusing specifically on energy consumption and carbon footprint in relation to universities' expanding use of AI-enabled technologies. Combining a large-scale bibliometric analysis with an institution-level case study approach, the study provides a structured overview of both the evolution of academic knowledge and its reflection in institutional sustainability practices. Given the methodological design, the findings should be interpreted as

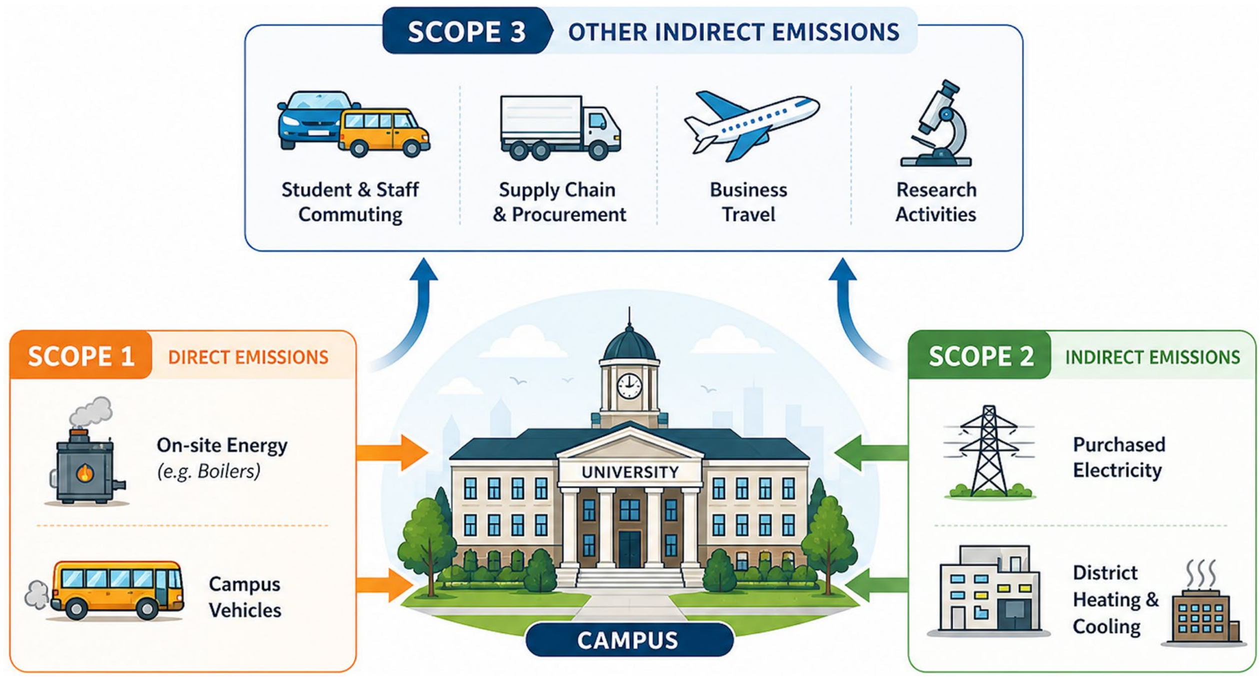


Fig. 7 Scope 1, Scope 2, and Scope 3 greenhouse gas emissions in higher education institutions, illustrating direct, indirect energy, and other indirect emission sources. Scope definitions adapted from Paredes-Canencio et al. [31], (source: figure by authors)

indicative of prevailing patterns rather than as a comprehensive or causal assessment, highlighting areas where research insights are only partially reflected in institutional reporting and governance.

The bibliometric analysis of 461 peer-reviewed publications reveals a rapidly expanding and increasingly interdisciplinary research field. Academic attention has shifted over time from technical and engineering-oriented studies of energy optimisation toward a broader engagement with sustainability, carbon footprint, and climate-related concerns. Although education-related terms have become more visible in recent years, higher education remains a secondary context within this literature, with universities rarely examined as organisational actors responsible for managing the environmental impacts of AI deployment. This finding indicates that much of the existing research addresses AI's environmental footprint in abstract or technical terms rather than in relation to institutional governance and reporting. The case study analysis provides complementary evidence at the institutional level. Universities included in the analysis demonstrate substantial engagement with AI through research-intensive computing infrastructure, specialised AI centres, and cloud-based digital platforms. Despite this widespread adoption, sustainability and environmental reporting remain largely aggregated at campus or ICT level. Publicly available reports consistently disclose energy use and greenhouse gas emissions at institutional scale, yet AI-specific energy consumption and carbon emissions are not explicitly identified or disaggregated. This pattern reflects structural limitations in current reporting frameworks rather than isolated institutional shortcomings and highlights a disconnect between scientific understanding of AI's environmental impact and the way sustainability is operationalised within universities.

The fact that AI-related energy is not separately reported may reflect both technical constraints—such as the difficulty of isolating AI workloads within shared computing infrastructure—and institutional discretion shaped by the absence of mandatory reporting standards. It likely represents a combination of these factors, compounded by the fact that sustainability reporting frameworks (e.g., STARS) do not yet require such granularity at the level of AI-specific energy use and carbon emissions. While such frameworks include provisions related to ICT and data-centre efficiency, these are generally embedded within broader infrastructure metrics, and do not typically mandate the disaggregation of AI-related computational workloads within institutional energy and emissions reporting. Future research could investigate whether universities possess the metering capability to report such data and what policy changes might incentivise greater transparency.

These findings carry important implications for both research and practice. To operationalise such improvements in practice, universities would need to develop more granular monitoring capabilities for digital and AI-related infrastructure. This includes the ability to measure energy consumption at the level of individual servers, GPUs, or high-performance computing workloads. In addition, institutions would need to collect and integrate workload-level data, such as the type of computational task, processing duration, and hardware specifications, in order to attribute energy use to specific AI activities. Achieving this would require closer coordination between facilities management, IT services, and research computing units, as well as the development of standardised reporting protocols. In the absence of such technical and organisational arrangements, AI-related energy consumption is likely to remain embedded within broader institutional energy figures, limiting the ability to identify targeted mitigation strategies.

For the academic community, the results underscore the need to move beyond technical assessments of AI energy use toward institutional and governance-oriented analyses that consider how universities account for and manage the environmental consequences of digital transformation. For higher education institutions, the absence of AI-specific metrics points to an urgent need for clearer reporting standards and governance frameworks capable of capturing the energy and carbon implications of data-intensive research and AI-enabled teaching. Developing such frameworks would support more transparent decision-making and align institutional sustainability strategies with emerging research insights on responsible and sustainable AI.

Several limitations should be acknowledged. The primary limitation of this study lies in the use of bibliometric analysis, which provides a structured overview of the literature but does not involve a detailed qualitative or content-based examination of individual studies. As a result, the analysis captures dominant trends and thematic patterns rather than the full conceptual depth of the field. Second, the case study component relies exclusively on publicly available institutional documentation, which reflects what universities choose to disclose rather than necessarily capturing internal practices or ongoing initiatives. Relatedly, the institutional reports analysed were published in different years, which may not fully capture the most recent developments in all cases. Third, the study does not attempt to quantify AI-specific energy consumption or carbon emissions, primarily due to the limited availability of disaggregated data at institutional level. Finally, the bibliometric dataset is restricted to publications indexed in Scopus and may not include relevant grey literature or policy reports. These limitations indicate that the findings should be interpreted as exploratory, while also highlighting important directions for future research.

Future research could address these limitations in several ways. Empirical studies involving direct collaboration with universities could explore internal data on AI-related energy use and develop methodologies for more granular carbon accounting. Comparative analyses across national or regional higher education systems could shed light on regulatory and policy factors shaping institutional responses to AI sustainability challenges. Further work could also examine the role of emerging standards, reporting guidelines, and responsible AI frameworks in supporting more systematic integration of environmental considerations into university governance. Future studies could also expand the range of case study institutions to assess the generalisability of the patterns identified across a broader set of higher education contexts.

Globally, this study demonstrates the growing importance of AI to the operations of higher education institutions, and the need for a greater understanding of the role its use plays when cross-checked against sustainability initiatives at universities. As major producers and users of AI technologies, universities are uniquely positioned to align technological innovation with environmental accountability. This can lead to transparent sustainability audits for AI systems, the implementation of energy-efficient computing standards, and the embedding of ecological ethics into both the computer science curriculum and campus-wide digital infrastructure. Such audits could be undertaken by institutional sustainability offices in coordination with IT services and research computing units, and, where appropriate, supported by external assurance providers. Emerging tools such as CodeCarbon and related machine-learning carbon accounting frameworks offer initial operational approaches, although standardised institutional methodologies for AI-specific energy and carbon reporting remain underdeveloped. Such integration can transform universities from passive consumers into architects of a sustainable digital future, ensuring that the pursuit of AI advances is not in spite of our planetary boundaries, but in harmony with them. The achievement of these goals will require closer integration between scientific research, institutional practice, and governance frameworks capable of responding to the environmental demands of an increasingly AI-driven academic landscape.

Abbreviations

AI	Artificial intelligence
CPU	Central Processing Units
GPU	Graphics Processing Units
HPC	High-performance computing
ICT	Information and Communication Technology
SDGs	Sustainable Development Goals
STARS	The Sustainability Tracking, Assessment & Rating System

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Author contributions
Following CRediT (Contributor Roles Taxonomy), the authors declare their contributions to this research as follows: Conceptualization, WLF; Data curation, AIA, MAPD, JML; Validation, AIA; Formal Analysis, WLF, JML, AIA, MAPD; Funding acquisition, JML; Investigation, WLF, JML, AIA, MAPD; Methodology, WLF, JML, AIA, MAPD; Resources, WLF, JML, AIA, MAPD; Visualization AIA, MAPD, JML; Writing—original draft, WLF, JML, AIA, MAPD; Writing—review & editing, WLF, JML, AIA, MAPD. All authors have equally contributed to writing this article.

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Data availability
The bibliometric data analysed in this study were retrieved from the Scopus database under licence. While the full dataset cannot be publicly redistributed, the search strategy is fully described in the Methods section, and the list of records analysed is available from the authors upon reasonable request. Data sources that underpin the multiple case study analysis are presented in Table 1.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
The authors declare no competing interests.

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