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10) Is AI a functional equivalent to expertise in organizations and decision-making? Opportunities and pitfalls for AI in the context of just transitions (2025)	FRONTIERS IN ARTIFICIAL INTELLIGENCE (Article From : FRONTIERS MEDIA SA)

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Discover Artificial Intelligence

Perspective

Climate change and artificial intelligence: assessing the global research landscape

Joanna I. Lewis[1] · Autumn Toney[2,3] · Xinglan Shi[4]

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Abstract

Artificial Intelligence (AI) could revolutionize our ability to understand and address climate change. Studies to date have focused on specific AI applications to climate science, technologies, and policy. Yet despite the vast demonstrated potential for AI to change the way in which climate research is conducted, no study has presented a systematic and comprehensive understanding of the way in which AI is intersecting with climate research around the world. Using a novel merged corpus of scholarly literature which contains millions of unique scholarly documents in multiple languages, we review the community of knowledge at the intersection of climate change and AI to understand how AI methods are being applied to climate-related research and which countries are leading in this area. We find that Chinese research institutions lead the world in publishing and funding research at the intersection of climate and AI, followed by the United States. In mapping the specific AI tasks or methods being applied to specific climate research fields, we highlight gaps and identify opportunities to expand the use of AI in climate research. This paper can therefore greatly improve our understanding of both the current use and the potential use of AI for climate research.

Keywords AI · Climate change · China · AI tasks and methods · Publication analysis

1 Background

Artificial Intelligence (AI) could revolutionize our ability to understand and address climate change. AI tasks and methods can increase the speed of problem solving with applications for better understanding the causes of climate change, responding to its impacts, and formulating solutions [1, 6, 11].

Today, scholars have begun to analyze the potential role that AI could play in addressing global climate change, both through improving our scientific understanding of the causes and impacts of climate change and by helping to develop solutions [22, 57]. We are increasingly seeing examples of how AI and machine learning can be used to improve the accuracy of climate system modeling [5], fill time series data gaps [26], estimate emissions inventories [20], refine climate scenario projections [44] and climate impact assessments [12], as well as develop applications for low carbon technology deployment through power, transportation and building system optimization [7, 8].

Multiple studies have shown that that AI simulations and machine learning are being integrated into weather and climate modeling, including emulating and forecasting weather patterns and climate processes with greater consistency,

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data efficiency, and improved generalization [28, 32, 36, 54, 55]. AI is used in in flood risk modeling frameworks to increase the performance and accuracy of prediction methods [43, 46, 61]. Using neural networks for weather and climate modeling has improved agriculture and crop yield predictions under a range of climate scenarios, and machine learning algorithms have been applied in areas such as monitoring soil quality, managing crops, and modeling evapotranspiration, rainfall, drought, and pest outbreaks [15, 50, 60].

AI algorithms are increasingly being used for improving the efficient management of natural resources. For example, combining deep learning with statistical techniques could create more useful assessments of the impact of deforestation on rising carbon emissions in metropolitan areas [34]. In addition, machine learning approaches are being applied in developing low carbon materials [19]; for example the application of machine learning in optimizing concrete and steel production have demonstrated how AI can be integrated into supply chain modeling for heavy industries [24, 39, 51]. AI frameworks have been applied to minimize water consumption and emissions from oil and gas reservoirs, while other research has demonstrated methods using machine learning in assessing the carbon footprint of buildings [13, 16, 29, 47].

Many studies have used AI methods in renewable energy research and demonstrated the broadening number of use cases for integrating AI into renewable energy systems. AI techniques are becoming a key tool in deploying data-integrated renewable energy networks [2, 4, 23, 37]; estimating and forecasting solar radiation resources [17, 30, 31, 38] and wind energy resources; [18, 25, 63] as well as in micro-grid management [27, 42, 58].

Additionally, AI has been shown to be a powerful tool to assess and develop carbon markets and generate more accurate carbon price models, including dynamic carbon pricing mechanisms [3], and more robust comparison models for carbon price forecasting [56]. Such methods have been applied to studies of emissions trading schemes including in China [35] and the UK [45].

While we have a sense of the general scope of climate change research being undertaken [21, 49, 52, 62], and studies have previously laid out the potential for AI to improve climate research and enable the achievement of global sustainable development goals [48, 53], no studies to date have taken a systematic and comprehensive approach to characterizing the way in which AI is intersecting with climate change research at a large scale, despite the vast demonstrated potential for AI to change the way in which climate research is conducted.

In this paper we map the community of knowledge at the intersection of climate change and AI to review how AI methods are being applied to climate related research, and which countries are leading in the application of AI to climate research. In mapping the specific AI tasks or methods being applied to specific climate research fields, we highlight gaps and identify opportunities to expand the use of AI in climate-related research.

Our analysis is based on a novel merged corpus of scholarly literature which contains millions of unique scholarly documents in multiple languages, and associated research clusters which are organized into a Map of Science. This is the first such study of the application of AI tasks and methods to climate change research using such a comprehensive data set. This paper can therefore greatly improve our understanding of both the current use and the potential use of AI for climate research.

2 Methods

In order to map the community of knowledge at the intersection of climate change and AI, we use a novel merged corpus of global scholarly literature, including Digital Science's Dimensions, Clarivate's Web of Science, Microsoft Academic Graph, China National Knowledge Infrastructure, arXiv, and Papers with Code, with CSET's Map of Science.[1] This dataset allows for a far more comprehensive review than most traditional bibliometric analyses. In addition, it includes more than 120,000 research clusters derived from citation relationships within the merged corpus. Research clusters are groupings of scholarly documents based on citation links, not on topic similarity or author networks; thus, research clusters are groupings of scientific publications that address similar research questions. Each research cluster includes a

[1] China National Knowledge Infrastructure is furnished for use in the United States by East View Information Services, Minneapolis, MN, USA. Dimensions is provided by Digital Science, Web of Science is provided by Clarivate Analytics, and China National Knowledge Infrastructure is furnished for use in the United States by East View Information Services, Minneapolis, MN, USA.

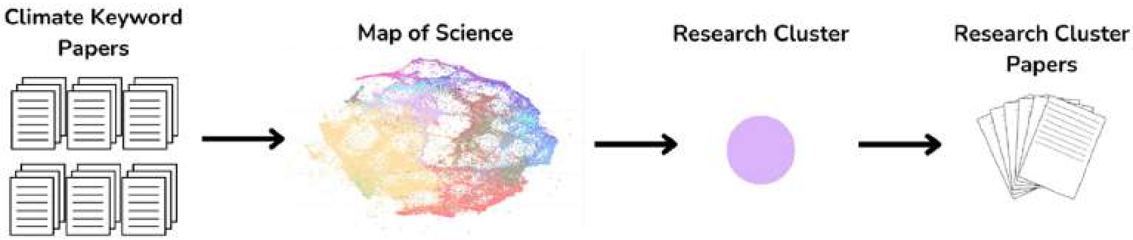

Fig. 1 Data Collection Pipeline using CSET's Merged Corpus and Map of Science

Table 1 Regular expression search terms used to generate $R_{climate}$

English	Chinese	SQL
climate change," "climate changes," "climatic change," and "climatic changes."	气候变化, 气候变迁	REGEXP_CONTAINS(str, r"(?i)((\bclimat.* change.*\b)|(气候变化)|(气候变迁))")
global warming	全球暖化, 全球升温, 全球气候变暖	REGEXP_CONTAINS(str, r"(?i)((\bglobal warming\b)|(全球暖化)|(全球升温)|(全球气候变暖)")
carbon emissions	碳排放	REGEXP_CONTAINS(str, r"(?i)((\bcarbon emission.*\b)|(碳排放))")
low carbon	低碳	REGEXP_CONTAINS(str, r"(?i)((\blow carbon\b)|(低碳))")

set of research publications and aggregated metadata generated from the member publications, such as, key areas of research (fields and topics), key researchers in the field, and key funders.[2]

We perform our analysis by identifying climate change related research papers via a keyword search, linking the publications to their research clusters, and then analyzing research clusters of interest. Figure 1 illustrates our data collection pipeline, starting with a set of keyword publications and ending with a set of research clusters and their member publications. Each dot in the map of science represents a research cluster and is colored by its broad area of research.

This scientific research data pipeline enables us to find research clusters of interest by locating research publications in the Map of Science. We can then look at a subset of research clusters and analyze aggregate statistics from their member papers. This approach to identifying scientific research of interest requires a seed set of publications. We generated a scientific research corpus of climate change literature ($R_{climate}$) using a regular expression search. We generated a scientific research corpus of climate change literature using a regular expression search in English and Chinese, including terms for climate change, global warming, carbon emissions and low carbon (Table 1).[3] If a publication contains one of the terms in its title or abstract it is included in our climate change publication set.

We ran a search through the CSET merged corpus using the terms generated above; publications were selected as being related to climate change research if their title or abstract contained at least one keyword. We based these keywords on other studies that have conducted bibliometric analysis [21]. This search resulted in 947,616 climate change-related publications, which we refer to as $R_{climate}$. We select RCs that contain at least one of these climate change publications, which results in 46,703 research clusters.

For each research cluster selected in this initial cluster search, we computed the percentage of papers that are contained in $R_{climate}$ out of the total number of papers in the RC. This allows us to sort and filter these resulting RCs based on the concentration of climate change-related papers. Our research cluster analysis for climate research includes 413,303 publications pulled from the 95th percentile of climate focused literature in our dataset which linked to 2,351 research clusters that have five percent or more $R_{climate}$ publications [33].

Our final filtering was through an identification of clusters with high percentages of AI-related publications. We use the AI percentage from the Map of Science, which identifies the concentration of AI-related publications in a given cluster. AI relatedness in English language publications were classified using a model trained on arXiv publications [14], and

[2] The data for this study was extracted on April 21, 2022. The latest version of the full database is available at https://sciencemap.eto.tech/?mode=map.

[3] Most non-English language publications translate the abstract into English so this search will include a range of non-English language publications. The most frequent exception to this is Chinese-language publications which is why we also include Chinese-language search terms.

Fig. 2 Climate Change and Climate Change AI Research Clusters Highlighted in the Map of Science

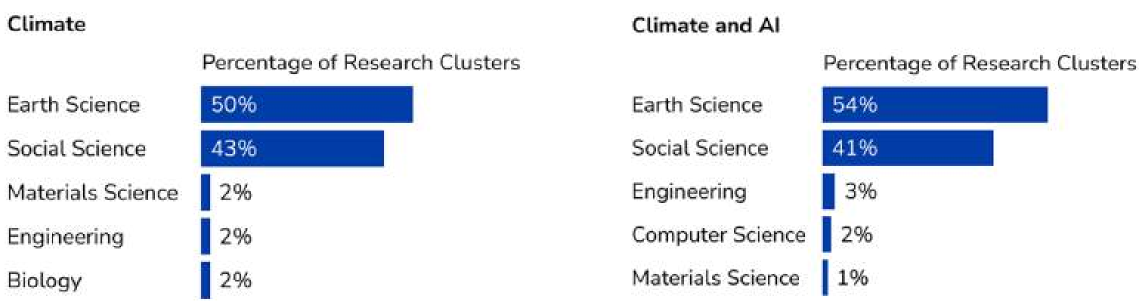

Fig. 3 Comparison of Climate and Climate + AI Research Clusters by Discipline

Chinese-language publications were classified using a regular expression query [10]. Thus, similarly to how we filter for climate change-related RCs, we can filter for AI-related RCs.

This allowed us to sort our dataset both by climate and AI relevance. We did this by looking at the clusters in both the 95th percentile of climate research and the 95th percentile of AI research. By selecting research clusters that have both 95% or more concentrations of climate change related publications and AI-related publications we identify 111 research clusters to analyze from the starting set of 2,351 climate change clusters.

Figure 2 displays the full Map of Science and the two subsets (climate change and climate change and AI) of research clusters we identify highlighted within it.

In the synthesis section we discuss further methods that were used to analyze and synthesize the dataset described above. This includes extracting 67 clusters that have either China, or the U.S. listed as the top country and have on average more than 2 citations per paper to filter for clusters with community engagement, and an examination of the leading AI and climate change tasks and methods by cluster at the individual publication level as described in Sects. 3.2 and 3.3.

3 Synthesis

3.1 Characterizing the climate change and AI research landscape

In order to contextualize the landscape of climate change and AI research, we compare the general research fields and countries of publication for each research cluster set. Each research cluster is assigned a broad discipline from the following list: Biology, Chemistry, Computer Science, Earth Science, Engineering, Humanities, Materials Science, Mathematics, Medicine, Physics, and Social Science. This discipline assignment represents the majority of member papers in a given research cluster and does not indicate that every member paper falls unambiguously under this area. Figure 3 displays the percentages of climate change related research clusters by their general discipline (displaying discipline areas that have at least a 1% share of publications).

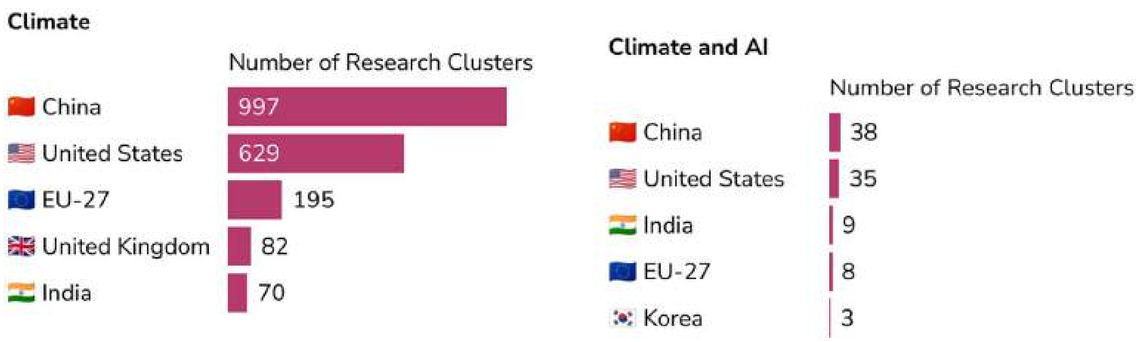

Fig. 4 Comparison of Climate and Climate and AI Research Clusters by Top Country

The climate research cluster set is comprised of 50% earth science publications and 43% social science publications, and includes materials science, engineering and biology publications. In contrast, the climate and AI dataset is comprised of 54% earth science and 41% social science publications, along with some engineering, computer science and materials science publications. While there is not a huge difference in fields between climate research and climate and AI research, biology drops off and is replaced by computer science in the second category as a leading field.

Articles at the intersection of climate and AI research include multiple disciplines from both the natural and social sciences. While the earth sciences dominate the research clusters identified, this is very closely followed by the social sciences. It is somewhat surprising that engineering and computer science do not show up in greater percentages in this area, likely because most climate related research is in fact not being done in these fields, but rather the models and techniques are being applied by climate researchers in their respective fields. A potential limitation of these categorizations however is that much of this work is interdisciplinary and may in fact span the natural and social sciences.

3.2 Leading countries, institutions and funders

Each research publication is assigned country data using the location of the organization that an author is affiliated with. This means that if there are multiple authors from different countries, a given publication will have multiple countries assigned. For all member publications in a given research cluster, a "top country" categorization is assigned based on the country being listed on the most publications in that research cluster. We treat all EU-27 countries as one entity due to their high rates of collaboration and research funding allocation. Figure 4 displays the top five leading countries by research cluster count.

We find that China produced more research in our climate research clusters and climate and AI research clusters, with U.S. authors producing the second highest number of research in both sets. It is perhaps not surprising given China's role in climate change research shown here, and its strong role in AI research [41]. Yet China has a more sizable publication output lead in climate research generally than in climate and AI research. The other countries that produce significant climate and AI research outputs differ from those that produce more climate research generally. The EU-27, UK, and India follow China and the United States in climate research generally, while India, the EU-27, and South Korea follow China and the United States in research on climate and AI. It is worth noting that if results were adjusted by factors such as population size or other measures of capacity, the analysis would yield different results.

Due to the publication output lead that China and the U.S. hold, we further refine our set of 111 climate change and AI research cluster to the 67 clusters that have either China or the U.S. listed as the top country and have on average more than 2 citations per paper to filter for clusters with community engagement [33]. This allows us to examine a variety of relevant variables including: (1) leading countries of author affiliation; (2) leading research fields; (3) leading author affiliations; (4) leading funding organizations; (5) leading industry affiliations; and (6) AI-related tasks and methods; thereby facilitating a more granular analysis of the research landscape at the intersection of climate and AI.

In order to identify research institutes with the highest global publication output at the intersection of climate and AI, we examine the research institutes that the study authors are associated with.[4] The top 10 institutes are listed in Table 2.

[4] Here, we shift our analysis here to the member publications of the research clusters, thus Tables 2–4 are counts of publications as opposed to research clusters.

Table 2 Top 10 publishers of research on climate and AI

Organzation	Country	Number of Publications
Chinese Academy of Sciences	China	1359
Beijing Normal University	China	228
University of Maryland, College Park	USA	191
Wuhan University	China	186
Wageningen University & Research	Netherlands	174
United States Geological Survey	USA	171
Tsinghua University	China	152
University of Wisconsin–Madison	USA	139
United States Forest Service	USA	138
University of New South Wales	Australia	135

Table 3 Top 10 funders associated with climate and AI publications

Organization	Country	Number of publications
National Natural Science Foundation of China	China	4391
Ministry of Science and Technology of the People's Republic of China	China	1938
National Science Foundation (US)	USA	1527
European Commission	EU	998
Chinese Academy of Sciences	China	710
National Aeronautics & Space Administration (NASA)	USA	676
Ministry of Education of the People's Republic of China	China	367
Brazilian Federal Agency for Support and Evaluation of Graduate Education	Brazil	319
United States Geological Survey	USA	307
United States Department of Energy	USA	248

As China is the leading country by author affiliation as presented above, we see that many research institutes publishing at the intersection of climate and AI research are based in China. The Chinese Academy of Sciences, the largest research institute in China, is by far the dominant research institute where research at the intersection of climate and AI is being conducted. Within the Chinese Academy of Sciences (CAS), the leading research institute associated with climate change and AI publications in our database is University of the Chinese Academy of Sciences (438 publications), followed by the Institute of Geographic Sciences and Natural Resources (277 publications), and the Institute of Remote Sensing and Digital Earth (246 publications). Other leading Chinese research institutes include Beijing Normal University, Wuhan University, and Tsinghua University.

Within the United States, the University of Maryland, College Park has the largest number of publications in our climate and AI dataset, followed by the United States Geological Survey, University of Wisconsin-Madison, and the United States Forest Service. The two other countries with research institutes that show up in the top ten are the Netherlands and Australia.

We examine the observable leading funding organizations associated with climate and AI publications and find that China-based funding organizations have supported research that contributed to the largest number of publications, including the National Natural Science Foundation of China (4,391 publications) and China's Ministry of Science and Technology (1,938 publications) in the first and second position. In third place is the United States National Science Foundation (1,527 publications), followed by the European Commission (998 publications) and the Chinese Academy of Sciences (710) which not only conducts but also funds research. The top ten funders are listed in Table 3.

While no private companies appear as leading research institutes or funders, we took a closer look to determine which companies are the most associated with climate and AI publications in our database. The top five companies that appear in our database in either a funding capacity or research affiliation are Google based in the United States (62

Table 4 Top producers within the Chinese Academy of Sciences of Climate/AI publications

Name of CAS Research Institute	Number of Publications	Website
University of the Chinese Academy of Sciences	438	https://english.ucas.ac.cn
Institute of Geographic Sciences and Natural Resources Research	277	http://english.igsnrr.cas.cn
Institute of Remote Sensing and Digital Earth	246	http://english.radi.cas.cn
Aerospace Information Research Institute	53	http://english.aircas.ac.cn
Northeast Institute of Geography and Agroecology	34	http://english.neigaehrb.cas.cn
Northwest Institute of Eco-Environment and Resources	28	http://english.nieer.cas.cn
Institute of Soil Science	25	http://english.issas.cas.cn
Institute of Tibetan Plateau Research	18	http://english.itpcas.cas.cn
Nanjing Institute of Geography and Limnology	13	http://english.niglas.cas.cn
Institute of Atmospheric Physics	11	http://english.iap.cas.cn

publications), Science Systems and Applications based in the United States (30 publications), State Grid Corporation based in China (30 publications),[5] IBM based in the United States (22 publications), and Volkswagen Group based in Germany (15 publications).

The Chinese Academy of Sciences (CAS) is listed in Table 2 as being associated with the largest number of publications at the intersection of climate and AI by far. However, CAS is a large organization comprised of multiple research institutes distributed throughout the country. As a result, we took a closer look at the specific research institutes within CAS to better understand their contributions to research in this area. We found that the University of Chinese Academy of Sciences is the source of the highest number of publications, followed by the Institute of Geographic Sciences and Natural Resources Research, and the Institute of Remote Sensing and Digital Earth as listed in Table 4.

The names of the CAS institutes give some indication of the type of research where AI is being applied to climate research, including in the areas of geographic sciences and remote sensing. More detail is available at the websites provided in Table 4.

3.3 AI tasks and methods used in climate research fields

To better understand exactly how AI is being utilized within climate research, we examined the AI-related tasks and methods that are automatically assigned to individual research publications in our database using a named entity recognition model trained on tasks and methods as developed in [59]. Each task and method label falls under several broad areas, such as "natural language processing" or "causal inference." For our analysis, we aggregated the tasks and methods that appeared in member publications of our 67 research clusters of interest. For each RC, we looked at the top five most frequent tasks and methods from the research clusters' member publications and represented them in nine distinct categorizations from the "Papers with Code" taxonomy: causal inference, computer vision, graphs, methodology, natural language processing, neural networks, reinforcement learning, robots, and time series [40].

Next, we manually verified nine climate-related categorization labels based on the occurrence of keywords in the research cluster metadata: climate impacts, climate modeling, emission trends, energy efficiency, energy technology, energy trends, land use change, public perception, and transportation, based in part on the categories used in [48]. We then identified all distinct pairings between the nine AI-related tasks and methods and the nine climate-related categories. For example, if a research cluster had both climate modeling and neural networks labels, that would be represented in Table 5 by a checkmark.[6]

In Table 5 we see a wide range of AI tasks and methods being applied to the 9 climate research areas that we extract from our climate and AI RC dataset. For example, we identify six AI tasks and methods being used in studies of climate impacts, including causal interference, computer vision, natural language processing, neural networks, robots and time

[5] The State Grid Corporation of China is technically a state-owned as opposed to a purely privately held company.
[6] In this way, Table 5 denotes the AI-related tasks and methods that have been applied to climate-related areas but does not represent the frequency of these pairings.

Table 5 Mapping AI Tasks and Methods within Climate Change Research Subfields

	Causal Interference	Computer Vision	Graphs	Methodology	Natural Language Processing	Neural Networks	Reinforcement Learning	Robots	Time Series
Climate Impacts	✓	✓			✓	✓		✓	✓
Climate Modeling		✓	✓			✓		✓	✓
Emissions Trends						✓		✓	✓
Energy Efficiency		✓				✓		✓	
Energy Technologies		✓		✓	✓		✓		
Energy Trends				✓					
Land Use Change		✓				✓	✓		
Public Perception					✓				
Transportation				✓		✓			

series. Studies involving climate modeling are using at least five AI tasks and methods including computer vision, graphs, neural networks, robots and time series.

This analysis also reveals some areas of climate research that are using fewer AI tasks and methods. While energy technologies research is using multiple methods (examples include computer vision, AI methodology, natural language processing, and reinforcement learning), we see other areas of energy research such as energy trends studies and public perception studies using fewer methods. As a result, there appear to be gaps in certain climate research areas where AI tasks and methods are not being used as widely and where there may be useful applications. Exploring these gaps identified in Table 5 is an area for future research.

4 Discussion and conclusions

Given the vast potential of AI tasks and methods to revolutionize all aspects of research and analysis, it is not surprising that they are being applied to one of today's most pressing global challenges, addressing climate change. Our study contributes to the understanding of how AI is being used in climate related research with three key findings.

First, we find that articles at the intersection of climate and AI research include multiple disciplines from both the natural and social sciences. While the earth sciences dominate the research clusters identified, this is very closely followed by the social sciences. It is somewhat surprising that engineering and computer science do not show up in greater percentages in this area, likely because most climate related research is in fact not being done in these fields. A potential limitation of these categorizations however is that much of this work is interdisciplinary and may in fact span the natural and social sciences.

Second, we find that Chinese research institutions lead the world in publishing and funding research at the intersection of climate and AI, followed by the United States. In examining the research institutes that the study authors are associated with, we find that just as China is the leading country by author affiliation as presented above, many of leading research institutes at the intersection of climate and AI research are based in China. The Chinese Academy of Sciences, the largest research institute in China, is by far the dominant research institute where research at the intersection of climate and AI is being conducted. We also find that the leading funders associated with climate and AI publications are also based in China: The National Natural Science Foundation of China and China's Ministry of Science and Technology. China's dominance in AI applications has been well documented, and we show that China also leads the world in climate released research, as well as at the climate-AI interface. This is also reflected in Chinese government policy; for example, the Chinese government has issued explicit guidance on the use of AI in climate research in the "Meteorological Science and Technology Development Plan (2021–2035)" issued by the Ministry of Science and Technology and Chinese Academy of Sciences in March 2022 [9].

Third, by mapping the specific AI tasks or methods being applied to specific climate research fields, we find gaps and identify opportunities to expand the use of AI in climate research. While we believe this is the first study to examine this in a systematic way, we acknowledge some deficiencies in our methods, namely that we manually identified subfields in climate research using some keyword analysis as well as some subjective judgement, and that our pairing of AI-related tasks and methods to climate-related research areas represents the occurrence but not the frequency of these pairings. However, our findings raise multipole questions that present opportunities for future research and inquiry, including why certain tasks and methods are being used in specific fields, and what other fields might learn from applications to date.

Of course, any effort to make broad generalizations about fields as vast and complex as the fields of climate change and AI comes with some limitations. There are likely applications of AI to climate research that are not included here due to limitations in our original search terms or in the way in which we develop climate subfields in order to map them against AI tasks and methods. These are rapidly involving fields of research in which new methods and applications are being developed all the time. Furthermore, the field of research at the intersection of AI and climate change is growing very rapidly, so any attempt to assess the state of the field could be quickly outdated.

Yet given the tremendous opportunity that emerging AI tools provide in addressing a challenge so vast and multi-faceted as climate change, the study of their application is no doubt of tremendous academic and practical importance. This paper allows for a more globally comprehensive and nuanced analysis of this relationship than past studies and consequently provides a tangible contribution to our broader understanding of the use of AI tasks and methods in climate change research.

This study also examines the role of specific countries and specific funding organizations in shaping the direction of climate and AI research which will be increasingly important to understand. Furthermore, tensions between China and the West are already shaping national decisions about investments in AI research and could influence future research directions.

Given the very limited time remaining to avoid even more dangerous impacts of climate change globally, the expanded use of AI tasks and methods presents the opportunity to transform our ability to understand and address climate change. This paper helps to identify opportunities to expand the use of AI tasks and methods in climate related research, and the predominance of China and the United States in this area raises important questions about national leadership and competitiveness.

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Data availability The data used in this analysis is available on Mendeley Data [Joanna I. Lewis and Autumn Toney, "AI Applications in Climate Research Dataset" (Mendeley Data, 2024), https://doi.org/10.17632/wjwbwrn28p.1.

Code availability Not applicable.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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ARTICLES FOR UTM SENATE MEMBERS

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REVIEW

Article Context and Technological Integration: AI's Role in Climate Change Research

Contexto del Artículo e Integración Tecnológica: El Papel de la IA en la Investigación sobre el Cambio Climático

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ABSTRACT

This article explores the transformative role of artificial intelligence and machine learning in tackling climate change. It highlights how advanced computational techniques enhance our understanding and response to environmental shifts. Machine learning algorithms process vast climate datasets, revealing patterns that traditional methods might overlook. Deep learning neural networks, particularly effective in climate research, analyze satellite imagery, climate sensor data, and environmental indicators with unprecedented accuracy. Key applications include predictive modeling of climate change impacts. Using convolutional and recurrent neural networks, researchers generate high-resolution projections of temperature rises, sea-level changes, and extreme weather events with remarkable precision. AI also plays a vital role in data integration, synthesizing satellite observations, ground-based measurements, and historical records to create more reliable climate models. Additionally, deep learning algorithms enable real-time environmental monitoring, tracking changes like deforestation, ice cap melting, and ecosystem shifts. The article also highlights AI-powered optimization models in mitigation efforts. These models enhance carbon reduction strategies, optimize renewable energy use, and support sustainable urban planning. By leveraging machine learning, the research demonstrates how AI-driven approaches offer data-backed solutions for climate change mitigation and adaptation. These innovations provide practical strategies to address global environmental challenges effectively.

Keywords: Advanced AI; Machine Learning; Deep Learning Techniques; Climate Change.

RESUMEN

Este artículo explora el papel transformador de la inteligencia artificial y el aprendizaje automático en la lucha contra el cambio climático. Destaca cómo las técnicas computacionales avanzadas mejoran nuestra comprensión y respuesta a los cambios ambientales. Los algoritmos de aprendizaje automático procesan grandes conjuntos de datos climáticos, revelando patrones que los métodos tradicionales podrían pasar por alto. Las redes neuronales de aprendizaje profundo, especialmente eficaces en la investigación climática, analizan imágenes satelitales, datos de sensores climáticos e indicadores ambientales con una precisión sin precedentes. Las aplicaciones clave incluyen la modelización predictiva de los impactos del cambio climático. Mediante redes neuronales convolucionales y recurrentes, los investigadores generan proyecciones de alta resolución sobre el aumento de temperaturas, el nivel del mar y la probabilidad de eventos climáticos extremos con notable precisión. La IA también desempeña un papel fundamental en la integración de datos, combinando observaciones satelitales, mediciones terrestres y registros históricos para crear modelos climáticos más fiables. Además, los algoritmos de aprendizaje profundo permiten el monitoreo ambiental en tiempo real, rastreando cambios como la deforestación, el derretimiento de los casquetes polares y las transformaciones de los ecosistemas. El artículo también destaca los modelos de optimización impulsados por IA en los esfuerzos de mitigación. Estos modelos mejoran las estrategias de reducción de carbono, optimizan el uso de energías renovables y apoyan la planificación urbana sostenible. A través del aprendizaje automático, la investigación demuestra cómo los enfoques basados en IA ofrecen soluciones respaldadas por datos para la mitigación y adaptación al cambio climático, proporcionando estrategias prácticas para abordar los desafíos ambientales globales de manera efectiva.

Palabras clave: IA Avanzada; Aprendizaje Automático; Técnicas de Aprendizaje Profundo; Cambio Climático.

INTRODUCTION

The article on advanced AI, machine learning, and deep learning techniques for climate change studies represents a pivotal intersection between cutting-edge computational technologies and environmental science.[1,2] Building upon traditional climate research methodologies, this approach introduces a transformative paradigm that leverages artificial intelligence's unprecedented analytical capabilities to address global environmental challenges.

Machine learning and deep learning algorithms offer researchers powerful tools to transcend conventional data analysis limitations.[3] By processing immense volumes of complex, multidimensional environmental data, these computational techniques can reveal intricate patterns and correlations that human analysts might overlook. The chapter emphasizes how neural networks can synthesize information from diverse sources—satellite imagery, ground-based sensors, historical climate records, and real-time environmental monitoring systems—creating more comprehensive and nuanced climate models. The technological framework presented demonstrates remarkable potential across multiple research domains.[4] Predictive modelling stands out as a critical application, with advanced AI algorithms generating high-resolution climate projections that significantly improve our understanding of potential future scenarios.[5,6] These models can forecast temperature variations, sea-level changes, and extreme weather event probabilities with unprecedented accuracy, providing policymakers and researchers with critical insights for strategic planning and mitigation efforts.

Moreover, the research highlights AI's role in environmental monitoring and strategy development. Deep learning algorithms enable real-time tracking of complex environmental changes, including deforestation, ecosystem transformations, and glacial melting. By converting massive datasets into actionable intelligence, these computational techniques bridge the gap between raw information and strategic environmental management.

The chapter also explores optimization models powered by machine learning, which can design more effective carbon reduction strategies and support sustainable urban planning.[2] These AI-driven approaches represent a sophisticated method of developing targeted interventions that balance environmental preservation with economic and social considerations.

Ultimately, this research underscores the critical importance of interdisciplinary collaboration. By integrating advanced computational techniques with climate science, researchers can develop more nuanced, data-driven approaches to understanding and mitigating global environmental challenges. The AI-enhanced methodologies presented offer a beacon of technological hope in addressing one of the most complex global issues of our time. As climate change continues to evolve as a critical global concern, the computational techniques outlined in this chapter demonstrate the transformative potential of artificial intelligence in developing innovative, responsive, and sophisticated environmental research and intervention strategies.

Literature review methods of inclusion and exclusion

Inclusion Criteria

The literature selection for this research follows a structured inclusion process to ensure relevance and quality. The following criteria were applied:

1. **Relevance to AI and Climate Change**: articles that specifically discuss artificial intelligence, machine learning, or deep learning applications in climate change research.
2. **Peer-Reviewed and Scholarly Sources**: only peer-reviewed journal articles, conference proceedings, and authoritative institutional reports are considered.
3. **Publication Date**: literature published within the last ten years (2014-2024) to ensure up-to-date technological and scientific advancements.
4. **English Language**: research articles and reports written in English to maintain consistency in interpretation and analysis.

5. Technological Integration: studies highlighting AI-driven models, algorithms, or computational techniques for climate prediction, environmental monitoring, and mitigation strategies.

6. Empirical Studies: research that includes case studies, experiments, or real-world applications of AI in climate change.

Exclusion Criteria

To maintain a focused scope, the following exclusion criteria were applied:

1. Non-AI-Based Climate Research: articles that discuss climate change without integrating AI methodologies.

2. Non-Peer-Reviewed Sources: blog posts, opinion pieces, and non-scientific sources are excluded.

3. Outdated Studies: research published before 2014 unless foundational to AI's role in climate science.

4. Irrelevant Technological Focus: studies focusing on general environmental science without a technological component.

5. Duplicate Studies: repeated studies with no new findings or methodological advancements.

Boolean Operators for Literature Search

To refine the literature search, Boolean operators were used in academic databases (Google Scholar, IEEE Xplore, Scopus, and Web of Science). The search queries included:

- ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Climate Change" OR "Global Warming")
- ("AI in Climate Science" OR "AI for Environmental Monitoring") AND ("Prediction" OR "Mitigation")
- ("Neural Networks" OR "Algorithmic Models") AND ("Sustainability" OR "Carbon Emission Reduction")

These Boolean strategies ensure comprehensive retrieval of relevant and high-quality research articles aligning with the study's objectives.

Table 1. Inclusion and Exclusion Criteria

Criteria	Inclusion (✓)	Exclusion (✗)	Count
AI and Climate Change Relevance	✓	✗	150
Peer-Reviewed Sources	✓	✗	120
Publication Date (2014-2024)	✓	✗	100
English Language	✓	✗	130
Technological Integration	✓	✗	110
Empirical Studies	✓	✗	90
Non-AI-Based Climate Research	✗	✓	50
Non-Peer-Reviewed Sources	✗	✓	40
Outdated Studies (Pre-2014)	✗	✓	60
Irrelevant Technological Focus	✗	✓	30
Duplicate Studies	✗	✓	20

DEVELOPMENT

Advancing Climate Modeling through Artificial Intelligence: A Technological Breakthrough

The exponential growth of information sources has unveiled unprecedented opportunities to leverage emerging technologies, particularly advanced artificial intelligence, in enhancing complex systems like global climate models. While current global climate models represent our most sophisticated tools for projecting climate change across regional and global scales, they remain fundamentally constrained by computational limitations in modeling turbulent atmospheric phenomena.[7,8]

Traditional climate models struggle with intricate atmospheric dynamics, especially in representing cloud formations and moist air convection. These models rely on subgrid parameterizations that function more like adaptive tuning mechanisms rather than providing precise representations of cloud motions—critical drivers of global climate variability. This computational constraint has long hindered our ability to generate highly accurate climate predictions.[9]

Artificial intelligence emerges as a transformative solution to these computational challenges. The convergence of rapidly expanding observational datasets and advanced AI technologies positions machine learning as a potential game-changer in climate science.[8] AI technologies promise to revolutionize global climate models by enhancing resolution, improving grid-scale interactions, and more accurately representing complex atmospheric processes.

The potential improvements span multiple critical atmospheric domains, including:

- Dry dynamical kernels
- Convective forcing mechanisms
- Grid-scale condensation
- Radiation interactions
- Cumulonimbus cloud formations
- Boundary layer dynamics
- Cloud microphysics
- Subgrid turbulence modeling

Current research demonstrates diverse machine learning approaches, from linear regression models to sophisticated neural network architectures. Support vector machines and advanced neural networks have shown particular promise in prediction, classification, pattern recognition, and numerical optimization of climate models.(10) This technological integration represents more than incremental improvement—it signals a paradigm shift in our approach to understanding global climate dynamics. Machine learning and deep learning technologies offer unprecedented capabilities to process and interpret massive, complex observational datasets, potentially transforming our predictive capabilities. By bridging computational limitations and providing more nuanced representations of atmospheric interactions, AI technologies hold the potential to significantly enhance our understanding of climate change, offering more precise, comprehensive models that can guide critical environmental policy and mitigation strategies.(11)

Deep Learning Paradigms in Climate Change Research: A Comprehensive Exploration

In the rapidly evolving landscape of climate science, deep learning has emerged as a transformative technological approach, offering unprecedented capabilities for modeling and understanding Earth's complex environmental systems. This chapter, aligned with the book's focus on "Advanced AI, Machine Learning and Deep Learning Techniques for Climate Change Studies," provides an extensive examination of deep learning's revolutionary potential in climate research(12), (figure 1).

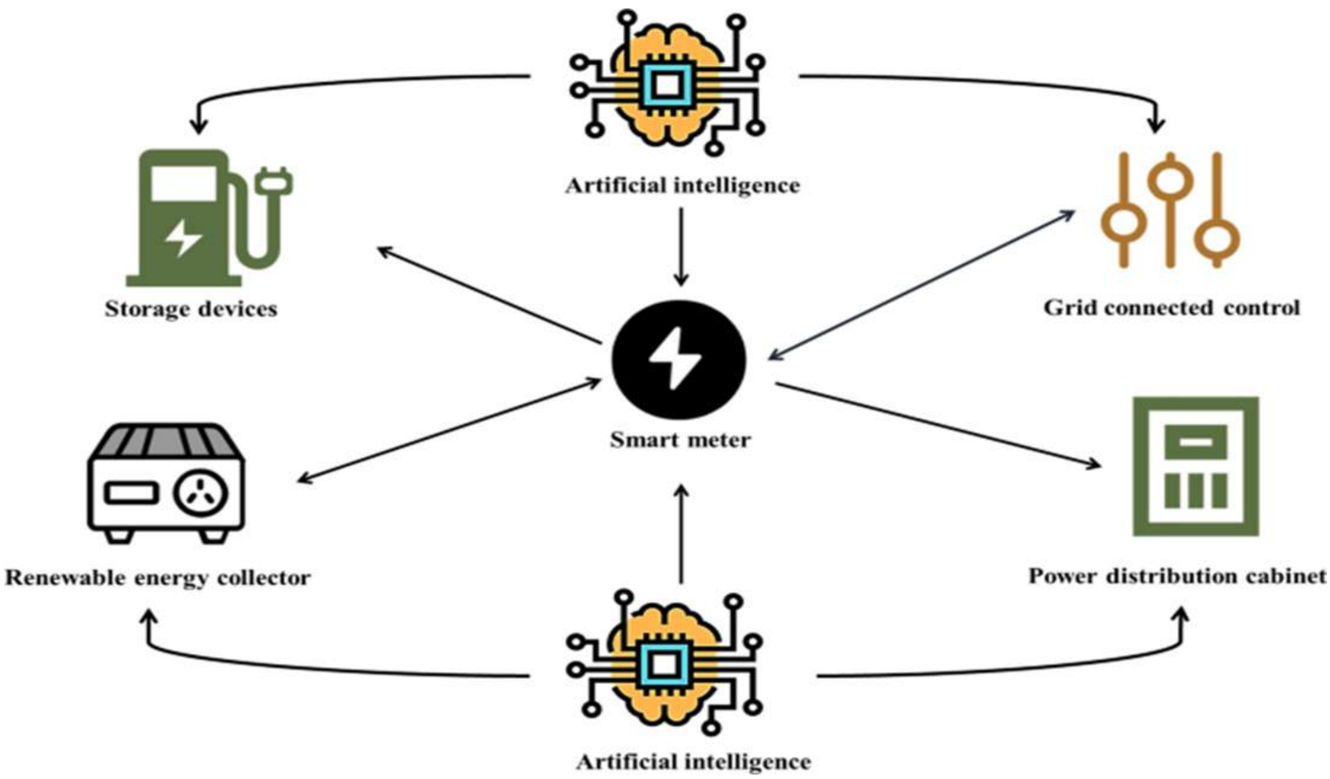

Figure 1. Depicting the role of AI(7,13,14)

Deep learning technologies distinguish themselves from traditional machine learning models through their sophisticated architectural design. Unlike conventional approaches that require manual feature extraction, deep learning models can autonomously learn optimal representations of spatiotemporal data, enabling more nuanced and comprehensive climate predictions. These models characteristically employ multiple hidden

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layers, allowing for increasingly complex and abstract representations of environmental phenomena.[15]

The technological advancement is particularly significant in climate science, where understanding intricate interactions between global systems demands computational approaches that can process massive, multidimensional datasets. Deep learning algorithms demonstrate remarkable capabilities in various critical domains.

RESULTS AND DISCUSSION

Climate and Weather Pattern Analysis

Deep learning algorithms have revolutionized our approach to understanding and predicting climate and weather patterns by processing vast historical and real-time meteorological datasets. These advanced neural networks can identify subtle, complex relationships within atmospheric data that traditional statistical models often overlook.[16] By integrating multiple data sources and employing sophisticated pattern recognition techniques, these models enable more accurate predictions of weather phenomena, including extreme events like hurricanes, heat waves, and prolonged drought conditions. The technology's ability to analyze intricate temperature, precipitation, and atmospheric interactions allows researchers to develop more comprehensive long-term climate trend forecasting and seasonal prediction models, providing critical insights into global environmental dynamics.[17]

Remote Sensing Data Interpretation

Convolutional neural networks have transformed remote sensing data analysis by offering unprecedented capabilities in processing satellite and aerial imagery. These advanced AI systems can rapidly classify and segment geographical features, detecting minute environmental changes such as deforestation, ice melt, urban expansion, and ecosystem transformations.[18] By automating the interpretation of high-resolution imagery, these technologies enable researchers to monitor global environmental changes in real-time with extraordinary accuracy. The ability to process massive geospatial datasets quickly allows for more responsive and dynamic environmental monitoring, supporting critical research into climate change impacts and ecological shifts across different geographical regions.

Cybersecurity Applications in Environmental Monitoring

As environmental monitoring becomes increasingly dependent on complex digital infrastructure, AI-powered cybersecurity systems have emerged as crucial guardians of critical climate research networks. These advanced systems employ sophisticated algorithms to detect potential cyber threats, analyze network traffic patterns, and identify unusual activities targeting environmental data systems.[19] By creating resilient communication networks and implementing intelligent threat detection mechanisms, these technologies protect sensitive climate research data from potential breaches or malicious manipulation. The integration of cybersecurity measures with environmental monitoring platforms ensures the integrity and continuity of global climate research efforts.

Complex System Modeling and Prediction

Advanced neural network architectures have opened new frontiers in modeling and predicting complex environmental systems. These computational approaches enable researchers to simulate intricate interactions between various environmental components, integrating diverse data sources to create holistic predictive frameworks. By developing multi-layered models capable of understanding non-linear environmental dynamics,[20] scientists can now generate more precise long-term climate change scenarios. These sophisticated simulation techniques support the development of more targeted and effective climate intervention and mitigation strategies, providing policymakers and researchers with nuanced insights into potential future environmental transformations.

Each of these domains represents a critical application of artificial intelligence in addressing global environmental challenges, demonstrating the transformative potential of advanced computational techniques in understanding, monitoring, and responding to complex climate systems. Therefore, the chapter delves into the theoretical foundations of deep learning architectures, exploring how multiple neural network layers can uncover hidden patterns in climate data that traditional statistical models might miss.[21] This approach transcends previous computational limitations, offering researchers unprecedented insights into global environmental dynamics. Technological infrastructure developments have been crucial in enabling these advanced modeling techniques. The proliferation of high-performance computing resources—including multi-core processors and specialized graphical processing units—has made training complex neural networks increasingly feasible. These technological innovations allow for more sophisticated, layered computational models that can handle the immense complexity of global climate systems.[22] By leveraging deep learning's ability to learn and abstract information across multiple computational layers, researchers can now develop more precise, adaptive

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climate models. These models represent a significant leap forward in our capacity to understand, predict, and potentially mitigate the impacts of climate change.The research underscores deep learning's transformative potential, positioning it as a critical tool in addressing one of the most complex scientific challenges of our time: comprehending and responding to global environmental transformation.[23]

Convolutional Neural Networks (CNNs)

Recently, CNN architectures have been widely used in the climate field. CNNs have several hidden layers to detect or exploit patterns related to the given input data. They act like a human visual perception system and have proven to be efficient in image and video recognition and classification. CNNs are suitable for handling multi-dimensional data such as time-series data, climate model data, agriculture-based data, and remote sensing data communications. The network first passes the data through several layers of convolution, normalization, scaling, and pooling using non-linear activations.[24] It sends the data to a kind of fully connected hidden layers similar to an artificial neural network to make predictions on the given dataset. These fully connected layers are just the multi-layer perceptron. Convolution is the mathematical process of combining two functions to produce a third function. In CNNs, it determines the input values and weights using the kernel function, creates the feature map, sweeps across the input data, and then modifies or processes it by using pooling techniques. Batch normalization is used to improve the training of the neural network to normalize the input activations. It is a simple and effective technique that allows for the use of much higher variances and minimal regularization inside the operation function. It improves learning in a network and the lateral speed of training. Batch normalization can be commonly used as a default.

Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNN) are a type of artificial neural network. The main advantage of a recurrent neural network, which makes it unique from other types of networks, is that it is capable of performing well with sequential as well as time series data due to its feedback loop that allows connection to previous inputs and outputs. There are two types of loops in RNN, namely, the temporal loop and the spatial loop.[25,26] A temporal loop connects previous layers to the current layer, and a spatial loop connects the same layers in time.

A recurrent neural network is trained to perform a specific task under a supervised learning setting. RNNs have internal memories, meaning they can remember important information from previous inputs and use it later in the future. In RNNs, when we calculate the next output given the current input, they consider previous knowledge as well as the current input. However, the main problem with recurrent neural networks is the vanishing gradient problem. This vanishing gradient problem occurs when the gradients flow back in time and become so small that they stop the learning process of the network. To solve this problem, Long Short-Term Memory (LSTM) networks, which are a more advanced form of RNN, have been introduced.

Generative Adversarial Networks (GANs)

GANs are a class of unsupervised deep learning-based generative models that can learn to generate authentic data samples. There are two major components of GAN: a discriminator network and a generator. The main characteristics of the GAN network are that they are context-specific, can extract, model, and replicate statistically frequent patterns among both discrete and continuous variables. It also helps understand higher-order interactions and can model nonlinearity more applicable for real-life problems than its linear counterparts. GANs generate new data by learning very complex relationships and structures among different kinds of data, and they can generate large amounts of data that then feed a wide variety of deep learning models.[27,28] The discriminative model, which tries to distinguish between the fake and real data, is modeled by deep neural networks that are often referred to as the classifier. The generative model, modeled by deep neural networks, is used to produce 'fake' data. These generated data are of similar nature to the initial data from the training set.

In terms of climate change, GANs have been used in various applications for diverse purposes such as anomaly detection and data utilization, from remote sensing and simulation outputs. Moreover, recent work demonstrates the advantages of GANs in climate science by using climate data to solve data-related problems, including remote sensing, weather forecasting, and climate model development. With the help of GANs, futuristic climate models are being developed more accurately and generating more precise data.[29] These models forecast temperature, precipitation, and sea level. By delivering better outputs, they will help make it possible for places around the world to understand and predict what conditions to expect in the future. A series of advances were discovered in remote sensing to characterize and detect uncertain conditions such as cyclones and to build a 3D tree model in local regions. GANs help in the generation of authentic data using unsupervised learning, which provides opportunities for invaluable but limited data applications.

Applications of AI and Machine Learning in Climate Change Studies

Deep learning and machine learning have been successfully applied in climate informatics on various themes, including weather and climate prediction, climate simulation, data-driven parameterization, and the development of simplified climate models. In this chapter, we present some important applications of advanced AI, ML, and DL techniques on different themes of climate change. These techniques have developed over time to solve a range of complex associated problems, from global climate forecasting to local severe weather prediction.[30,31] The success of statistical weather prediction and climate prediction methods mostly depends on numerous features. ML and DL approaches have achieved state-of-the-art results in various computer vision, natural language processing, and quantitative analysis tasks (figure 2).

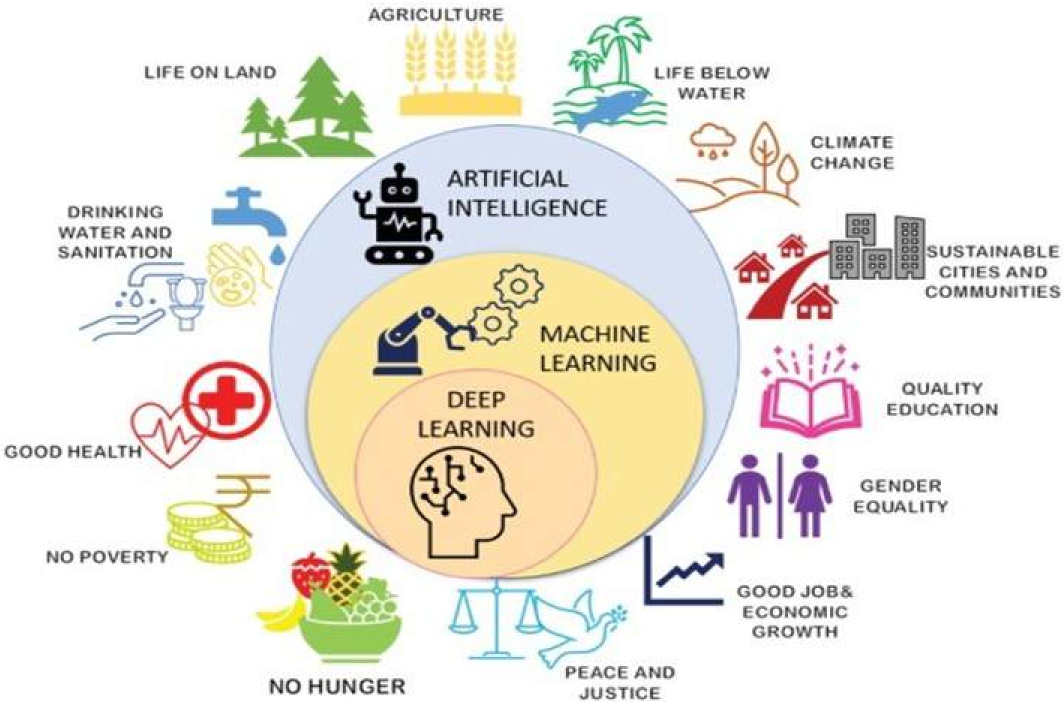

Figure 2. Introduction of AI and Machine learning[8,10,17]

The primary contribution of this study has been a comprehensive review of advanced machine learning and deep learning approaches that contribute to the fields of weather forecasting and climate change studies. Our review showed that many sophisticated deep learning architectures have been developed over the years in application to various fields, including geophysical datasets. However, due to space constraints, the number of applications in weather and climate science is relatively limited.[32] A proper and future-oriented sense of weather forecasting is really necessary to take necessary measurements on time. Moreover, existing forecasting methods suffer from rapid land-use changes and climate change, and this limitation is forcing the meteorological community to improve existing methods or create new ones to achieve accurate forecasts.

Climate Pattern Recognition

Climate patterns can be associated with the availability of sunshine or wind for renewable energy applications, flooding or drought patterns for water management, and, at finer scales, they may also affect the predictability of those weather variations that could compromise the collection activities of solar or wind generation forecasting systems, or could challenge the structural resilience of hydroelectric power generation systems. Historical data about temperature, pressure, humidity, and wind shifts are usually employed in numerical weather models and in climate studies, offering regional and global coverage for machine learning techniques.[33]

Interestingly, features associated with reanalysis data are more suited for climate pattern recognition purposes than those of direct measurements, especially at finer scales. Direct measurements are composed of point data, gathered at locations with specific latitudes and longitudes that, being specific to well-defined regions, may poorly represent geospatial patterns, tensioned wave patterns,[34] spatial correlations, or complex atmospheric dynamics; direct measurements are not capable of capturing microclimates, which is a disadvantage for climate studies. In contrast, reanalysis data have a more widespread spatial distribution, providing source data for the numerical weather models responsible for generating forecasts, as well as for the atmospheric-oceanic and physical state models that support climate studies.

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Extreme Weather Event Prediction

Extreme weather events are one of the biggest concerns regarding the impacts of climate change. There is a consensus that these events will most likely increase in frequency and intensity. With the prediction of these events, it is possible to have action plans for when they occur, reducing their impact. Some solutions use statistical methods to predict extreme events by combining data from a few variables, some data preparation, feature engineering, and time series forecasts within specified tolerances. Others use data classification methods to predict the classes of extreme events with more data preprocessing and feature engineering techniques and a window to include past event data.(35)

Combined data feature engineering time series forecasts were remediated using a neural network-based solution. The initial dataset consisted of 18 attributes for a period of 84 months. Simple transformations of the original data were carried out based on the values for wind speed and the day of the event.(36) Due to the success of deep learning in solving various business problems and the possibility of using these models to find the correlations that classical statistical models have difficulty finding, the study analyzed the impact of a deep learning neural network model.

Climate Data Analysis and Visualization

Climate change spatial patterns may be described, processed, and interpreted using software tools, GIS technologies, and language libraries. These include interactive cartographic tools, Geographic Information System (GIS) software, and language libraries, which are often used for processing and evaluating geographic data. These software tools may be used to process environmental data and are sometimes linked to advanced visualization tools, which help to transfer bare numbers to comprehensive data visualization forms such as maps, timelines, trends, or pie and bar charts and show clear climate meanings to users.(37)

Visualization tools incorporate statistical data into different graphs and maps to give the map and different graphs colors, legends, and sizing properties, and enable developers to interact with these datasets clearly. A color gradient may be used as a legend, enabling developers to quickly understand and interpret various climate and environmental data.(38) Map-based visualization may also show changes in climate variables such as temperature increases and rainfall patterns by region. Symbols or heatmap overlays may be used to show climate change on top of energy-related datasets. In urban environmental studies, for instance, users may interact with maps to improve their understanding of temperature, air quality, rainfall, water levels, and other environmental patterns.

Challenges and Future Directions

Climate change represents one of the most critical challenges to global sustainability, demanding innovative interdisciplinary approaches to understand, predict, and mitigate environmental transformations. The convergence of artificial intelligence, machine learning, and deep learning technologies offers unprecedented computational capabilities for addressing this complex global issue. This chapter provides a comprehensive examination of advanced AI and machine learning techniques applied to climate change research, exploring their transformative potential in solving and predicting environmental challenges. By leveraging sophisticated computational methodologies, researchers can now develop more nuanced, precise models of complex climate systems that traditional approaches could not effectively capture.(39,41)The research focuses on critical areas of climate change investigation, including:

I'll provide concise notes on these climate modeling and atmospheric research topics.

Dynamical Downscaling of Climate Models

- A technique to enhance spatial resolution of global climate models
- Uses regional climate models to generate high-resolution climate projections
- Captures localized terrain effects and micro-scale meteorological processes
- Bridges gap between broad global simulations and detailed regional climate understanding

Advanced Weather Simulations

- Utilizes high-performance computing and sophisticated algorithms
- Integrates complex atmospheric physics and real-time data assimilation
- Enables more accurate short-term and medium-range weather predictions
- Incorporates machine learning and AI to improve predictive capabilities

Precise Climate Forecasting

- Combines multiple data sources including satellite, ground, and oceanic observations
- Employs advanced statistical and machine learning techniques
- Focuses on reducing uncertainty in long-term climate projections
- Develops probabilistic forecasting models for different climate scenarios

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Precipitation Pattern Analysis
- Examines spatial and temporal variations in rainfall distribution
- Uses statistical techniques to identify trends and anomalies
- Crucial for water resource management and agricultural planning
- Integrates remote sensing and ground-based precipitation data

Extreme Weather Event Prediction
- Develops early warning systems for severe weather phenomena
- Uses ensemble forecasting and probabilistic approaches
- Analyzes historical data and climate change impacts on event frequency
- Supports disaster preparedness and risk mitigation strategies

Time-Dependent Climate Studies
- Investigates climate changes across different temporal scales
- Explores historical climate reconstructions and future projections
- Analyzes decadal and centennial climate variability
- Integrates paleoclimate data with contemporary climate models

Large-Scale Feature Learning and Classification
- Applies machine learning techniques to climate data analysis
- Identifies complex atmospheric and oceanic patterns
- Uses deep learning for feature extraction and climate pattern recognition
- Supports climate change research and predictive modeling

A key contribution of this article is the comprehensive categorization of AI and machine learning techniques specifically tailored to climate change research.(42) This taxonomical approach provides researchers with a structured framework for implementing advanced computational strategies in future environmental studies. The investigation goes beyond mere technical analysis, offering a critical exploration of how artificial intelligence can revolutionize our understanding of global climate dynamics. By synthesizing diverse computational techniques, the research demonstrates the potential to transform climate change research from retrospective analysis to predictive, proactive modeling. The chapter systematically examines the application of advanced AI methodologies across multiple research domains, highlighting their capacity to process massive, complex datasets and uncover intricate environmental patterns.(43) These techniques enable researchers to develop more sophisticated models that can simulate long-term climate scenarios with unprecedented accuracy. Moreover, the research critically assesses current technological limitations and outlines future research directions.(39) By identifying existing challenges and potential avenues for technological innovation, the chapter provides a roadmap for continued advancement in AI-driven climate change research. Ultimately, this comprehensive study underscores the critical role of artificial intelligence in addressing one of the most significant environmental challenges of our time, offering hope through technological innovation and sophisticated computational approaches.

CONCLUSIONS

The comprehensive exploration of advanced artificial intelligence, machine learning, and deep learning techniques for climate change studies reveals a transformative landscape of computational methodologies with significant potential for environmental research and intervention. Our systematic investigation has demonstrated the remarkable capabilities of these advanced computational techniques across multiple critical domains, uncovering new pathways for understanding and addressing global environmental challenges. The research highlights the multifaceted nature of AI applications in climate science, emphasizing not only traditional data sources but also the critical role of emerging computational approaches in environmental modeling. By integrating sophisticated machine learning algorithms with complex climate datasets, researchers can now generate more nuanced, precise representations of environmental dynamics that were previously impossible to conceptualize.

Key findings underscore the significant advancement of AI and machine learning techniques, which have achieved a sophisticated level of development offering unprecedented efficiency, accuracy, interpretability, and generalizability in climate change studies. These computational approaches provide valuable supplementary tools to expert-led climate research, enabling more comprehensive and dynamic investigation of environmental systems. Advanced techniques show particular promise in spatiotemporal weather forecasting, complex environmental modeling, and predictive climate change analysis. Looking forward, the research community must prioritize expanding the application domains of these computational techniques. This involves diversifying research beyond current focus areas of atmospheric physics, ecological processes, and remote sensing, and exploring interdisciplinary approaches that integrate AI techniques with broader environmental research domains. The goal is to develop more holistic, adaptive frameworks that can capture the intricate, interconnected nature of global climate systems. Critical recommendations for future research include enhancing computational methodologies, developing more sophisticated machine learning algorithms capable of processing increasingly complex, multidimensional climate datasets, and improving model interpretability and transparency. Researchers should also focus on integrating emerging technologies and creating synergies between AI, machine learning, and other computational innovations. A paramount objective is translating advanced computational research into actionable policy and intervention strategies. By supporting data-driven decision-making processes in climate change mitigation and adaptation, these technologies can bridge the gap between scientific understanding and practical environmental management. This requires fostering interdisciplinary collaboration, encouraging knowledge exchange between climate scientists, computer scientists, and domain experts. While current AI techniques demonstrate significant potential, substantial research opportunities remain. Future investigations must continue to expand application areas, improve computational methodologies, and develop more comprehensive approaches to climate change modeling. The research ultimately underscores artificial intelligence's transformative potential in addressing global environmental challenges, offering a beacon of technological hope in our collective effort to understand and mitigate climate change impacts.

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Writing - proofreading and editing: Fredrick Kayusi, Srinivas Kasulla, S J Malik, Petros Chavula.

ARTICLES FOR UTM SENATE MEMBERS

“Decoding the Climate Crisis: How AI is Fighting Climate Change”

TITLE	SOURCE
3) Developing trustworthy AI for weather and climate (2024)	PHYSICS TODAY (Article From : AMER INST PHYSICS)

30th JULY 2025
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PHYSICS TODAY

Developing trustworthy AI for weather and climate FREE

By improving the prediction, understanding, and communication of powerful events in the atmosphere and ocean, artificial intelligence can revolutionize how communities respond to climate change.

Amy McGovern; Philippe Tissot; Ann Bostrom

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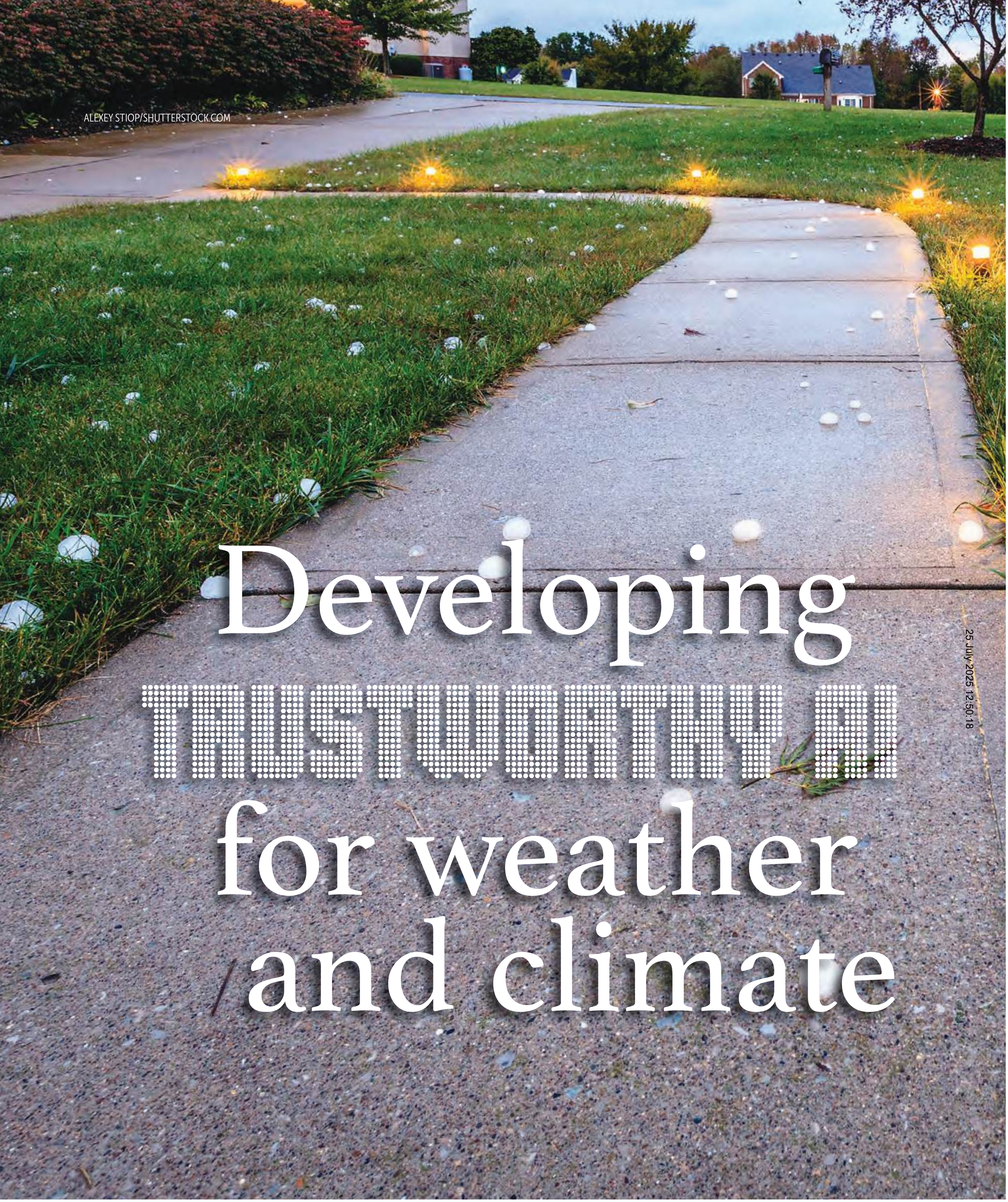


ALEXEY STIOP/SHUTTERSTOCK.COM

Developing TRUSTWORTHY AI for weather and climate

Amy McGovern directs the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES) and is a professor in computer science and meteorology at the University of Oklahoma in Norman. **Philippe Tissot** coleads the coastal oceanography team at AI2ES and is the chair for coastal artificial intelligence at Texas A&M University–Corpus Christi. **Ann Bostrom** coleads the risk communication team at AI2ES and is an environmental policy professor at the University of Washington in Seattle.

Amy McGovern, Philippe Tissot, and Ann Bostrom

By improving the prediction, understanding, and communication of powerful events in the atmosphere and ocean, artificial intelligence can revolutionize how communities respond to climate change.

The year is 2028 and the weather continues to produce climate-induced extremes, but something has changed. Your phone is now giving you early, accurate warnings to help you prepare.

Major heat wave hitting the SW United States in 3 weeks. Be prepared for an extended period of extreme temperatures and higher humidity than usual.

Warning: Baseball-sized hail and strong winds from the north are extremely likely to hit your house in approximately 20 minutes. Move belongings inside, and stay away from any north-facing windows.

Extreme cold temperatures are arriving in your area in 3 days and will last for at least 4 days. Prepare now to ensure your pipes do not freeze, and be ready for potentially extended periods of electrical outages.

Imagine that high-impact weather phenomena, such as those described above, are forecast with sufficiently advanced warning and precision that humankind is able to significantly mitigate the effects of such events globally. Furthermore, the predictions are known to be trustworthy, so individuals and local and state governments can act immediately to save lives and property.

Such a scenario is not just a vision: It may be a reality in a few years. As the climate changes, weather extremes are affecting species and ecosystems around the globe—and are becoming more extreme (see the article by Michael Wehner, Physics Today, September 2023, page 40). At the same time, recent developments in artificial intelligence (AI) and machine learning (ML) are showing how that vision might be realized.

AI offers multiple methods for handling large quantities of data, helping automate processes, and providing information to human decision makers.[1] Traditional AI methods have been used in environmental sciences for years.[2] Such methods include statistical techniques, such as linear regression, and basic object-grouping methods, such as clustering. Both have a history in environmental-science dating back several decades.[3] A little over a decade ago, weather and climate phenomena began to be understood with more-modern AI techniques, including decision trees—basically flowcharts created by an algorithm rather than constructed by hand—and groups of trees known as random forests.

ML, a subset of AI, focuses on methods that use data to learn and adapt so that they're

SEA TURTLES were rescued off the coast of Texas by volunteers in February 2022 **(left)** and January 2018 **(right)** after the successful prediction of a cold-stunning weather event by an artificial-intelligence-based forecasting model. After measurements of the turtles were taken, they were transported to a rehabilitation facility. (Courtesy of AI2ES.)

generalizable to novel situations. When AI is discussed in the news, it is most often referring to a specific form of ML called deep learning,[4] which has become popular lately. The key changes facilitating the explosion of deep learning have been the creation of innovative ways to handle spatial and temporal dependencies in the data and corresponding hardware improvements, which have made it possible for neural networks, a type of deep learning, to be trained with millions of parameters.

Deep learning has revolutionized the field of AI across various applications, including language translation, game theory, and image recognition (see, for example, the article by Sankar Das Sarma, Dong-Ling Deng, and Lu-Ming Duan, Physics Today, March 2019, page 48). AI methods can do the same for weather and climate predictions too (see reference 5 and Physics Today, May 2019, page 32). For example, multiple recent papers have introduced global weather-forecasting systems based entirely on AI methods. Although those systems need to be trained by traditional numerical weather-prediction models, their predictions are made solely through a deep-learning algorithm and do not depend on physics-based equations.[6]

Despite the long development history of AI methods for predicting weather and climate events, few have been implemented operationally by NOAA and private industry. Early operational AI models were based on relatively simple architectures, such as tree-based designs that can be read by humans. Several new startup companies and larger, established companies, however, are focused on applying more complex AI methods to commercial weather-prediction products. NOAA has also recently begun to deploy AI methods for targeted applications. With all the changes, it is critical that AI methods are beneficial to society, that they can be gauged by their users for their applicability, and that their predictions can be trusted.

Developing and deploying trustworthy AI requires a diverse multidisciplinary research team. The team at the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES), for which the three of us work, consists of AI developers, social scientists, atmospheric and ocean scientists, and end users. AI2ES is rapidly developing new AI methods that will enable us to improve our scientific understanding and prediction of high-impact weather and climate phenomena, user trust in AI products, and our communication of AI's risks.[7]

Developing trustworthy AI

The diagram on page 29 outlines how the different pieces of AI2ES work together to create trustworthy AI. Traditional AI work is often done by only computer-science researchers, but our synergistic team is made up of researchers in AI, atmospheric science, coastal oceanography, and risk communication. Our goal is to ensure that we meet the needs of our end users—primarily forecasters and emergency managers—and that we understand what it means for AI to be trustworthy.

In any risky situation, successfully communicating and managing risk depends on the trust between those involved.[8] When applying AI methods to climate and extreme-weather forecasting, the uncertainties of AI need to be added to the uncertainties of the environmental predictions. The compounding uncertainties raise the stakes for effectively communicating the risks and make trust even more critical. When trust in AI is low, AI-based forecasts and warnings may be ignored or misconstrued. AI, therefore, needs to be both trusted and trustworthy to be used in various high-risk situations.

Trust is usually enhanced by relevant evidence of competence and reliability,[9] but trust in an AI model is also contingent on people believing that the model aligns with their own interests. Biased or poor-quality training data can lead to biased or more-uncertain AI forecasts, which have the potential to harm those whose actions depend on the forecasts.

Models in Earth sciences are used for many purposes. Some examples at AI2ES include predicting freezes for various environmental-management purposes, protecting endangered species, and forecasting and warning for severe convective storms to protect people and save lives. Risk attitudes and trust are known to vary by the nature of the decision and the decision context[10]—who controls the decision making, for example, and how catastrophic the consequences might be—and by the attributes of the modeling system and modeling context.[11] For those reasons, understanding the nature of trust and developing trustworthy AI for Earth sciences requires codeveloping it with end users. For applications where AI can affect vulnerable or large populations, it's particularly important that AI developers working with end users employ a convergence approach—that is, have experts in the environmental, decision, and AI disciplines work together closely on specific, compelling problems.

AI2ES is developing and testing explainable AI methods to help describe to end users how AI models function. Existing physics-based prediction models have the advantage of being driven by the underlying physics of the problem; one can numerically represent the Navier–Stokes equations, for example. But because AI is unconstrained by the laws of physics, it could come up with a solution that violates those laws. Providing end users with different methods to understand what the AI model has learned may improve trust, and we are interviewing end users to understand the efficacy of those methods.

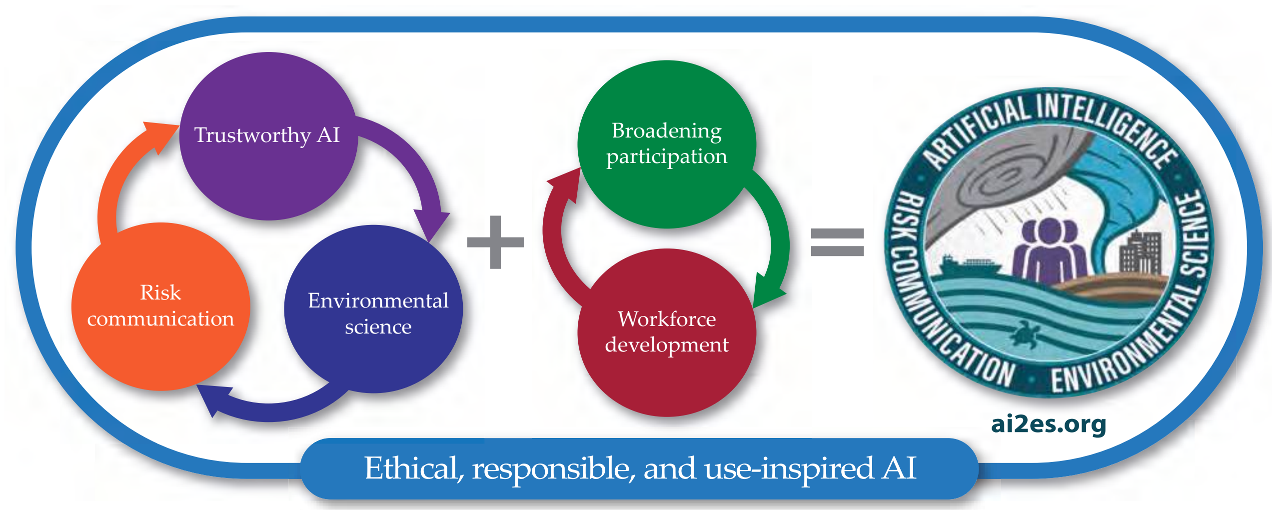
Trust, however, is contextual and subjective, and trust in AI models for weather and climate depends on a number of additional factors beyond peering inside the AI model. Those factors include having experience with the model over time, documenting performance and lack of bias across a range of extreme events for which the models are designed, and working with end users to ensure that their needs are met.

Saving sea turtles

When strong cold fronts, such as the 2021 winter storm dubbed Uri, reach the southeast US, the temperatures of bays, lagunas, and other shallow bodies of water cool down rapidly. Below certain water temperature thresholds,[12] fish and endangered sea turtles become lethargic, or cold stunned, and most perish if they're not rescued. A community-wide effort for the Texas coast has grown since the mid 2000s to prepare for and mitigate the events. The program was updated following Uri, during which a record 13 000-plus sea turtles became cold stunned. Volunteers and employees of local, state, and federal agencies collect cold-stunned sea turtles along the shores or in bodies of water, and barge operators voluntarily interrupt their navigation through those waters. As climate change increases the frequency of extreme events, those types of large-scale organized human interventions will arguably need to become more frequent and more urgent if increasingly endangered species and fragile ecosystems are to be preserved.

To coordinate the rescue of cold-stunned turtles, a team needs real-time predictions of key environmental parameters, such as localized water temperature. When AI has access to time series of parameters from past extreme events, it is particularly well suited to develop targeted operational models, such as one for predicting when a cold-stunning event will happen. AI can take advantage of big, diverse data, such as gridded numerical weather predictions, satellite imagery, and ground-sensor readings.

Although the calibration of AI models can be lengthy, and care must be taken to maximize and test generalization, operational computations are fast once the information is available, particularly when done for just a few locations. The operational cold-stunning model is a type of neural network and has been used since the late 2000s. The first advisory and voluntary navigation interruption took place 8–10 January 2010 with a pre-



THE COMPREHENSIVE APPROACH created by AI2ES, the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography. (Courtesy of AI2ES.)

Hail as large as Ping-Pong balls reached the Oklahoma house of one of the authors (McGovern) in May 2013 (left) and May 2015 (right). Early-warning predictions of hailstorms are difficult to make, but AI methods may be able to help improve the forecasting of those storms and other weather events. (Courtesy of Amy McGovern.)

diction lead time of 48 hours. The system has been used several times since, including during the past three winters, with prediction lead times extended to 120 hours. The model is an essential decision tool that local, state, and federal agency representatives use when discussing with the private sector the optimal timing of activity interruptions in Texas's Laguna Madre. The specifically designed AI model provides the long lead time critical for redirecting cargo, contacting volunteers, and carrying out other actions.

The sea-turtle program brings the possibility to test how and why the trust in its AI model came about. The research team and end users are further developing AI ensemble models to quantify uncertainties around the predicted timing of the cold stunnings. An events' end is particularly challenging to predict with a longer lead time.

As the frequency of extreme events increases, sea levels rise, and other climate-driven challenges develop, even small flooding events will have large effects. So decision makers will have to start prioritizing and preparing for a broad range of emergency events beyond the largest ones, such as hurricanes, for which state and federal resources are deployed to assist local responders. Results are demonstrating that AI is a well-suited methodology to take advantage of large, diverse data sets and model the nonlinear processes of coastal zones and other environmental systems. Other coastal environmental models developed by AI2ES researchers include predictions of coastal fog,[13] coastal inundation, harmful algal blooms, eddy loop currents in the Gulf of Mexico, and compound flooding.

Severe storms

Thunderstorms worldwide produce various dangerous hazards: strong wind, lightning, hail, and tornadoes—all of which cause significant loss of life and property. Of the billion-dollar weather and climate disasters counted by NOAA every year, thunderstorms account for the majority of the cleanup cost. AI2ES is currently creating novel AI approaches to improve the prediction and understanding of such hazards.

One such example is predicting the initiation of thunderstorms up to an hour before they begin. Even 30 minutes of trustworthy warnings will save lives and property. Airplanes could be rerouted, boats could be brought back to shore and sheltered, and event planners could safely evacuate large outdoor events to avoid disasters, such as the hailstorm that hit Red Rocks Amphitheatre in Morrison, Colorado, in June and injured 80–90 people.

AI2ES's approach to modeling convective storms is codeveloped with researchers in NOAA's National Severe Storms Laboratory. Our work builds on NOAA's warn-on-forecast system (WoFS).[14] It is a numerical weather-prediction system that is run in real time at a high resolution over areas of the US where the Storm Prediction Center expects a higher probability of severe storms. AI2ES developed an AI postprocessing system that uses numerical weather-prediction models and current observations and outputs a real-time prediction of where storms are most likely to occur in the next 30 minutes. To help ensure that the system is trustworthy, AI2ES and NOAA will continue to develop it at NOAA's Hazardous Weather Testbed, a unique facility that allows forecasters and emergency managers to try out new technologies during severe weather events and to provide feedback to the developers.

AI2ES is also working to improve the understanding and prediction of tornadoes and hail. They are small-scale phenomena that are challenging to predict, especially on a short time scale and with high spatial precision, with current operational weather models. One of our most recent methods is codeveloped with NOAA researchers working on the WoFS. Our focus is on improving the nowcasting of severe hail events, which predicts such events at high resolution spatially and within an hour of their arrival. The WoFS runs in real time, but because of the computational complexity of the model, which ingests all the current observations, there is about a 15- to 30-minute lag between the observations and the system's predictions. We developed an AI prediction system that uses deep learning to combine WoFS predictions with data from the National Light-

ning Detection Network, operated by Vaisala,[15] and we demonstrated a significant improvement in the accuracy of short-term hail prediction.

Ethical, responsible AI

An integral part of trustworthy AI is ensuring that it is developed ethically and responsibly. If not, AI for environmental sciences can go wrong in numerous ways.[16] Extreme events tend to disproportionately harm areas with fewer resources and places with histories of systematic discrimination. It is critical that society ensures that AI is not deployed in any manner that will perpetuate environmental or climate injustices. That way, society as a whole can be more resilient to climate change.

Another potential issue with AI for weather prediction is bias, which affects all aspects of the AI training process. In recent work, we have developed a categorization of bias in AI for Earth sciences by breaking it into four main categories, each of which influences the others.[17]

- **Systemic and structural biases** include institutional and historical biases that can influence the choices of data that are made available, the labels on the data used for training AI, and other aspects of AI model development and use. For example, we demonstrated that tropical-cyclone initiation prediction is more likely to occur after sunrise than before because of institutional practices around examining the visible satellite imagery.
- **Data bias** can occur because of the data selected to train the models and the processing techniques used to prepare the data for training. Those choices can result in data that are not representative of the intended populations, areas, or events being modeled. Once the data are prepared and the AI model trained, biases can be present in the validation of the model. Humans must choose which score they will use to validate the model and which cases will be used as a case study. The choices can be affected by human judgment and decision biases, such as confirmation bias.[18]
- **Statistical and model biases** can affect the actual model that is trained and can be strongly affected by human biases. For example, human programmers must choose the methods that they will use to evaluate the model.
- **Human biases** are present throughout AI methods, from data selection to the choice of model, but they are also present in the deployment and use of the model. End users, such as forecasters and emergency managers, for example, may have information overload or may need to make split-second decisions, which can bias their use of AI.

Three of the perhaps most common ethical theories are applicable to AI for the environmental sciences: consequentialism, which judges the morality of an action by its consequences, such as through a benefit–cost analysis; deontology, which judges whether an act is ethical by how the act conforms to duties or moral principles, such as the imperative to be honest; and virtue ethics, which argues that a "right" action is important to achieve human well-being. Protecting the most vulnerable might not always pass a benefit–cost rule, but deontological and virtue ethics could require it, making it imperative.

But even to understand how AI models might affect specific decisions or users in particular circumstances generally requires an insider perspective, achievable only through developing AI with the people likely to be affected. Many of those concerns and needs can be addressed, and trustworthy AI can be developed by early and continued codevelopment of AI models with direct representation; meaningful, ongoing participation of likely end-user communities; and communication throughout the development process with risk-communication experts. But such capabilities require organizational intent from the teams developing the AI models.

The future of trustworthy AI

Given the current exponential growth of AI in the sciences, society stands at the cusp of major developments in AI for science and society in general. New methods could be developed and deployed with a swiftness that was not possible even a few years ago. That gives us an unprecedented opportunity to shape the process of how AI models are developed to fully benefit society and to address environmental and climate-justice issues. The process, however, must ensure that the models are ethical, responsible, and deserving of trust if society is to realize the full benefits of AI.

To achieve such goals, and to minimize problems during the release of new technology, more comprehensive processes and development teams must be engaged. Funding from federal agencies, private-sector entities, and other places must be structured to reflect those needs. Codevelopment of AI requires funding that allows for and encourages the development of multidisciplinary teams committed to working with end users. The benefits include acting ethically, avoiding large disparities, increasing resilience to climate change, and broadening the viewpoints, knowledge, and values represented on the modeling teams.

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ARTICLES FOR UTM SENATE MEMBERS

"Decoding the Climate Crisis: How AI is Fighting Climate Change"

TITLE	SOURCE
4) Challenges of Artificial Intelligence Development in the Context of Energy Consumption and Impact on Climate Change (2024)	ENERGIES (Article From : MDPI)

energies

Review

Challenges of Artificial Intelligence Development in the Context of Energy Consumption and Impact on Climate Change

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Abstract: With accelerating climate change and rising global energy consumption, the application of artificial intelligence (AI) and machine learning (ML) has emerged as a crucial tool for enhancing energy efficiency and mitigating the impacts of climate change. However, their implementation has a dual character: on one hand, AI facilitates sustainable solutions, including energy optimization, renewable energy integration and carbon reduction; on the other hand, the training and operation of large language models (LLMs) entail significant energy consumption, potentially undermining carbon neutrality efforts. Key findings include an analysis of 237 scientific publications from 2010 to 2024, which highlights significant advancements and obstacles to AI adoption across sectors, such as construction, transportation, industry, energy and households. The review showed that interest in the use of AI and ML in energy efficiency has grown significantly: over 60% of the documents have been published in the last two years, with the topics of sustainable construction and climate change forecasting attracting the most interest. Most of the articles are published by researchers from China, India, the UK and the USA, (28–33 articles). This is more than twice the number of publications from researchers around the rest of the world; 58% of research is concentrated in three areas: engineering, computer science and energy. In conclusion, the review also identifies areas for further research aimed at minimizing the negative impacts of AI and maximizing its contribution to sustainable development, including the development of more energy-efficient AI architectures and new methods of energy management.

Keywords: artificial intelligence; energy consumption; climate change; socially responsible business; sustainability

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1. Introduction

Climate change and rising energy consumption are among the most pressing challenges facing the modern society. The rapid growth in energy consumption, driven by economic expansion and technological development, contributes to increased greenhouse gas emissions and accelerates global climate change. In this context, the urgency of finding innovative solutions to enhance energy efficiency is becoming increasingly apparent. Artificial intelligence (AI) and machine learning (ML) have advanced rapidly in recent years, showing significant potential to solve complex environmental challenges, such as enhancing energy efficiency and reducing carbon emissions [1,2]. However, their impact on energy consumption and climate change remains ambiguous.

On the one hand, AI holds significant potential to address global challenges outlined by the UN [3], including climate change and other complex environmental and social issues, which includes the following:

- By predicting energy consumption, optimizing energy systems and integrating renewable energy sources, AI has the potential to become a key tool in the fight against climate change [4,5].
- Improving the energy efficiency of buildings and industrial infrastructure, optimizing the operation of energy systems in real time helps reduce overall energy consumption and minimize the impact on the environment [6–9].
- Machine learning (ML) is used to predict climate change and its impact on energy systems. Machine learning models allow us to build scenarios of future energy consumption and adapt infrastructure to new conditions [10,11].
- AI can enhance the efficiency of renewable energy sources, such as wind and solar power plants [6,9], which is particularly important in the decarbonization process [12].
- AI plays a key role in monitoring, managing and forecasting energy needs, taking into account future climate change. This includes optimizing energy distribution, integrating renewable sources and reducing the load on power systems during periods of peak demand [7,13,14]. These studies propose solutions to enhance the sustainability of energy systems and reduce their carbon footprint [14,15].

On the other hand, the rapid growth in AI usage, particularly in large language model (LLM) training, has led to a substantial increase in energy consumption [16]. Tech giants, such as Google, OpenAI, Microsoft and others, despite their ambitious goals, face significant challenges in achieving carbon neutrality by 2030 [17,18]. The high energy costs associated with creating and operating powerful AI models highlight the contradiction between technological progress and its environmental consequences [19]. Moreover, the rise in energy consumption is directly linked to an increasing carbon footprint [18,19]. Therefore scientific efforts are aimed at finding solutions to improve the energy efficiency of AI systems and minimize their negative impact on the environment [3,18].

Investigating the application of AI and ML to improve energy efficiency holds significant potential for creating a more sustainable future with minimal negative consequences for the environment [20,21]. However, a full understanding of the current situation requires analyzing current achievements and existing barriers to determine the effectiveness of integrating AI into business models of enterprises to solve global humanity's challenges [22,23]. Further research is crucial to understand how AI and ML can contribute to reduce global energy consumption without introducing additional climate risks.

Thus, the aim of this review is to synthesize and systematize the existing scientific literature, demonstrating how artificial intelligence (AI) and machine learning (ML) techniques can contribute to energy efficiency in different industries and countries. The review also aims to analyze the role of AI in addressing current climate challenges, including reducing carbon emissions and optimizing resource use.

In order to achieve the set goal, the following tasks are defined:

- identify the main trends and research directions in which AI and ML are applied to improve energy efficiency and address climate challenges;
- assess the main technical barriers that limit the widespread adoption of AI and ML in practice and identify directions for overcoming them;
- examine how AI and ML can contribute to reducing carbon footprints and optimize resources for long-term sustainable development.

This review provides an in-depth and comprehensive study of the impact of AI and ML on energy efficiency, addressing the interrelated energy and climate aspects of these digital technologies. Unlike previous studies, this review focuses on a comprehensive analysis of technological barriers and innovative solutions and outlines specific directions for future research. The findings are aimed at contributing to the knowledge for both the scientific community and practitioners working in the field of sustainable development and energy management.

Section 1 contains a description of the relevance of the topic, the aims and tasks of the study and a summary of the current review.

Section 2 describes the methodology used to select and screen peer-reviewed articles, ensuring a thorough and structured approach to the topic.

Section 3 contains a chosen selected list of research questions that are explored in the research and deals with each topic individually.

Finally, Section 4 concludes the review by offering perspectives on future research directions, emphasizing the critical need for continuous innovation to improve the energy efficiency of companies and reduce the electricity consumption of LLMs by improving their architecture.

2. Materials and Methods

This literature review addresses key issues related to the application of artificial intelligence (AI) and machine learning (ML) techniques in the context of energy efficiency and their impact on climate change. The following research questions were formulated to structure the analysis:

- What energy-efficiency projects using AI and machine learning are currently being implemented? This question aims to explore specific examples of AI and ML applications in energy-efficiency projects, with the goal of identifying successful cases and innovative approaches.
- Which major industries, companies or countries are benefiting from the application of AI and machine learning in energy efficiency? This question focuses on identifying key players, such as industries, companies, and countries, that are most actively utilizing AI and ML to achieve energy-efficiency solutions.
- What are the main problems and challenges facing companies, cities and states when implementing energy-efficiency projects? This question seeks to uncover the existing barriers for integrating AI into energy-efficiency practices, including technological, financial and organizational obstacles.
- What are the prospects for applying AI and ML in energy-efficiency projects? This question explores future research directions and innovations that could enhance the use of AI in achieving energy-efficiency objectives.

The methodology of this literature review was developed to systematically analyze existing research on the application of artificial intelligence and machine learning techniques in the field of energy efficiency and their impact on climate change. The primary goal is to identify trends and challenges in the implementation of these technologies and forecast their future impact on climate change. A systematic approach is used to emphasize the transparency and reproducibility of the results.

The literature search was conducted using the Scopus database, which encompasses a broad spectrum of peer-reviewed scientific articles and patents. The aim was to capture a wide range of research across different fields and disciplines. Key terms relevant to the research questions were used to develop the search strategy. The logical search string was constructed as follows: TITLE-ABS-KEY ((“artificial intelligence” OR “machine learning”) AND “energy efficiency” AND “climate change”) AND PUBYEAR AFT 2010 AND PUBYEAR BEF 2025. The search string was designed to capture both fundamental and recent publications from 2010 to 2024, aiming to identify intersections between energy efficiency and climate solutions through AI and ML. The keywords used in this literature review were carefully selected to ensure both the completeness and relevance of the documents to the study’s objectives and key research questions.

The search identified 237 relevant papers and 388 patents. Over 60% of the documents were published in the last two years (2023–2024), reflecting a growing interest in the topic. This rising trend is also evident in industry, with 243 patents filed in the past three years (2022–2024), representing 63% of the total for the fourteen-year period. The increasing number of patents is noT, with 59 filed in 2022, 85 in 2023 and 99 patents filed in 2024 (as of 16 October).

The resulting review data were categorized into key categories, including industries, geographic distribution and types of research documents. Figure 1 illustrates the annual distribution of published papers (as of 16 October 2024), highlighting trends and research activity over time. Source: Scopus Analytics.

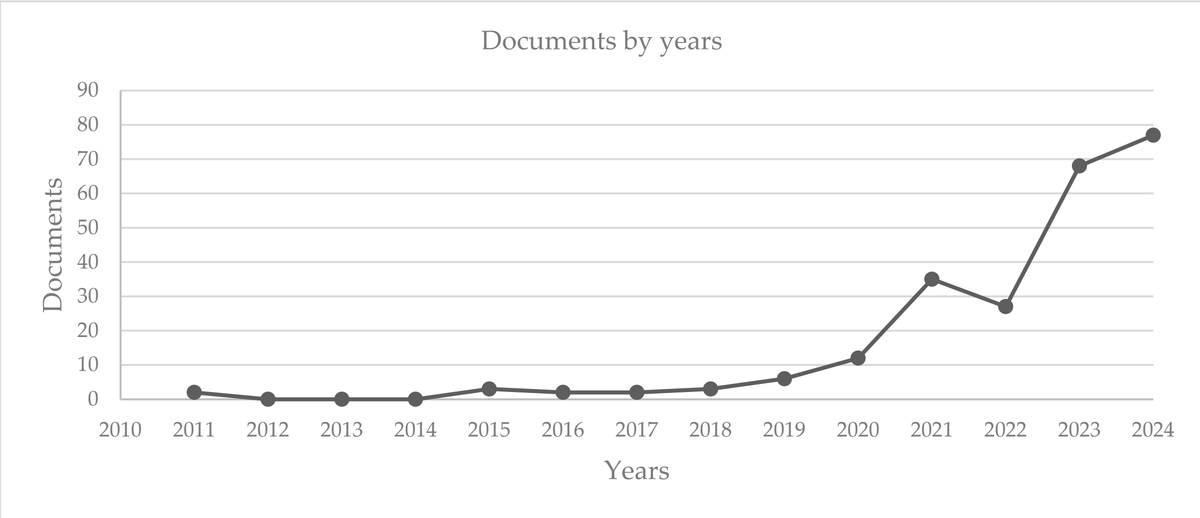

Figure 1. Distribution of documents by years. Source: compiled by authors.

Figure 2 illustrates the distribution of scientific articles retrieved from the Scopus database categorized by subject area (Source: Scopus Analytics). The figure reveals that nearly 60% of the articles are concentrated in three fields: Engineering, Computer Science and Energy.

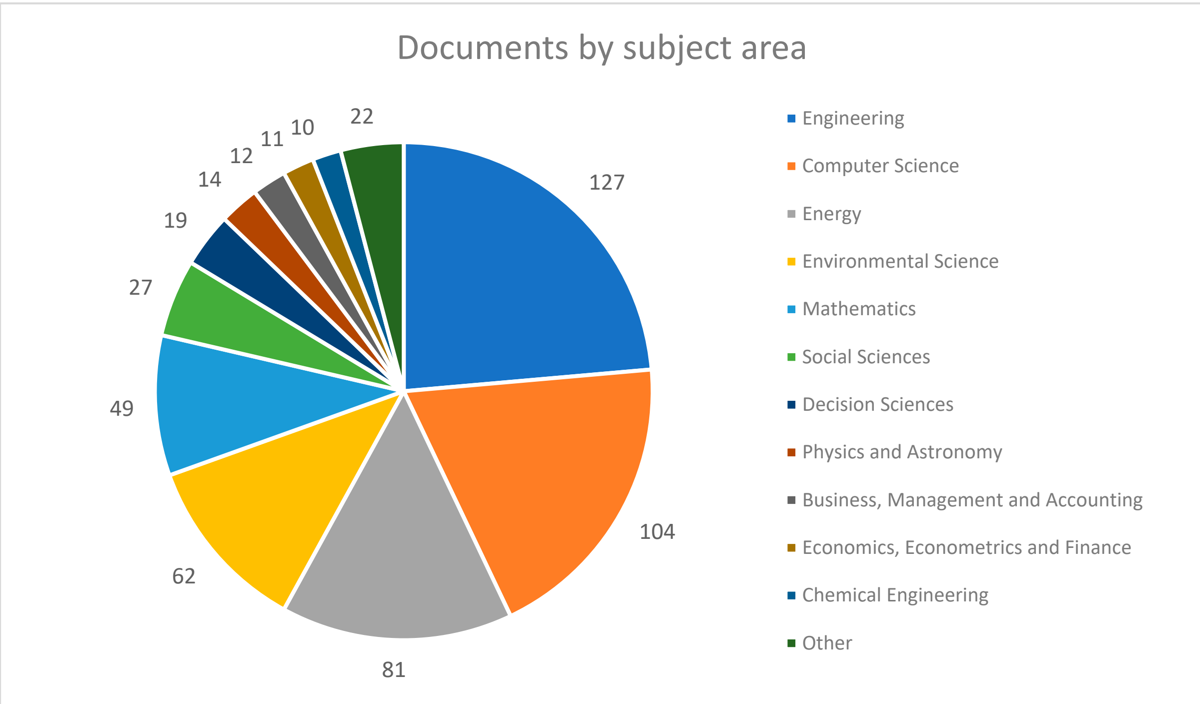

Figure 2. Distribution of documents by industries. Source: compiled by authors.

Figure 3 presents the number of articles published by researchers from various countries, highlighting the geographic diversity and concentration of research efforts, particularly in China, India, the UK and the US (Source: Scopus Analytics).

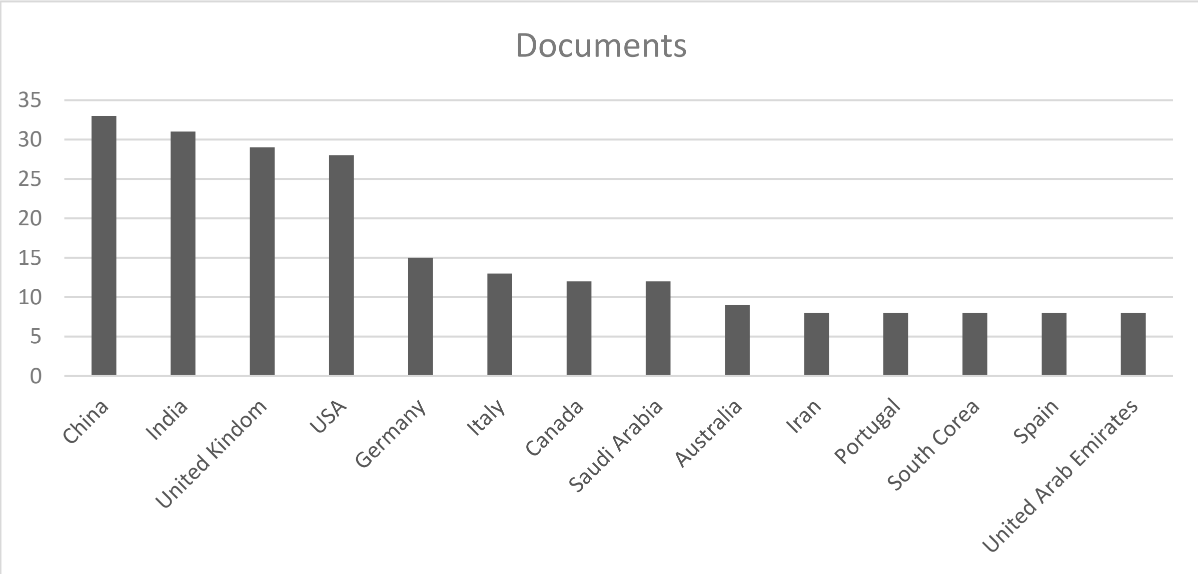

Figure 3. Distribution of documents by countries. Source: compiled by authors.

Figure 4 illustrates the distribution of documents by types, indicating that articles and conference publications account for over 80% of the total, with articles comprising the largest share (Source: Scopus Analytics).

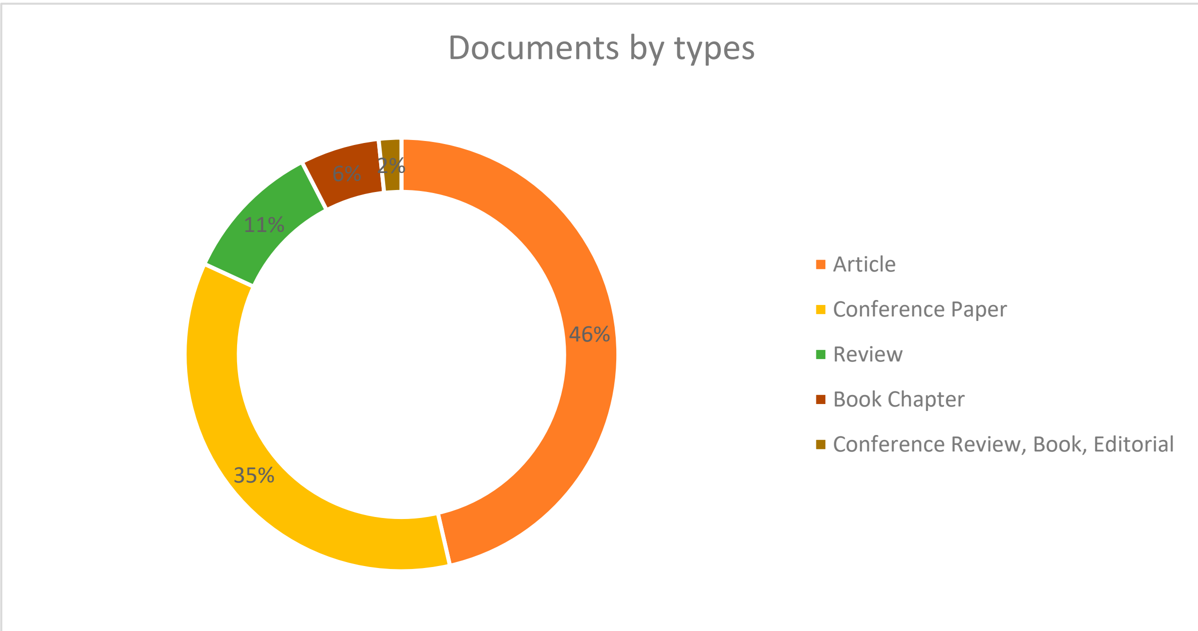

Figure 4. Distribution of documents by types. Source: compiled by authors.

A systematic approach was employed to ensure comprehensive coverage of the field. The selection process followed the methodology outlined in [24] and adhered to the guidelines set out in [25], ensuring transparency and rigor. Publications were evaluated using a 3-point quality scoring system to assess relevance and validity (see Table 1). Each study was reviewed based on several criteria, including innovation, practical application and strength of evidence. The systematic review method recommended in [26] was applied to ensure the transparency and reproducibility of the results.

Table 1. Evaluation of source quality.

Evaluation Question	Description	Evaluation Metric
1	Stage of implementation of the energy efficiency project using AI and ML	1: Experiments; 2: Economic impact; 3: Scalability.
2	The magnitude of the energy efficiency effect from AI and ML projects.	1: Negligible; 2: Enterprise level; 3: Country level.
3	Identification and discussion of challenges in implementing AI and ML for energy efficiency projects.	1: Minimal; 2: Key issues; 3: Detailed.
4	Proposing future research directions to improve ML models.	1: Some; 2: General; 3: Detailed and innovative.

Source: compiled by authors.

This study focused on four key questions related to the application of AI and ML in energy efficiency. These evaluative questions (see Table 1) facilitated a comprehensive assessment of the research findings while adhering to the principles of relevance and objectivity.

Consequently, this approach enabled in-depth analysis and the identification of the most significant areas for further research.

3. Results

The analysis made it possible to identify the following topics in scientific research that have undergone their evolution during the analyzed period.

1. Sustainable construction and green technologies that utilize AI and ML to enhance the energy efficiency of buildings.
   This topic centers on optimizing the energy efficiency of buildings, particularly in urban areas affected by climate change and urban heat island effects. It encompasses the use of physical simulation models, multi-criteria optimization, digital twins and cloud technologies to enhance the energy efficiency and resilience of buildings in the face of climate change. Additionally, it addresses methods and approaches for improving building energy efficiency through passive measures, the use of sustainable ecological materials and thermographic and AI-assisted optimization of the building life cycle.
2. Enhancing energy efficiency in transportation and e-mobility.
   This topic addresses issues related to the development of electric vehicles, hybrid transportation systems and the charging infrastructure. It encompasses transportation energy management, energy efficiency and the safety of autonomous vehicles through the application of AI and ML.
3. The role of AI in sustainable production and industrial automation.
   This topic focuses on utilizing AI to optimize manufacturing processes, reduce energy consumption and minimize the carbon footprint of the industry. It encompasses predictive maintenance, energy management and automation to enhance sustainability and productivity, as well as the application of AI in agriculture.
4. Energy efficiency in smart energy grids.
   This topic explores the role of AI and machine learning in optimizing energy management within smart grids. It addresses demand management, real-time forecasting and the integration of distributed energy sources to enhance grid stability and efficiency.
5. Climate change forecasting and the adaptation of energy systems.
   This topic involves the application of mathematical models and machine learning to predict climate change and its impact on energy systems. It includes the assessment of future energy consumption scenarios, infrastructure adaptation and the development of strategies to mitigate the negative effects of climate change on energy systems.
6. Machine learning for water resources management.
   This topic addresses the use of machine learning to optimize membrane distillation

processes, enhance the energy efficiency of solar desalination and solve global water shortage problems through innovative technologies and bioreactors.

7. AI in renewable energy sources.
This topic involves the application of AI to optimize, predict and integrate renewable energy sources, such as solar, wind and geothermal, into energy systems. The focus is on enhancing the performance of geothermal heat pumps and developing predictive models for energy management and grid interactions.
8. Energy transition and decarbonization through innovative technologies.
This topic focuses on reducing the carbon footprint across various sectors, including construction, energy and transportation, while transitioning to a low-carbon economy through the integration of renewable energy sources and innovative technologies. It encompasses the use of blockchain, AI and cyber-physical systems (CPSs) to manage energy consumption and promote sustainable development. Additionally, it includes an analysis of economically feasible energy investments.
9. Carbon footprint of large AI language models.
This research focuses on the carbon footprint of large language models and explores potential strategies for reducing it.
10. Post-combustion carbon capture and its optimization through multi-objective optimization (MOE).
The application of machine learning to optimize post-combustion carbon capture (PCCC) technologies encompasses enhancing the energy efficiency of carbon capture processes, reducing emissions and integrating PCCC into industrial processes.
11. Climate change mitigation through AI.
This theme focuses on strategies to reduce carbon emissions, enhance energy efficiency and promote sustainable practices across various sectors. It emphasizes the integration of energy-efficient technologies, the modernization of infrastructure and the use of AI to monitor climate impacts and adapt to climate change. Additionally, it includes the monitoring and mitigation of ocean acidification.
12. Social, economic and political aspects of energy management.
The topic examines the role of public policies in promoting renewable energy, reducing emissions and supporting sustainable development in the energy sector, as well as government regulation and policies for energy transition. It includes programs to reduce energy consumption, rewards for energy savings and an analysis of the impact of policy decisions on sustainable development and the UN Sustainable Development Goals.

In Table 2, the distribution of sources by important topics (key research questions) and years is presented.

Table 2. Thematic analysis by years.

	Summary	2024	2023	2022	2021	2020
The impact of AI and ML on energy efficiency						
Sustainable construction and green technologies using AI and ML to enhance the energy efficiency of buildings.	44	10	8	8	9	9
Enhancing energy efficiency in transportation and e-mobility.	12	3	1	1	7	0
AI in sustainable production and industrial automation.	22	6	8	2	4	2
Energy efficiency in smart grids.	17	7	4	2	4	0
Climate change forecasting and adaptation of energy systems to climate change.	27	8	5	5	6	3
ML for water resources management.	19	7	4	1	5	2
AI in renewable energy sources.	21	7	5	5	2	2

Table 2. *Cont.*

	Summary	2024	2023	2022	2021	2020
The impact of AI and ML on climate change.						
Energy transition and decarbonization through innovative technologies.	19	8	5	3	2	1
Carbon footprint of LLM.	10	5	2	1	0	2
Post-combustion carbon capture.	8	4	3	0	0	1
Mitigating the effects of climate change with the help of AI.	11	5	3	2	1	0
Policy and regulation.						
Social, economic and political aspects of energy consumption management.	27	8	5	5	6	3
Total						

Source: compiled by authors.

3.1. Sustainable Construction and Green Technologies Using AI and ML to Enhance the Energy Efficiency of Buildings

As indicated in the literature survey, sustainable building and the implementation of green technologies using artificial intelligence and machine learning have emerged as the most significant research topics in the face of global climate change over the past five years. AI and ML technologies have been actively applied to develop energy prediction and optimization models, particularly in urban areas, where urbanization and phenomena, such as the urban heat island effect (UHI), necessitate solutions to enhance thermal comfort and reduce energy consumption. The combination of physical simulation and AI can accurately predict energy consumption under various climate scenarios, which not only improves energy efficiency but also contributes to increase indoor thermal comfort [27].

A key challenge of sustainable building research is the application of ML and multi-criteria optimization methods to enhance the energy performance of buildings and reduce their carbon footprint, particularly in the context of climate change and urbanization. In recent years, artificial intelligence (AI) and optimization (ML) have been actively utilized to create models for predicting and optimizing energy consumption, especially in urban areas affected by the urban heat island effect (UHI) and climate change.

3.1.1. Modeling and Forecasting

A study [28] emphasizes the significance of modeling heating, ventilation and air conditioning (HVAC) systems using neural networks to enhance the energy efficiency and comfort of buildings. The utilization of AI-based models enables the prediction of HVAC system performance and their adaptation to specific environmental conditions, resulting in a significant reduction in energy consumption. Additionally, in study [29], the application of machine learning models for weather forecasting and the design of energy-efficient building structures is explored, highlighting the creation of sustainable urban environments capable of withstanding climate change.

Furthermore, study [30] analyzes mechanical cooling in high-rise buildings, demonstrating that the application of ML to model climate conditions can improve the energy efficiency of ventilation systems and promote energy savings. Study [31] highlights the considerable potential of AI to manage variations in climate scenarios by predicting the future energy demands of buildings and facilitating their adaptation to changing conditions.

Particular attention is given to optimizing heat transfer and enhancing comfort in buildings. The use of advanced machine learning techniques, such as CNN-LSTM, effectively simulates the thermal dynamics of buildings and optimizes HVAC systems, resulting in a reduction of energy consumption from 15.7% to 22.3% [10]. Additionally, study [32] investigates gradient boosting models, including LightGBM, CatBoost and XGBoost, which provide accurate predictions of energy consumption in office buildings, offering optimal solutions for improving energy efficiency.

Work [33] highlights the significance of machine learning in predicting thermal loads in residential buildings. This aids in reducing energy consumption and improving the sustainability of energy management systems. Also, study [34] indicates that the more AI and IoT devices are deployed in energy-intensive sectors of the economy, the higher their energy efficiency becomes. Study [35] explores a hybrid strategy that integrates AI with modeling tools, such as EnergyPlus™, to forecast annual cooling energy consumption. This study offers a practical guide for reducing cooling costs by analyzing building materials and design solutions.

3.1.2. The Use of Digital Twins

Digital twins and the Internet of Things (IoT) play a key role in predicting and optimizing the energy efficiency of buildings. These technologies facilitate the real-time monitoring and management of energy systems, contributing to a more sustainable and environmentally friendly urban environment [11]. The use of digital twins allows for the integration of real-world data to enhance operational efficiency and reduce energy costs, representing an important step towards the environmental sustainability of buildings.

The application of digital twins and the Internet of Things (IoT) offers unique opportunities for the real-time monitoring and control of energy systems, leading to improved heat management and enhanced energy efficiency in buildings [14].

Digital twin and predictive models, such as LSTM and the Kalman filter, play a crucial role in accurate energy consumption prediction through the processing of time series data and optimization of energy processes [36]. The use of machine learning algorithms and the Petri Net control system allows the thermal energy efficiency of vertical and horizontal building envelopes to be achieved [37]. These technologies provide new opportunities for sustainable building, particularly in the face of uncertainties associated with climate change [38].

Research underscores the significance of utilizing digital twins and autonomous machine learning agents to manage the energy consumption of buildings in the face of unpredictable environmental changes. Specifically, the work in [39] highlights that adaptive systems capable of learning from real-world data can substantially enhance the energy efficiency of buildings. These methodologies are illustrated in work [37], which employs machine learning and a Petri Net-based control system to optimize thermodynamic parameters of buildings, including the window type and insulation selection.

The utilization of digital twins and multi-criteria optimization enables the more accurate modeling of the energy performance of buildings, providing effective solutions for enhancing their energy efficiency [40]. These technologies contribute to the creation of adaptive and resilient systems capable of responding effectively to variations in climatic conditions while minimizing energy consumption, although delaying their implementation may result in multi-billion-dollar losses [41].

3.1.3. Green Technologies and Ecological Materials

The development of sustainable construction and the implementation of green technologies aimed at enhancing the energy efficiency of buildings have become crucial components in the battle against climate change. Key research areas encompass a broad spectrum of topics, ranging from the physical modeling of buildings to the application of artificial intelligence and machine learning for predicting and optimizing energy consumption.

A study [42] investigates the application of AI in designing green buildings within healthcare facilities, emphasizing the selection of environmentally friendly materials and energy consumption optimization during the operational phase. Techniques, such as random forests and ant colony optimization, highlight the increasing interest in automated energy and material management systems in the construction industry.

Work [43] investigates green building techniques, including the use of recycled and advanced materials, as well as the life-cycle optimization of buildings through simulation and AI to reduce overall energy consumption and minimize the environmental impact. A key focus of this study is the application of phase change materials (PCMs) and hybrid cladding to decrease energy consumption for heating and cooling. An example includes a hybrid system composed of 10% polycarbonate and 90% aluminum, which demonstrates improved energy efficiency compared to using pure aluminum or polycarbonate [44].

Moreover, digitalization is crucial across all phases of the building life cycle, from design to operation, which is especially significant for developing countries [14]. This underscores the importance of employing AI and ML to enhance the energy efficiency of buildings in the context of climate change.

The utilization of adaptive materials, such as aerogels, is increasingly recognized as a significant factor in enhancing the thermal performance of buildings. A study [45] explores the uncertainties associated with the use of these materials in subtropical climates. In particular, the application of machine learning to optimize the thermal performance of buildings highlights the necessity of adapting materials to changing climatic conditions in order to improve energy efficiency.

Therefore, the application of green technologies, AI and adaptive materials, such as phase change materials (PCMs) and aerogels, along with digital technologies and machine learning, contributes to enhancing the sustainability of buildings, reduces energy consumption and minimizes their carbon footprint [46].

3.1.4. Passive Energy Efficiency Measures

Passive building design strategies, including bioclimatic approaches and the incorporation of natural ventilation, continue to be important components of sustainable construction. However, in the context of a changing climate, there is an urgent need to develop more precise models that can adapt to varying weather conditions, thereby enabling the more effective utilization of passive elements [15]. This underscores the necessity of integrating artificial intelligence to predict climate risks and optimize passive solutions.

Studies [38] highlight the significance of such passive measures, such as thermographic and building life cycle optimization, within the framework of Near Zero Energy Buildings (NZEBs). The application of AI aids in predicting future energy consumption and optimizing energy management, which is crucial for minimizing energy loss.

Study [47] examines the application of AI and thermography to assess heat loss through building envelopes. The utilization of drones and infrared cameras enables the identification of heat-loss areas, facilitating the development of targeted strategies to enhance energy efficiency.

Additionally, a study [48] investigates the application of machine learning algorithms to analyze the thermophysical performance of ventilated facades (VFs) and predict heat fluxes. This research underscores the significance of machine learning in modeling building behavior under varying temperature and structural parameters, thereby contributing to the development of more accurate and adaptive energy-consumption models.

Therefore, the integration of AI and ML with passive measures, such as bioclimatic design, thermography and building life cycle optimization, is essential for enhancing energy efficiency and building resilience in the face of a changing climate.

3.1.5. Ventilation Systems and AI

The application of artificial intelligence and big data to optimize ventilation systems and predict energy consumption has emerged as a key area of research aimed at reducing the carbon footprint of buildings and enhancing their sustainability [49]. Optimizing ventilation systems is particularly important for sustainable construction in the context of a changing climate. A study [50] illustrates the use of machine learning models to forecast the cooling load and energy consumption of buildings, enabling an evaluation of the effectiveness of various ventilation management strategies in high-rise structures.

The findings indicate that employing optimal ventilation systems can significantly enhance energy efficiency, particularly during transitional seasons.

Mechanical ventilation and air conditioning systems constitute over half of the energy costs associated with buildings [51], and climate change is exacerbating this issue by intensifying the connection between rising greenhouse gas emissions and fluctuating weather patterns. One effective approach is to incorporate passive measures, particularly in regions with hot climates. However, the variability of climate conditions necessitates the adaptation of these measures to optimize the utilization of natural resources, such as daylight and natural ventilation. This highlights the importance of effectively managing building systems to regulate their performance.

Therefore, the integration of artificial intelligence, big data and passive measures can enhance the energy efficiency of ventilation systems while simultaneously adapting buildings to the impacts of climate change. This holistic approach ultimately contributes to a significant reduction in their carbon footprint over the long term.

3.1.6. Carbon Footprint of Buildings and Structures

A significant challenge in the context of sustainable development is the substantial contribution of buildings to global energy consumption and greenhouse gas emissions. Buildings account for up to 50% of global energy consumption and around 30% of greenhouse gas emissions, highlighting the urgent need to enhance their energy efficiency to achieve sustainable development goals [52]. The application of artificial intelligence and machine learning to predict energy efficiency, both at the individual building level and across urban areas, has emerged as a crucial strategy for solving these issues. Research indicates that accurately predicting energy consumption requires taking into account climate change factors and the functional characteristics of buildings [53].

Despite advancements in AI applications, the prediction of energy efficiency at the city level remains insufficiently explored, particularly regarding the interactions among various spatial functions and climate scenarios [52]. Modern research indicates that machine learning (ML) and artificial intelligence (AI) can significantly enhance energy consumption management and reduce the carbon footprint of buildings. For instance, in smart and energy-efficient buildings (SEEs), ML-based control systems allow thermal comfort and energy consumption to be effectively balanced [54]. Prediction models utilizing ML and genetic algorithms can improve the energy efficiency of existing buildings by analyzing historical data [55], including taking into account climate change forecasting [56]. Additionally, the application of multi-criteria optimization techniques for assessing the thermal performance of buildings further underscores the critical role of AI in adapting structures to shifting climatic conditions [57].

A significant innovation in building energy management is the application of artificial intelligence (AI) and cloud technologies to automate energy consumption processes, for example, using time series data [58]. These systems not only optimize energy consumption but also identify anomalies, producing tailored reports for various stakeholders [59]. This integration contributes to more efficient energy utilization and a reduction in carbon emissions [60].

Building life cycle optimization techniques that leverage artificial intelligence (AI) and digital technologies are employed to minimize the overall environmental impact, including energy consumption and carbon emissions, at every stage of the life cycle—from design to operation and disposal [40]. These approaches are crucial for achieving sustainability in the construction and operation of buildings, which is particularly important in the context of global climate change.

3.1.7. Adaptation of Buildings to Climate Change

Other studies focus on the adaptation of buildings to specific climatic conditions. For example, the use of XGBoost and genetic optimization algorithms, due to their ability to accurately predict building performance with respect to multiple parameters, such as thermal comfort, energy efficiency, structural parameters and daylight levels, helps to improve thermal insulation and natural lighting in tropical regions. It highlights the need of climate-adapted solutions to improve building energy efficiency [61].

XGBoost, learned from historical data, provides high accuracy in modeling the building response to different climatic conditions, allowing for the adaptation of design solutions to the specific weather conditions of the tropical region. As a result, the combined application of XGBoost and genetic optimization allowed for the creation of an integrated structure capable of adapting and improving design solutions, as confirmed by the high R^2 values (0.95 for point blocks and 0.87 for slab blocks). The above indicates the high predictive accuracy of the models adapted to tropical climatic conditions.

The adaptation of building management systems to changing climatic conditions is also an important area of research. For example, the use of machine learning to predict thermal loads and model thermodynamic characteristics of buildings helps to significantly reduce their energy consumption [62]. Predicting changes in climate conditions using explainable AI and adapting control systems to these changes are found to be important for maintaining energy efficiency [63].

Research also highlights the importance of reliability, safety and climate change adaptation in building design, which reinforces the importance of implementing AI to effectively manage these factors [54]. Optimizing the energy efficiency of buildings in the face of climate change becomes a key challenge. For instance, a study [55] introduces an energy-prediction model that utilizes ML and genetic algorithms to enhance the energy efficiency of existing buildings based on historical energy consumption and weather data. Similarly, study [56] emphasizes the need to incorporate climate scenarios in building design to optimize parameters, such as insulation thickness, to improve their energy efficiency.

Study [63] significantly enhances our understanding of the effects of climate change on building energy consumption. An explainable AI (XAI) model was employed to predict energy usage under various climate scenarios, including "business-as-usual" and sustainable energy transition scenarios. The findings indicate that climate change could substantially increase cooling energy costs, underscoring the need for adaptation measures to mitigate adverse economic and environmental consequences.

Thus, studies emphasize the important role of applying AI and ML to predict climate change and adapt building systems, ensuring buildings resilience in a changing climate [61].

3.1.8. Energy Efficiency and Thermal Comfort

The optimization of heating, ventilation and air conditioning (HVAC) systems through the application of neural networks facilitates an effective balance between energy savings and the maintenance of thermal comfort within buildings [28]. Adaptive AI systems that can learn from real-world data are crucial for the development of sustainable buildings in the future, as they can automatically adjust HVAC parameters in response to fluctuations in the external environment and evolving user needs [39].

Research [54] focuses on modern control systems for smart and energy-efficient buildings (SEEs), where the balance between minimizing energy consumption with the maintenance of comfortable indoor temperatures is a central concern. Machine learning techniques, including supervised, unsupervised and reinforcement learning methods are actively employed to achieve this balance.

The integration of physical simulation and artificial intelligence to predict energy consumption across various climate scenarios not only facilitates the optimization of energy costs but also enhances the thermal comfort level within buildings [27]. For instance, precise predictions derived from AI models enable better adaptation of indoor conditions to a changing climate, thereby maintaining comfort while reducing cooling and heating expenses.

The study conducted by [62] highlights the significance of selecting optimal parameters for window structures, which allows for improving thermal insulation and subsequently reduces energy consumption while maintaining a comfortable indoor temperature. This underscores how contemporary machine learning techniques contribute to developing energy-efficient solutions that balance resource conservation with user comfort.

3.1.9. Energy Efficiency of Buildings in the Context of Sustainable Development and Financial Efficiency

The trend of utilizing artificial intelligence to predict and optimize energy consumption is steadily gaining momentum. However, the slow adoption of these technologies may result in substantial economic losses, underscoring the importance of expediting their integration into the construction industry [41]. The implementation of energy-efficient solutions is increasingly recognized not only as an environmental necessity but also as an economically reasonable step for sustainable development.

A study [49] investigates the challenges and opportunities associated with the application of big data, artificial intelligence (AI) and Internet of Things (IoT) technologies to enhance the energy efficiency and sustainability of buildings in Europe. The research highlights the need for technology integration to meet the requirements of policy, business and technology, emphasizing the importance of coordinating these elements for a successful transition to sustainable building practices.

Particular emphasis is placed on the role of digitalization and the application of artificial intelligence (AI) throughout all stages of the building life cycle from design to operation and renovation, which is especially important for developing countries [14]. Digital technologies, such as Building Information Modeling (BIM) and Building Management Systems (BMS), can significantly enhance resource efficiency and minimize the environmental impact. These technologies are increasingly recognized as an important element of sustainable construction, providing both economic advantages and reductions in the carbon footprint.

The integration of AI and the ML into the design and operation of buildings not only improves energy efficiency but also increases resilience to climate change, positioning these technologies as essential components of the future building industry. Nevertheless, there is still a need for further investigation of the practical aspects of their integration, as well as an assessment of their long-term economic impacts and contribution to sustainable urban development [64].

Current research demonstrates that green technologies and sustainable construction play an important role in the face of climate change. For instance, study [61] proposed an integrated platform for predicting and optimizing the performance of residential buildings in tropical climates, utilizing machine learning (XGBoost) and genetic optimization algorithms. Particular attention is paid to improving thermal insulation and optimizing the use of natural light, which confirms the importance of adapting building materials and structures to improve energy efficiency.

A study [41] highlights the economic importance of the rapid implementation of energy-efficient technologies. Delayed implementation could result in billions of euros in lost opportunities and additional expenses linked to rising energy consumption. This underscores the necessity of actively utilizing AI and digital solutions to reduce costs and enhance resilience in the face of a climate change.

3.2. Improving Energy Efficiency in Transport and e-Mobility

This topic encompasses a broad spectrum of issues, ranging from optimizing energy consumption in transportation systems to developing infrastructure for charging electric vehicles. A key area of research is the application of artificial intelligence and machine learning to enhance the energy efficiency and safety of vehicles, particularly in hybrid and autonomous transportation systems.

Studies indicate that one of the most promising areas is the use of AI to predict vessel arrival times (ETA) in maritime logistics, which contributes to reduce greenhouse gas emissions and improves energy efficiency in international transportation [65]. Optimizing the energy efficiency of shipping and minimizing the carbon footprint are key priorities in this field. A study [66] highlights the use of big data and machine learning to enhance fuel efficiency in large ships, marking a step towards more sustainable transportation solutions. Similar approaches are also applicable to land transportation, particularly for electric vehicles and hybrid systems.

The application of machine learning is being actively utilized to enhance the energy efficiency of vehicles. A study [67] indicates that intelligent transportation systems have the potential to reduce CO_2 emissions by 60%. Specifically, AI can optimize fuel consumption in hybrid transportation systems, leading to significant reductions in energy costs and improved environmental performance, and this allows for the more efficient use of unmanned aerial vehicles [68]. Research [69] focuses on developing a machine learning-based hybrid architecture to predict the battery health of electric vehicles, which is crucial for extending battery life and optimizing energy consumption, ultimately resulting in more efficient electric vehicle operation. This approach is also being explored in transportation logistics, where AI helps to optimize routes and forecast energy consumption [19].

Studies also demonstrate the significant role of electric vehicles in urban energy strategies. The adoption of electric vehicles helps to reduce energy consumption and carbon dioxide emissions, which is crucial for sustainable urban development [70]. Furthermore, research, such as [71], explores the broader integration of AI and IoT into the urban infrastructure, where smart systems can optimize energy management in transportation, contributing to more sustainable cities. Additionally, the energy-demand analysis in the study by [72] highlights key aspects of managing energy demand in the transportation sector. As energy demand for charging electric vehicles increases, efficient energy management becomes essential to prevent overloading the power grid.

Study [73] utilizes machine learning to map the drivetrain efficiency of electric vehicles, enhancing energy management and predicting energy efficiency. This helps to improve energy management and predict energy efficiency, contributes to reduced fuel costs and accelerates the shift towards more sustainable transportation solutions. Additionally, the use of AI and ML to predict and optimize thermal and cooling loads in electric vehicles further improves their energy efficiency and reduces operating costs.

The safety of autonomous vehicles, alongside their energy efficiency, is another crucial area of research. AI technologies have been applied to enhance the safety management of autonomous vehicles, improving their reliability and reducing the likelihood of accidents by better predicting critical situations [74].

Thus, key trends in improving energy efficiency in transport include the application of AI and machine learning to optimize energy consumption in both land and maritime transportation systems, as well as expanding the use of electric vehicles in cities as a tool to achieve energy sustainability. Additionally, there is an increasing focus on developing charging infrastructure and the management of transport networks powered by renewable energy sources.

3.3. AI in Sustainable Manufacturing and Industrial Automation

The integration of artificial intelligence in industrial automation and sustainable manufacturing is becoming a crucial strategy for optimizing production processes, reducing energy consumption and minimizing carbon footprints. The implementation of AI enables predictive maintenance and energy consumption management and fosters automation, leading to increased productivity and sustainability across various industrial sectors.

A key focus area is the implementation of AI for predicting and optimizing energy consumption. For instance, machine learning is employed to enhance energy-consumption efficiency in logistics and industrial settings, aiming to minimize carbon footprints and optimize resource utilization [75]. However, a study [76] showed that R&D expenditures are only effective in reducing CO_2 in low-CO_2-emitting countries, and conversely, patent applications contribute to higher CO_2 emissions.

Studies emphasize the importance of using AI to manage energy consumption in manufacturing processes to improve sustainability and efficiency [77]. In addition, Internet of Things (IoT) and AI technologies can significantly improve automation in industrial buildings, leading to lower energy costs and improved overall energy efficiency [34].

The application of AI significantly reduces energy intensity by optimizing production processes and minimizing energy consumption [78]. Economies of scale are also crucial: large enterprises that have integrated AI technologies achieve higher economic efficiency and reduce energy intensity, highlighting the potential of AI to enhance the sustainability of industrial production. However, reliable methods suitable for all levels of production have not yet been sufficiently developed [79].

In addition to industrial enterprises, AI enhances household energy management through the implementation of home energy management (HEM) systems [80]. These systems optimize energy usage by employing advanced meta-heuristic algorithms, such as Social Spider Algorithm (SSA) and Strawberry Algorithm (SWA), which effectively reduce energy costs and peak loads.

AI also plays a crucial role in managing carbon dioxide emissions in the industrial sector. Specifically, AI technologies are utilized to monitor and control CO_2 emissions, which contributes to the achievement of carbon-footprint-reduction targets [81]. Furthermore, AI plays an important role in the integration of industrial systems with renewable energy sources, enabling the optimization of resource allocation and real-time energy management [82], which contributes to environmental sustainability [83].

The transportation industry remains a major source of emissions, which requires the implementation of intelligent systems to improve energy efficiency. Since 2016, with the increasing popularity of deep learning, 219 patents focused on energy management, sustainable driving and behavior optimization applied, of which more than 70% are registered in China [84].

Research indicates that AI can substantially reduce inefficient energy usage, for instance, by automatically adjusting equipment operation depending on demand levels [85] or fuel economy in the maritime industry [86]. Conscious energy utilization enhanced by AI mechanisms [87] promotes sustainable development by helping businesses reduce their carbon emissions and increase the environmental responsibility of enterprises [88].

One promising area is the application of AI in agriculture to enhance the sustainability and energy efficiency of agricultural production. In this sector, AI facilitates the optimization of resource consumption, improves harvesting processes and enhances irrigation management, ultimately reducing the carbon footprint and increasing the environmental sustainability of agricultural production [89]. Additionally, AI is employed to optimize production processes and reduce energy costs, thereby increasing the sustainability and productivity of agribusinesses. AI technologies can automate processes related to the management of agricultural resources, improving their efficiency and minimizing environmental impacts, including through post-combustion carbon capture [90].

Predictive maintenance is emerging as one of the key application areas of AI in the industrial sector. Specifically, AI allows industrial enterprises not only to automate processes but also to implement predictive maintenance systems, which significantly reduces repair costs and extends equipment lifespan, as well as buildings [91]. In this context, predictive analytics is extensively employed to detect potential breakdowns in advance, thereby avoiding costly downtime [75]. Consequently, this approach enhances the resilience of industrial systems while also contributing to reductions in energy consumption.

A particular area of research is the application of AI to enhance resource efficiency in manufacturing systems. This encompasses both material usage optimization and waste reduction, resulting in leaner and more environmentally responsible production practices [75]. Furthermore, AI facilitates the development of intelligent control systems that adapt to changing production conditions and automatically adjust processes to achieve maximum efficiency [92].

3.4. Energy Efficiency in Smart Grids

The application of artificial intelligence and machine learning has emerged as a crucial element in enhancing energy efficiency within smart grids. Key components include real-time demand forecasting and management, the integration of distributed energy resources, such as solar and wind power, and process automation, all of which are essential for the advancement of smart grid technology.

Artificial intelligence plays a key role in optimizing energy consumption within smart grids, improving power system management through real-time demand forecasting and increasing grid resilience. For instance, the application of AI techniques, such as machine learning and data analytics, allows for more precise predictions of energy demand and enables immediate responses to fluctuations in the load, thereby reducing costs and improving the efficiency of power systems [93].

An important aspect of the efficient integration of renewable energy sources into smart grids is the ability to predict their power output. Study [4] examines various methods for predicting solar radiation and photovoltaic (PV) power using machine learning and deep learning techniques. These methods aim to reduce uncertainty and improve energy management within smart grids. Demand-side management techniques combined with machine learning also help to optimize the operation of distributed energy sources, such as solar panels and wind turbines, thereby increasing the share of renewable energy sources within the overall energy system [94]. Artificial intelligence is employed to manage distributed energy resources, enabling efficient predictions of energy intensity and optimizing the utilization of renewable sources, like solar and wind energy [95]. A study [96] investigates the integration of distributed energy sources, such as solar panels, utilizing AI to effectively manage energy consumption and distribution within a proposed nanogram and microgrid architecture, thereby improving system stability.

Machine learning techniques, such as the Multivariate Temporal Fusion Transformer, enhance the accuracy of energy-demand forecasting [9]. This forecasting accuracy is essential for optimizing energy flow management, particularly for variable energy sources like solar installations.

The Internet of Energy (IoE) plays a crucial role in smart grids, allowing devices and systems to be connected to monitor and manage energy consumption. A study [97] investigates the combined application of IoE and ML to optimize energy-consumption management and enhance the overall energy efficiency of the grid. This includes load forecasting, system state monitoring and the automation of energy consumption management processes.

Carbon forecasting is increasingly recognized as a vital component of smart grids, as it impacts investment decisions and risk management. Real-time forecasting and distributed sources energy management significantly reduce carbon emissions and contribute to the development of sustainable energy infrastructure [93]. A study [98] employs machine learning to predict the carbon emissions of corporations, enabling investors to make more informed decisions in response to emerging environmental regulations.

The focus of research is on energy-demand management and the development of cost-effective models for smart grids. A study [99] proposes a blockchain and artificial intelligence-based “cap and trade” model for demand management, utilizing AI to incentivize consumers to save energy. This is accomplished by introducing a system of energy credits that can be traded if energy consumption remains below a specified limit. Intelligent AI algorithms, such as predictive analytics and optimization algorithms, enable power grids to efficiently allocate resources and manage electricity demand and consumption, thereby minimizing peak loads and ensuring grid stability [100]. Additionally, a study [101] presents an open-access decision support system (NESSI) for energy consumption and generation planning at both the household and neighborhood levels. This system uses AI and machine learning to calculate and optimize energy consumption and forecast demand.

The utilization of Information and Communication Technology (ICT) platforms for energy consumption management in buildings is emerging as a significant trend within smart grids. ICT platforms enable the collection and processing of massive amounts of data in real time, which is critical to accurately monitor, analyze and predict energy consumption. ICT platforms provide smart grids with the analytics they need to respond instantly to changes in demand and manage loads to prevent congestion and improve the efficiency of energy distribution. A study [77] provides a real-world example of an ICT platform employed to predict and optimize energy consumption, leveraging data collected from sensors in smart buildings. This approach results in enhanced energy efficiency and sustainability.

Internet of Things (IoT) technology facilitates real-time data collection and processing, thereby enabling the automation of energy management processes both at the micro-grid level [102] and at the level of smart energy infrastructure in general [103]. A study [104] demonstrates the potential of utilizing IoT data to predict peak energy demand and optimize energy consumption across various types of buildings. This capability enhances energy management flexibility and reduces the overall load on the grid.

As a result of the conducted research, the following most effective methods for managing distributed energy resources (DER) can be identified:

1. Using AI to predict and optimize DERs. Methods, such as Temporal Fusion Transformer, improve forecasting accuracy, which is especially important for DERs with variable capacity, such as solar and wind installations. High-quality forecasts minimize load peaks and improve grid stability.
2. Demand management using AI and blockchain. Demand management allows users to adjust energy consumption based on grid conditions and helps prevent grid congestion, especially during periods of high demand, by economically incentivizing users to reduce consumption. Thus, DER owners can adapt consumption and even offer surplus energy to the market.
3. IoE and IoT for monitoring and managing DER. IoE and IoT devices collect data in real time, allowing for rapid monitoring of the network status and when using AI together, automatically adjust energy consumption.
4. ICT platforms for data collection and analysis in smart grids. ICT enables the collection and processing of large amounts of real-time data from DERs, which is critical for accurate demand management and prediction.
5. Microgrids and nano-grids allow DERs to operate autonomously, providing energy to the local community or sites, while being able to connect to the main grid for additional flexibility.

3.5. Climate Change Forecasting and Adaptation of Energy Systems

Current research increasingly employs mathematical models and machine learning to predict the impact of climate change on energy systems. These technologies enable the consideration of various climate scenarios, facilitating assessments of future energy needs and potential risks [105]. Mathematical models and machine learning make it possible not only to predict but also to optimize energy systems by developing adaptive algorithms that dynamically adjust energy strategies, taking into account changing climate conditions in real time.

For instance, the application of machine learning techniques, such as multi-criteria optimization and Explainable AI (XAI), enables the assessment of the impact of various climate scenarios on energy consumption in buildings and the development of adaptation strategies [106], which is important for understanding and informing decisions to reduce climate risk.

Additionally, ref. [107] discusses the use of machine learning-based models and dynamic panel estimation to manage nonlinear and chaotic systems related to climate vulnerability and energy infrastructure. Taking into account non-linear relationships between climate factors and energy consumption helps to improve the accuracy of long-term forecasts.

A significant area of research is the adaptation of infrastructure to the new conditions brought about by climate change [108]. Study [39] explores building adaptation through the use of AI and digital twins to predict changes in climate conditions and adjust energy systems accordingly. Meanwhile, [50] focuses on forecasting changes in building cooling loads and energy consumption to develop long-term adaptation strategies and optimize the energy system infrastructure in response to climate change. Research indicates that employing climate models and optimization techniques can lead to a reduction in energy consumption in buildings by up to 54% when adapting to the climate change scenario SSP585 [27]. Additionally, studies [109] concentrate on regional approaches to adapting energy systems to climate change, which confirms the growing overall interest in the impact of climate change on energy systems that has been observed in recent years [110]. There are also investigations into the adaptation of energy systems in arid regions, where increased energy consumption necessitates the implementation of sustainable and energy-efficient solutions [44].

The use of machine learning not only makes it easier to predict energy demand but also takes into account changes in the structure of electricity demand. For instance, electricity demand forecasting employing techniques, such as Blade Element Momentum (BEM) and Explainable AI, enables the prediction of changes in energy consumption depending on weather conditions and adapting energy systems to minimize losses [111]. Furthermore, a study [112] reveals the adaptation of energy systems to climate change through fault detection in the power electronic circuits of the wind turbine system, allowing it to adjust to changing demand in the face of population growth and increasing extreme weather events.

Research underscores the necessity of developing strategies to minimize the negative consequences of climate change on energy systems. The integration of AI and quantum computing technologies is enhancing the resilience of energy networks, improving the management of renewable energy and reducing carbon emissions and carbon dioxide removal (CDR) [113]. These advanced technologies facilitate the development of strategies that enable energy systems to adapt to evolving conditions and maintain stable operations amidst climate uncertainties.

A crucial area of research is the development and implementation of climate-resilient solutions for urban and industrial systems [31]. Forecasting climate change and its effects on urban infrastructure is essential for creating climate-resilient cities that can adapt to changing conditions and minimize adverse impacts on energy systems [114]. Such strategies encompass the integration of smart grids and renewable energy sources, which contribute to enhanced energy consumption efficiency and a reduction in carbon emissions.

3.6. Machine Learning for Water Resource Management

The use of Intelligent Energy Monitoring Systems (IEMSs) to manage glacial ecosystems demonstrates how machine learning (ML) and artificial intelligence (AI) can be powerful tools in managing water resources in the face of climate change [115]. IEMS applies remote sensing technologies, sophisticated sensors and ML algorithms to track real-time changes, which opens up opportunities to better understand and conserve glacial ecosystems.

Approaches to improving energy efficiency in the shipping industry based on behavioral change and operator involvement provide meaningful insights for the application of AI and ML in water resource management [116]. The use of autonomous ML-based systems for data collection and analysis in the shipping industry will overcome the lack of standardization, enabling more informed decisions and optimizing the use of limited water resources.

One of the primary applications of machine learning in water resource management is the optimization of membrane distillation processes [85]. Studies show that ML, which optimizes key system parameters and forecasts its behavior with high accuracy, can be used to improve the accuracy of performance forecasting of membrane distillation processes. It helps to reduce energy costs and improve desalination efficiency [117]. Also, machine learning algorithms help to accurately model water flow, forecast pollution and take into account the impact of micropollutants on the treatment and desalination process. Modern technologies make it possible to improve membrane material selection, automate water quality control, optimize distillation processes and minimize energy consumption. The use of AI and machine learning helps to minimize the amount of data required for process modeling and optimizes the tuning of system parameters, which increases the interpretability of models and process stability [118].

Machine learning (ML) contributes to the optimization of solar desalination systems by reducing energy consumption and increasing the water production volume [96]. Specifically, ML has been employed to predict and optimize the performance of solar membrane desalination systems, in order to minimize energy consumption through the more precise selection of system parameters [117].

Machine learning is also actively employed to address global issues related to water scarcity. The use of AI and machine learning for energy consumption management in the textile industry provides useful approaches for optimizing water resources [119]. Innovative technologies, such as bioreactors [120] and solar-powered water purification systems, are being improved through machine learning algorithms that help minimize energy consumption and improve productivity [121], particularly within water treatment systems, which is crucial for regions facing water shortages. Study [122] examines the use of IoT and machine learning for monitoring ocean acidity, while [123] explores the application of artificial intelligence and big data for water resource monitoring through the use of sensors on the plants, which helps manage water resources as part of global initiatives.

Machine learning not only facilitates the optimization of treatment processes but also aids in predicting water resource demand. By analyzing data on climate, demographics and water consumption, accurate forecasts are generated to help the development of effective water management strategies. This capability is particularly significant for both industry and agriculture, as precise predictions can help minimize water losses and enhance planning efforts [124]. Additionally, [125] describes innovative technologies for water consumption monitoring that employ wireless systems and optical sensors, which can be integrated with ML to optimize water consumption and management.

3.7. AI in Renewable Energy Sources

One of the key trends in renewable energy is the application of AI to enhance the efficiency of geothermal heat pumps. Research indicates that AI can help optimize the performance of these systems through more accurate heat load predictions, real-time data analysis and automation of controls. The use of machine learning makes it possible to better predict the output temperatures from heat pumps [126] and regulates temperature flows [96], thereby improving control mechanisms and reducing operating costs. Additionally, various approaches are being explored to optimize pump parameters to improve their energy efficiency [127].

AI not only helps in predicting energy consumption but also facilitates the management of interactions between the grid and renewable energy sources. The application of machine learning algorithms enhances the accuracy of energy consumption forecasts, thereby optimizing the management of energy resources [6]. This capability is particularly crucial for energy systems operating with variable renewable sources, such as solar and wind energy [5]. For instance, study [128] explores the processes of the integration of solar energy into conventional power systems, while another study [129] analyzes the prediction of solar radiation and the performance of solar panels, including strategies for preventing panel failures.

AI also plays a crucial role in the integration of various renewable energy sources into energy networks. Green AI and digitalization moving to low-power peripherals, such as TinyML, support the efficient management of renewable energy [130]. The application of AI techniques enhances grid stability, improves energy resource management and reduces carbon emissions. Studies [131] investigate strategies for incorporating renewable sources, such as solar and wind energy, into existing urban energy systems. Additionally, the use of AI in wind energy systems improves power forecasts under varying weather conditions, thereby increasing the overall stability of the grid [111]. Furthermore, AI technologies enable the real-time management of renewable sources, which reduces the grid load and improves the interaction between consumers and energy producers [103].

A crucial aspect of applying AI to renewable energy sources is the creation of models that take into account the instability of natural conditions and assist in predicting energy output [132]. For instance, wind turbines are influenced by fluctuating weather conditions and AI can accurately predict how these changes will impact their performance [111]. Additionally, the use of AI for fault detection enhances the reliability and efficiency of wind energy systems [112]. AI also aids in predicting geothermal resources, enabling a more efficient utilization of their potential for energy supply [126].

Research indicates that utilizing AI to manage renewable energy sources enhances the resilience of power systems in the face of climate change and other unforeseen circumstances. Predictive models developed through AI allow us to assess risks and make decisions under conditions of uncertainty, thereby improving the stability of the power system and reducing its dependence from traditional energy sources [22].

3.8. Energy Transition and Decarbonization Through Innovative Technologies

One of the primary challenges of the current energy transition is achieving decarbonization through the integration of renewable energy sources (RESs), such as solar, wind and geothermal energy. For instance, the implementation of smart grids equipped with AI can enhance the stability of energy systems and minimize energy losses through more accurate forecasting and resource management [22].

Artificial intelligence (AI) plays a crucial role in managing energy consumption, optimizing energy systems and minimizing CO_2 emissions. The use of machine learning and big data analytics enables real-time predictions of energy consumption, improves the energy efficiency of industrial processes and reduces the overall carbon footprint [133]. This is particularly relevant for the electronics industry sector, where optimizing energy management can significantly reduce emissions [134].

Blockchain technology is actively being investigated as an innovative tool for managing distributed energy sources, fostering transparency and enhancing the security of transactions within energy systems. For instance, blockchain facilitates the creation of sustainable energy ecosystems by enabling distributed users to engage in renewable energy markets REM, thereby promoting the growth of localized clean energy production and contributing to the reduction in carbon emissions.

Cyber-Physical Systems (CPSs) and Energy Management Automation: CPSs play a crucial role in optimizing energy resource management, particularly within the transportation and industrial sectors. These systems enable more the efficient utilization of energy resources and support the transition to sustainable technologies, including the development of decentralized energy systems [102]. They are actively employed to manage the integration of renewable sources into energy systems, effectively reducing the carbon footprint by enhancing the accuracy of control and monitoring processes.

With the energy crisis, in the context of accelerated climate change, conflict in Ukraine and the past 2019 coronavirus pandemic, carbon emissions are growing rapidly [135], requiring the use of innovative technologies to reduce these emissions [136].

Artificial intelligence (AI) and machine learning are helping to model investment scenarios for new energy technologies, such as wind and solar power, and evaluate their economic and environmental impacts. Research [1] underscores the necessity for economically reasonable investments in the energy transition, highlighting the significance of developing strategies that integrate renewable energy sources that include renewable energy, which will contribute to the transition to a low-carbon economy.

3.9. The Carbon Footprint of Large AI Language Models

Despite the significant potential of AI and ML in promoting energy conservation, a critical concern is the high carbon footprint associated with the training and operation of large language models (LLMs). These models demand substantial computational resources and consume considerable amounts of energy [137]. The training of LLMs, especially for natural language processing tasks, involves the repeated processing of vast datasets, which significantly contributes to CO_2 emissions [18]. This presents a challenge for researchers and AI developers in finding ways to minimize environmental losses, despite the fact that artificial intelligence can support environmental sustainability [138] and solve environmental problems.

One proposed approach to reducing the carbon footprint of language models is to adopt more energy-efficient computing architectures and to optimize learning algorithms, thereby reducing the number of computational operations required [139].

Methods to reduce energy consumption by employing specialized hardware solutions and utilizing renewable energy sources for data center operations are also being actively explored [19]. Some studies propose integrating green energy and implementing energy-efficient solutions to support AI computing, which contributes to reducing carbon emissions [18].

Another important aspect is the use of more energy-efficient hardware for computational tasks. For instance, some studies suggest the use of hardware accelerators, such as specialized processors and graphics processing units (GPUs), to reduce power consumption during the training and implementation of language models [19].

Study [92] highlights that the computational resources required to train and operate large language models (LLMs) consume substantial amounts of energy, contributing to carbon emissions. Research indicates that reducing the training time through more efficient allocation of computational resources can significantly reduce the overall carbon footprint [138]. This can be achieved by developing new algorithms that can minimize the number of repetitive operations during the training process.

Work [130] explores the potential of using Green AI technologies to minimize energy consumption, such as shifting computation from the cloud to edge computing. This approach can reduce the amount of data transmitted over the network and decrease the computational demands for training and deploying models.

3.10. Post-Combustion Carbon Capture and Its Optimization Using Machine Learning

Global warming caused by increasing carbon emissions requires immediate action. Study [140], emphasizes the need to develop global policies with specific targets to stabilize atmospheric carbon, including low-carbon technologies and improved energy efficiency.

Post-combustion carbon capture (PCCC) is a complex process that requires significant energy input. The application of machine learning for optimizing these processes is becoming an urgent task, as it can significantly enhance energy efficiency, reduce operational costs and reduce the carbon footprint of industrial enterprises [2]. Some studies have employed machine learning to improve modeling and prediction, enabling the precise identification of parameters that need adjustment for the optimal performance of carbon-capture systems [141].

One of the main challenges in implementing post-combustion carbon capture (PCCC) is its high energy intensity, which reduces its economic efficiency. Machine learning can optimize CO_2-absorption processes by improving process control and minimizing heat loss, thereby reducing energy consumption. Specifically, machine learning can help identify the most efficient operating conditions for carbon filters and adsorbents, maximizing carbon dioxide capture [90].

The successful implementation of carbon capture technologies necessitates their integration into existing industrial systems, which account for 50% of the world's energy consumption [142], such as steel and cement production, which are significant sources of CO_2 emissions [143]. In this context, machine learning optimization (ML) plays a crucial role by predicting how variations in operating parameters impact the performance of carbon-capture systems. This capability allows for the flexible integration of post-combustion carbon capture (PCCC) into production cycles without substantial losses in efficiency [113]. Some studies indicate that the application of ML models can not only enhance capture processes but also predict emissions at various stages of the production process, contributing to a reduced carbon footprint during both the planning and operational phases [90].

Machine learning is also actively applied in the search for new materials and catalysts that can enhance the efficiency of carbon capture. By simulating the behavior of materials under various conditions, machine learning optimization (ML) accelerates the discovery of innovative solutions [140]. This is particularly important in environments where traditional carbon capture methods require significant energy inputs.

The study shows that the most promising way to improve the economic efficiency of PCCC using AI and ML are integrated approaches, including the prediction of thermal fluctuations and energy requirements using ML algorithms. It allows for the optimal regulation of heat exchange and increases the efficiency of heat recovery; the modeling of new sorbents at the molecular level, analysis and forecasting of their behavior under different conditions, in order to find materials with the lowest energy requirements; the use of co-generative materials with the lowest energy requirements; the use in co-generation facilities to manage the balance between heat production for PCCC and real-time electricity generation; and other economically feasible methods, including integration of renewable distributed energy sources and the optimization of energy efficiency of the PCCC process itself.

3.11. Mitigating the Effects of Climate Change with AI

AI plays a crucial role in monitoring climate change and predicting its impacts. Study [107] explores methods for monitoring climate vulnerability using AI, while [144] applies AI to analyze vegetation and urban air data to help predict and model the effects of climate change. These applications help to adapt energy-management strategies, enabling more accurate predictions and the implementation of targeted climate mitigation measures for energy systems and other industries [145].

A study [146] explores the use of drones and sensors to monitor climate change. This technology enables quicker responses to environmental changes and supports the development of strategies to adapt to evolving conditions.

An important aspect of climate change mitigation is the modernization of infrastructure with advanced energy-efficient technologies. For example, a study [39] explores the use of AI to adapt buildings to climate change and enhance their energy efficiency. Additionally, AI is being employed in enterprises to optimize the use of renewable energy and reduce CO_2 emissions. These innovations not only make industrial facilities more resilient to climate change but also significantly reduce their carbon footprint [147].

AI plays a critical role in predicting and managing climate risks. By utilizing machine learning and big data, models can be developed to forecast the impact of climate change on the infrastructure and energy supply. For instance, AI can predict energy-consumption patterns based on weather conditions, enabling businesses and energy networks to better adapt to climate risks [145]. Additionally, a study [141] explores the development of AI algorithms for the prediction of carbon emission and energy system management, which adjust their operations according to climate conditions, helping to mitigate the effects of climate change.

3.12. Social, Economic and Political Aspects of Energy-Consumption Management

One of the key challenges for governments is to develop and implement effective policies that promote the adoption of renewable energy and reduce carbon dioxide emissions. These efforts often involve programs that provide financial support for renewable energy projects, subsidies for solar panel installations and the development of infrastructure for electric vehicles [133]. A study [65] examines the role of international policies aimed at reducing greenhouse gas emissions in the maritime industry. An important element of government policy includes measures that encourage reductions in energy consumption in various sectors of the economy, along with incentives for both citizens and businesses to participate in energy-saving initiatives [148].

An important aspect of government policy is regulating the transition to sustainable energy. This includes implementing standards and regulations directed to reduce carbon footprints and ensure the long-term sustainability of energy systems [149]. A study [1] explores the role of support programs and investments in green technologies. Numerous studies indicate that policies promoting improved energy efficiency can not only reduce emissions but also stimulate economic growth by creating new jobs in the renewable energy sector [150].

An important aspect of energy-consumption management is the social and economic consequences of the implementation of renewable energy sources [34,108]. The transition to sustainable energy can have a significant impact on social groups, especially workers in traditional sectors, such as the coal industry, where the development of retraining and support programs is required.

A critical role is played by programs to support socially vulnerable groups affected by the increase in energy costs during the energy transition [151]. The results of study [152], based on the analysis of carbon emission reductions during the COVID-19 pandemic, show that planned economic slowdown and energy efficiency improvements can significantly reduce carbon emissions.

Many national and international programs for energy-consumption management and sustainable energy development are based on the UN Sustainable Development Goals (SDGs) [153]. Policies focused on decarbonization and the transition to renewable energy sources contribute directly to goals, such as reducing emissions (SDG 13—Climate Action, combating climate change) and ensuring access to affordable, clean energy (SDG 7) [137]. A key component of these programs is promoting the increased use of renewable energy sources, enhancing energy efficiency and developing more sustainable energy systems. This requires developing strategies for engaging the private sector and international organizations to collaborate on SDG initiatives.

The issue of energy poverty remains critical in a number of regions, particularly in the context the global energy crisis. A study [154] examines the role of policy in combating energy poverty in the EU and the UK. The application of AI and ML allows for the more precise identification of vulnerable households and the development of support mechanisms, helping to reduce social inequality and expand access to energy resources. Government programs are being aimed at lowering household energy consumption, promoting energy-efficient technologies and providing financial assistance to low-income households to improve their access to energy resources [151].

Our research shows that the interest in different topics fluctuated between 2011 and 2024. Figure 5 illustrates the distribution of topics based on the number of references in the cited sources.

If we look at the dynamics over the years, the topics can be divided into different trends: for some topics, the interest decreased, others just emerged and for some topics, the interest was and still is high. For example, the topics of "Sustainable building and green technologies with AI and ML application for energy efficiency in buildings", "Climate change prediction and adaptation of energy systems to climate change" and the "Social, economic and political aspects of energy consumption management" maintained high interest throughout the period from 2021 to 2024. In fact, interest in these areas even increased in 2024.

For the topics "AI in renewable energy sources", "Energy transition and decarbonization through innovative technologies" and "Climate change mitigation through AI", interest grew steadily each year, reaching its peak in 2024. In contrast, the topic "Improving energy efficiency in transportation and e-mobility" saw its highest level of interest in 2021, after which interest significantly declined. This trend is depicted in Figure 6.

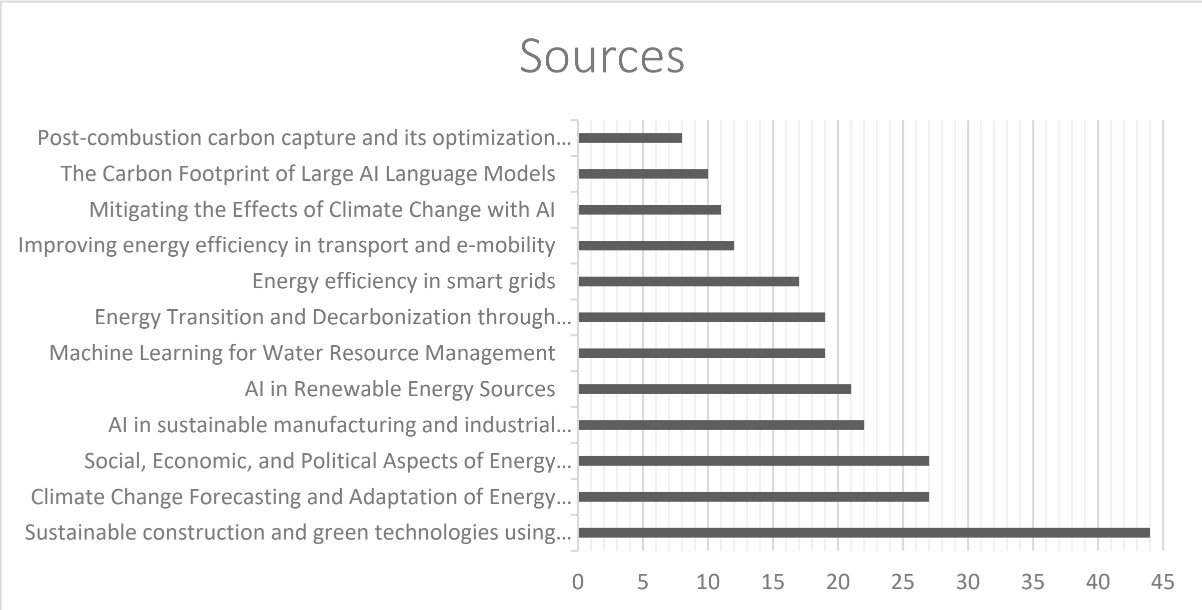

Figure 5. Distribution of topics by number of references in sources. Source: compiled by authors.

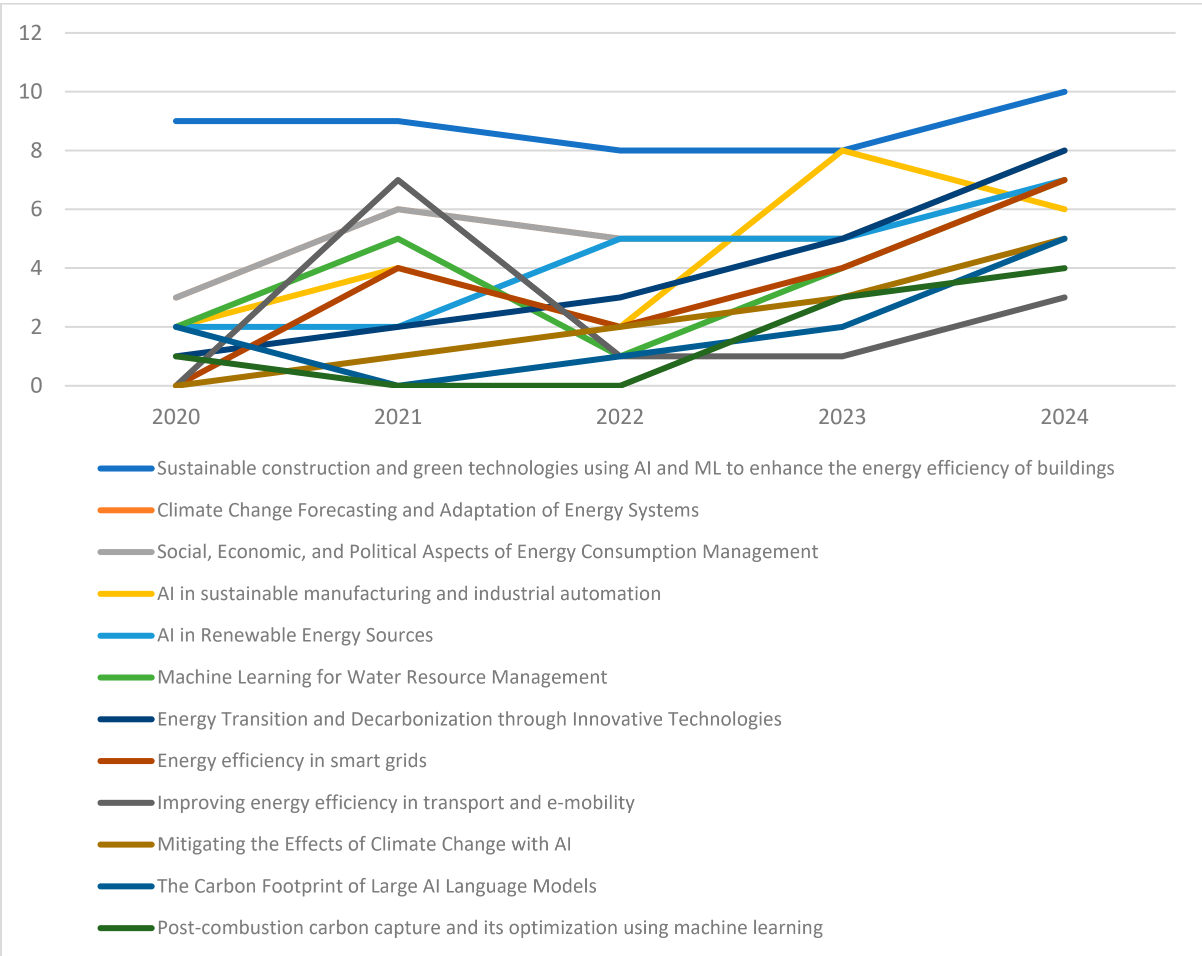

Figure 6. Dynamics of changes in interest in the topics over the last years. Source: compiled by authors.

4. Discussions and Conclusions

The study focused on systematizing the existing scientific literature to identify significant common themes and trends in the use of AI and ML tools in improving energy efficiency in different sectors and countries, with a focus on addressing climate challenges, such as reducing carbon emissions and optimizing resource use.

This literature review highlights substantial progress in the application of artificial intelligence (AI) and machine learning (ML) techniques aimed at enhancing energy efficiency and address climate change issues. A systematic analysis encompassing 237 research papers and 388 patents reveals a notable upward trend in research and innovation, particularly over the past two years. The focus of this trend spans several domains, including engineering, computer science and energy. These findings suggest a growing interest from both academic and industrial sectors in using AI to solve urgent environmental challenges.

The literature review conducted allows us to draw several key conclusions regarding the role and potential of AI and ML in improving energy efficiency and addressing climate challenges.

One of the key trends of scientific interest observed over the last 5 years is the integration of artificial intelligence (AI) and machine learning (ML) in sustainable building practices and green technologies. These technologies are particularly significant in urban environments, as they contribute to mitigating the urban heat island effect and reducing carbon emissions. The combination of physical simulations and AI predictive models shows great potential for energy consumption optimization, particularly within heating, ventilation and air conditioning (HVAC) systems. The results indicate that neural networks, CNN-LSTM models and gradient-boosting methods, such as LightGBM and XGBoost, can enhance the accuracy of energy consumption predictions, leading to improvements in building energy efficiency by as much as 22.3%. This underscores the transformative potential of AI in promoting sustainable urban development and green building practices.

The concept of the Internet of Energy (IoE), which is the integration of the Internet of Things, cloud computing and big data analytics technologies to create smart and integrated energy grids, is currently a relevant and rapidly growing area of research and practical application. The critical role of the IoE is to act as a bridge between the various components of smart grids, ensuring their optimal performance by predicting energy consumption, monitoring system health and automating control. IoE improves network efficiency, reduces energy costs and makes the network adaptive and resilient to changes in energy consumption.

The results also indicate the expanding role of artificial intelligence (AI) in smart grids, where real-time data collected from Internet of Things (IoT) sensors, combined with AI-based algorithms, improve energy distribution and load management. The integration of renewable energy sources, such as solar and wind power, is particularly benefited by AI's capacity to predict energy generation and optimize resource distribution. Nevertheless, these achievements are accompanied by challenges, including the maintenance of grid stability and the need to ensure the scalability of AI-based solutions.

AI also has an important role to play in the integration of renewable energy, which is a key factor in the global transition to a low-carbon economy. The ability of AI to manage and predict energy consumption in intermittent renewable energy systems is an important advantage. However, ensuring the reliability of these systems in a changing environment remains a subject of active research.

Another significant topic for discussion is the application of artificial intelligence (AI) in climate change mitigation. The predictive capabilities of AI are crucial for predicting the impact of climate change on energy systems and for developing effective adaptation strategies. The successful implementation of ML in post-combustion carbon capture (PCCC) illustrates AI's potential to enhance the efficiency of carbon capture processes, which is essential for reducing industrial emissions. However, the economic feasibility of these technologies remains a challenge due to their high energy consumption, emphasizing the need for further research on low-energy technologies and materials, as well as materials science and chemistry.

Finally, policy and regulatory frameworks play an important role in supporting the adoption of artificial intelligence (AI) in energy efficiency projects. The results indicate that government initiatives, particularly those aligned with the United Nations Sustainable Development Goals, serve as significant incentives for the utilization of renewable energy sources and AI-based energy efficiency measures. However, energy poverty continues to be a challenge in many regions, and AI has the potential to provide targeted solutions for identifying vulnerable households and enhancing access to energy-efficient technologies.

Despite this progress, the review identified significant barriers to the adoption of AI in energy efficiency projects, especially in transportation and industrial automation. While AI and ML improve energy management and predictive maintenance in industrial sectors, the high energy consumption of these technologies, especially large language models (LLMs), poses a challenge. The carbon footprint associated with LLMs underscores the need to develop more energy-efficient computing architectures and optimize learning algorithms to reduce their environmental impact.

Limitations of the research. As with any research, this study has its limitations. It primarily focused on technological aspects, particularly the influence of digital technologies on energy efficiency and climate change. However, the long-term return on investment for energy efficiency solutions, particularly in the context of environmentally friendly materials and innovative methods, remains insufficiently explored. This gap restricts the economic evaluation of such projects.

Furthermore, the majority of the studies and patents examined are primarily focused on developed economies and major markets, including the United States, United Kingdom, China and India. This concentration may constrain the applicability of the findings to other regions, particularly low- and middle-income countries, where infrastructure and access to technology can vary significantly.

Although artificial intelligence contributes to enhancing energy efficiency, our research does not broadly address the carbon footprint associated with the training of large language models and the AI implementation process itself. This is an important aspect in the context of measuring the positive and negative effects of AI on climate change and requires more detailed consideration and further research to comprehensively evaluate the impact of technology on the environment.

Prospects for Future Research. Despite significant advancements in the application of artificial intelligence and machine learning to improve energy efficiency, there are many areas that require deeper research and development. One of the key areas for future investigation is the integration of AI and digital twins into the existing building infrastructure. Practical examples are essential to illustrate the long-term economic and environmental benefits of using these technologies, particularly in the context of climate change. Additionally, evaluating the long-term return on investment for energy-efficient solutions and ecological materials remains a pressing concern that necessitates further analysis.

Another critical area of research is the integration of artificial intelligence with renewable energy sources and the development of methods for their optimal utilization in industrial and urban systems. This encompasses the creation of adaptive models for energy-consumption management in smart grids that are capable of taking into account extreme climatic conditions. A promising direction in this field is the creation of integrated solutions to improve the interaction among various renewable energy sources and their integration into urban energy systems.

Particular attention should be paid to cybersecurity challenges in smart grids and the development of sustainable solutions to prevent the risk of cyberattacks. The rapid development of IoT technologies and the increasing number of connected devices require the increased security and reliability of these systems. Additionally, research focused on developing new energy-storage methods and integrating artificial intelligence with these technologies to improve grid stability and reliability is also critical.

Additionally, a promising area for research is the development of standards and protocols for evaluating the energy efficiency of various AI-controlled systems. This may include the creation of metrics to assess the efficiency of automated industrial processes and their adaptation across different industries. Furthermore, research is necessary to improve water-management practices, particularly in regions vulnerable to climate risks, where artificial intelligence can play a key role in ensuring the sustainability of water systems.

The integration of artificial intelligence with blockchain technology to manage distributed energy systems, particularly at the community and small business levels, represents a significant area for further research. This direction has the potential to support the development of localized energy production and contribute to more sustainable energy management models.

One of the pressing challenges is the reduction of the carbon footprint associated with large AI language models. This requires research focused on developing more energy-efficient computing architectures and learning algorithms that minimize energy costs. Additionally, investigating the life cycle of language models from development to implementation and operation is essential for assessing their environmental impact.

Finally, research is essential to understand the socio-economic consequences of the energy transition. It is important to investigate how these changes affect local communities, the creation of jobs in the green economy and the development of retraining programs for workers displaced from traditional sectors. Furthermore, the development of socially oriented strategies and financial instruments to support sustainable development will help minimize the negative consequences for vulnerable groups of the population.

Thus, future research on the application of artificial intelligence and machine learning for enhancing energy efficiency necessitates an integrated approach focused on developing technological solutions, enhancing the sustainability of energy systems and considering socio-economic factors. Key priorities for the scientific community in the coming years should include integrating renewable energy sources, improving system reliability and cybersecurity and reducing the carbon footprint of AI technologies.

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Global climate change mitigation technology diffusion: A network perspective

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ABSTRACT

There is a rapidly growing number of studies on transnational climate change mitigation technology (CCMT) diffusion. Most of these studies have adopted a bilateral perspective, treating countries as primary agents driving the diffusion process. However, CCMT diffusion typically arises from the interactions between firms and involves strong network effects. In this paper, we explore the global CCMT diffusion from a network perspective, with multinational corporations (MNCs) as network makers. We first propose a methodology to construct the global CCMT diffusion networks, leveraging CCMT-related patent data, intra-firm relationships, and business scales of the selected MNCs. We then calculate the network capital for each country, utilizing it as the input for the econometric analysis to investigate the network effects on CCMT development. The network statistical analysis reveals an uneven geographical distribution of network capital, underscoring the presence of global disparities in CCMT development. Moreover, the econometric analysis identifies significant network effects originating from linkage volumes and structural positionalities within the CCMT diffusion networks.

1. Introduction

An expanding coalition of countries, cities, firms, and institutions is collaboratively striving to cut greenhouse gas emissions to as close as zero by 2050 (IEA, 2021). However, achieving net-zero emissions by mid-century presents challenges primarily due to the magnitude of the fluxes (Allen et al., 2022; Arora and Mishra, 2021). There is a substantial emission gap between the projected emissions based on the Nationally Determined Contributions announced prior to COP26 and the emission levels necessary to align with modeled mitigation pathways that limit global warming to 1.5 °C or below 2 °C (Chen et al., 2022; ICPP, 2023). In this regard, accelerating the development and diffusion of CCMTs presents a strategic way to bridge the gap between political rhetoric and net-zero carbon reality (Herman, 2022; Probst et al., 2021; Vakulchuk et al., 2020; Wang et al., 2021).

Several strands of literature have examined the drivers of CCMT development. On the one hand, some literature suggests that technology development is a path- and place-dependent process (Aguirre and Ibikunle, 2014; Martin, 2021; Monasterolo et al., 2019; Nelson and Winter, 1982). This perspective emphasizes the significance of domestic factors such as policies (Popp et al., 2011) and social-technical configurations (Hansen and Coenen, 2015; Przychodzen and Przychodzen, 2020) in shaping technology development. On the other hand, recent literature sheds light on the role of cross-border CCMT diffusion driven by international knowledge transfer (Fadly and Fontes, 2019; Holm et al., 2020; Lopolito et al., 2022; Shih and Chang, 2009; Yu et al., 2022). However, most recent empirical studies have two potential limitations. First, they tend to focus on bilateral relationships between countries as a measure of international connections. Yet, technology diffusion is not a straightforward bilateral process; it often involves strong network effects originating from agents' indirect linkages (Aldieri et al., 2019; Derudder, 2021; Halleck-Vega et al., 2018; Jackson et al., 2017). The second concern arises with the idea of countries as agents in transnational CCMT diffusion. While countries certainly wield significant influence in certain industries like aerospace and nuclear energy (Vega and Mandel, 2018), in the case of most CCMTs, the diffusion process is ultimately shaped by interactions at the firm level (Chaney, 2014; Horbach and Rammer, 2018; Yeung, 2005).

To address these issues, this paper adopts a network perspective to explore the network effects arising from the global CCMT diffusion processes on CCMT development. In network theory, a network consists of nodes and links that display a pattern of connections (Freeman, 2004). In this paper, we explicitly incorporate a critical sub-nodal level, namely firms, into the network structure, aligning with the approach

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employed in relevant previous studies (see, e.g., Taylor, 2001, Sassen, 2013 and Neal et al., 2021). We argue that it is the firms operating within and across countries that essentially shape countries as nodes within the global diffusion networks (Beaverstock et al., 2000; Sassen, 2013; Taylor and Derudder, 2015; Taylor, 2001; Wall et al., 2011).

In this regard, the selection of firms and the types of their relationships are crucial. We focus on the intra-firm relationships of multinational corporations (MNCs) with significant CCMT innovation capacities for several reasons. First, MNCs possess extensive knowledge pertaining to innovative technologies, owing to their substantial R&D investment and their pursuit of economic gains (Hotz-Hart, 2000; Popp, 2020). Second, certain types of knowledge are more prone to internal transmission (Gaur et al., 2019; Markusen, 1995; Spraggon and Bodolica, 2012). For example, tacit knowledge tends to circulate more efficiently among individuals or groups within a well-structured framework, facilitated by established organizational routines, ultimately becoming an integral component of a firm's cumulative knowledge bases (Grant and Phene, 2022; Howells, 1996). Furthermore, to prevent knowledge from falling into a competitor's hands and to maximize the returns on R&D investment, strategic innovations are often held in strict confidence (Abdul Wahab et al., 2009; Archibugi and Filippetti, 2018; Liebeskind, 2009). Third, the internationalization strategies and local market operations of MNCs facilitate knowledge transfer on a global scale (Bathelt et al., 2004; Hitt et al., 2016). Finally, cross-border intra-firm relationships encompass dynamic interactions between headquarters and subsidiaries, inherently promoting international knowledge diffusion through these connections (Athreye et al., 2016; Ferraris et al., 2020; Van Wijk et al., 2008).

Specifically, we first identify the 228 most innovative MNCs in CCMTs based on their patent activities up to and including 2021. We then construct the CCMT diffusion networks, incorporating data on sustainable innovation capacities, business scales, and geographical information regarding the headquarters and subsidiaries of these 228 MNCs. The weighted networks involve 656,586 transnational linkages across 185 countries/regions. Once these networks are established, we calculate the network capital of each country within the diffusion networks with respect to linkage volumes and structural positionalities. Finally, we incorporate these network capital measures into the econometric regression models to investigate the network effects originating from the diffusion networks on CCMT development.

This paper offers two innovations. First, we investigate the global CCMT diffusion networks with a focus on the global deployment of sustainable innovation MNCs, whereas the existing empirical studies primarily consider countries as network makers. Moreover, over the past decades, numerous studies have constructed global relational networks using data from various types of firms, including MNCs (Alderson and Beckfield, 2004), advanced producer service firms (Beaverstock et al., 2000; Taylor and Derudder, 2015), and financial firms (Diebold and Yılmaz, 2014). However, we are not aware of any studies that approach global corporate networks in the context of sustainability transitions and CCMT diffusion. Second, we adopt a network perspective to assess the impact of different forms of network capital on CCMT development. Existing literature mainly focuses on bilateral relationships. In contrast, our network-based approach not only captures the effects of direct linkages but also systematically provides insights into network effects arising from structural positionalities within the networks.

This paper proceeds as follows. In Section 2, we briefly review the relevant literature, highlighting the necessity of integrating network capital into analysis of factors that influence CCMT development. In Section 3, we outline the methodology for network statistical analysis and econometric model specification. Section 4 presents the data, while Section 5 discusses the findings. We conclude and propose directions for future studies in Section 6.

2. Literature review

Literature on technology development and diffusion is pervasive. Technological progress is often considered as a path- and place-dependence process (Boschma et al., 2018; Heimeriks and Boschma, 2014; Nelson and Winter, 1982). In the context of CCMTs, existing research mainly identifies relevant domestic determinants that influence green innovations from a host country perspective (Halleck-Vega et al., 2018; Lopolito et al., 2022). These factors include technological relatedness (Hidalgo et al., 2018), reliance on natural resources (Best, 2017), and socio-economic configurations including environmental and energy policies (Johnstone et al., 2010), market liberalization (Nicolli and Vona, 2019), and access to financial capital (Nicolli and Vona, 2016; Veugelers, 2012). There exist more comprehensive studies that examine the role of these domestic determinants in CCMT development (see, e.g., Aguirre and Ibikunle, 2014, Popp et al., 2011 and Przychodzen and Przychodzen, 2020).

With increasing globalization, recent literature has begun to explore the impact of international relationships on transnational technology diffusion, subsequently driving technological advancements (see, e.g., Ferrier et al., 2016, Lopolito et al., 2022, Perkins and Neumayer, 2005 and Popp, 2020). Countries' technological development reaps several benefits from transnational technology diffusion (Mancusi, 2008). From the perspective of individual nation/state, access to the knowledge embedded in the technologies disseminated from abroad is instrumental in advancing their own technological capacities (Hansen and Lema, 2019). This access is crucial for mitigating uncertainties and risks associated with inventing and introducing new technologies (Giuliani et al., 2016). New technologies are generally costly and unreliable during the incubation and early commercialization stages (Negro et al., 2012). In particular, CCMTs often carry significant uncertainties concerning their investment returns (Shakeel et al., 2017). Furthermore, countries can enhance the efficiency of their energy R&D investments by leveraging knowledge generated elsewhere (Bosetti et al., 2008). This is particularly relevant for the developing countries who can benefit from the technological advancements of the forerunners (Pegels and Altenburg, 2020).

When considering global challenges, transnational CCMT diffusion assumes a crucial role in achieving global sustainability transition goals. Given that most developing countries orient their policies on poverty reduction and economic modernization, the landscape of CCMT innovations is currently dominated by a handful of highly developed countries (IEA, 2021; Kaygusuz, 2012; Probst et al., 2021). Since innovations already exist in certain countries, facilitating the transfer of these technologies from inventors to late adopters becomes paramount in addressing global challenges (Ockwell et al., 2008).

Current literature outlines three primary channels through which technologies can be transferred across borders. The first channel is international trade, which allows countries to acquire products and the associated knowledge that have been innovated or produced elsewhere (Garsous and Worack, 2022; Keller, 2004). This knowledge encompasses various aspects, including production costs, technical performance, industrial chains, and experience, all of which is enriched through both formal and informal interactions among trading partners (Athreye et al., 2023). It is also suggested that the intensification of market competition has increased the demand for new technologies. The second channel involves foreign investment facilitated by MNCs. MNCs produce, manufacture and control most advanced technologies worldwide (Dunning and Lundan, 2008; Younas, 2021). When MNCs expand into foreign markets, they export their experience and innovations to other countries through project investments or subsidiary operations, thereby enhancing the technological capacities of the recipient countries (De Beule and Van Beveren, 2019). The presence of MNCs is widely acknowledged for its role in facilitating the transfer of information, know-how, and skills associated with cutting-edge technologies (Antras et al., 2009). The third channel involves licensing agreements with local firms. MNCs transfer knowledge abroad by selling their intellectual property rights to overseas companies (Casson and Wadeson, 2018). Licensing often avoids many potential trade barriers when compared to direct investments (Nagaoka, 2009).

In the context of CCMT diffusion, recent literature has explored how these channels operationalize with different types of relationships between countries (De Coninck and Sagar, 2015; Fadly and Fontes, 2019; Mandel et al., 2020). However, there are two potential drawbacks. First, literature mainly focuses on bilateral relationships, treating each pair of countries independently. The second concern arises from the notion that countries are the primary agents in the process of CCMT diffusion.

The first drawback lies in neglecting the network effects, which facilitate the diffusion of technologies between indirectly connected countries through intermediaries. For example, even in cases where there is no direct connection between countries A and C, technologies and knowledge could still be exchanged between them via an intermediary country like B. This means that once knowledge is acquired by the immediate partners of innovators, it can be further disseminated to the partners of the direct partners and so forth (Faems et al., 2020; Ferrier et al., 2016). Recent network-based models of technology diffusion have approached how knowledge spreads across various network configurations, suggesting the significance of network capital in international knowledge acquisition (Allan et al., 2014; Chesbrough, 2003; Harris, 2011).

Network capital, a relational asset derived from complex interactions with external actors, plays a vital role in facilitating knowledge exchange by establishing network connections to distant resources (Huggins et al., 2012; Huggins and Thompson, 2014). Actors with higher network capital tend to occupy advantageous positions to reinforce local innovation efforts owing to their enhanced capacity to transfer complex knowledge across spatial boundaries (Rodríguez-Pose and Crescenzi, 2008). Nevertheless, previous research on CCMT diffusion has predominantly embraced a bilateral perspective, with limited exploration of network effects. A notable exception is the work of Halleck-Vega et al. (2018). In their study, the authors adopt a network-based approach to analyze the global transnational diffusion of wind energy technologies from 1983 to 2016. They access various network centralities, including degree, closeness, betweenness and eigenvector, across 94 countries. Their findings highlight the significant network effects arising from the structural positionalities within these networks, which play a pivotal role in facilitating the transnational diffusion of wind energy technologies.

Nevertheless, within these studies, the idea of countries acting as agents of CCMT development and network makers of global CCMT diffusion networks raises another concern. Most network analysis relies on a two-level structure, consisting of members as nodes, i.e. countries, and their interactions that constitute the networks. While the literature notes that cities or countries function as nodes in the networks, they are not the primary agents in the formation of networks (Beaverstock et al., 2000; Taylor and Derudder, 2015; Taylor, 2001, 2019). Instead, the interlocking network model introduces the concept of sub-nodes as the foundational element of network formation (Derudder, 2012; Taylor and Derudder, 2015; Taylor, 2001, 2011). It is suggested that the behavior of the sub-nodes, i.e. firms, play the fundamental roles in shaping cities or countries as nodes within the network (Derudder and Parnreiter, 2014; Liu and Derudder, 2012; Neal et al., 2021).

Our paper demonstrates how cross-border activities of MNCs establish connections between countries. We identify these relationships between countries by essentially analyzing the behaviors of firms. This is particularly important in the context of CCMTs, as transnational diffusion primarily emerges from interactions between private firms (Horbach and Rammer, 2018). While countries undeniably play important roles in CCMT diffusion, they often function as intermediaries or facilitators, for instance, by offering incentives and providing R&D investments to support firms (Moss, 2009). Accordingly, this paper aims to tackle these two potential challenges and pitfalls by examining the roles of sustainable innovation MNCs in accelerating CCMT diffusion. We account for the network capital generated throughout the CCMT diffusion process when assessing the factors that influence CCMT development.

3. Methods

The methodological framework employed in this paper consists of two parts. Section 3.1 introduces the method for network statistical analysis. Drawing from Derudder (2021) and Taylor and Derudder (2015), we analyze firms' behaviors with the goal of constructing country-level networks. Section 3.2 discusses the econometric specification, where we incorporate the network variables calculated in Section 3.1 into the econometric regression model to examine the relationship between network capital and CCMT development.

3.1. Network statistical analysis

In this analysis, the global CCMT diffusion networks are represented by weighted intra-firm networks of MNCs with substantial sustainable innovation capacities. This is mainly motivated by their extensive knowledge bases, global deployments, and internal knowledge flows within them resulting from intra-firm relationships. To construct these networks, we identify the top MNCs with strong sustainable innovation capacities in CCMTs based on their CCMT-related patent activities. We select MNCs that have obtained a minimum of 15 CCMT-related patents up to and including 2021. We set a threshold of 15 CCMTs to ensure that the selected MNCs devote substantial resources to CCMT research during the study period, excluding those only involved in short-term, sporadic activities. This threshold also filters out smaller MNCs with less influence in the global CCMT landscape. This results in a total of 228 MNCs worldwide.[1] Subsequently, we construct firm-to-country two-mode networks based on the country-level geographical locations of these MNCs' headquarters and subsidiaries. These networks are assigned weights using information on their sustainable innovation capacities and business scales. Finally, we convert these two-mode networks into country-dyad one-mode networks, which allow us to calculate the network capital for each country.

3.1.1. Constructing weighted matrices

When constructing the weighted matrices, we consider three factors that potentially influence the magnitude of knowledge transfer, including the number of MNCs within a country, the sustainable innovation capacities of these MNCs, and their business scales.

Regarding the first factor, we quantify it by counting the presence of selected MNCs' headquarters and subsidiaries in each country. Similar to Alderson and Beckfield (2004), Wall et al. (2011) and Derudder and Parnreiter (2014), we measure the intensity of CCMT diffusion between two countries by considering the cumulative number of intra-firm linkages that connect the home countries, where headquarters are based, to the host countries, where subsidiaries are located. Mathematically, the directed network $G(V,E)$ consists of a set of countries $N = |V|$ and a set of linkages $E = |\varepsilon|$, fully presented by its adjacency matrix $M = \{m_{ij}\}$. In this binary matrix, each element $m_{ij} = \{0,1\}$ indicates whether the subsidiary of the MNC headquartered in country i is present (1) or absent (0) in country j in 2021. Here, we assign the adjacency matrix M a weighted matrix $W_1 = \{w_{ij}\}$, where $w_{ij} = \sum_{a=1}^{n} v_{i,a} * v_{j,a}$. It quantifies the overall strength of the connection between any given pair of countries i and j by summing the number of subsidiaries located in country j across all MNCs $(a \rightarrow n)$ which have their headquarters in country i. Each element of the adjacency matrix M_1 is

[1] For MNCs with CCMT rankings below 228, there is a significant decrease in the total number of CCMT-related patents.

denoted as

$$\{m_{ij}{*}w_{ij}\} = \left\{m_{ij}{*}\sum\nolimits_{a=1}^{n} v_{i,a}{*}v_{j,a}\right\} \tag{1}$$

Next, building on M_1, we consider variations in sustainable innovation capacities among the MNCs. We assign a normalized patent weight $W_p = \{p_n/P\}$ to each element of the adjacency matrix M_1, where p_n represents the number of patents held by MNC n, and P represents the total patents held by these 228 MNCs. Consequently, each element in the adjacency matrix M_2 can be expressed as

$$\left\{m_{ij}{*}w_{ij}{*}\frac{p_n}{P}\right\} = \left\{m_{ij}{*}\sum\nolimits_{a=1}^{n} v_{i,a}{*}v_{j,a}{*}\frac{p_a}{P}\right\} \tag{2}$$

Finally, we consider the business scales of these 228 MNCs, which suggest their diverse knowledge bases and influence potential. To assign greater weights to MNCs with larger business scales, we introduce a normalized turnover weight $W_t = \{t_n/T_n\}$ to each element of the adjacency matrix M_2. Here, t_n represents the average turnover of firm n from 2000 to 2021, and T is the sum of average turnovers for these 228 MNCs over this period.[2] Each element of the adjacency matrix M_3 is denoted as

$$\left\{m_{ij}{*}w_{ij}{*}\frac{p_n}{P}{*}\frac{t_n}{T}\right\} = \left\{m_{ij}{*}\sum\nolimits_{a=1}^{n} v_{i,a}{*}v_{j,a}{*}\frac{p_a}{P}{*}\frac{t_a}{T}\right\} \tag{3}$$

The subsequent analysis is based on the adjacency matrix M_3, which incorporates all three factors that can influence a firm's technology and knowledge transfer capacities.

3.1.2. Calculating network capital

Upon constructing the company-to-county two-mode weighted networks, we convert them into country-dyad one-mode networks. In this study, we consider the network as an outcome rather than a process, aiming to assess the network capital of countries across various dimensions of centrality measures. Consequently, we employ centrality-based network analysis techniques, rather than techniques that are mainly used for network formation studies such as the tie-oriented exponential random graph model (Lusher et al., 2013). Following the approach adopted in relevant studies (see, e.g., Huggins et al., 2012, Huggins and Thompson, 2014 and Shi et al., 2022), network capital is measured with respect to linkage volumes and structural positionalities, considering whether the capital is generated through direct linkages or structure positions.

Linkage volumes reflect a country's capacity to establish interactions with other countries. We measure linkage volumes by considering transnational intra-firm linkages, encompassing weighted indegree, weighted outdegree, and weighted total degree. Specifically, weighted indegree represents the sum of weighted inbound connections, denoting the number of subsidiaries received by a country. It provides insight into a country's centripetal force and attractiveness to source countries. Weighted outdegree measures the sum of weighted outbound connections, indicating the number of headquarters located in a country. It reflects a country's centrifugal force and prestige in expanding its influence within the network. Weighted total degree is the sum of weighted indegree and weighted outdegree, calculating the total weighted connections occurring within a country's borders. This metric represents a country's self-maintained capacity within the network (Table 3). Mathematically, following Newman (2018) and Alderson and Beckfield (2004), the degree centrality of country v is given by

[2] We use turnover data starting from 2000 mainly due to the unavailability of turnover data for many firms before 2000. Furthermore, among these 228 MNCs, 6 of them were established after 2000. We calculate their average turnover by dividing the total turnover between the year of their establishment and 2021 by the number of years since their establishment.

$$D(v) = \frac{Td_v}{|N|-1} \tag{4}$$

where N represents the set of nodes in the network, and Td_v denotes the total degree of country v, i.e., the count of linkages that are directly connected to country v. Td_v consists of two components, namely indegree Id_v measures the number of incoming linkages to country v, and outdegree Od_v represents the number of outgoing linkages from country v.

Furthermore, structural positionalities evaluate a country's significance within the network by considering its connections with influential counterparts. These are assessed using metrics including eigenvector, betweenness, and closeness. Specifically, eigenvector evaluates a country's ability in enhancing its standing by establishing its connections with influential peers. It suggests that a country may not be advanced in CCMTs, it can still benefit from being highly connected to countries with high CCMT capacities. Mathematically, the eigenvector $E(v)$ of country v is written as

$$E(v) = \frac{1}{\lambda}\sum\nolimits_{t\in M(v)} x_t = \frac{1}{\lambda}\sum\nolimits_{t\in G} a_{vt}x_t \tag{5}$$

where $M(v)$ is a set of neighbours of v, a_{vt} is 1 when v and t are directly connected, and λ is a constant. Betweenness quantifies how frequently a country appears on the shortest paths between two indirectly connected countries, indicating its gateway position within the network. The betweenness $B(v)$ of country v is written as

$$B(v) = \sum\nolimits_{u\neq v\neq t\in V} \frac{\sigma_{u,t}(v)}{\sigma_{u,t}} \tag{6}$$

where σ_{ut} is the number of shortest paths between u and t, and $\sigma_{u,t}(v)$ is the number of shortest paths between u and t that pass through country v. Lastly, closeness quantifies a country's network proximity to others by averaging the shortest path lengths from that country to every other country within the network. The closeness measure $C(v)$ of country v is written as

$$C(v) = \frac{1}{\sum\nolimits_{u\in N/v} d(v,u)} \tag{7}$$

where N is the set of countries in the network, and $d(v,u)$ is the length of the shortest paths from v to all the other vertices u. We employ Gephi software for network visualization and network capital calculation.

3.2. Econometric regression analysis

To explore the relationship between network capital generated during the CCMT diffusion process and CCMT development, we estimate the following econometric equation:

$$Y_i = \alpha + \beta_1 N_i + \beta_2 X_i + \varepsilon \tag{8}$$

where Y_i is the level of CCMT development in country i in 2021, proxied by the logarithm of per capita net renewable electricity production. The inherent unpredictability of renewable energy resources introduces several challenges during the renewable electricity production process (Denholm et al., 2021). First, it requires balancing supply and demand, which involves addressing short-term fluctuations of variable renewable energy resources, diurnal mismatches, and seasonal mismatches. This is particularly evident in technologies reliant on short-term weather conditions, such as highly distributed solar photovoltaics and wind (Rai and Henry, 2016; Zhang et al., 2023). Second, it requires the design of reliable inverter-based grids to ensure frequency stability, voltage stability, rotor angle stability, power protection, and voltage control (Kundur et al., 2004). Furthermore, economic viability entails considerations of advancing materials, manufacturing processes, energy conversion systems, as well as establishing a resilient and stable supply chain. Tackling these challenges requires integrating various technologies, and CCMTs offer numerous solutions. For example, Y02B highlights technologies related to end-user applications, Y02E emphasizes energy generation through various renewable energy sources, Y02P concentrates on technologies in the production or processing of goods and products, Y02T encompasses solutions for electric vehicles, and Y04S focuses on power networks operations and smart grids. Therefore, we utilize per capita renewable electricity production as a proxy to gauge a country's development level in CCMTs. The rationale is that addressing the challenges mentioned often requires the effective and innovative integration of various CCMTs. Similar to Fadly and Fontes (2019) and Przychodzen and Przychodzen (2020), this indicator is calculated by dividing the total renewable electricity net generation (in million kWh) by the total population of the country in 2021.

Furthermore, α is the intercept, β is the vector of coefficients of the independent variables, and ε represents the random error term. N_i is the network capital calculated in section 3.1, measured in terms of linkage volumes and structural positionalities. Linkage volumes consist of weighted indegree, weighted outdegree, and weighted total degree. Structural positionalities encompass eigenvector, betweenness, and closeness. Moreover, X_i represents the control variables obtained from the literature that could potentially influence renewable electricity generation. They include GDP per capita, energy policy instrument, and government's administrative capacity. GDP per capita accounts for the economic size and the development level of a country. Energy policy instrument, included as a dummy variable, aims to control for countries' different industrial strategies and policy support. We access whether a country had climate change mitigation policy in effect in 2021. These policies encompass measures related to energy efficiency, renewable energy, technology R&D and innovation, electrification, and carbon capture utilization and storage. The variable takes a value of 1 if a policy was in effect in a country in 2021 and 0 if no such policy was introduced or had ended by 2021. Lastly, government's administrative capacity is measured through regulatory quality and governance effectiveness. This variable reflects a government's ability to manage the local clean energy market and the ease or difficulty for private investors to conduct business in that country. See Section 4.2 for more information on the data sources used for these variables.

4. Data

4.1. Firm-level data

Three types of firm-level data are employed to construct the global CCMT diffusion networks, namely cumulative CCMT-related patent data up to and including 2021, country-level geographic data of headquarters and subsidiaries in 2021, and the average turnover of these 228 MNCs from 2000 to 2021.

We employ patent data related to CCMTs to identify the MNCs with high sustainable innovation capacities in CCMTs. Patent data is widely used to study knowledge generation and dissemination (Jaffe et al., 2002; Verendel, 2023), as well as to characterize the knowledge bases of countries and firms (Antonelli et al., 2010; Furman et al., 2002). The CCMT-related patent data comes from the Worldwide Patent Statistical Database (PATSTAT 2022 spring version), published by the European Patent Office, which contains data from 84 patent offices worldwide and covers all inventor countries (EPO, 2021; Popp et al., 2011). In 2012, the European Patent Office introduced the Y02/Y04S classification scheme within the PATSTAT to categorize technologies that are broadly associated with climate change mitigation (Angelucci et al., 2018; Li et al., 2020; Veefkind et al., 2012).Within the Y02/Y04S category, there are nine subcategories, as detailed in Table 1. Our study aims to provide an overview of the overall development and diffusion of CCMTs without placing specific emphasis on individual CCMTs. Therefore, our analysis encompasses all CCMTs categorized within the Y02/Y04S classification.

Fig. 1 illustrates the change in the number of CCMT-related patents for the top 10,000 firms or individuals from 2003 to 2021. Patents for all nine CCMTs have experienced substantial growths, particularly since 2009. Among these categories, the CCMTs related to energy generation, transmission and distribution (Y02E) exhibit the highest patent count, totaling 165,578 patents. Conversely, CCMTs associated with the capture, storage, sequestration or disposal of greenhouse gases (Y02C) display the lowest patent activity, with a total of 16,298 patents.

Table 1
Description of the Y02/Y04S category.

Y02	Climate change mitigation technologies
Y02A	Related to adaptation to climate change.
Y02B	Related to buildings, including housing and appliances or related end-user applications.
Y02C	Capture, storage, sequestration or disposal of greenhouse gases.
Y02D	Information and communication technologies aiming at the reduction own energy use.
Y02E	Related to energy generation, transmission and distribution.
Y02P	Related to the production or processing of goods.
Y02T	Related to transportation.
Y02W	Related to wastewater treatment or waste management.
Y04S	Smart grid technologies.

Source: EPO (2023).

The PATSTAT database contains various types of firms, including private versus state-owned firms, and multinational versus non-multinationals firms. We focus on MNCs as we are interested in firms that are capable of transnationally transferring technologies through intra-firm linkages. We choose the MNCs that have filed a minimum of 15 CCMT-related patents up to and including 2021. This results in 228 MNCs globally and a total of 145,716 patent in our sample.[3] Among these 228 MNCs, the average number of CCMT-related patents is 639.11, with Siemens AG having the most (6913) and Moderna Inc. the least (15).

Table 2 provides information on the leading MNCs which exhibit the most robust sustainable innovation capacities among firms in our sample. Fig. 2 compares the total count of CCMT-related patents for these 228 MNCs, categorized by their respective countries/regions of headquarters. Countries with more CCMT-related patents are shaded darker. These 228 MNCs are headquartered in 20 countries/regions. The top 10 countries boasting the largest number of CCMT-related patents are Japan (46,529), the US (31,972), Germany (22,967), South Korea (12,639), France (6077), the Netherlands (4631), the UK (4474), Mainland China (3255), Sweden (2485), and Switzerland (2224). Additionally, the figure provides a list of prominent MNCs headquartered in these 20 countries/regions with the highest number of CCMT-related patents.

We obtain ownership information, country-level locations of headquarters and subsidiaries in 2021, and turnover data from 2000 to 2021 for these 228 MNCs from Bureau van Dijk's Osiris database. In the cases of missing data for some firms in the Bureau van Dijk's Osiris database, we source them from the annual reports of the respective companies. In total, we extract a dataset comprising 88,863 ownership relationships, of which 22,277 are domestic and 66,586 are transnational. To construct global CCMT diffusion networks, we aggregate the data at the country level. These networks connect 20 home countries/regions with at least one outgoing corporate connection to 185 host countries/regions with at least one incoming corporate connection. For example, Siemens AG, headquartered in Germany, operates 1167 overseas subsidiaries across 85 countries in 2021. Among these, the US has the most Siemens AG subsidiaries, totaling 456, whereas countries like Oman and Tanzania have only one Siemens AG subsidiary each. We use the number of subsidiaries as a measure to assess the extent of Germany's connections with

[3] In the original database, 11 out of the top 240 firms are either state-owned or non-multinational. They have been excluded from our firm sample.

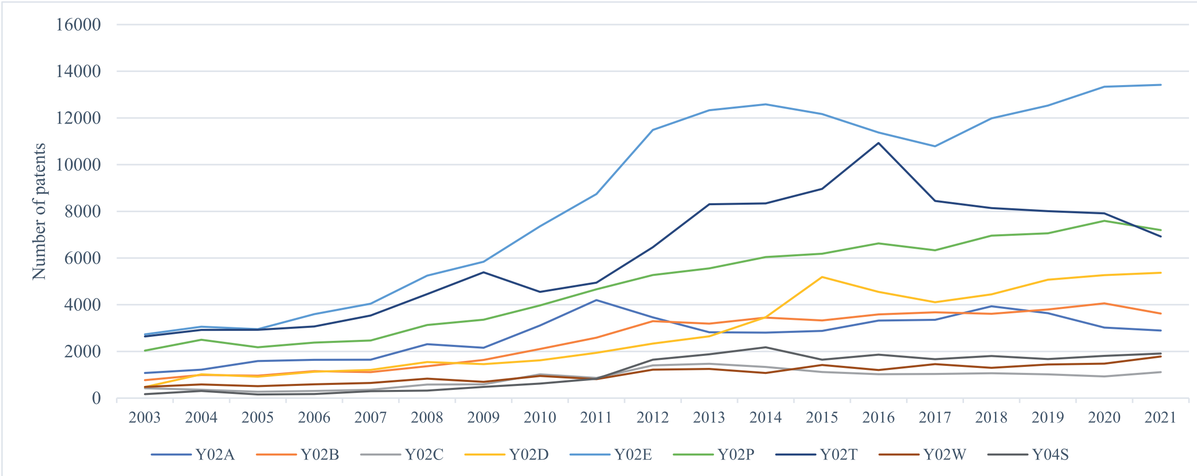

Fig. 1. Number of CCMT-related patents by type from 2003 to 2021.

Table 2
Top five sustainable innovation MNCs and relevant information.

MNC	Number of CCMT-related patents	Average turnover 2000–2021 (billion USD)	Headquarter locations	Top 5 overseas subsidiary locations	Number of receiving subsidiaries
Siemens AG	6913	$ 91.415	Germany	USA	456
				China	81
				Canada	75
				UK	39
				India	34
Toyota Motor Corporation	6563	$ 207.749	Japan	USA	216
				China	29
				Canada	21
				Thailand	18
				Indonesia	14
General Electric Company	6398	$ 125.715	USA	UK	116
				Canada	76
				France	52
				Netherlands	45
				China	39
Raytheon Technologies Corporation	4911	$ 48.337	USA	Canada	63
				UK	50
				Australia	50
				France	20
				Italy	16
Panasonic Holdings Corporation	4850	$ 74.313	Japan	USA	274
				China	74
				Malaysia	24
				Canada	21
				Germany	20
				Spain	20

other countries facilitated through Siemens AG. The list of these countries/regions can be found in the Appendix.[4]

4.2. Country-level data

We source data for renewable electricity generation in 2021, the most current year for which the data is made available, from the U.S. Energy Information Administration.[5] Regarding the control variables, GDP per capita data is from the World Bank's Open Data platform.[6] Energy policy instrument information, reflecting countries' different industrial strategies and policy supports, are gathered from the Policies Databases of the International Energy Agency and the International Renewable Energy Agency.[7] This database is widely used in comparative studies of cross-country policies in clean technologies (Baldwin et al., 2017; Carley et al., 2017; Kim, 2020). Data on government's administrative capacity is collected from World Bank Worldwide Governance Indicators.[8] Table 3 presents details on variable operationalization, data

[4] We source information about countries and regions from the United Nations' list of member states.
[5] https://www.eia.gov/

[6] https://www.worldbank.org/en/home
[7] https://www.iea.org/policies
[8] https://info.worldbank.org/governance/wgi/

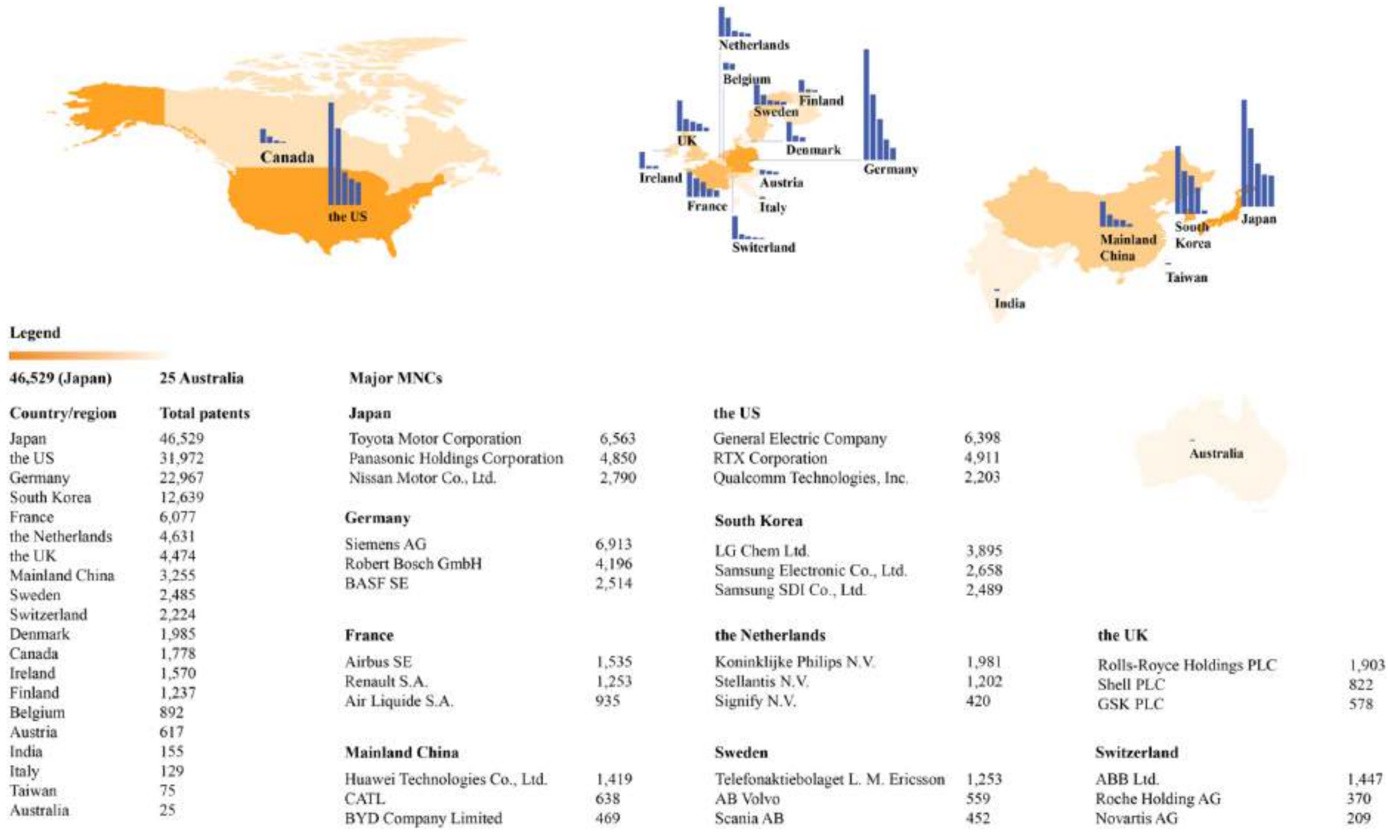

Fig. 2. Comparison of CCMT-related patents by country/region.

sources, and descriptions. Notably, the econometric analysis retains 173 countries/regions due to missing data on one or more crucial variables in some countries/regions, whereas the network statistical analysis maintains a sample size of 185.[9]

5. Results and discussion

5.1. Network statistical analysis results

Figs. 3–8 illustrate the global CCMT diffusion networks using six network capital measures. In these visualizations, each node represents a country, while the links between nodes reflect CCMT diffusion level among pairs of countries. Node size and the corresponding country name indicate the magnitude of network capital within each country, while edge thickness denotes the strength of CCMT diffusion between connected countries.

Specifically, Fig. 3 exhibits the global CCMT diffusion network based on weighted total degree, revealing an uneven spatial pattern. Countries with substantial network capital are predominantly clustered in Western Europe, North America, and East Asia, with Germany, the US, and Japan as regional centers. Regarding interregional linkages, the US maintains close ties with several Western European countries, especially the UK, the Netherlands, France and Germany. Among the connections between North America and East Asia, the link between the US and Japan stands out prominently. Furthermore, connections between Western Europe and East Asia are relatively weaker, except for the strong links with Japan and China. Additionally, intraregional interactions are less pronounced compared to interregional connections. There exists a significant proportion of interregional connections, irrespective of geographical distance. However, there are instances of diffusion that can be partly attributed to spatial proximity, such as Germany – the UK, the US – Canada, and Japan – China.

Table 4 compares the top 10 countries across six different network capital measures. Weighted outdegree analysis highlights that a small group of countries predominantly controls the majority of outbound connections. These influential countries include Germany, Japan, the US, the UK, South Korea, the Netherlands, France, Canada, Switzerland and Sweden. Together, these ten countries account for nearly 98.92% of all weighted outgoing connections. A similar, though less pronounced, pattern emerges when examining weighted indegree. The top 10 countries, namely the US, Canada, China, the UK, the Netherlands, France, Australia, Germany, Mexico, and India, account for approximately 63.91% of all incoming connections. Concerning structural positionalities, i.e. eigenvector, closeness, and betweenness, the US, China, Canada, the UK, and the Netherlands also emerge as significant hubs and authorities, reinforcing their dominant roles within the network. Finally, concerning bilateral linkages, the global CCMT diffusion network demonstrates a similar imbalance, with only 1.1% of country pairs accounting for approximately 50% of all connections.

Interestingly, some countries, such as Australia, excel in terms of linkage volumes but do not necessarily score highly in structural positionalities. Likewise, other countries, such as Belgium and Denmark, appear to hold significance in structural positionalities even though they may not stand out in terms of linkage volumes. This aligns with the findings of Vega and Mandel (2018), who argue that a country that is neither the most important source nor the most important technology

[9] These 12 countries/regions that are excluded in the econometric analysis are Andorra, Bermuda, Curacao, East Timor, Federated States of Micronesia, Gambia, Gibraltar, Ivory Coast, Liechtenstein, Monaco, San Marino, and Tonga with only a few connections in total.

Table 3
Description and summary statistics of the variable used.

Variable	Indicator	Obs.	Mean	Std. Dev.	Max	Min
Firm-level data						
Firms' sustainable innovative capacity	Numbers of CCMT-related patents granted in or before 2021	228	639.105	1,019.168	6,913	15
Firms' business scale	Firm's average annual turnover between 2000 and 2021 (billion USD)		32.011	46.575	309.673	0.080
Firms' ownership	Number of headquarters a country/ region host	20	11.4	19.313	77	1
	Number of subsidiaries a country/ region receives	185	357.443	1,673.149	21,637	1
Country-level data						
CCMT development	Net renewable electricity production in 2021 (million kWh)	173	44,825.44	200,218.6	2,363,284	1.22
	Net renewable electricity production per capita in 2021 (million kWh)		0.0016	0.005	0.052	6.20e-07
Network capital						
Weighted total degree	"Self-maintained capacity", scores measuring HQ-subsidiary linkages occurring within a country's boundary (see e.q. 4)		0.050	0.224	2.155	1.00e-06
Weighted indegree	"Attractiveness", scores measuring subsidiaries a country receives (see e.q. 4)		0.025	0.108	1.341	1.00e-06
Weighted outdegree	"Prestige", scores measuring HQ a country hosts (see e.q. 4)		0.025	0.154	1.392	0
Eigenvector	"Authority", scores measuring relative ranking of connectedness taking into account the whole network (see e.q. 5)		0.249	0.221	1	0.018
Betweenness	"Gateway", scores measuring the number of shortest paths from all countries to all others through a given country (see e.q. 6)		0.0004	0.001	0.011	0
Closeness	"Propinquity", scores measuring the average shortest distance length between a country and all other countries in a network (see e.q. 7)		0.076	0.215	0.844	0
Economic factor	GDP per capita in 2021 (USD)		17,309.63	23,242.76	133,590.1	221.158
Energy policy instrument	Dummy variable: 1 if a country has at least one related policy in effect in 2021, or 0 otherwise		0.792	0.408	1	0
Government's administrative capacity	Scores measuring regulatory quality and government effectiveness in a given country		2.541	0.948	4.761	0.313

adopter can still be influenced by networks due to its connectedness with influential counterparts.

In conclusion, the sustainable innovation capacities of MNCs and their strategies for global expansion result in countries assuming varying roles in transnational CCMT diffusion. Throughout this process, leading countries, notably the US, Germany, and Japan, control the majority of network resources, leaving others in a relatively disadvantaged position. The disparities in countries' network capital allow us to investigate whether these network advantages can indeed facilitate the development of CCMTs.

5.2. Econometric regression results

Table 5 presents the estimated results concerning the relationship between network capital and CCMT development. Given that different network measures conceptually capture different facets of network capital, they are introduced separately into the econometric models. This mitigates issues related to over-identification and multicollinearity issues (Shi et al., 2022). Consequently, we estimate six separate econometric regression models, each emphasizing a single network capital.

Regarding the linkage volume variables, both weighted total degree and weighted indegree show a statistically significant positive relationship with renewable electricity production at the 5% level. Additionally, weighted outdegree demonstrates significance at the 10% level. These results suggest that a country's CCMT development can be positively influenced by the presence of sustainable innovative MNCs (Antras et al., 2009).

The significant estimate of the coefficient of weighted indegree suggests that recipient countries benefit from receiving subsidiaries of MNCs with advanced CCMT capacities. This finding may be attributed to the substantial consumer markets for certain CCMTs in less developed countries, such as China and Brazil. Considering that countries hosting MNCs' headquarters tend to be more developed than countries receiving subsidiaries (Pfeiffer and Mulder, 2013), driven by market and return-on-investment interests, MNCs actively promote innovations originating in countries where their headquarters are located to other nations through their globally deployed subsidiaries (Caleb et al., 2021).

Another plausible explanation is the latecomer advantages in recipient countries, where less developed countries can rapidly adopt innovative technologies across their industrial structures (Perkins and Neumayer, 2005). First, late industrializers reap advantages from learning from technological pioneers (Grubler, 2012). The initial R&D phase of CCMT development typically involves high cost, limited flexibility, and unpredictability. Risk-taking MNCs tend to drive down application costs, enhance performance, and render the technologies economically viable, albeit at the cost of substantial expenditures (Hoskisson et al., 2011). Second, governments in advanced economies have been actively pursuing policies aimed at accelerating the adoption of emerging CCMTs such as residential solar photovoltaics and electric vehicles. Latecomer nations can leverage the experience and effective policies of these forerunners to accelerate the proliferation rates of such technologies. Fadly and Fontes (2019) and Lopolito et al. (2022) demonstrate the positive cross-country spillover effects stemming from policies designed to accelerate the development of CCMTs. Moreover, considering that most recipient countries have not yet established substantial capacity in this domain, they have the flexibility to choose and integrate new technologies as part of their capital expansion efforts (Bank, 1992; Popp, 2020).

The significant coefficient estimate for weighted outdegree suggests that a country can benefit from hosting the headquarters of MNCs with advanced CCMT capacities. Several arguments explain this finding. First, technologies tend to spread from their origins and initial markets due to geographical proximity (Corradini et al., 2021; Ernst, 2002). Face-to-face interactions, which decay with distance increases, further expedite this diffusion process (Bahar et al., 2014). Therefore, countries hosting the headquarters of these MNCs gain early access, allowing them to adopt advanced CCMTs before widespread commercialization (Aldieri, 2011). Moreover, domestic diffusion of new technologies typically face fewer policy and regulatory barriers compared to transnational diffusion (Rao and Kishore, 2010). For instance, concerns over intellectual property rights can be more manageable when technologies are disseminated within a country, as opposed to cross-border transfers with varying intellectual property regulations (Dechezleprêtre and

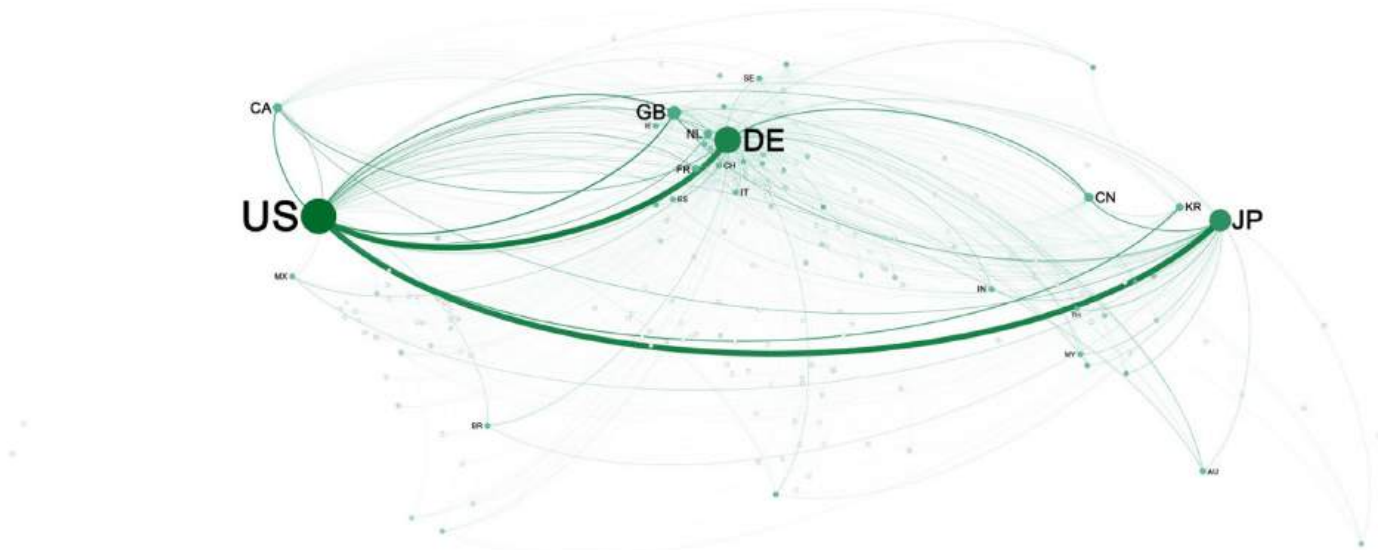

Fig. 3. Global CCMT diffusion network based on weighted total degree.

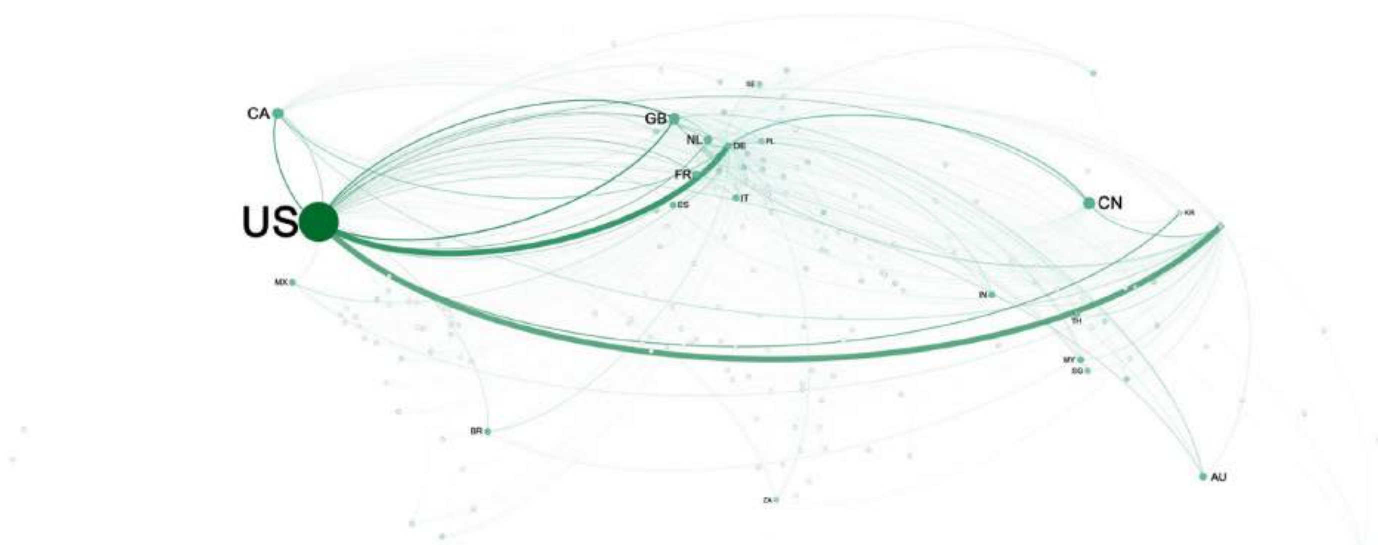

Fig. 4. Global CCMT diffusion network based on weighted indegree.

Glachant, 2014; Popp, 2020). Consequently, both geographic and institutional proximity to innovators serve as effective and efficient means for disseminating knowledge.

Regarding structural positionalities, all three measurements, namely eigenvector, closeness, and betweenness, are identified as important factors affecting renewable electricity production. This supports the argument that an economy, which may not be the primary source or recipient of CCMTs in terms of quantity, can still derive benefits from innovators thanks to its pivotal position within the network (Fadly and Fontes, 2019; Vega and Mandel, 2018).

Structural proximity to other innovators within the networks confers two significant network advantages that facilitate CCMT development in the intermediate countries. First, central positioning in various capital flows provides these economies with access to a diverse range of resources, capabilities, and markets (Lin, 2011). This creates great opportunities for knowledge sharing and learning (Cheng, 2022). Such opportunities are strategically valuable, enabling economies to acquire new technologies ahead of widespread adoption. Second, their hub and gateway positions allow for the convergence of interdisciplinary knowledge, effectively transforming these economies into “chemical containers” where various innovations intersect (Penco, 2015). Within these economies, entities such as firms and governments do not merely act as passive knowledge recipients but also function as knowledge processors through local market exploration. Throughout these processes, network synergy facilitates knowledge reproduction, drawing from a broad pool of information initially held by each individual agent (Bathelt and Cohendet, 2014; Bathelt et al., 2004). This is particularly crucial in the context of CCMTs, which can be regarded as radical

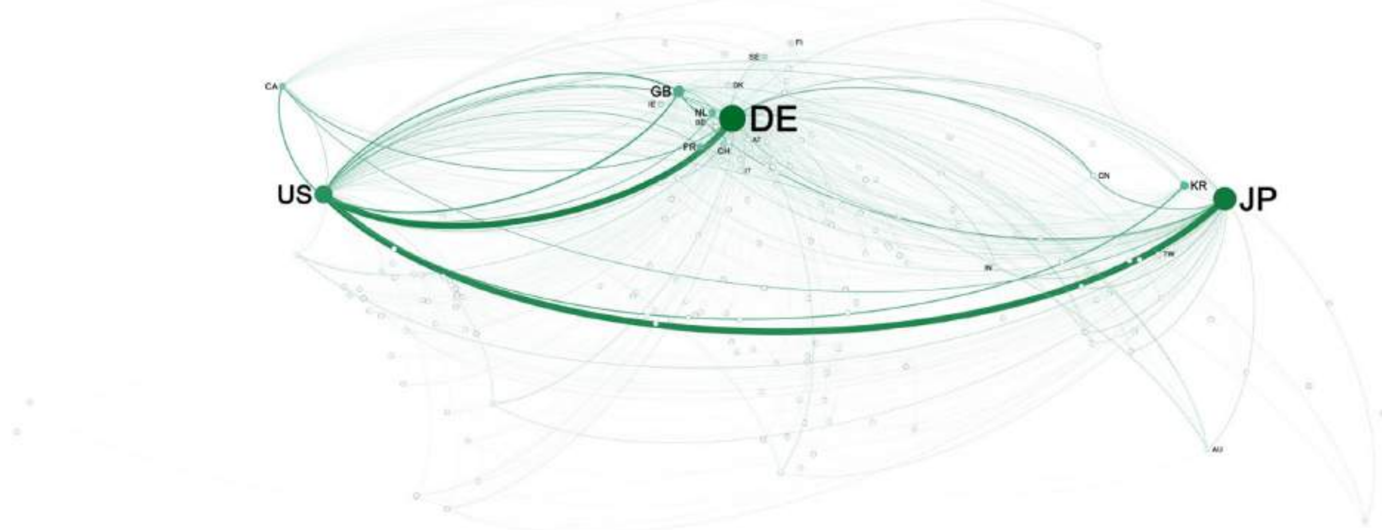

Fig. 5. Global CCMT diffusion network based on weighted outdegree.

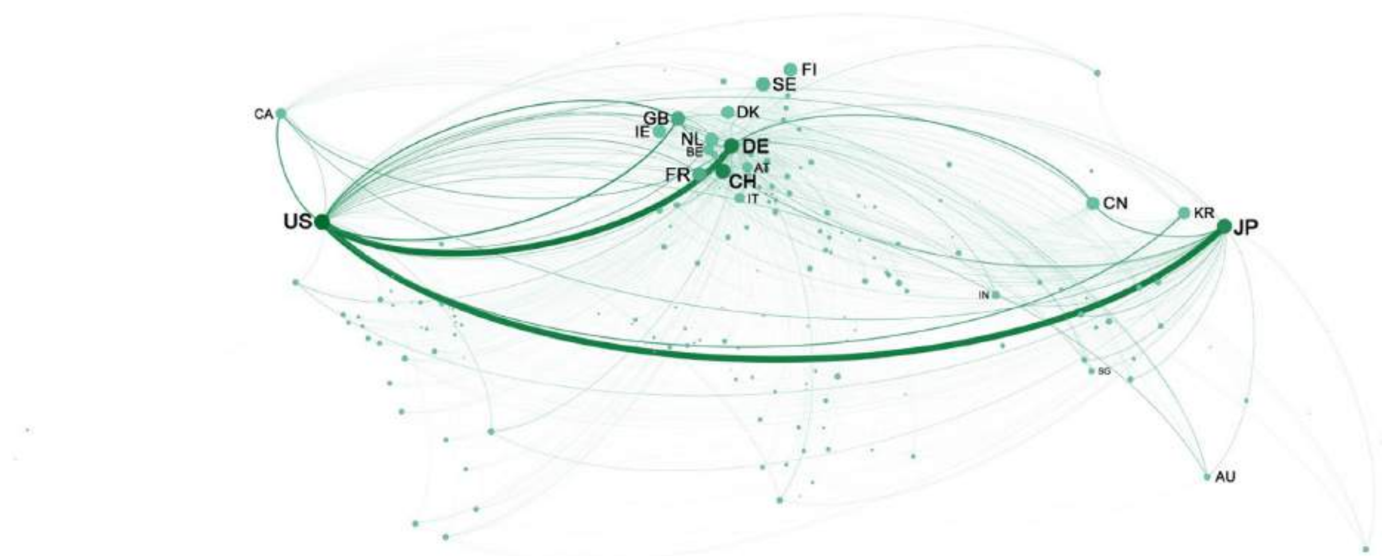

Fig. 6. Global CCMT technology diffusion network based on eigenvector.

innovations emerging from the synthesis of existing technologies in novel ways (Li et al., 2020).

In the CCMT diffusion network, these MNCs can adapt their international investment strategies through interactions with local stakeholders. Simultaneously, regional policymakers can leverage network capital generated by participating in MNCs' global expansion to drive regional development. This point can be further highlighted with the use of an illustrative example. In particular, we can consider BYD, a Shenzhen-based Chinese company that has established three factories in Brazil to domestically produce chassis and batteries for electric buses, and solar panels. In 2015, BYD initiated its operations in Campinas, Brazil, manufacturing chassis for electric buses. In 2017, the Brazilian Development Bank introduced a new policy known as FINAME, aimed at enhancing local manufacturer competitiveness and sustain national supply chains. Under this policy, customers seeking financial loans were required to ensure that the nationalization index of the products they purchase reached a minimum of 50%. In response, BYD established another factory in Manaus to produce lithium iron phosphate batteries locally. These batteries, which were previously imported, are now manufactured to supply the electric buses assembled in Campinas. In addition to localizing production, BYD also consolidates its R&D efforts locally, collaborating with local universities and research institutes to adapt its technologies to Brazil's local conditions and requirements. This collaborative approach allows BYD to access and incorporate existing local technological competencies, fostering synergy with the local technological ecosystem.[10]

In this case, Brazil benefits in various ways from participating in the

[10] For a more detail discussion, please refer to https://carnegieendowment.org/2022/10/18/why-brazil-sought-chinese-investments-to-diversify-its-manufacturing-economy-pub-88194

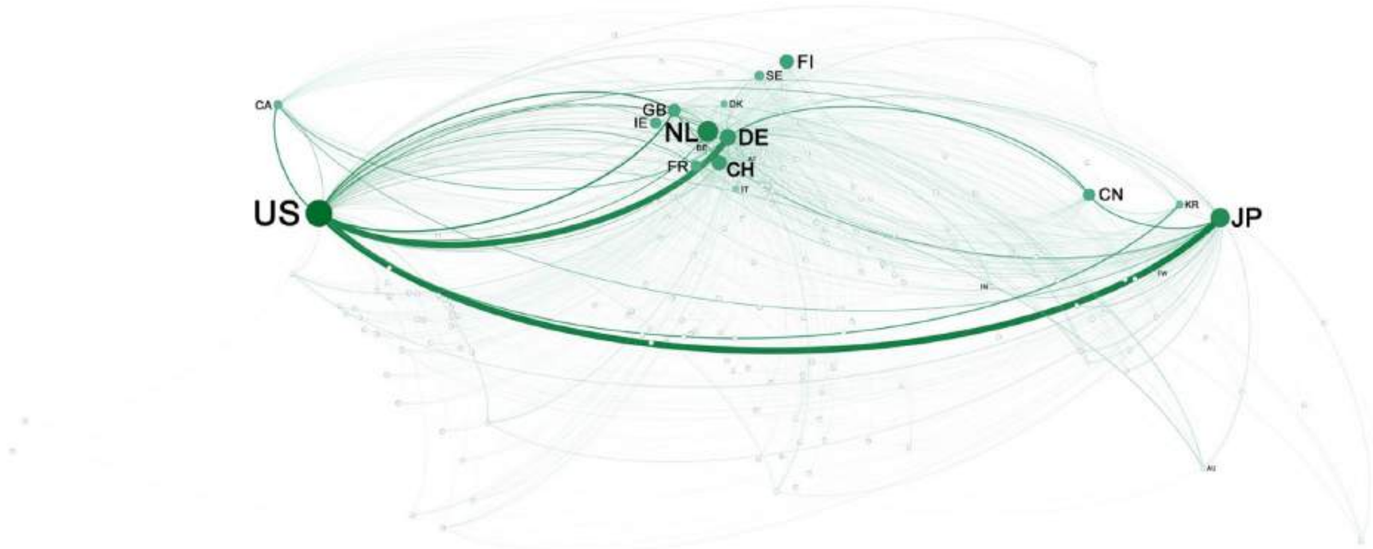

Fig. 7. Global CCMT technology diffusion network based on betweenness.

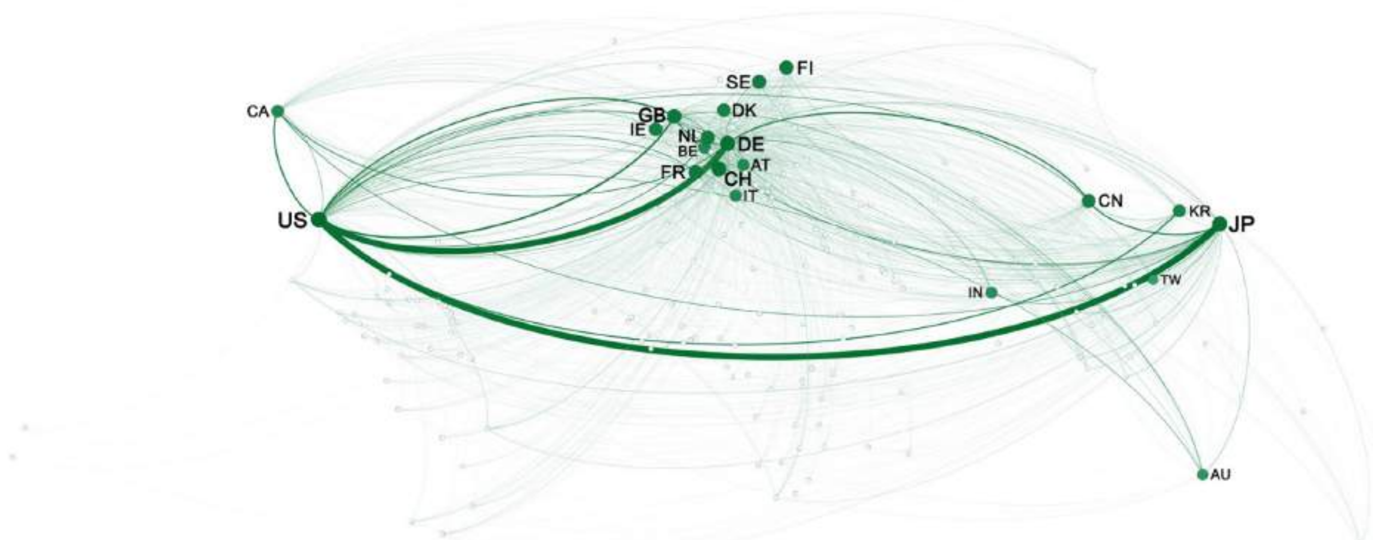

Fig. 8. Global CCMT technology diffusion network based on closeness.

Table 4
Top 10 countries by network capital.

Linkage volume						Structural positionalities						Directed pairs	
Weighted total degree		Weighted indegree		Weighted outdegree		Eigenvector		Betweenness		Closeness			
US	2.155	US	1.341	DE	1.392	US	1	US	0.0109	US	0.844	JP – US	0.493
DE	1.48	CN	0.28	JP	1.175	DE	0.969	NL	0.0078	JP	0.793	DE – US	0.472
JP	1.204	CA	0.258	US	0.813	CH	0.965	JP	0.0071	DE	0.793	UK – US	0.132
GB	0.594	GB	0.24	GB	0.354	JP	0.956	DE	0.0056	CH	0.786	US – CA	0.112
CA	0.311	NL	0.137	KR	0.191	GB	0.91	CH	0.0049	GB	0.736	US – UK	0.11
CN	0.282	AU	0.122	NL	0.125	FR	0.905	FI	0.0046	FR	0.724	DE – CN	0.105
NL	0.261	FR	0.12	FR	0.088	SE	0.89	GB	0.0038	FI	0.716	KR – US	0.097
KR	0.232	DE	0.088	CA	0.053	NL	0.876	CN	0.0035	SE	0.71	JP – CN	0.094
FR	0.208	IN	0.075	CH	0.033	FI	0.86	FR	0.0032	NL	0.702	DE – CA	0.066
AU	0.122	IT	0.073	SE	0.025	CN	0.815	IE	0.0031	CN	0.676	DE – CA	0.057

Table 5
Regression results ($n = 173$).

Variable	Dependent variable: Log renewable electricity production per capita					
	1	2	3	4	5	6
Weighted total degree (log)	0.142**					
	(0.063)					
Weighted indegree (log)		0.147**				
		(0.065)				
Weighted outdegree (log)			0.086*			
			(0.046)			
Eigenvector (log)				0.478***		
				(0.177)		
Closeness (log)					0.070**	
					(0.035)	
Betweenness (log)						0.131**
						(0.063)
GDP per capita (log)	0.325**	0.329**	0.389**	0.308*	0.385**	0.378**
	(0.158)	(0.158)	(0.152)	(0.156)	(0.152)	(0.152)
Policy support (dummy)	0.527	0.519	0.793**	0.410	0.790**	0.791**
	(0.383)	(0.385)	(0.365)	(0.390)	(0.364)	(0.364)
Government's administrative capacity (log)	0.907*	0.919*	0.816	0.891*	0.790	0.807
	(0.525)	(0.526)	(0.530)	(0.522)	(0.530)	(0.528)
Constant	−11.279	−11.281	−11.744	−11.031	−11.936	−11.040
Adjusted R-squared	0.305	0.304	0.298	0.313	0.300	0.301

Note: Standard error in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We log-transform all the variables to produce normally distributed model residuals. Additionally, a small constant is added to variables with zero value before log-transform to address the presence of zeros in the dataset.

global electric vehicle production networks. First, local manufacturing of eco-friendly products like electric buses and cost-effective solar panels directly contributes to Brazil's emission reduction goals. Additionally, policies encouraging MNCs like BYD to source from local suppliers stimulate domestic manufacturing, foster learning, and facilitate innovation localization. Furthermore, active engagement in sustainable innovation networks can advance local industrial ecosystems, presenting Brazil with opportunities to be more integrated into knowledge-intensive supply chains (Hiratuka, 2022).

Regarding the control variables, countries with stronger economic performance are more inclined to generate electricity from renewable resources, which align with previous research on clean technology diffusion. Given that CCMT development requires significant inputs of human capital and financial resources, its development tends to be more feasible for economically prosperous nations. Additionally, the results indicate that countries that have implemented climate change mitigation policies tend to exhibit stronger performance in CCMT development. These policies not only reflect a country's commitment to environmental conservation and clean technology development, but also play a regulatory role in shaping the nation's industrial strategies and standards. Finally, the results indicate the positive impact of a government's administrative capacity in fostering CCMT development, emphasizing the crucial role of a supportive regulatory environment in driving progress in this field.

6. Conclusion

Given the magnitude of the sustainability target flux, current literature and policy debates place significant emphasis on the role of CCMTs in achieving net-zero carbon emission goals. In this paper, we contribute to this discussion by constructing the global diffusion networks of CCMTs and assessing the impact of network capital on CCMT development. We argue that, beyond domestic factors, a country's progress in CCMT development is also influenced by various forms of network capital embedded within the global CCMT diffusion networks. Our findings demonstrate that countries, that establish stronger connections with global CCMT diffusion networks through sustainable innovative MNCs, tend to exhibit superior performance in CCMT development.

Specifically, we first identified the top 228 sustainable innovation MNCs using CCMT-related patent data up to and including the year 2021. Next, we constructed the global CCMT diffusion networks represented by weighted intra-firm networks of these 228 MNCs. These networks took into account several factors, including the number of MNCs a country hosts, the sustainable innovation capacities of these MNCs, as well as their business scales. Subsequently, we quantified various aspects of network capital for each country within these networks with respect to linkage volumes and structural positionalities. Finally, we incorporated these network capital measures into the econometric regression models to investigate the extent to which network capital may influence CCMT development on a national level.

Among the key findings, the network statistical analysis reveals a global disproportionate pattern of CCMT diffusion network, wherein only a small group of countries holds the majority of CCMT resources. Nonetheless, countries exhibited varying performance across different network capital metrics. Regarding the econometric regression outcomes, we identified positive effects associated with various forms of network capital, highlighting the pivotal role of transnational technology diffusion in advancing CCMT development.

Our findings have several important policy implications. First, a country's CCMT development benefits from the presence of sustainable innovation MNCs, whether they host their headquarters or establish subsidiaries within the country. Consequently, policymakers should proactively seek to attract MNCs possessing strong innovation capacities in CCMTs. This can be achieved by incentive-based policies focused on attracting foreign investment in domestic clean technology innovation activities such as financial measures include tax benefits, grants, subsidies, and interest-reduced loans. These measures lower the costs associated with development projects and simultaneously mitigate the risks of foreign investment for MNCs. Meanwhile, governments can also establish investment promotion agencies to assist MNCs with location selection, talent recruitment, and financing. Moreover, countries can increase their appeal by fostering a regulatory environment that encourages competition, protects intellectual property rights, and simplifies business registration process. Such favorable regulations can boost MNCs' confidence and alleviate concerns related to cross-border technology transfer.

In addition to incentive-based policies, countries can also leverage capacity-building strategies to enhance their competitiveness in attracting CCMT-related investment. First, nations can identify their existing technological and knowledge strengths to prioritize the development of certain CCMT industries. Simultaneously, investments in infrastructure, higher education, public services, and amenities that are necessary for CCMT innovation activities should be made. This strengthens the country's expertise in these technologies and fosters international collaborations with MNCs. Furthermore, besides developing technologies directly belonging to CCMTs, countries can explore their existing capacities that are relevant to CCMTs. Enhancing these related capacities facilitates them to enter new specializations within the CCMT domains. To leverage on network capital, policymakers can employ network analysis, as demonstrated in this paper, to precisely identify their countries' global positions within the CCMT diffusion networks. This involve assessing existing MNC investment, available international capital, and connections with other countries through these MNCs. Once existing capacities as well as international linkages are identified, policymakers can strategically focus on developing these complementary capacities.

Third, the findings highlight the potential for intermediary countries to acquire valuable relational assets due to their structural proximity to other key CCMT innovators. These intermediary countries, positioned as hubs and gateways within the diffusion networks, are well-placed to benefit from knowledge flows and information exchanges, functioning as hubs where interdisciplinary knowledge converge. This is primarily because MNCs need to engage with diverse local stakeholders when exploring new markets. Such collaborative engagement not only facilitates knowledge dissemination from headquarters to the subsidiary locations but also stimulates the generation of new knowledge as technologies are adapted to local contexts. In this regard, policymakers should consider establishing various communication platforms, such as regular conventions and incubators. These platforms can effectively facilitate interactions among different stakeholders and sectors, fostering an environment where various forms of knowledge synergize.

There are several limitations in our study. First, we measured CCMT diffusion using intra-firm relationships which did not consider knowledge exchanges and spillovers between firms. Future studies could incorporate indicators capturing inter-firm relationships like mergers and acquisitions, and joint ventures to measure the strength of knowledge flows between companies. Second, our analysis was conducted at the national level. Yet, within a single country, there can be significant regional disparities in CCMT development, spatial concentrations of MNCs, industrialization levels, and industrial strategies. Conducting studies at finer spatial scales can provide a deeper insight into this regional heterogeneity, allowing for more locally tailored policy recommendations that can address the unique contextual challenges and opportunities within each region. Third, we employed CCMT-related patent data up until and including 2021 to identify sustainable innovation MNCs. However, our analysis relied solely on corporate ownership and the geographical information of these MNCs' headquarters and subsidiaries as of 2021. This failed to account for changes that might have occurred during the study period, including those that might have influenced network capital calculation. Changes in corporate ownership, such as mergers and acquisitions, and restructuring can significantly impact a company's innovation strategies and practices within the CCMT domain. Moreover, we examined the entire patent category Y02/Y04S without differentiating across its nine sub-classifications. Different CCMTs may exhibit distinct diffusion dynamics due to factors like market demand and technological complexity. Future studies can investigate individual sub-classifications within CCMTs to gain deeper insights into the global landscape of sustainable innovation and inform targeted strategies for promoting the diffusion of specific CCMTs. Finally, this study utilized the network as an outcome for nodal-level analysis. Future research could investigate the formation and evolution of networks using models such as the exponential random graph model. These models facilitate the simultaneous modeling of the endogenous structural characteristics of a network along with the impact of exogenous variables.

CRediT authorship contribution statement

Jianhua Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Dimitris Ballas:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Xiaolong Liu:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization.

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Appendix A. Countries or regions included in this analysis

Country/ region	Country/ region code	Outgoing linkages	Incoming linkages	Number of CCMT-related patents
Afghanistan	AF	0	2	0
Albania	AL	0	15	0
Algeria	DZ	0	68	0
Andorra *	AD	0	1	0
Angola	AO	0	29	0
Antigua and Barbuda	AG	0	2	0
Argentina	AR	0	304	0
Armenia	AM	0	4	0
Aruba	AW	0	2	0
Australia	AU	1	1,891	25
Austria	AT	3	476	617
Azerbaijan	AZ	0	19	0
Bahrain	BH	0	24	0
Bangladesh	BD	0	43	0
Barbados	BB	0	34	0
Belarus	BY	0	28	0
Belgium	BE	2	566	892
Benin	BJ	0	11	0
Bermuda *	BM	0	183	0
Bhutan	BT	0	1	0

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Country/ region	Country/ region code	Outgoing linkages	Incoming linkages	Number of CCMT-related patents
Bolivia	BO	0	20	0
Bosnia and Herzegovina	BA	0	51	0
Botswana	BW	0	27	0
Brazil	BR	0	1,135	0
British Virgin Islands	VG	0	90	0
Brunei	BN	0	13	0
Bulgaria	BG	0	137	0
Burkina Faso	BF	0	9	0
Burundi	BI	0	1	0
Cambodia	KH	0	23	0
Cameroon	CM	0	15	0
Canada	CA	4	3,075	1,778
Cape Verde	CV	0	3	0
Cayman Islands	KY	0	176	0
Chad	TD	0	2	0
Chile	CL	0	303	0
China Mainland	CN	6	4,455	3,255
Colombia	CO	0	238	0
Costa Rica	CR	0	73	0
Croatia	HR	0	120	0
Cuba	CU	0	4	0
Curaçao *	CY	0	34	0
Cyprus	CW	0	19	0
Czech Republic	CZ	0	376	0
Democratic Republic of the Congo	CD	0	14	0
Denmark	DK	3	380	1,985
Djibouti	DJ	0	2	0
Dominica	DM	0	5	0
Dominican Republic	DO	0	33	0
Ecuador	EC	0	70	0
Egypt	EG	0	204	0
El Salvador	SV	0	30	0
Equatorial Guinea	GQ	0	1	0
Eritrea	ER	0	2	0
Estonia	EE	0	85	0
Ethiopia	ET	0	5	0
Federated States of Micronesia *	FJ	0	2	0
Fiji	FO	0	1	0
Finland	FI	3	278	1,237
France	FR	10	1,475	6,077
Gabon	GA	0	9	0
Gambia *	GM	0	3	0
Georgia	GE	0	11	0
Germany	DE	26	2,213	22,967
Ghana	GH	0	39	0
Gibraltar *	GI	0	20	0
Greece	GR	0	212	0
Guatemala	GT	0	59	0
Guinea	GN	0	10	0
Guyana	GY	0	1	0
Haiti	HT	0	1	0
Honduras	HN	0	23	0
Hong Kong SAR, China	HK	0	649	0
Hungary	HU	0	301	0
Iceland	IS	0	11	0
India	IN	1	986	155
Indonesia	ID	0	492	0
Iran	IR	0	34	0
Iraq	IQ	0	14	0
Ireland	IE	3	535	1,570
Israel	IL	0	219	0
Italy	IT	1	1,068	129
Ivory Coast *	CI	0	24	0
Jamaica	JM	0	8	0
Japan	JP	77	541	46,529
Jordan	JO	0	17	0
Kazakhstan	KZ	0	67	0
Kenya	KE	0	76	0
Kosovo	XK	0	5	0
Kuwait	KW	0	10	0
Kyrgyzstan	KG	0	1	0
Laos	LA	0	7	0
Latvia	LV	0	61	0
Lebanon	LB	0	26	0
Lesotho	LS	0	1	0
Liberia	LR	0	10	0

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Country/ region	Country/ region code	Outgoing linkages	Incoming linkages	Number of CCMT-related patents
Libya	LY	0	2	0
Liechtenstein *	LI	0	6	0
Lithuania	LT	0	66	0
Luxembourg	LU	0	488	0
Macao SAR, China	MO	0	7	0
Macedonia	MK	0	32	0
Madagascar	MG	0	7	0
Malawi	MW	0	6	0
Malaysia	MY	0	808	0
Mali	ML	0	4	0
Malta	MT	0	49	0
Marshall Islands *	MH	0	62	0
Mauritania	MR	0	2	0
Mauritius	MU	0	51	0
Mexico	MX	0	1,163	0
Moldova	MD	0	7	0
Monaco *	MC	0	3	0
Mongolia	MN	0	7	0
Montenegro	ME	0	17	0
Morocco	MA	0	164	0
Mozambique	MZ	0	27	0
Myanmar	MM	0	45	0
Namibia	NA	0	32	0
Nepal	NP	0	1	0
Netherlands	NL	7	1,702	4,631
New Zealand	NZ	0	235	0
Nicaragua	NI	0	18	0
Niger	NE	0	1	0
Nigeria	NG	0	86	0
Norway	NO	0	330	0
Oman	OM	0	37	0
Pakistan	PK	0	70	0
Palestine	PW	0	1	0
Panama	PA	0	128	0
Papua New Guinea	PG	0	22	0
Paraguay	PY	0	26	0
Peru	PE	0	129	0
Philippines	PH	0	335	0
Poland	PL	0	606	0
Portugal	PT	0	412	0
Qatar	QA	0	35	0
Republic of Serbia	RS	0	121	0
Republic of the Congo	CG	0	10	0
Romania	RO	0	270	0
Russia	RU	0	555	0
Rwanda	RW	0	6	0
San Marino *	SM	0	4	0
Saint Kitts and Nevis	KN	0	1	0
Saint Lucia	LC	0	7	0
Saint Vincent and the Grenadines	VC	0	2	0
Samoa	WS	0	6	0
Saudi Arabia	SA	0	188	0
Senegal	SN	0	22	0
Seychelles	SC	0	3	0
Sierra Leone	SL	0	2	0
Singapore	SG	0	943	0
Slovakia	SK	0	234	0
Slovenia	SI	0	120	0
Solomon Islands	SB	0	1	0
South Africa	ZA	0	540	0
South Korea	KR	11	647	12,639
Spain	ES	0	1,010	0
Sri Lanka	LK	0	38	0
Sudan	SD	0	5	0
Suriname	SR	0	1	0
Swaziland	SZ	0	5	0
Sweden	SE	5	620	2,485
Switzerland	CH	5	637	2,224
Syria	SY	0	4	0
Taiwan, China	TW	1	401	75
Thailand	TH	0	906	0
The Bahamas	BS	0	58	0
Togo	TG	0	5	0
Tonga *	TO	0	1	0
Trinidad and Tobago	TT	0	29	0
Tunisia	TN	0	85	0

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Country/ region	Country/ region code	Outgoing linkages	Incoming linkages	Number of CCMT-related patents
Turkey	TR	0	465	0
Uganda	UG	0	11	0
Ukraine	UA	0	259	0
United Arab Emirates	AE	0	298	0
United Kingdom	GB	8	3,600	4,474
United Republic of Tanzania	TZ	0	40	0
United States of America	US	51	21,637	31,972
Uruguay	UY	0	109	0
Uzbekistan	UZ	0	14	0
Venezuela	VE	0	135	0
Vietnam	VN	0	340	0
Zambia	ZM	0	22	0
Zimbabwe	ZW	0	28	0

* Countries/regions included in statistical network analysis but excluded from econometric regression analysis.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107497.

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Review Article

Revolutionizing carbon sequestration: Integrating IoT, AI, and blockchain technologies in the fight against climate change

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ABSTRACT

The escalating concentration of atmospheric carbon dioxide presents a critical challenge in mitigating climate change, necessitating more efficient and verifiable carbon sequestration strategies. This review critically examines the integration of Internet of Things (IoT), Artificial Intelligence (AI), and blockchain technologies as a novel, synergic framework to enhance the efficacy, scalability, and transparency of carbon sequestration processes. IoT systems facilitate high-resolution, real-time environmental data acquisition is essential for monitoring carbon fluxes. AI methodologies enable advanced data analytics, predictive modeling, and optimization of carbon capture and storage mechanisms. Concurrently, blockchain technology provides a secure and immutable platform for transparent carbon accounting and verification. The article synthesizes current advancements and presents case studies that demonstrate practical applications and outcomes. Ethical considerations, technical limitations, and regulatory challenges are critically analyzed. Future research directions include the refinement of sensor networks, the development of adaptive machine learning algorithms, and the evolution of decentralized ledger systems tailored to environmental data. This integrated technological paradigm holds substantial potential to enhance carbon sequestration efforts, thereby contributing meaningfully to global climate change mitigation strategies.

1. Introduction

In recent times, the escalating impacts of climate change have brought forth an urgent need for innovative solutions (Agbor et al., 2023). Addressing the rise in global temperatures, mitigating extreme weather events, and preserving vulnerable ecological systems have become imperatives of paramount importance (Lopez-Gomez et al., 2023). At the crux of this challenge lies the vital task of efficient carbon sequestration, a linchpin in our collective endeavour to stabilize greenhouse gas concentrations and avert potentially catastrophic consequences (Kazemian and Shafei, 2023).

While traditional methods of carbon sequestration have played a crucial role, they grapple with logistical, financial, and technological constraints (Denich et al., 2019). These established approaches reveal their limitations when confronted with the monumental scale of the task before use (Chen et al., 2022).

In response, a new wave of transformative technologies has emerged, reshaping the landscape of carbon sequestration (Snæbjörnsdóttir et al., 2020). This paradigm shift is propelled by the convergence of three pioneering forces: AI (Chen et al., 2023a), IoT (Mishra and Singh, 2021), and blockchain (Chen et al., 2023b). Together, they offer an unprecedented opportunity to transcend the boundaries of conventional sequestration methods.

This review article embarks on an exploration of the interplay between these cutting-edge technologies, uniting in a concerted effort to combat climate change. This endeavour transcends disciplinary boundaries, drawing from the realms of computer science, environmental engineering, and blockchain technology to forge a path forward.

Over the ensuing sections, we will embark on a journey through the distinct roles that AI, IoT, and blockchain play in advancing carbon sequestration. From the real-time data acquisition facilitated by the expansive networks of IoT to the predictive power of AI-driven models, and the immutable transparency provided by blockchain, these technologies combine forces to confront the intricate challenges of carbon management.

Yet, their true potential lies not in isolation, but in the seamless

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integration into a cohesive ecosystem. This amalgamation holds the promise of unlocking hitherto uncharted dimensions of efficacy, heralding a paradigm shift in our collective ability to combat climate change.

As we navigate this transformative terrain, we are acutely aware of the ethical and privacy considerations that accompany such progress. Balancing the imperative for technological innovation with the preservation of individual rights and liberties is a paramount facet of this evolving landscape.

In the pages that follow, we traverse this uncharted territory, propelled toward a future where carbon sequestration transcends its scientific imperative to become a resounding technological triumph.

1.1. Novelties

The motivation for this research stems from the urgent need for more effective, scalable and transparent solutions to mitigate climate change. Traditional methods of carbon sequestration are often limited by inefficiencies, lack of real-time data, and inadequate transparency. By integrating AI, IoT, and blockchain, this article seeks to address these limitations, offering a cohesive, data-driven approach to carbon management that is both more efficient and trustworthy. The innovative application of these technologies promises to not only improve the current state of carbon sequestration but also provide a roadmap for future advancements that could play a critical role in combating climate change.

- **Integration of Cutting-Edge Technologies in carbon sequestration**: This article pioneers the integration of AI, IoT, and blockchain in the domain of carbon sequestration, an area traditionally approached with less technological sophistication. By combining these advanced technologies, the article proposes a forward-thinking solution that addresses the multifaceted challenges of carbon management in real-time, offering greater scalability, efficiency, and accountability than existing methods.
- **Synergistic potential for climate change mitigation**: The article emphasizes how the synergy between AI, IoT, and blockchain can create a more robust and adaptive framework for carbon sequestration. The novel approach provides not only technical solutions but also a holistic strategy that enhances the overall effectiveness of sequestration efforts. This integrated approach has the potential to outperform traditional methods, offering significant improvements in monitoring, optimization, and verification.
- **Real-Time Monitoring and Data Collection with IoT**: A key innovation in this work is the application of IoT for real-time monitoring and data acquisition, enabling continuous, dynamic tracking of carbon sequestration projects. This technology facilitates timely and highly accurate assessments of sequestration activities, enhancing decision-making processes and improving the overall management of carbon capture efforts.
- **AI-Driven Optimization and Prediction Models**: The application of AI in the optimization and prediction of carbon capture and storage represents a cutting-edge solution to enhance the efficiency of sequestration efforts. Machine learning algorithms offer the potential for more precise and adaptable strategies. This ensures that carbon capture efforts are not only more efficient but also tailored to evolving environmental and operational conditions.
- **Transparent carbon accounting with blockchain**: One of the most significant innovations in this article is the use of blockchain technology to ensure transparent, immutable, and verifiable carbon accounting. This innovation addresses long-standing concerns over the integrity of carbon credit systems and project reporting, reducing the risk of fraud, inaccuracies, and double-counting. It ensures that sequestration efforts are auditable and traceable, providing stakeholders with confidence in the accuracy and legitimacy of carbon reduction claims.
- **Case Studies and Demonstrations**: The inclusion of real-world case studies and demonstrations provides concrete examples of successful projects that have leveraged the combined power of AI, IoT, and blockchain for carbon sequestration. This practical application reinforces the feasibility and effectiveness of the proposed approach.
- **Ethical and Privacy Considerations**: The article acknowledges and addresses the ethical and privacy implications associated with the deployment of these technologies. This recognition reflects a conscientious approach to the potential societal impacts of the proposed solutions.
- **Comprehensive Overview and Future Directions**: The article not only provides an in-depth exploration of the current state of these technologies in carbon sequestration but also offers insights into future research directions and potential advancements. This forward-looking perspective contributes to the ongoing discourse on climate change mitigation.

These novelties collectively position the review article as a significant contribution to the field, offering a comprehensive and forward-thinking perspective on the integration of AI, IoT, and blockchain in carbon sequestration efforts.

2. Carbon sequestration techniques and challenges

Carbon sequestration stands as a critical component in our fight against climate change, aiming to capture and store atmospheric carbon dioxide (CO_2) in various natural or engineered reservoirs. Understanding the range of techniques and challenges associated with carbon sequestration is pivotal in formulating effective and sustainable strategies.

2.1. Natural carbon sequestration methods

2.1.1. Afforestation and reforestation

One of the most recognized natural methods for carbon sequestration involves afforestation, the deliberate establishment of forests in previously non-forested areas, and reforestation, the restoration of depleted or degraded forests (Lal, 2005). These processes harness the carbon-absorbing power of trees, which accumulate CO_2 through photosynthesis, storing it in their biomass and in the soil (Gorte, 2009). Through these methods, we have the potential to sequester substantial amounts of carbon over time. Based on the study developed by Burke et al. (2021), it is possible to map the existing barriers towards afforestation in different parts of the world and obtain the afforestation capability of each region based on that. Burke et al. (2021) showed the example of the UK based on different scenarios as illustrated in Fig. 1. As shown in this figure, 4.7 million ha will be available for planting for the UK, but the problem is the sustainability goals set by the UK to reach the carbon neutrality by 2050. Based on those, the UK needs to use 21 % of the available land with limited woodland expansion.

2.1.2. Ocean-Based Sequestration

Our oceans play an invaluable role in carbon sequestration. Phytoplankton and marine organisms absorb CO_2 from the atmosphere, and carbon is subsequently transported to the deep ocean through the biological pump process (Buesseler et al., 2007). Additionally, researchers are exploring techniques such as ocean alkalinity enhancement, a form of geoengineering, as a means to augment carbon uptake in the oceans (Renforth and Henderson, 2017).

Regarding the carbon sequestration in the ocean, Shen et al. (2020) emphasized on the harmful roles of microplastics as shown in Fig. 2. The existence of microplastics in the ocean have adverse impacts on the growth and photosynthesis of phytoplankton and zooplankton leading to harmful results in their community and instability in the marine ecosystem. As shown by Sjollema et al. (2016), phytoplankton' photosynthetic rates will be reduced by 45 % after exposure to the

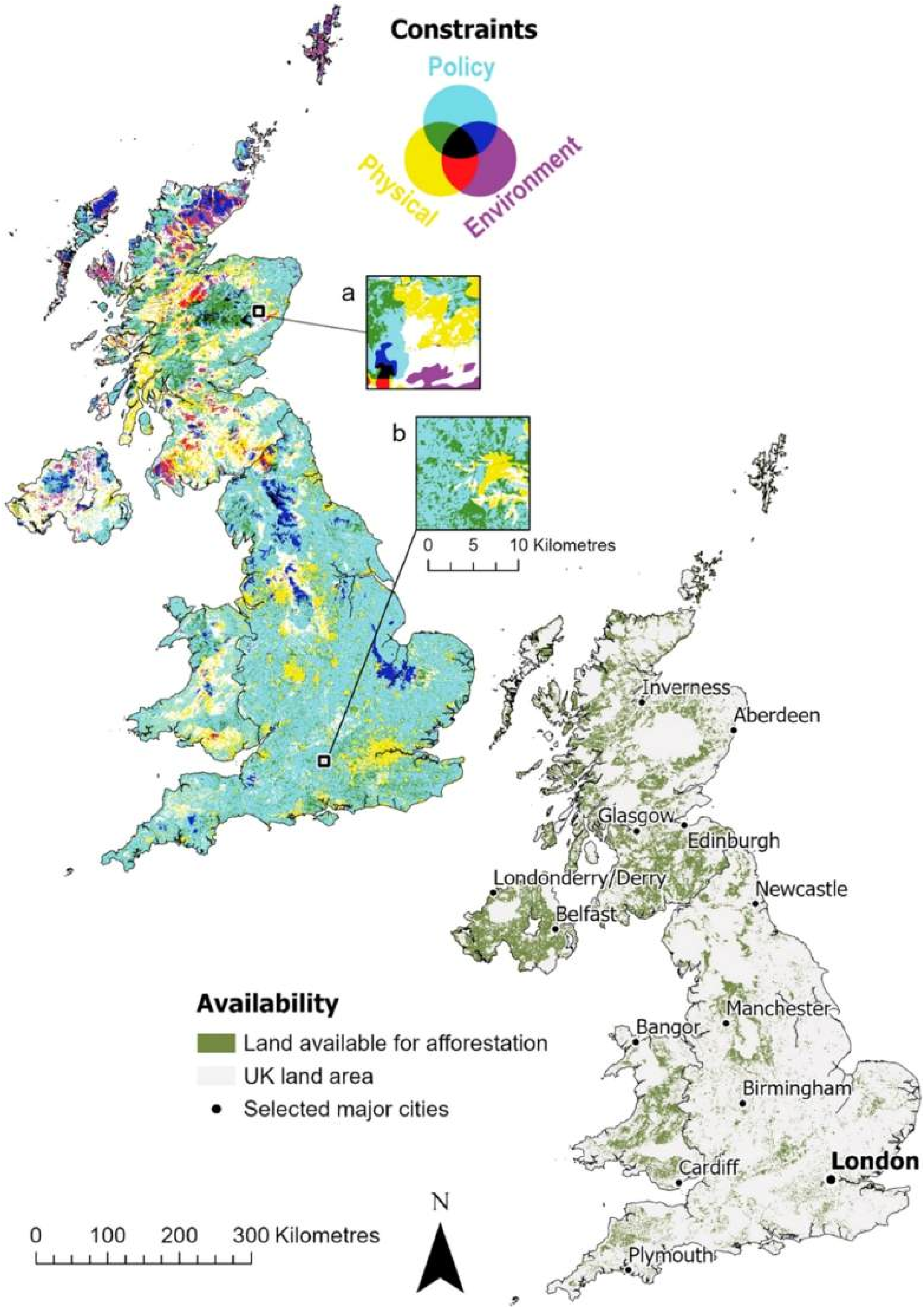

Fig. 1. The illustrated map by Burke et al. (2021) on the restrictive scenario for the afforestation of the UK. As shown, the white color mentions that there are no constraints, hence available for planting. The green indicator of the map demonstrates the potential for afforestation considering the existing barriers (Copyright license number: 5791630052614). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

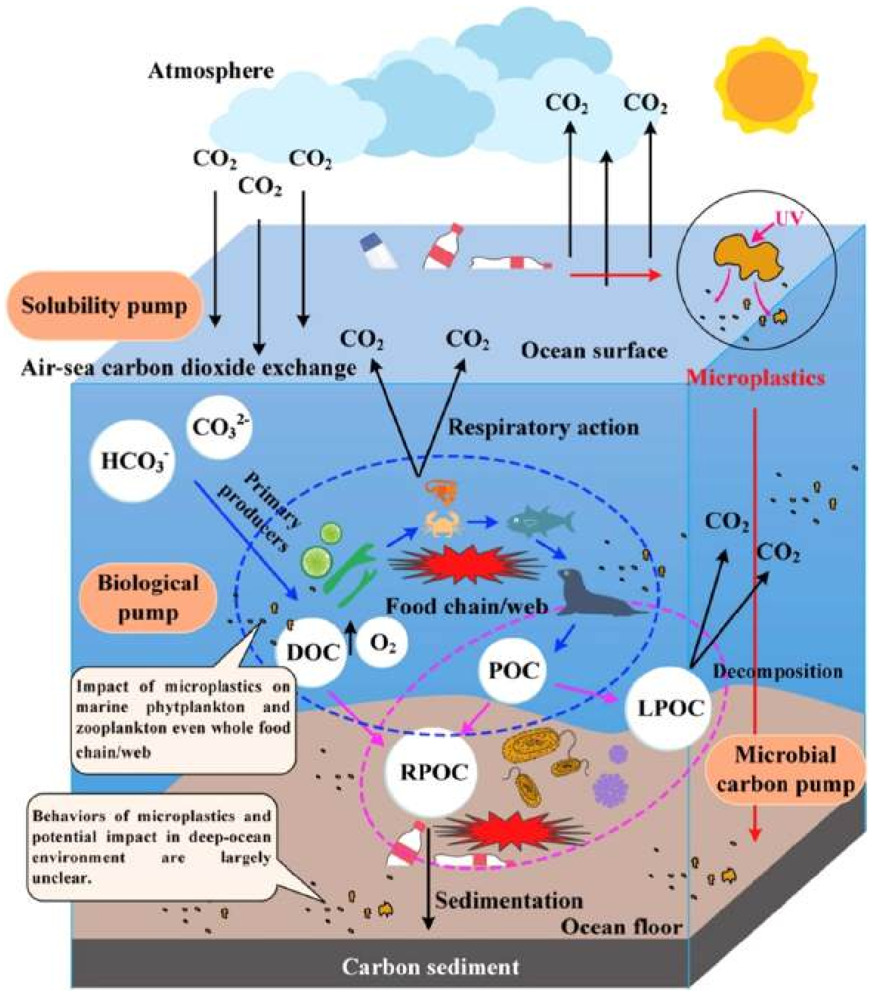

Fig. 2. The illustrated carbon sequestration cycle in the ocean by Shen et al. (2020), where, DOC is Dissolved Organic Carbon, POC is the particulate organic carbon, LPOC is the labile dissolved organic carbon, and RPOC is the recalcitrant dissolved organic carbon. Phytoplankton and Zooplankton have important role in the carbon sequestration cycle in the ocean which will be affected negatively by the existence of microplastics. (Copyright license number: 5795461271415).

microplastics (250 mg/L). The reason is due to the combination and aggregation of the phytoplankton to the decomposed microplastics.

2.2. Engineered carbon sequestration technologies

2.2.1. Direct air capture (DAC)

Emerging as a promising technology, DAC involves mechanically extracting CO_2 directly from ambient air. This method is gaining traction for its potential to capture CO_2 emissions directly from industrial sources or from the atmosphere itself (Lackner, 2003). A common usage of DAC systems is to be integrated to the Solid Oxide Electrolysis Cells (SOEC) to improve the efficiency and the overall goal of carbon capture as shown in Fig. 3 (Coppitters et al., 2023). Nonetheless, DAC faces challenges related to energy consumption and cost-effectiveness (Zeman, 2007). The system shown by Coppitters et al. (2023) is interesting specifically due to the size, which is double the existing commercial solid sorbent DAC units, with up to 4000 tCO_2/year. In the adsorber of this system, carbon dioxide and water are adsorbed at ambient conditions. The sorbent will be regenerated at a desorption temperature of water boiling temperature at the saturated conditions that will result in a gas outlet stream.

2.2.2. Carbon capture and storage (CCS)

CCS represents a pivotal technology involving the capture of CO_2 emissions from industrial processes or power plants, followed by injection into geological formations for long-term storage (Change, 2014). This technology is considered vital in reducing emissions from large point sources (Bui et al., 2018). However, it encounters challenges including the identification of suitable storage sites, ensuring long-term containment, and addressing public acceptance (Steffe and Gale, 1995). Based on the developed study by Deutz and Bardow (2021), in 2019, 3683 DAC plants with the capacity of 100,000 tCO_2/year were needed to capture one percent of the global annual Carbon Dioxide production.

2.3. Challenges in carbon sequestration

While these techniques hold promise, they are not without their challenges. Table 1 presents the main existing challenges with the required description.

Addressing these challenges necessitates collaborative efforts across disciplines, bringing together scientists, engineers, policymakers, and stakeholders to advance the field of carbon sequestration and contribute to global climate goals.

3. The convergence of IoT and carbon sequestration

The innovative intersection of IoT technology and carbon sequestration presents a revolution in how the vital task of capturing and storing carbon emissions can be approached. The collaboration between the IoT and the carbon sequestration processes promises to significantly

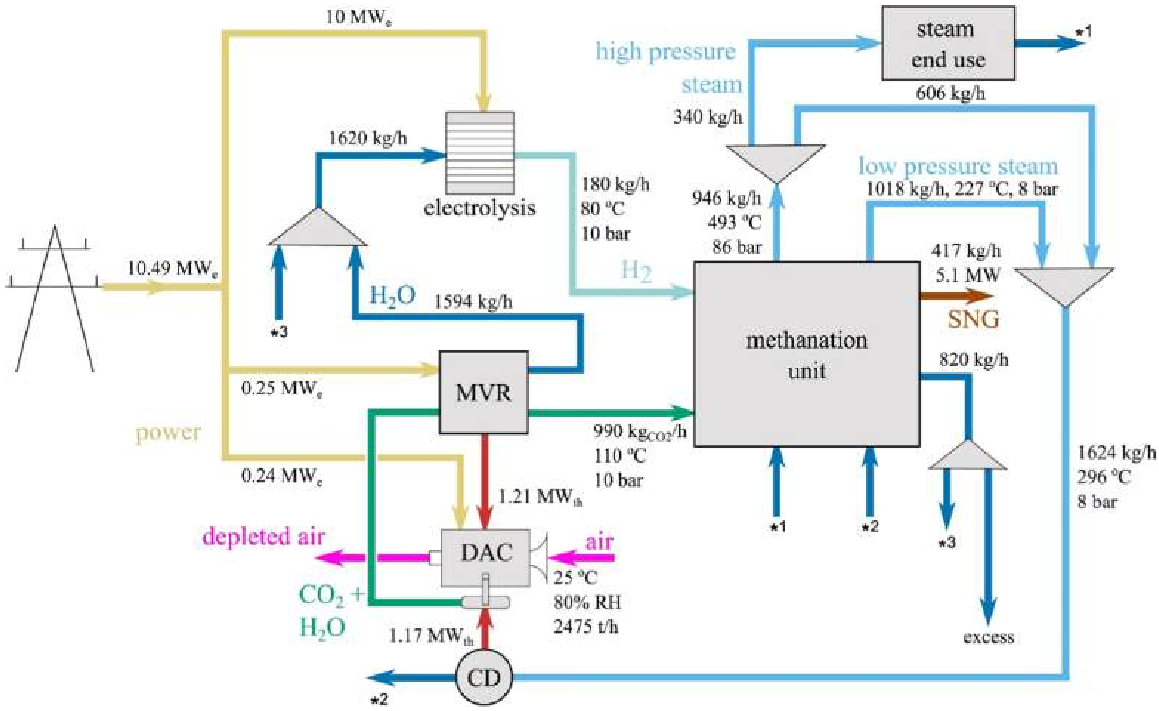

Fig. 3. A schematic of integrated DAC unit to the Solid Oxide Electrolysis Cell (SOEC) illustrated by Coppitters et al. (2023). The heat flows and the excess heat during methanation are also shown. The excess heat will be partially used to provide the remaining heat demand for the DAC through a condenser. (Copyright license number: 5795550875235).

Table 1
The main challenges in the carbon sequestration.

Challenge	Description
Economic viability	Many carbon sequestration methods face economic barriers, such as high initial costs and uncertain revenue streams (Thamo et al., 2017).
Environmental impacts	Some methods may have unintended environmental consequences, such as habitat disruption or alterations in ecosystem dynamics (Houghton, 2018).
Regulatory and policy frameworks	Developing effective regulatory frameworks and policies to govern carbon sequestration activities is critical for ensuring compliance, safety, and accountability (Gren and Aklilu, 2016).
Technological advancements	Continued research and development are essential for improving the efficiency, scalability, and cost-effectiveness of carbon sequestration technologies (Fagorite et al., 2023).
Public Perception and Acceptance	Engaging communities and gaining public trust is crucial for the successful implementation of carbon sequestration projects (Tcvetkov et al., 2019).

enhance the effectiveness and efficiency of our efforts in carbon capture and storage.

3.1. Empowered monitoring with real-time data

By locating sensors across sequestration sites to continuously communicating the main servers with data streams on key parameters like CO_2 levels, temperature, pressure, and soil conditions (Bui, 2020), the carbon sequestration process can be improved. This real-time data allows spotting the changes as they happen, enabling quick responses. For instance, if CO_2 concentrations or environmental conditions shift suddenly, automated adjustments can kick in to optimize the sequestration process. One of the similar projects in this field was developed by Li et al. (2019), where the ecosystem of soil including air, water, soil, carbon, and the ratio of 13 C and 12 C carbons were monitored using IoT-based systems as shown in the proposed structure in Fig. 4. This suggested structure is made of three main steps, which are making smart ecosystem monitoring devices, networking the devices and integrating them with the information system using the IoT, and testing the applicability of the ecosystem monitoring IoT in a variety of typical ecosystems.

3.2. Fine-tuning through advanced analytics and AI

Powerful analytics and machine learning algorithms (Fuss et al., 2018) should be implemented to enable the data streaming through IoT. The role of these machine learning algorithms is to uncover patterns, relationships, and irregularities. The AI allows fine-tuning sequestration operations. AI-driven models can predict the perfect injection rates, adjust for geological quirks, and minimize the risk of leaks based on real-time sensor feedback.

3.3. Providing early warnings for system protection

IoT systems have become vigilant guardians, raising the alarm if anything strays from the expected sequestration performance (Pidgeon et al., 2013). Anomalies in the data patterns can signal potential issues, like a potential breach in containment integrity or unexpected environmental influences. This timely heads-up empowers us to take swift corrective action, keeping the sequestration process safe and effective.

3.4. Remote monitoring: a digital blessing

With IoT in action, the sequestration sites can be monitored remotely. This is particularly invaluable for projects spread across diverse geographic locations. Maintenance schedules and interventions can be planned in advance strategically, guided by real-time data trends. In other words, IoT can act as a virtual team of experts on the ground, optimizing resource allocation (Steffe and Gale, 1995). As an example, Rajak et al. (2023). Integrated IoT and smart sensors for the optimized crop growth and remote monitoring, as shown in Fig. 5. Electromechanical sensors, biosensors, and physical property sensors have key

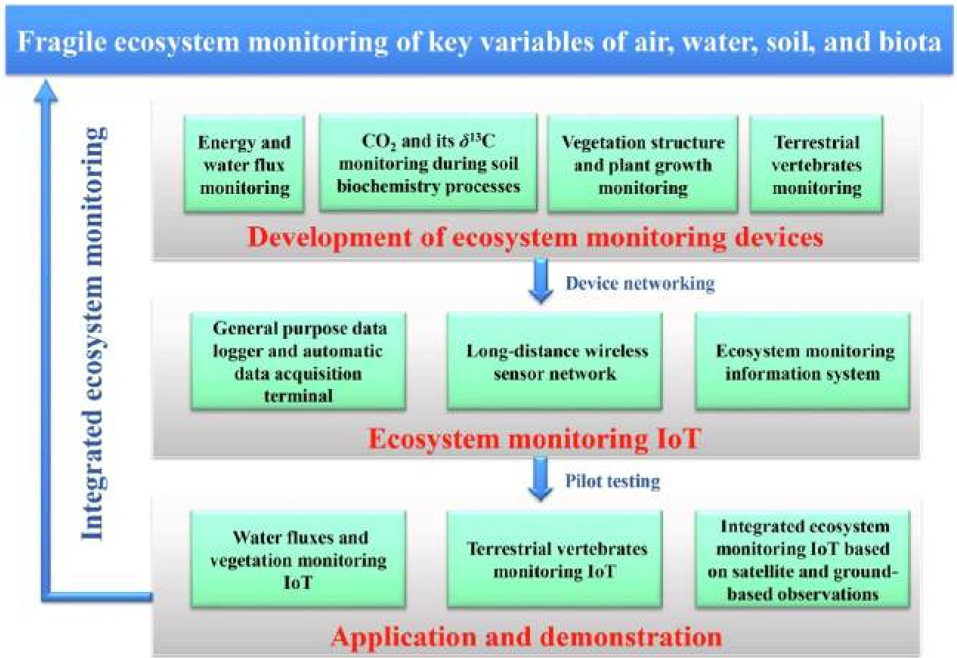

Fig. 4. The novel structure for the IoT based real-time control of ecosystem parameters proposed by Li et al. (2019). (Copyright license number: 5798951371163).

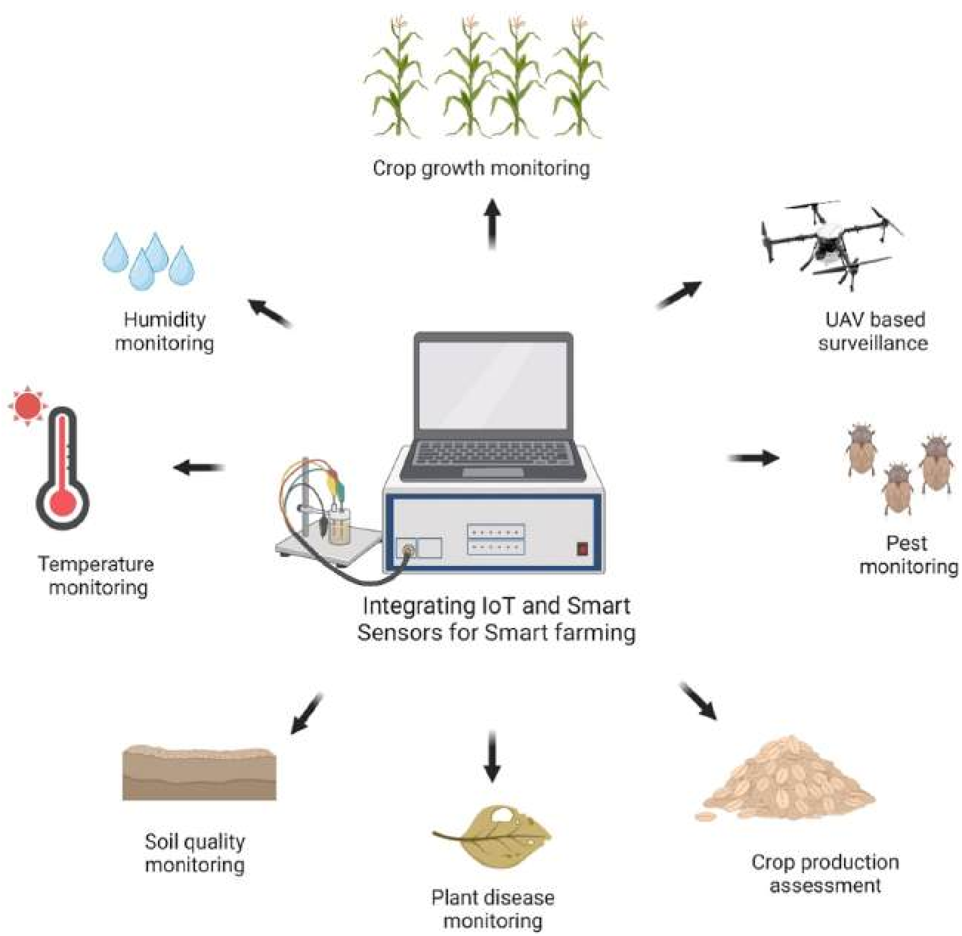

Fig. 5. The use case of IoT and smart sensors in advanced farming to monitor environmental parameters such as temperature, mass flow, moisture, humidity, nitrate levels, and water content (Rajak et al., 2023). The pest control can be done using advanced cameras, and unmanned aerial vehicles will help to control the crop growth. (Copyright license number: Open access under a Creative Commons License).

usages in agricultural fields. Biological sensors enable biological sensitive components from the outside world, but physical property sensors employ devices sensitive to alterations in the physical environment.

3.5. Mindful of ethics and privacy

In addition to the technological aspects, the ethical and privacy considerations should be included as well (Renforth and Henderson, 2017). It's essential to safeguard individual rights and liberties while technological innovations are progressed. While the convergence of IoT and carbon sequestration represents a major leap forward, challenges may arise. Issues related to data security may be encountered in addition to the sensor reliability or ensuring that IoT devices can communicate seamlessly.

The integration of IoT technology into carbon sequestration projects marks a significant shift, offering a dynamic and data-driven framework for optimizing the efforts. By uniting interconnected sensors with advanced analytics, a new level of precision and adaptability in carbon capture and storage will be unlocked that creating a more sustainable and resilient future.

4. AI-driven optimization and prediction models

The inclusion of AI into carbon sequestration projects stands as a game-changer. AI brings a powerful set of tools to the table, using algorithms and machine learning to dissect complex datasets, spot trends, and make educated predictions. The implementation of this technology in carbon capture and storage unlocks a new level of precision and efficiency.

4.1. Seeing the future with AI

AI's real talent lies in foreseeing outcomes based on historical data (Fuss et al., 2018). In carbon sequestration, this means AI can help to understand how factors like injection rates, geological conditions, and environmental variables will affect the sequestration efforts. AI enables real-time monitoring in addition to making sure that the entire process is running optimally.

4.2. Adaptability at its core

One of the most amazing things about AI is its ability to learn and adapt as it encounters new data (Bui, 2020). By the progress of carbon sequestration projects, AI continuously fine-tunes its understanding of the system. This adaptability ensures that the sequestration process becomes more efficient over time. The developed project by You et al. (2020) proposed the usage of machine learning to enable the optimization of CO_2 sequestration and oil recovery processes. Fig. 6 Shows the suggested algorithm to achieve this goal. Based on the work by You et al. (2020), a field-scaled numerical simulation model was structured to analyzed the fluid dynamics of an actual CO_2 sequestration project in the Farnsworth unit in Texax. In that model, AI based proxy models are developed to predict time-series project responses including hydrocarbon production, CO_2 storage, and reservoir pressure data. The outputs of the proxy model were also providing physical and economic constraints for the optimization of the oil recovery and the CO_2 sequestration volume.

4.3. Navigating complexity

Carbon sequestration is a complex puzzle with numerous variables, each influencing the overall outcome. AI acts like a puzzle-solver, uncovering intricate relationships between factors that might not be immediately obvious. This skill is invaluable in optimizing injection strategies, selecting the right storage sites, and managing potential risks tied to geological formations.

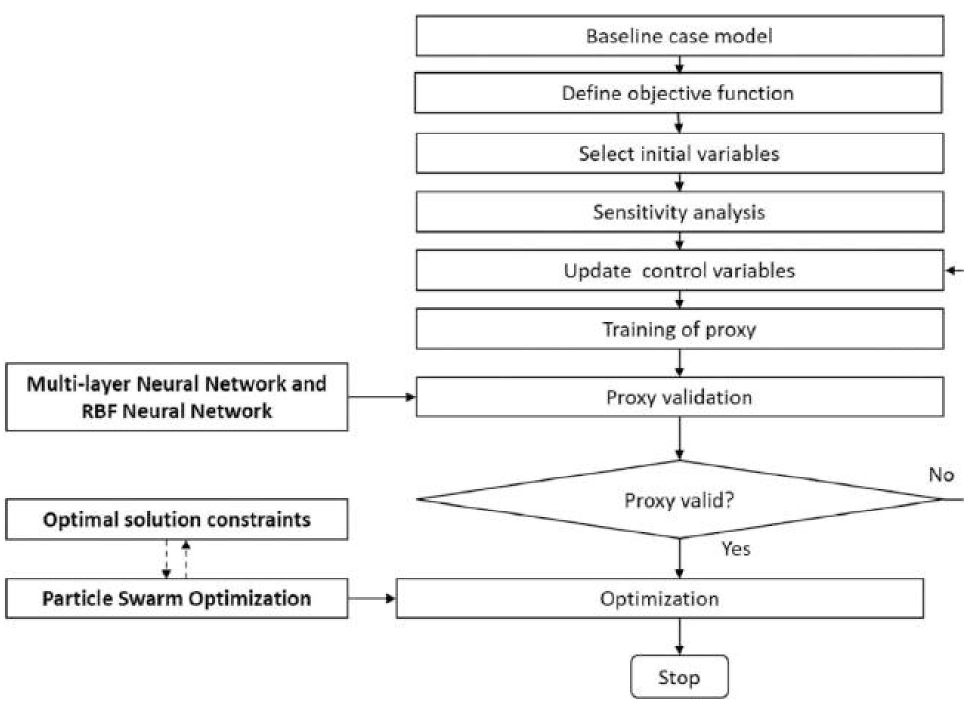

Fig. 6. The proposed algorithm by You et al. (2020) for the optimization of CO_2 sequestration and oil recovery processes. The algorithm starts with particle swarm optimization (PSO) followed by matching history with the produced data and including the multi-layer neural network to develop the proxy models that will be used in the optimization. PSO as a representative of a metaheuristic algorithm has the responsibility of reaching the optimized values while the neural model will be a representative of the physical phenomena of carbon storage and oil production. (Copyright license number: 5799010204293). Here RBF indicates the Radial Basis Function.

4.4. Identifying and managing risks

AI excels at risk assessment, spotting potential challenges and vulnerabilities in sequestration projects (Pidgeon et al., 2013). By sifting through historical data and simulating different scenarios, AI points out areas of concern and suggests ways to address them. This proactive approach minimizes the chances of unexpected setbacks, ensuring the sequestration efforts proceed with confidence. In the study developed by Al-Sakkari et al. (2024), AI was used as a tool to smooth the carbon sequestration operation by predicting the leakages of carbon dioxide, as shown in Fig. 7. This operation will be based on using AI for the diagnosis and prognosis of carbon dioxide leakage from sequestration wells based on infrared imaging and seismic visualizations under human supervision.

4.5. Always getting better

AI fosters a culture of ongoing improvement. As more data is gathered, the models become sharper and more sophisticated (Renforth and Henderson, 2017). This process of continuous learning and refinement leads to innovative strategies for carbon sequestration. It's an invitation to explore new approaches and technologies that could further enhance the sequestration outcomes.

4.6. Harmony with IoT and blockchain

The combination of AI, IoT, and blockchain technologies packs a powerful punch in carbon sequestration. AI uses the real-time data from IoT sensors to make dynamic decisions, while blockchain ensures the transparency and integrity of that data. Together, they form a trio that boosts the overall effectiveness and accountability of sequestration projects.

In conclusion, the integration of AI-driven optimization and prediction models marks a pivotal moment in the world of carbon sequestration. This technology enables informed decisions, adapts to changing conditions, and continually refines the existing approach to enhance problem-solving. By tapping into the predictive capabilities of AI, a path towards more efficient and effective carbon capture and storage will be reached, ultimately contributing to a sustainable and resilient future.

5. Blockchain for transparent carbon accounting

In the pursuit of effective carbon sequestration, the role of blockchain technology emerges as a beacon of transparency and accountability. Blockchain, often associated with cryptocurrencies, proves to be a transformative force in the realm of carbon accounting. It offers a decentralized ledger system that records every transaction or event, creating an immutable chain of information.

5.1. The promise of immutable records

At the heart of blockchain lies its ability to create unchangeable records (Narayanan et al., 2016). In the context of carbon sequestration, this means every piece of data - from sequestration volumes to project details - is etched in digital stone. This transparency leaves no room for disputes or alterations, establishing a foundation of trust.

5.2. Enhancing accountability in carbon reporting

Blockchain ensures that every participant in the carbon sequestration process, from project developers to auditors, has access to the same set of information. This shared ledger leaves no room for discrepancies or hidden data. In this regard, the culture of accountability will be improved.

One of the most critical elements of blockchain-enabled carbon accounting is the use of smart contracts. These self-executing scripts stored on the blockchain automatically trigger actions when predefined conditions are met. For instance, a smart contract can be programmed to issue a carbon credit token only when a third-party verifier uploads a certificate confirming a sequestration milestone has been reached. This automation reduces human intervention and the risk of manipulation, making the carbon credit issuance process more transparent and

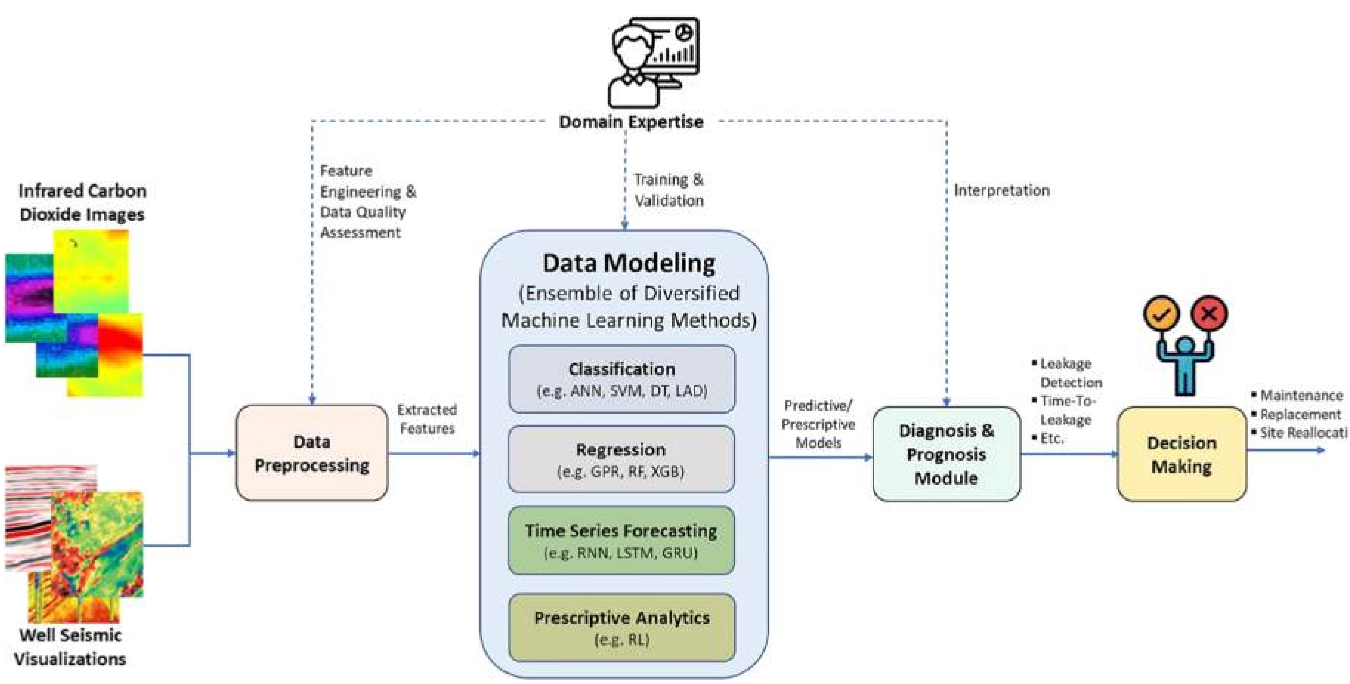

Fig. 7. The proposed methodology by Al-Sakkari et al. (2024) to detect the carbon dioxide leakage from the sequestration wells. (Copyright license number: 5799011000749). Here, ANN, SVM, DT, LAD, GPR, RF, XGB, RNN, LSTM, GRU, and RL indicate the Artificial Neural Network, Support Vector Machine, Decision Tree, Linear Discriminant Analysis, Gaussian Process Regression, Radio Frequency, eXtreme Gradient Boosting, Recurrent Neural Network, Long Short-Term Memory, Gated Recurrent Units, and Reinforcement Learning, respectively.

trustworthy.

Blockchain systems also rely on consensus mechanisms to validate transactions. In the context of carbon markets, Proof of Stake (PoS) is often preferred over energy-intensive methods like Proof of Work (PoW) to maintain environmental integrity. PoS systems validate transactions based on participants' stake in the network, offering faster processing and lower energy consumption.

To ensure interoperability with carbon standards, many blockchain platforms incorporate metadata tagging and APIs that align with established protocols such as the Greenhouse Gas Protocol or Verra's Verified Carbon Standard (VCS). This allows real-time synchronization of carbon data across different registries and enhances transparency for stakeholders, including governments, NGOs, and the public.

Another innovation is tokenization, where each verified carbon credit is converted into a digital token that can be traded on blockchain platforms. These tokens are often non-fungible to preserve their unique project characteristics, such as location, date, and methodology. Some platforms also implement traceability layers, allowing users to follow the lifecycle of a carbon credit, thus preventing double-counting or resale fraud.

Despite these advantages, challenges remain in areas such as legal recognition of blockchain records, cross-chain interoperability, and the technical complexity of integrating on-chain (blockchain) systems with off-chain (real-world) carbon projects. Nevertheless, the integration of these technical features positions blockchain as a powerful tool in building trust, scalability, and traceability in carbon accounting systems.

5.3. Tracing carbon credits with certainty

In the world of carbon markets, accurately tracking and verifying carbon credits is paramount. Blockchain provides a streamlined mechanism for this. Each credit is tied to a unique, verifiable record on the ledger (Arasteh et al., 2020). This ensures that credits are not double-counted or fraudulently created, instilling confidence in the market. In this regard, Muzumdar et al. (2022) has proposed an Emission Trading System (ETS) as shown in Fig. 8 based on two transaction units of carbon credit (CC) and cash coin. The system operates on the three main processes of CC buying, selling, and trading using smart contracts.

5.4. Smart contracts for automated compliance

Smart contracts, self-executing contracts with the terms directly written into code, add another layer of automation and transparency (Kosba et al., 2016). They can be programmed to enforce compliance with regulatory requirements. For example, a smart contract could automatically retire carbon credits once they've been used, reducing the risk of double-spending.

5.5. Empowering stakeholders with real-time data

With blockchain, stakeholders can access real-time data on sequestration projects (Tian et al., 2019). This includes details on carbon capture rates, storage integrity, and overall project performance. This real-time project's data sharing empowers stakeholders with the information they need to make informed decisions.

5.6. Overcoming trust barriers

Trust has always been a central concern in carbon accounting. Blockchain addresses this by removing the need for a central authority or intermediary. Instead, trust is built into the system itself through cryptographic verification and consensus mechanisms (Swan, 2015). This decentralized approach fosters a more robust and reliable ecosystem.

5.7. Challenges and considerations

While blockchain holds immense promise, it's not without its challenges. Scalability, energy consumption, and regulatory frameworks are areas that require careful attention (Tapscott and Tapscott, 2016). Additionally, ensuring data privacy and security in a public blockchain network is a critical consideration.

In essence, blockchain technology brings a new level of integrity to carbon accounting. It introduces a level playing field where data is transparent, unchangeable, and accessible to all stakeholders. By leveraging blockchain's capabilities, a path towards a more accountable and trustworthy approach to carbon sequestration will be made.

6. Integrating technologies for synergistic impact

Navigating the frontier of carbon sequestration, it becomes evident that the true power lies in the convergence of technologies. When AI, IoT, and blockchain come together, they create a synergistic force that transforms the existing approach to carbon capture and storage.

6.1. Harmonizing real-time insights with IoT

The Internet of Things is like the eyes and ears of the sequestration projects. Sensors and devices scattered across the project site continuously collect data on everything from temperature and pressure to carbon dioxide concentrations (Tian et al., 2019). This real-time stream of information provides a level of insight previously unattainable. In this regard, the real-time optimization of the system becomes feasible.

6.2. AI as the cognitive engine

Artificial Intelligence steps in as the brain of the operation. It takes the influx of data from IoT and processes it with remarkable speed and precision (Fuss et al., 2018). AI can identify patterns, predict future

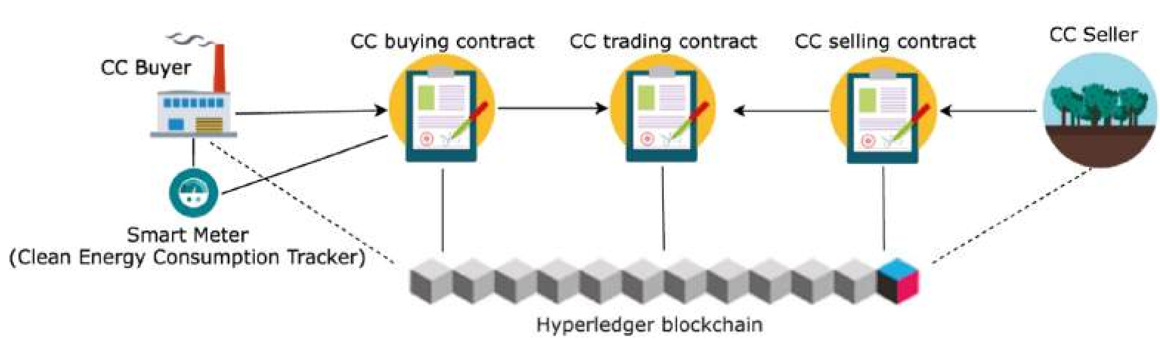

Fig. 8. A schematic of the suggested Emission Trading System by Muzumdar et al. (2022). (Copyright license number: 5799020384560).

trends, and even make autonomous decisions. AI can be considered an expert capable of analyzing vast amounts of information and distilling it into actionable insights. In the developed project by You et al. (2020), AI was used as a tool to predict the Oil production, and CO_2 storage in sequestration projects as shown in Fig. 9.

6.3. Blockchain's immutable record

At the foundation of this technological trinity lies blockchain, providing an unchangeable ledger of every transaction, every data point, and every decision (Narayanan et al., 2016). It ensures that the information generated by IoT and analyzed by AI remains tamper-proof and trustworthy. This is similar to have an incorruptible archive, a testament to the integrity of the endeavors.

6.4. Smart contracts orchestrating operations

Smart contracts, powered by blockchain, serve as the orchestrators of the sequestration efforts (Kosba et al., 2016). They autonomously execute predefined actions based on the insights generated by AI and the data collected by IoT. For example, if certain conditions indicate the need for an adjustment in injection rates, a smart contract can initiate the change. It's akin to having a dynamic conductor, fine-tuning the performance in real-time.

6.5. A collective intelligence ecosystem

The integration of these technologies creates an ecosystem where each component strengthens the others. IoT feeds AI with real-world data, empowering it to make more accurate predictions. AI, in turn, guides the decision-making process, ensuring that actions are based on data-driven insights. Blockchain secures the entire operation, providing an unassailable record of every event.

6.6. Ensuring ethical considerations

While marveling at the technological prowess, the human dimensions must not be forgotten. Ethical and privacy considerations are paramount (Swan, 2015). While proceeding with these integrated technologies, a commitment should be made to safeguard individual rights and ensuring that the innovations benefit society as a whole.

6.7. The future of carbon sequestration

This integration is more than just a technological feat; it's a glimpse into the future of carbon sequestration. It's a testament to human ingenuity, showcasing the existing capabilities when cutting-edge technologies are integrated in the fight against climate change.

In this integrated landscape, not only efficiency and effectiveness is found but also a profound sense of possibility. It's a frontier where technology and environmental stewardship join hands, propelling towards a future where carbon sequestration is not just a scientific necessity, but a technological triumph.

7. Case studies and demonstrations

In examining the integration of IoT, AI, and blockchain technologies in carbon sequestration efforts, several noteworthy case studies and initiatives have emerged. These real-world projects exemplify the potential for transformative impact in the fight against climate change.

- **Microsoft's Project Natick (Pellegrino et al., 2021): IoT-Enabled Underwater Data Centers**
  - Microsoft's Project Natick represents a groundbreaking initiative that explores the feasibility of deploying data centers underwater. Equipped with a sophisticated array of IoT sensors, these submerged data centers continuously collect a wealth of environmental data (Shelar et al., 2020). This includes critical parameters such as temperature, pressure, and carbon dioxide levels. This real-time data acquisition not only informs efficient data center operations but also presents an innovative approach to harnessing IoT for environmental monitoring and carbon sequestration.
- **IBM's Green Horizons Initiative (Kale and Ma, 2023): AI-Driven Air Quality Management**
  - IBM's Green Horizons Initiative is a pioneering effort that leverages artificial intelligence to enhance air quality management, particularly in urban environments. By employing advanced AI models, the initiative processes vast amounts of data from various sources (Li et al., 2021). These sources include IoT sensors, satellite imagery, and other environmental monitoring systems. This capability enables precise predictions of air quality patterns, facilitating targeted interventions to reduce emissions and enhance carbon sequestration efforts.
- **Climate Ledger Initiative (Schulz and Feist, 2021): Blockchain for Carbon Accounting**
  - The Climate Ledger Initiative is at the forefront of utilizing blockchain technology to revolutionize carbon accounting and emissions tracking. By employing distributed ledger technology, the initiative ensures transparent and immutable records of carbon credits and emissions data. This approach enhances trust and accountability in carbon markets, offering a robust framework for sustainable carbon sequestration strategies.

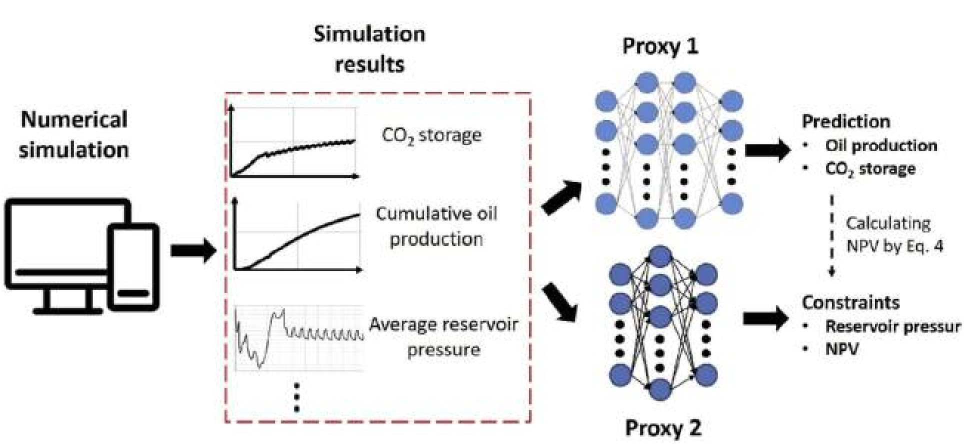

Fig. 9. The training method used by You et al. (2020) for the optimization of CO_2 sequestration and oil recovery processes. The first proxy was aimed to predict oil production and carbon dioxide sequestration while the second one had the goal of predicting the average reservoir pressure change during the lifetime of the system. (Copyright license number: 5799010204293).

- **CarbonCure Technologies (Salehi, 2023): AI-Optimized Carbon Utilization**
  - CarbonCure Technologies is a trailblazer in the field, employing artificial intelligence to optimize carbon dioxide utilization in concrete production. Through AI-driven algorithms, the company systematically analyzes data related to concrete mixtures and curing processes. This enables precise control over carbon dioxide incorporation, resulting in reduced emissions and enhanced carbon sequestration within construction materials.
- **Ocean Cleanup's System 001 (Ramphal, 2021): IoT-Enabled Marine Plastic Removal**
  - The Ocean Cleanup's System 001 stands as a testament to the power of IoT technology in addressing the global issue of marine plastic pollution. Equipped with an arsenal of sensors and satellite tracking capabilities, the system continuously monitors and collects data on the movement and concentration of plastic debris in oceans. This real-time information guides the efficient deployment of cleanup operations, contributing not only to ocean conservation but also to carbon sequestration efforts.
- **Carbon Engineering's DAC Facility (Izikowitz, 2021): AI-Enhanced Carbon Removal**
  - Carbon Engineering's DAC facility is an exemplary application of AI-driven optimization to enhance carbon dioxide removal from the atmosphere. AI algorithms continuously analyze operational data to fine-tune the capture process. This dynamic adjustment maximizes efficiency and minimizes energy consumption, exemplifying a cutting-edge approach to carbon sequestration.
- **Google's DeepMind for Cooling Data Centers (Al Munem et al., 2023): AI-Optimized Energy Efficiency**
  - Google's collaboration with DeepMind in optimizing data center cooling showcases the remarkable potential of AI in energy efficiency. Through the application of deep reinforcement learning, the project achieved significant reductions in energy consumption for data center cooling. This achievement not only demonstrates the power of AI in sustainable practices but also contributes to carbon footprint reduction in data center operations.
- **Sony CSL's OpenAI Project (Alto, 2023): AI-Enhanced Renewable Energy Integration**
  - Sony Computer Science Laboratories, Inc.'s OpenAI project represents a notable endeavor to harness the power of AI in integrating renewable energy sources into the electrical grid (Verma, 2021). Through the application of advanced algorithms and machine learning techniques, the project seeks to optimize the utilization of renewable energy, ultimately contributing to reduced carbon emissions in the energy sector.
- **Walmart's Blockchain-Based Food Traceability (Xu et al., 2020): Carbon Footprint Reduction**
  - Walmart's pioneering use of blockchain technology in food traceability is a multifaceted initiative with significant environmental implications. By leveraging distributed ledger technology, Walmart enables transparent and immutable tracking of food products through the supply chain (Westerlund et al., 2021). This not only enhances food safety but also contributes to the reduction of carbon emissions associated with food production and distribution.
- **Tesla's Gigafactories (Cooke, 2021): Sustainable Energy Production with AI Integration**
  - Tesla's Gigafactories represent a transformative paradigm in sustainable energy production. By integrating advanced manufacturing technologies with renewable energy sources, Tesla aims to produce electric vehicles and energy storage solutions at an unprecedented scale. The incorporation of AI technologies within these Gigafactories further optimizes production processes, ultimately contributing to the reduction of carbon emissions associated with traditional manufacturing.
- **Maersk's Carbon Accounting with Blockchain (Wong et al., 2023): Maritime Industry Innovation**
  - Maersk, a global leader in container shipping, has embarked on a ground-breaking initiative to leverage blockchain technology for carbon accounting in the maritime industry. Through the application of distributed ledger technology, Maersk aims to provide transparent and verifiable documentation of carbon emissions associated with shipping operations. This initiative not only enhances transparency but also contributes to the overall reduction of carbon emissions in the shipping industry.
- **Siemens' MindSphere IoT Platform for Industrial Sustainability (Kulawiak, 2021)**
  - Siemens' MindSphere IoT platform is a powerful tool for advancing industrial sustainability. By integrating IoT technologies, Siemens enables comprehensive data collection and analysis within industrial environments. This facilitates informed decision-making for optimizing energy efficiency, reducing resource consumption, and ultimately minimizing carbon emissions in industrial processes.
- **Sprint's IoT for Fleet Management (Zhang et al., 2020) Carbon Emissions Reduction**
  - Sprint's utilization of IoT technologies in fleet management represents a significant step towards reducing carbon emissions in transportation. Through the integration of IoT sensors within vehicles, Sprint enables real-time monitoring of key performance metrics such as fuel efficiency and vehicle maintenance. This data-driven approach empowers companies to make informed decisions that lead to the reduction of carbon emissions associated with their fleets.
- **Nestle's Blockchain-Based Supply Chain Transparency (Скаско et al. 2021): Carbon Accountability**
  - Nestle's adoption of blockchain technology for supply chain transparency has far-reaching implications for carbon accountability. By leveraging distributed ledger technology, Nestle establishes an immutable record of product origin, processing, and distribution (Schilhabel et al., 2023). This not only enhances product traceability but also contributes to the reduction of carbon emissions associated with supply chain operations.
- **Amazon's AI-Powered Energy Optimization in Fulfillment Centers (Varghese, 2022)**
  - Amazon's innovative use of AI technologies for energy optimization in fulfillment centers demonstrates the potential for significant carbon emissions reduction in the logistics industry. Through the deployment of AI algorithms, Amazon optimizes energy usage based on real-time data and operational patterns. This results in increased energy efficiency and a corresponding reduction in the carbon footprint of fulfillment center operations.

In addition to the above-mentioned case studies, followings are the real systems exist for carbon sequestration:

- **Climeworks (Switzerland/Iceland)**
  - Climeworks is a company specializing in direct air capture (DAC) technology, working with Carbfix in Iceland to mineralize captured CO_2 underground. The system utilized IoT sensors for environmental monitoring and is exploring blockchain for credit verification.
- **Northern Lights Project (Norway)**
  - A pioneering full-scale carbon capture and storage project backed by Equinor, Shell, and TotalEnergies. It captures CO_2 from industrial sites, transports it via ship, and stores it under the North sea seabed. The project is exploring digital twins and AI for operational efficiency.
- **CarbonCure (Canada)**
  - Integrates CO_2 into concrete production, locking it in the building material. They're using AI to optimize CO_2 usage and emissions reduction per batch of concrete.

These expanded case studies provide in-depth insights into successful projects that have harnessed the combined power of IoT, AI, and blockchain technologies for carbon sequestration. They not only demonstrate the efficacy of these integrated approaches but also offer valuable insights for the broader implementation of innovative technologies in the fight against climate change. Table 2 shows a structured categorization of each case study by organization/project, technology used, application area, and impact on carbon sequestration or emission reduction.

7.1. Technology implementation on local commodities and its implications

The integration of AI, IoT, and blockchain technologies holds significant potential for transforming carbon management practices in sectors tied to local commodities. In agriculture, for instance, IoT sensors can be deployed to monitor critical parameters such as soil moisture, nutrient levels, and carbon content in real time. Combined with AI-driven analytics, these systems can optimize irrigation and fertilizer application, thereby enhancing soil health and promoting carbon sequestration through regenerative farming practices. Blockchain technology can further support this transformation by creating transparent and verifiable records of sustainable practices, enabling farmers to participate in carbon credit markets. This approach not only contributes to emissions reduction but also creates new revenue streams for rural communities.

In forestry, which often plays a vital role in national carbon sinks, the use of AI and IoT can significantly improve monitoring and management. Remote sensing technologies, including drones equipped with AI-based image analysis, can track forest growth, health, and deforestation activities. IoT-based ground sensors provide additional insight into soil and ecosystem conditions. Blockchain can be used to document conservation efforts and carbon offset credits in a tamper-proof manner. These technologies empower local and indigenous communities to engage in decentralized forest management, ensuring accountability while supporting livelihoods tied to ecosystem preservation.

Livestock and dairy farming, another key sector in many regions, can also benefit from these technologies. IoT-enabled wearable devices can track animal health and methane emissions, while AI models can optimize feeding strategies to reduce greenhouse gas emissions. Blockchain platforms offer transparent traceability in sustainable meat and dairy production, thereby increasing consumer trust and market value. These interventions collectively support a shift toward climate-smart livestock systems, balancing productivity with sustainability.

The energy sector, particularly renewable energy initiatives such as solar, wind, and biomass, also stands to gain from the integration of digital technologies. AI algorithms can forecast energy demand and optimize supply, while IoT devices continuously monitor generation efficiency. Blockchain solutions enable the secure trading of clean energy certificates and decentralized energy transactions. Together, these innovations enhance grid reliability and support the scaling of low-carbon energy systems, further reducing emissions at the source.

By focusing on these locally relevant sectors, the application of emerging technologies not only enhances carbon sequestration and emissions management but also drives broader socio-economic benefits. These include job creation, improved data-driven decision-making, and increased access to sustainable development opportunities. Therefore, the localization of technological frameworks is essential for ensuring the long-term viability and scalability of climate mitigation efforts.

8. Policy and regulatory considerations

As the integration of IoT, AI, and blockchain technologies gains momentum in carbon sequestration efforts, it is imperative to assess the necessary policy and regulatory frameworks. These frameworks play a pivotal role in providing a conducive environment for the widespread adoption of these technologies and ensuring their effective

Table 2
Summary of case studies involving AI, IoT, and blockchain for carbon sequestration.

Project/ Organization	Technology used	Application area	Impact on carbon sequestration
Microsoft – Project Natick	IoT	Underwater data centers & environmental monitoring	Real-time environmental data for optimizing operations; potential use for environmental sensing
IBM – Green Horizons	AI, IoT	Urban air quality and pollution prediction	AI-based emission forecasting; supports better policy and urban planning
Climate Ledger Initiative	Blockchain	Carbon markets and accounting	Transparent, immutable carbon credit tracking; enhances trust in carbon markets
CarbonCure Technologies	AI	Carbon utilization in concrete	Embeds CO_2 in concrete; reduces carbon footprint in construction
Ocean Cleanup – System 001	IoT, Satellite tracking	Marine plastic removal	Indirect impact via cleaner oceans and improved carbon sinks
Carbon Engineering (DAC)	AI	Direct air capture (DAC)	AI optimizes CO_2 capture process, improving energy efficiency and removal capacity
Google – DeepMind	AI	Data center cooling	Significant reduction in energy use and related emissions
Sony CSL – OpenAI Project	AI	Renewable energy integration	AI enhances energy distribution and lowers fossil fuel reliance
Walmart – Blockchain Traceability	Blockchain	Food supply chain	Reduces emissions from inefficient logistics and food waste
Tesla – Gigafactories	AI, Renewable Energy	Sustainable manufacturing	Scales green tech production; AI-driven process efficiencies
Maersk – Carbon Accounting	Blockchain	Shipping industry carbon accounting	Transparent emissions tracking in maritime logistics
Siemens – MindSphere	IoT	Industrial sustainability	Optimizes resource use and energy efficiency
Sprint – Fleet Management	IoT	Transportation	Real-time fuel and maintenance tracking; reduces transport emissions
Nestle – Supply Chain Transparency	Blockchain	Food supply chain	Immutable product traceability; supports lower-emission sourcing and logistics
Amazon – Energy Optimization	AI	Fulfillment centers	AI-based dynamic energy management reduces carbon footprint
Climeworks (w/ Carbfix)	IoT, AI, Blockchain (in progress)	Direct air capture and mineralization	Permanent CO_2 removal; blockchain planned for credit verification
Northern Lights Project	AI (digital twins)	Industrial CCS and offshore storage	Scalable CO_2 capture and secure underground storage
CarbonCure (also listed above)	AI	Green building materials	Reduces lifecycle emissions of construction by locking in CO_2

implementation in mitigating climate change. At the current state, most global and regional regulatory frameworks are still evolving to keep pace with the rapid advancement of these technologies. Several real-world issues must be acknowledge before proposing forward-looking solutions.

8.1. Current policy gaps and real-world challenges

Despite growing interest in digital solutions for climate action, many countries lack dedicated policies addressing the integration of IoT, AI, and blockchain into carbon management. For example, regulations surrounding IoT deployment often fail to specify standards for secure environmental data transmission or long-term storage, leading to inconsistent implementation across projects. Moreover, AI applications in carbon optimization and monitoring frequently operate in regulatory grey zones, with limited guidance on ethical use, bias mitigation, or algorithmic accountability.

In the blockchain space, the absence of standardized protocols for digital carbon credits and emission tracking results in fragmented efforts that hinder trust and scalability. Different jurisdictions apply varying degrees of oversight, and many lack legal recognition for blockchain-based records. Furthermore, existing carbon markets are often criticized for their lack of transparency, weak verification mechanisms, and susceptibility to greenwashing or fraud.

There is also a lack of interoperability between national and international systems, which complicates data sharing and the harmonization of standards. Without cohesive policies, even the most advanced technologies risk being underutilized or misapplied in carbon sequestration projects.

8.2. Establishing clear standards for data privacy and security

The deployment of IoT technologies for real-time data acquisition in carbon sequestration necessitates robust measures to safeguard data privacy and security. Regulatory bodies must collaborate with technology stakeholders to establish clear standards and guidelines. These standards should encompass data encryption, access control, and secure transmission protocols. Additionally, mechanisms for informed consent and transparent data handling practices should be integrated to ensure compliance with privacy regulations (Shayesteh et al., 2020).

8.3. Addressing ethical implications of AI in carbon sequestration

The utilization of AI-driven optimization and prediction models raises ethical considerations, particularly concerning decision-making processes. Regulatory frameworks should encourage transparency and accountability in AI algorithms, ensuring they prioritize environmental and societal well-being. Additionally, mechanisms for addressing bias, fairness, and accountability in AI applications should be established to foster trust and ethical deployment (Roberts et al., 2022). The main pillars to reach the accepted robustness, lawfulness, and ethics in AI are presented in Table 3.

Table 3
The main pillars and requirements to reach trustworthy AI for carbon sequestration projects inspired by Cannarsa (2021).

Pillar	Description
1	Human agency and oversight
2	Technical robustness and safety
3	Privacy and data governance
4	Transparency
5	Diversity, non-discrimination, and fairness
6	Societal and environmental well-being
7	Accountability

8.4. Blockchain and Transparent Carbon Accounting: Regulatory Oversight

The implementation of blockchain for transparent carbon accounting requires a regulatory framework that ensures integrity and accuracy in emissions reporting. Smart contracts and consensus mechanisms should align with established emissions protocols. Regulatory bodies should work in tandem with industry experts to develop and enforce standards for blockchain-enabled carbon accounting, reducing the potential for fraud or inaccuracies (Schletz et al., 2020)

8.5. Incentivizing technology adoption through carbon markets

To encourage the widespread adoption of IoT, AI, and blockchain technologies in carbon sequestration, regulatory bodies should explore mechanisms such as carbon markets. These markets can provide financial incentives for organizations and projects that implement innovative technologies for carbon reduction. Establishing clear guidelines for participation and accreditation within carbon markets will be essential in driving technological advancements. However, it's important to acknowledge that the effectiveness of carbon markets can vary based on regional and industry-specific factors, and ongoing monitoring and adjustment of policies will be crucial (Qi et al., 2021).

8.6. International collaboration and harmonization of standards

Given the global nature of climate change, international collaboration is paramount in establishing cohesive regulatory frameworks. Regulatory bodies should engage in dialogue to harmonize standards and guidelines for the integration of IoT, AI, and blockchain technologies in carbon sequestration efforts. This collaborative approach will ensure consistency and effectiveness across regional and international initiatives. However, it's important to note that achieving consensus on global standards may require diplomatic negotiations and ongoing coordination among participating nations (Agreement, 2015).

Incorporating these policy and regulatory considerations will be instrumental in creating an enabling environment for the successful integration of IoT, AI, and blockchain technologies in carbon sequestration efforts. By addressing privacy, ethics, accountability, and international collaboration, regulatory frameworks can play a pivotal role

9. Addressing ethical and privacy concerns

As embarked on this technological frontier to revolutionize carbon sequestration through the integration of IoT, AI, and blockchain, it is essential to navigate potential ethical and privacy considerations. These cutting-edge technologies, while promising, bring forth a range of concerns that must be thoughtfully addressed to ensure responsible and equitable implementation.

9.1. Ensuring fairness and equity in AI-driven solutions

The application of AI in carbon sequestration introduces questions of fairness and equity. It is imperative to scrutinize algorithms for biases that may inadvertently disadvantage certain communities or regions. Striving for transparency in algorithmic decision-making and actively seeking to mitigate biases is crucial in ensuring that the benefits of technological advancement are distributed equitably (Hagendorff, 2022).

9.2. Balancing innovation with data privacy

The extensive data collection inherent in IoT networks for real-time monitoring raises important privacy considerations. It is essential to establish clear protocols for data handling, storage, and access. Anonymization techniques and strict access controls should be employed to safeguard individual privacy rights. Additionally, providing individuals with informed consent regarding data collection practices is paramount (Van den Hoven et al., 2012).

9.3. Transparency and accountability in blockchain-based carbon accounting

While blockchain offers unprecedented transparency in carbon accounting, it also raises questions about data integrity and accountability. Smart contracts and consensus mechanisms should be designed with transparency and auditability in mind. Furthermore, mechanisms for dispute resolution and error correction should be in place to address potential inaccuracies in recorded data (Kshetri, 2017).

9.4. Engaging stakeholders and communities

Ethical considerations extend beyond technology itself to encompass the broader engagement of stakeholders and affected communities. Inclusive decision-making processes and community consultations should be prioritized. Ensuring that the deployment of these technologies aligns with local values and addresses community needs is fundamental to ethical implementation (Gupta, 2014).

Addressing these ethical and privacy concerns is pivotal in building public trust and ensuring the responsible deployment of IoT, AI, and blockchain technologies in carbon sequestration. By prioritizing fairness, transparency, and community engagement, a path towards technological solutions can be forged that not only combats climate change but also does so with integrity and respect for all stakeholders involved.

10. Future directions, challenges, and research priorities

The integration of IoT, AI, and blockchain presents a dynamic landscape with numerous opportunities for innovation. This section identifies key areas for further exploration and discusses potential advancements on the horizon.

10.1. Enhancing machine learning algorithms for predictive modelling

While AI has shown immense promise in optimizing carbon capture and storage, there is room for refinement. Future research should focus on enhancing machine learning algorithms to improve the accuracy and adaptability of predictive models. This includes incorporating more comprehensive datasets and exploring advanced modelling techniques such as deep learning (Ließ et al., 2016).

10.2. Exploring decentralized ledger technologies for enhanced transparency

The potential of blockchain in transparent carbon accounting is immense, but there is ongoing research into even more efficient and scalable decentralized ledger technologies. Future studies may include the development of novel consensus mechanisms and smart contract platforms to further enhance transparency and accountability in carbon sequestration efforts (Chen et al., 2018).

10.3. Integrating sensor networks for comprehensive environmental monitoring

The IoT ecosystem can be expanded to incorporate a wider array of sensors for holistic environmental monitoring. Future research should explore the integration of diverse sensor technologies to capture a broader spectrum of environmental data, allowing for more nuanced and accurate assessments of carbon sequestration projects (Li et al., 2019).

10.4. Evaluating the ecological impact of carbon sequestration efforts

While the focus has primarily been on carbon capture and storage, it is crucial to assess the broader ecological implications. Future research should delve into comprehensive environmental impact assessments to understand how carbon sequestration initiatives influence ecosystems, biodiversity, and other vital ecological factors (Pan et al., 2019).

These future directions and research priorities represent a roadmap for the continued advancement of the integration of IoT, AI, and blockchain in carbon sequestration efforts. By pushing the boundaries of technology and knowledge, a more sustainable and resilient future will be made in the fight against climate change.

10.5. Challenges and limitations of emerging technologies in carbon sequestration

While the integration of IoT, AI, and blockchain offers transformative potential for carbon sequestration, it is crucial to acknowledge the associated challenges and limitations that may hinder their effectiveness and scalability. One significant issue lies in the technological infrastructure and accessibility, particularly in developing regions. Many carbon sequestration projects are located in remote or rural areas where stable internet connectivity, sensor deployment infrastructure, and access to cloud computing resources remain inadequate, limiting the practical implementation of these technologies.

Data privacy and cybersecurity pose another critical challenge. IoT systems collect vast amounts of environmental and operational data, often in real time. Without robust safeguards, this data may be vulnerable to breaches or misuse. Similarly, AI algorithms can be opaque or biased, especially when trained on limited or non-representative datasets. This can lead to skewed results or decisions that fail to reflect on-the-ground realities, especially in complex ecosystems or diverse communities.

In the case of blockchain, scalability and energy consumption are persistent concerns. Although blockchain enables transparent and immutable records, many consensus mechanisms (e.g., Proof of Work) consume significant energy, potentially offsetting some of the carbon reduction goals. Additionally, regulatory uncertainties and interoperability issues between different blockchain platforms create barriers for wide-scale adoption and integration with existing systems.

There are also economic and social implications. The upfront costs of deploying IoT sensors, training AI models, or developing blockchain infrastructure can be prohibitive for small-scale projects or communities with limited funding.

Lastly, there is a governance and accountability gap. Clear roles, responsibilities, and oversight mechanisms are still emerging for how these technologies should be deployed and who should own or control the resulting data and systems. Without inclusive and transparent governance models, the deployment of these technologies could exacerbate existing inequalities or fail to gain public trust.

11. Conclusion

The integration of IoT, AI, and blockchain technologies represents a ground-breaking advancement in the pursuit of efficient carbon sequestration. This comprehensive review has illuminated the remarkable synergies that arise when these cutting-edge technologies converge to combat climate change.

Through the expansive networks of IoT, real-time data acquisition has emerged as a linchpin, providing a dynamic feedback loop that empowers precise and timely assessment of carbon sequestration projects. Meanwhile, AI-driven optimization and prediction models have demonstrated their transformative potential in revolutionizing the efficiency of carbon capture and storage. These machine learning algorithms hold the key to unlocking even more accurate and adaptable strategies in the future.

The advent of blockchain technology has ushered in a new era of transparency and accountability in carbon accounting. Its immutable ledger ensures an unassailable record of sequestration efforts, mitigating the potential for fraud or inaccuracies. This technological triumph is poised to reshape the landscape of carbon management, setting a new standard for integrity in environmental stewardship.

As we navigate this transformative terrain, ethical and privacy considerations remain paramount. Striking a balance between technological innovation and safeguarding individual rights stands as a critical facet of this evolving landscape. Clear regulatory frameworks and ethical guidelines must accompany technological advancement to ensure responsible deployment.

Looking ahead, the evolution of machine learning algorithms, decentralized ledger technologies, sensor integration, and ecological impact assessments promises to amplify the efficacy of carbon sequestration efforts. The integration of diverse sensor technologies holds the potential to provide even more nuanced and accurate assessments of environmental parameters. Additionally, a more comprehensive understanding of the ecological impact of carbon sequestration initiatives will be vital in crafting holistic and sustainable strategies.

In conclusion, this review article not only serves as a comprehensive resource for researchers and practitioners but also sounds a clarion call for continued research and development in this critical field. By embracing innovation, collaboration, and ethical considerations, we are poised to unlock the full potential of these technologies, propelling us toward a more sustainable and resilient future in the fight against climate change. The time for action is now, and the integration of IoT, AI, and blockchain stands as a beacon of hope in our collective efforts to combat one of the greatest challenges of our time.

CRediT authorship contribution statement

Masoud Talebi Amiri: Writing – review & editing, Investigation, Formal analysis, Conceptualization. **Hossein Madi:** Writing – review & editing, Validation, Investigation, Formal analysis. **Owusu Jerry:** Writing – review & editing, Validation, Supervision, Formal analysis, Conceptualization. **Hossein Pourrahmani:** Writing – original draft, Methodology, Investigation, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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RESEARCH

Monitoring carbon emissions using deep learning and statistical process control: a strategy for impact assessment of governments' carbon reduction policies

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Abstract Across the globe, governments are developing policies and strategies to reduce carbon emissions to address climate change. Monitoring the impact of governments' carbon reduction policies can significantly enhance our ability to combat climate change and meet emissions reduction targets. One promising area in this regard is the role of artificial intelligence (AI) in carbon reduction policy and strategy monitoring. While researchers have explored applications of AI on data from various sources, including sensors, satellites, and social media, to identify areas for carbon emissions reduction, AI applications in tracking the effect of governments' carbon reduction plans have been limited. This study presents an AI framework based on long short-term memory (LSTM) and statistical process control (SPC) for the monitoring of variations in carbon emissions, using UK annual CO2 emission (per capita) data, covering a period between 1750 and 2021. This paper used LSTM to develop a surrogate model for the UK's carbon emissions characteristics and behaviours. As observed in our experiments, LSTM has better predictive abilities than ARIMA, Exponential Smoothing and feedforward artificial neural networks (ANN) in predicting CO2 emissions on a yearly prediction horizon. Using the deviation of the recorded emission data from the surrogate process, the variations and trends in these behaviours are then analysed using SPC, specifically Shewhart individual/moving range control charts. The result shows several assignable variations between the mid-1990s and 2021, which correlate with some notable UK government commitments to lower carbon emissions within this period. The framework presented in this paper can help identify periods of significant deviations from a country's normal CO2 emissions, which can potentially result from the government's carbon reduction policies or activities that can alter the amount of CO2 emissions.

Keywords Carbon emissions · LSTM · Statistical process control · Artificial intelligence · Climate change · Energy policy · Deep learning · ARIMA · Exponential smoothing · ANN

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Introduction

Climate change is one of the most pressing global environmental issues, with carbon emissions contributing significantly. Due to the urgency of this issue, governments across the world have developed and implemented various policies and plans to reduce carbon emissions. Examples of these efforts include the Paris

Agreement (Dimitrov, 2016), the US Environmental Protection Agency's Clean Power Plan (U.S. Environmental Protection Agency, 2016) and the UK's Sixth Carbon Budget (Committee on Climate Change, nd). Crucial aspects of these policies include incentivising renewable energy sources, promoting energy efficiency, and implementing carbon pricing mechanisms. Even though these carbon reduction policies can help to reduce future carbon emissions, monitoring their impact is essential but daunting.

Carbon emissions are the product of diverse operations, including manufacturing, transportation, and agriculture. As such, monitoring all of these emissions requires a vast amount of data aggregated from multiple sources. In addition to the difficulty in obtaining these data due to a lack of transparency in the industrial reportage of emissions data (Deane et al., 2017), the monitoring process is complex and requires advanced computations. Technologies such as deep learning (LeCun et al., 2015) and statistical process control (SPC) (Oakland & Oakland, 2018) have evolved as effective computational techniques for data analysis and process monitoring, with applications in several sectors, including manufacturing, healthcare, and finance. This study explores the applications of these technologies in environmental monitoring, considering the impact of governments' carbon reduction initiatives, using UK annual CO2 emission (per capita) data from 1750 to 2021 (Ritchie et al., 2020).

Recurrent Neural Networks (RNNs) are the most popular deep learning architecture for time series analysis because they can model sequential data, using the output of past time steps as inputs to the current time step (Medsker & Jain, 2001). The feedback connections in RNN and its variants make them suitable for processing audio, videos, and texts, with applications in machine translation (Wu et al., 2016), handwriting recognition (Graves et al., 2008), speech recognition (Zia & Zahid, 2019), robot control (Mayer et al., 2006), and time series analysis (Karim et al., 2017; Siami-Namini et al., 2018a). Standard RNNs struggle with modelling long-term dependencies due to their susceptibility to the vanishing gradient problem. To solve the vanishing gradient issue in RNN, Long Short-Term Memory (LSTM) has been introduced (Hochreiter & Schmidhuber, 1997). LSTMs learn long-dependencies by incorporating a memory cell that selectively retains or forgets information from previous time steps. In contrast to traditional time series models, like autoregressive integrated moving average (ARIMA) model (Shumway et al., 2017), which often require strong pre-existing assumptions about the underlying data distribution and relationships between variables, deep learning techniques such as LSTMs can learn sequential representations without the need for such suppositions, making them effective in modelling complex, non-linear relationships (Karim et al., 2017; Siami-Namini et al., 2018b). Moreover, unlike traditional time series models, which often use seasonal dummies to capture the effect of seasonality, including annual seasonality, ANN, such as LSTM models, do not typically use dummies for seasonal effects, as they can capture seasonal patterns implicitly (Heshmatol Vaezin et al., 2022; Zhang & Qi, 2005).

In this study, we first compared the performances of LSTM, ARIMA, Exponential Smoothing (Ostertagová & Ostertag, 2011) and feedforward ANN (Sazli, 2006) in predicting CO2 emissions on a yearly prediction horizon. Due to its superior performance compared to other models, LSTM was selected for developing a surrogate model of the UK's carbon emissions characteristics and behaviours based on the experiment's outcomes. Using SPC, specifically the Shewhart individual-moving range (I-MR) control chart, we evaluate the variations and trends in these behaviours using the deviations of the recorded emission data from the surrogate process. SPC is a statistical technique that can provide insight into the variability within a process. With SPC techniques, it is possible to spot and interpret anomalies or unusual changes in the emissions data. The combination of deep learning and SPC, which has successfully been used in analysing SCADA data associated with wind turbines (Udo & Muhammad, 2021), can provide an effective tool for monitoring the impact of the efforts by the UK government to reduce carbon emissions.

The contributions of this paper can be summarised as follows:

- Available research publications in this area demonstrate that this paper is the first to apply a hybrid technology, consisting of LSTM and SPC, to carbon emissions monitoring, using LSTM to model the baseline behaviours of UK carbon emissions (per capita) and SPC to detect assignable variations.
- This paper is also the first to discuss the control chart obtained from applying computational and statistical process techniques to CO_2 emission data

in line with known UK government carbon reduction commitments.

These contributions are vital to monitoring the effectiveness of the government's carbon reduction policies, which are crucial in combating climate change. By continuously evaluating the outcomes, we can identify effective strategies and pinpoint areas that need improvement to ensure that the policies align with the government's climate objectives towards a sustainable and low-carbon future.

Review of related literature

Several researchers have successfully applied artificial intelligence and machine learning to forecast carbon emissions, supporting the development of effective environmental policies for reducing carbon emissions. Acheampong and Boatang used ANN in training models for forecasting the intensity of carbon emissions in Australia, Brazil, China, India, and the USA with minimal error (Acheampong & Boateng, 2019). Their study selected nine crucial parameters contributing to carbon emissions intensity as input variables, including economic growth, energy consumption, R&D, financial development, foreign direct investment, trade openness, industrialisation, and urbanisation. The ANN models were validated and can be used by international organisations and environmental policymakers to forecast and make climate change policy decisions.

Agbulut proposed a framework relying on three machine learning algorithms — deep learning, support vector machine(SVM), and ANN — to forecast energy consumption and CO2 emissions relating to Turkey's transportation sector (Ağbulut, 2022). The study used gross domestic product per capita, population, vehicle kilometres, and year as inputs. It concluded that policymakers need future energy investments to establish regulations, policies, norms, restrictions, legislations, and initiatives to mitigate energy consumption and emissions from the transportation sector.

Dozic and Urosevic (2019) examined an ANN model of the EU's energy system, which predicts CO2 emissions until 2050, considering the current Energy Policy of the EU (Dozic & Urosevic, 2019). The study concluded that the model is highly effective in predicting the behaviour of CO2 emissions. It can facilitate timely corrections to energy and economic strategies by adjusting relevant indicators to meet the ambitious CO2 emission reduction targets set by the Energy Roadmap 2050 document of the European Commission. Their research analysed several ANN structures to identify the most effective model for large energy systems.

Huang (2021) contributed to China's national policy plan for achieving a carbon peak in the mid-to-long term, focusing on the Yangtze River Economic Belt basin (Huang et al., 2021). The author's goal was to comprehensively promote energy conservation and reduce emissions using a hybrid model of LSTM and support vector regression (SVR) to manage and forecast carbon emissions. The model in their research uses information indicators such as industry investment, labour efficiency output, and carbon emission intensity to predict carbon emissions accurately. Other researchers have employed schemes based on SPC to monitor and recommend reducing carbon emissions.

Shamsuzzaman et al. (2021) developed a technique for monitoring carbon emissions from the industrial sector using SPC (Shamsuzzaman et al., 2021). The authors introduced an economic-statistical design for the combined Shewhart $\bar{X}$ and exponentially weighted moving average (EWMA) scheme, which can help to monitor carbon emissions for prompt action to control excessive emissions. The proposed Statistical Process Monitoring (SPM) scheme parameters have been optimised to minimise the total cost, including carbon emissions and operational costs. Actual data from different industrial facilities have been used to demonstrate the application of the proposed SPM scheme and its effectiveness in reducing costs associated with excessive carbon emissions from industries.

Although the above papers demonstrate excellent applications of AI or SPC in carbon emission monitoring or control, their results suffer limitations associated with these techniques. For example, while ANNs can learn complex non-linear patterns and relationships in time series data, unlike SPC, they cannot effectively monitor and control a process to ensure it operates within specified limits. ANNs are better suited for predictive modelling and forecasting, while SPC is better for monitoring and control. This paper proposes a hybrid technique consisting of LSTM and SPC. LSTM can be used to model carbon emission characteristics from historical carbon emission data. At the same time, SPC can identify whether this process entails a natural or a caused variation.

Methodology

Data description

The data used for this research is the UK annual CO2 emission (per capita) data, covering between 1750 and 2021 (Ritchie et al., 2020). Figure 2a presents the raw data. The records are based on production or territorial emissions from burning fossil fuels or cement production within the UK's borders and do not include emissions from traded goods. Moreover, the numbers are specific to CO2 emissions, not total greenhouse gas emissions. Table 1 presents the descriptive statistics of the dataset. As can be seen, the data is continuous, negatively skewed, and platykurtic.

The workflow

Figure 1 presents the workflow involving the techniques developed for this research.

Data pre-processing

This phase involves outlier removal, filtering, and normalisation. This paper applies isolation forest (Liu et al., 2008) for outlier detection and removal. Isolation forest can detect outliers by scoring how easy it is to isolate a single data point from the rest of the data points using a binary search tree. The higher the number of splits required to isolate a data point, the less likely the data point is identified as an outlier.

Filtering, specifically moving averages, follows the outlier removal process to further remove noise from the data and to replace missing values with the mean of their five nearest neighbours. This step is relevant in filtering out false signals, which can obscure the underlying trend in the data and consequently affect the computation of the control limits. The data undergoes z-score normalisation, scaling it down to the interval [0,1] to ensure that the models have consistent scale and distribution, contributing to the efficiency of the learning algorithm.

Table 1 Descriptive statistics

Statistic	Value
Count	227.000000
Mean	7.471925
Standard deviation	3.213397
Minimum	1.006713
Kurtosis	−1.139382
Skewness	−0.626540
Median	8.912930
Maximum	11.818837

Model development

The initial phase of the study involves evaluating the predictive accuracy of four distinct models on the UK annual CO2 emissions: LSTM, ARIMA, Exponential Smoothing, and Feedforward ANN. The accuracy of the surrogate model is essential for minimising the potential interference of the model inaccuracy with the CO2 emissions monitoring process. The dataset is partitioned into 80% training and 20% testing subsets for the analysis. The training data encompasses annual carbon emissions per capita between 1803 and 1976, while the test data spans from 1977 to 2021.

Among these models, LSTM, ANN, and ARIMA leverage data from the previous three years to predict CO2 emissions for each year, whereas Exponential Smoothing relies on immediate past values for prediction. As a first step towards developing a framework for accurately identifying variations in CO2 emissions within the UK, the goal of the model development process is to effectively represent the typical pattern in the UK's annual carbon emission data. By utilising SPC, this model can then be used to detect out-of-control situations.

To achieve this aim, the predicted value is subsequently compared with the actual value for the corresponding timestamp, allowing for monitoring changes in CO2 emissions. For example, when predicting the CO2 emissions for 1977, the actual emissions data from 1974 to 1976 is used as input. The disparity between the predicted and actual values is calculated and can be leveraged to monitor fluctuations in CO2 emissions, and this process continues throughout. This approach aligns with the research goal, which is not long-term forecasting of UK CO2 emissions but tracking assignable variations within the emission data.

Hyperparameters for the LSTM, ARIMA, Exponential Smoothing, and ANN were selected using Bayesian Optimisation (Frazier, 2018) available in hyperopt library (Bergstra et al., 2013). Table 2 presents the hyperparameters for models.

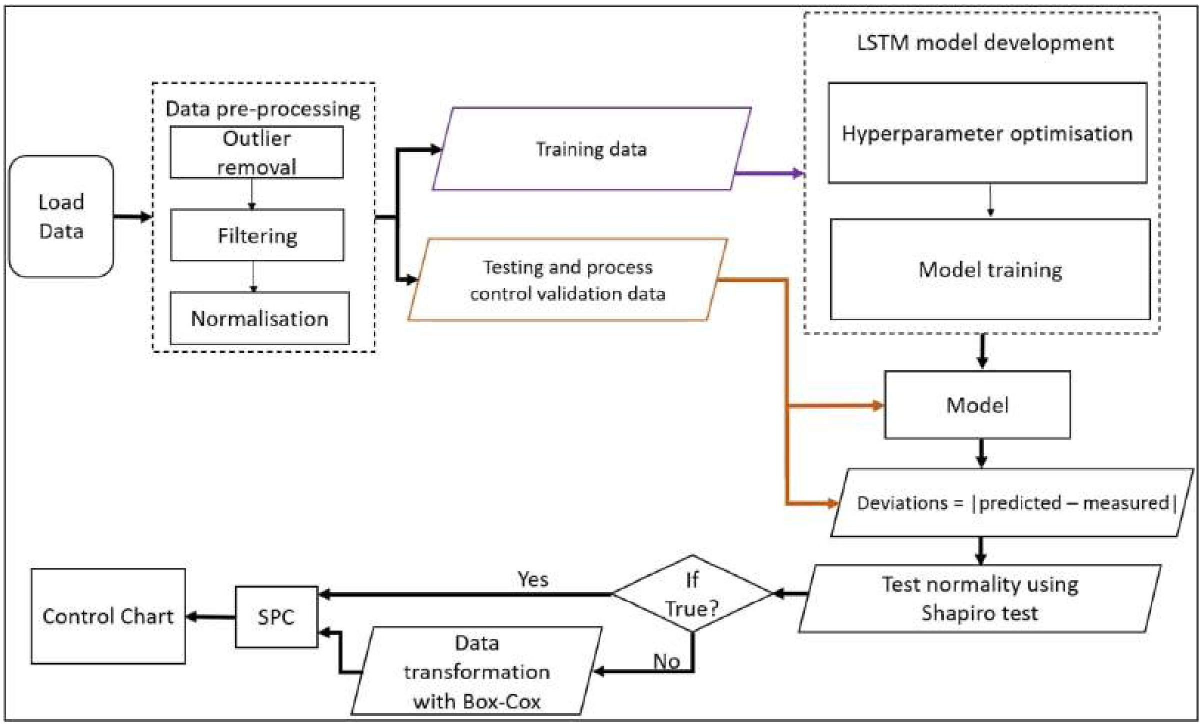


Fig. 1 Research workflow

Monitoring the carbon emissions process

The actual monitoring of the carbon emissions process follows the successful model development. Using the data from 1977 to 2021, set aside for model testing and process monitoring, the surrogate model predicts each year's carbon emission per capita. The absolute deviation of the measured emission from the predicted emission for the year k is calculated as follows: $\delta_k = |predicted_k - measured_k|$

Although SPC approaches have been developed for non-normal data, researchers have demonstrated that serious errors can occur in results from non-normal data (Andrássyová et al., 2012; Chou et al., 1998; Xiao et al., 2020). To avoid poor results due to non-normal data, the Shapiro-Wilk test of normality is first used to identify if the deviations are normally distributed or not (Shapiro & Wilk, 1965). The null hypothesis of the Shapiro-Wilk test is that the sample comes from a normally distributed population. The test statistic is calculated as follows:

$$W = \frac{(\sum_{i=1}^{n} a_i \delta_{(i)})^2}{\sum_{i=1}^{n} (\delta_i - \bar{\delta})^2} \tag{1}$$

where n is the sample size, $\delta(i)$ is the $i-th$ order statistic (i.e., the ith smallest value in the sample), $\bar{x}$ is the sample mean, and a_i are constants that depend on n and the chosen level of significance. The constants are chosen so that the expected value of W is approximately equal to 1 for normal data. The Shapiro-Wilk test compares the value of W to critical values obtained from a Shapiro-Wilk critical values table. If the calculated value of W is less than the critical value, then the null hypothesis is not rejected, and the sample is considered consistent with normality; otherwise, the null hypothesis is rejected, and the sample is considered to be non-normal.

To avoid challenges posed by non-normal data, the deviations undergo Box-Cox transformation (Box & Cox, 1964) before the SPC process if they are non-normally distributed. The Box-Cox equation is given by

$$y^{(\lambda)} = \begin{cases} \frac{y^{\lambda}-1}{\lambda} & \text{if } \lambda \neq 0 \\ \ln(y) & \text{if } \lambda = 0 \end{cases} \tag{2}$$

$y^{(\lambda)}$ is the transformed variable; y represents the original variable; and λ is the transformation parameter. The

Table 2 Hyperparameters

Model	Hyperparameter	Value
LSTM	LSTM_1 units	128
	Activation_1	Relu
	LSTM_2 units	64
	Activation_2	Relu
	Dropout	0.2
	Optimizer	Adam
	Learning rate	0.00001
	Loss function	Mean squared error
	Epochs	250000
	Batch size	8
	Validation split	0.2
ARIMA	Autoregressive order (p)	3
	Differencing order (d)	4
	Moving Average order (q)	9
Exponential Smoothing	Damping factor	0.875
ANN	Learning rate	0.2071
	Number of hidden neurons	4
	Momentum term	0.0797
	Maximum iteration	830
	Activation	Relu

value of λ can be any real number but is often bounded within a range of values depending on the context and the nature of the data. For example, λ must be positive if y is strictly positive. λ is selected to maximize the log-likelihood function to find the best transformation for the data.

Next, SPC can help to investigate regions along a time series to determine if natural or special variations drive them. Natural variations are inherent to a process and are caused by random factors, while special variations are non-random and driven by specific factors, such as a government's carbon reduction policy, as in the case of this research. To investigate the deviations between the recorded carbon emissions and the value predicted using the surrogate model and to identify the nature of the cause of the deviation for each specific period, we have employed SPC. Specifically, the Shewart control chart (the individual/moving-range (I-MR) chart) has been used to evaluate the deviations over time. I-MR-chart combines the moving range (MR) and the individual control charts in determining the out-of-control situations within a process. Each chart is based on two control limits, the Upper Control Limit (UCL) and Lower Control Limit (LCL), to assess the variations within the data. The control limits establish the chart's sensitivity to variations within the data points. MR of the deviation distribution, $\{\delta_i\}_{i=1}^{m}$, is estimated as the absolute difference between the $i-th$ deviation and its predecessor, the $(i-1)th$.

The process of computing the control limits for MR is as follows:

- The difference between a data point δ_i and its predecessor δ_{i-1} is given by

$$MR = |\delta_i - \delta_{i-1}| \tag{3}$$

- The centre line is computed as the arithmetic mean of the values obtained from step 1 above as follows:

$$\overline{MR} = \frac{\sum_{i=1}^{m-1} MR_i}{m-1} \tag{4}$$

- Calculate control limits

$$UCL = D_4 * \overline{MR} \tag{5}$$

$$LCL = D_3 * \overline{MR} \tag{6}$$

- Using these values, plot the control chart and provide interpretations.

For the individual chart, the control limits are computed as follows:

- Centre line

$$\overline{x} = \frac{\sum_{i=1}^{m} \delta_i}{m} \tag{7}$$

- Control limits

$$UCL = \overline{x} + 3\frac{\overline{MR}}{d_2} \tag{8}$$

$$LCL = \overline{x} - 3\frac{\overline{MR}}{d_2} \tag{9}$$

where d_2, D_3, and D_4 are anti-biasing constants, with values as 1.128, 0, and 3.267, respectively, being the recommended factors for sample size, n = 2 (Montgomery, 2020).

Results and discussions

Data cleaning and transformation

Figure 2a and b demonstrate the improvements achieved in the data after passing it through the pre-processing pipeline. The data points before 1800 were considered outliers and were deleted from the dataset. As well as smoothing out and removing noise from the dataset, the moving average is also used to replace missing values. The data is then normalised to the scale [0,1] to ensure that the models have consistent scale and distribution.

Evaluation of the surrogate model

Figure 3 presents the performance of the models on the data. The first part of the figure showcases how well the models perform on the training subset, while the second part depicts their ability to predict the next CO2 emissions using values from the past three years. Metrics such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and R-squared are used to evaluate the models and are summarised in Table 3. The results show that the LSTM outperforms the other models while the ARIMA performs the worst. Due to its superior performance, the LSTM is selected as the surrogate model for representing the UK carbon emissions during the process monitoring phase. The accuracy of the surrogate model is paramount in reducing the potential interference of model inaccuracy with the CO2 emissions monitoring process.

Process monitoring using SPC

The absolute difference (or deviation) between the actual UK annual carbon emissions (per capita) and the predicted emissions is first calculated across the time series for the monitoring process. The Shapiro-Wilk normality test demonstrates that the data significantly deviates from a normal distribution with p-value ($= 7.997 \times 10^{-13}$) < 0.05. Applying the Box-Cox transformation to the deviation data significantly produced a normally distributed output, with the significance value of the Shapiro-Wilk test, p-value($= 0.596 > 0.05$). Figure 4 demonstrates the data distributions before and after applying the Box-Cox transformation.

Figure 5 presents I-MR control charts obtained from the absolute difference between the model predictions and the recorded UK carbon emissions. Following Nelson's rules for control chart interpretations (Nelson, 1984, 1985), the data points presented in red have been identified as "out-of-control" situations (or assignable causes or special cause variations). Unlike the common cause variations (i.e., data points in blue), which are the natural variations within a system, assignable causes are unexpected. They are often due to external reasons. SPC aims to eliminate assignable variations in several processes, including manufacturing, production, asset management, and service delivery, because they imply a deviation from predictable or known behaviours. However, for a process that seeks to introduce a departure from existing practice, assignable causes could be desirable because they can represent

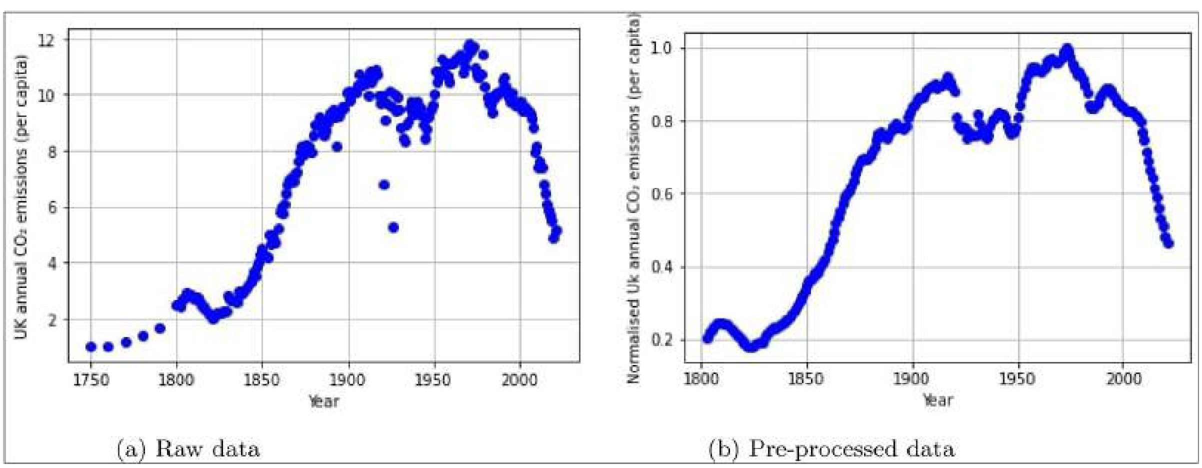


Fig. 2 UK annual CO2 emission (per capita) data

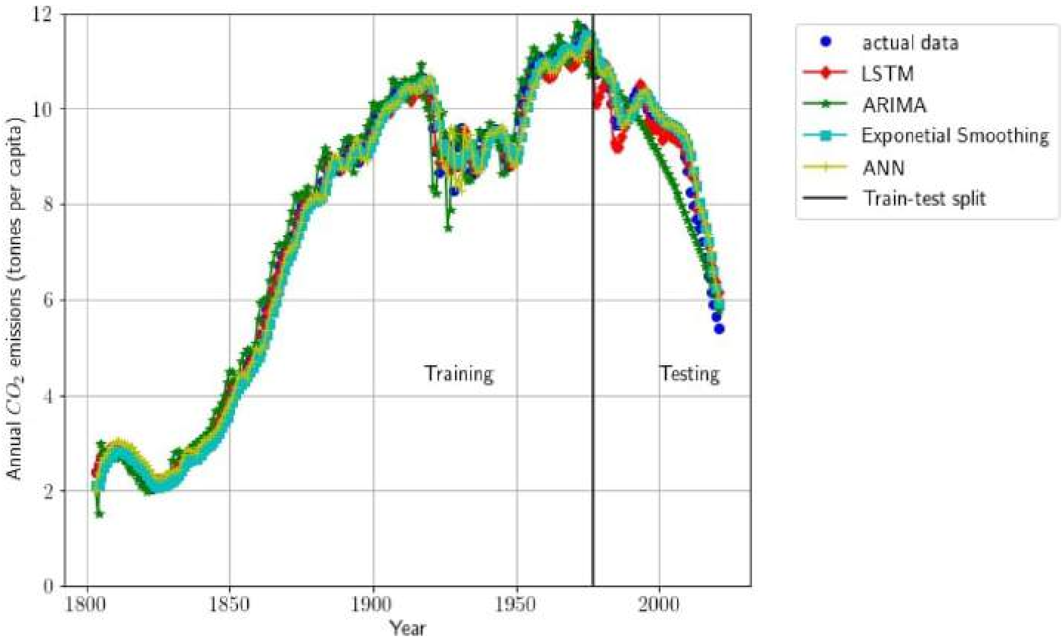


Fig. 3 Models' performance

the effect of the actions introduced to cause the change. An example of the situation above where assignable causes can portray a positive change is the effect of a government's carbon reduction plan on carbon emissions, which is the thesis of this paper. Below are the descriptions of Nelson's eight rules and their general practical insights:

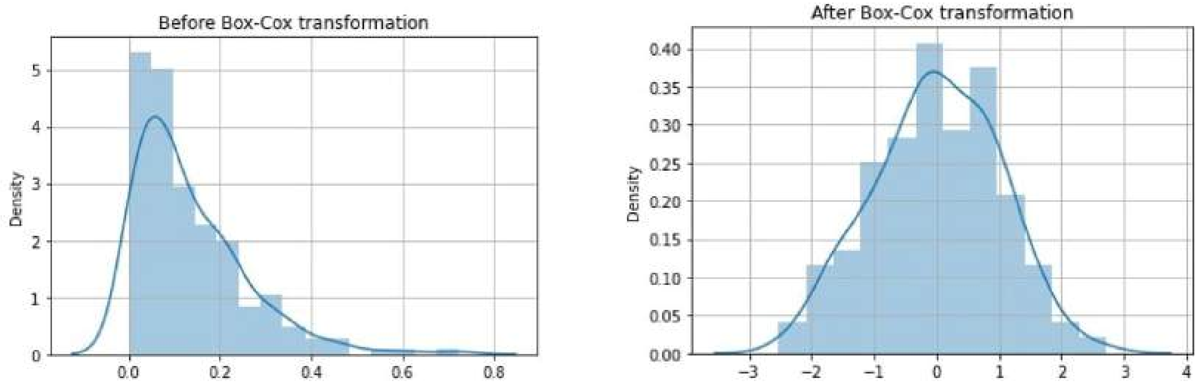
- **Rule 1:** One point is over three standard deviations from the mean — an unusual event or a measurement error.
- **Rule 2:** Nine (or more) points in a row are on the same side of the mean — a slight shift from the average.
- **Rule 3:** Six (or more) points in a row continually increase (or decrease) — a trend pattern.

Table 3 Performance scores of the model

Metric	LSTM	ARIMA	Exponential smoothing	ANN
MSE	0.00044	0.2643	0.0249	0.0737
RMSE	0.020	0.211	0.158	0.272
MAE	0.016	0.403	0.125	0.190
R^2	0.997	0.971	0.997	0.993

- **Rule 4:** Fourteen (or more) points alternate in direction, increasing then decreasing — an over-control pattern.
- **Rule 5:** Two (or more) out of three points in a row are more than two standard deviations from the mean in the same direction — a significant shift from the average.
- **Rule 6:** Four (or more) out of five points in a row are more than one standard deviation from the mean in the same direction — a slight shift from the average.
- **Rule 7:** Fifteen points in a row are all within one standard deviation of the mean on either side of the mean — stratification nature of the process.
- **Rule 8:** Eight points in a row exist, but none within one standard deviation of the mean, and the points are in both directions from the mean — a mixture property of the process.

The numbers on the red data points in Fig. 5 indicate the rules used to confirm the points as out-of-control. In the individual (I) and the moving range (MR) charts, only rules 1, 2, 5 and 6 have been violated. Combining I-chart and MR-chart provides a clear picture of the process behaviours using these rules. I-charts can identify any common or assignable causes within a process by monitoring the mean and shifts in the process. In contrast, MR charts monitor



(a) The deviation data before Box-Cox transformation

(b) The deviation data after Box-Cox transformation

Fig. 4 Box-Cox transformation of the deviation data

the process variations by tracking the absolute difference between known and measured behaviours of the system. Out-of-control situations due to the violation of rule 1 have been highlighted on the I-chart (in 1982,1983,1995,2006,2008, and 2017–2021) and the MR-chart (in 1984 and 2009). Violation of rule 1 can

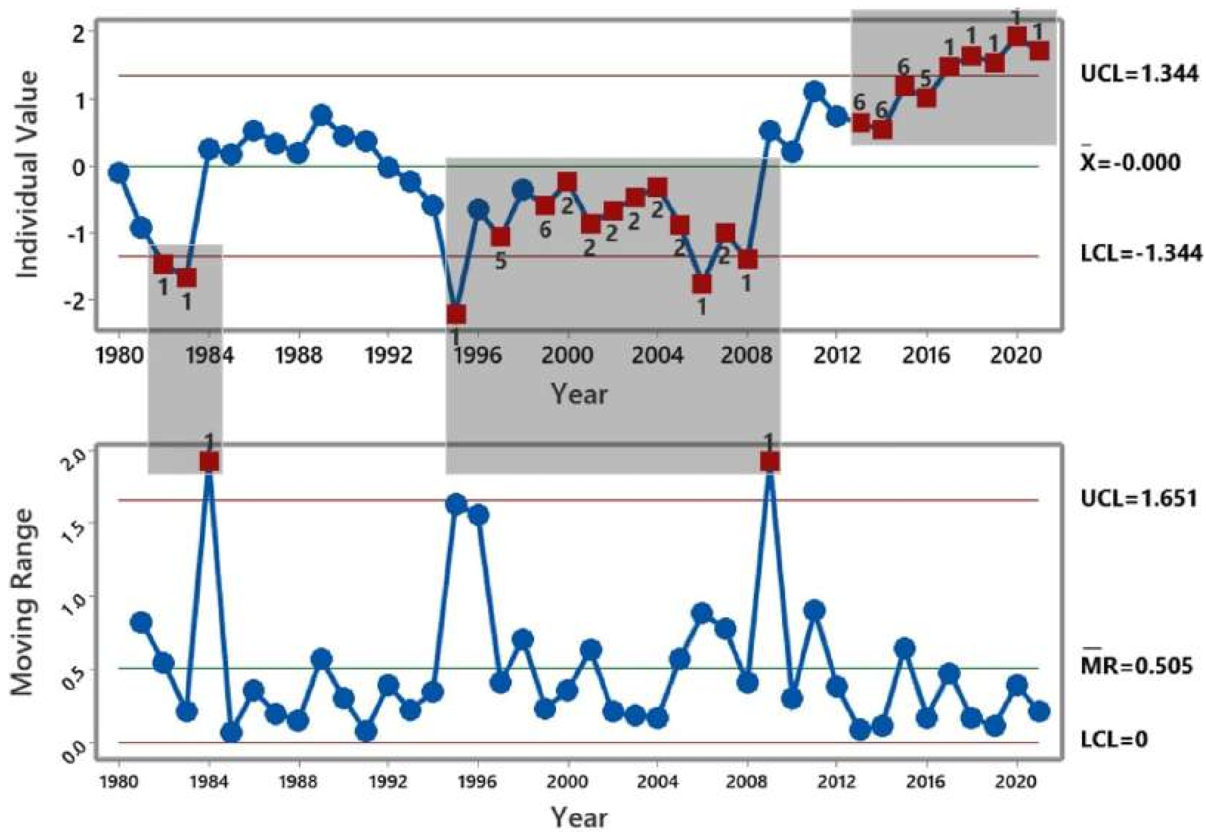


Fig. 5 I-MR Charts of the absolute deviation between the actual and predicted carbon emissions values

be interpreted as the occurrence of an unusual event or an erroneous measurement of data. Deviations from the then-existing pattern in the UK carbon emissions (per capita) have been recorded between 1997–2004 and 2012–2016 and 2000, as highlighted by the data points numbered 2, 5, and 6 in the I-chart, illustrating violations of the corresponding rules. The control charts reveal that activities that impacted the UK's carbon emissions per capita intensified from the mid-1990s to 2021.

In line with the observations from the control charts, according to a technical report from the European Environment Agency, between 1990 and 2012, greenhouse gas emissions in the EU decreased, with Germany and the UK accounting for 50% of the EU's net decrease in emissions within this period (Agency & Agency, 2015). The UK's main contributor was the liberalisation of energy markets and the subsequent switch from oil and coal to gas as a fuel for electricity production (Agency & Agency, 2015).

Moreover, the intensification of the UK's commitments towards carbon reduction from the 1990s follows its choice of 1990 as a baseline year for carbon emissions reductions. This baseline commitment choice was primarily due to the United Nations Framework Convention on Climate Change (UNFCCC), established in 1992 but became effective in 1994 (Bodansky, 1993; Greene, 2000). The convention aimed to stabilise greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. The developed nations agreed to execute national strategies for tackling climate change to lower anthropogenic greenhouse gas emissions to levels observed in a baseline year.

By setting the baseline year at 1990, the UK committed to reducing its emissions to levels below that year's emissions (Barrett et al., 2018; Kelly et al., 2014) through several schemes, including the Paris Agreement and the Kyoto Protocol, involving the first and second commitments, covering the periods 2008–2012 and 2013–2020 respectively. Since then, the UK has set several emissions reduction targets, including achieving net zero emissions by 2050 (Pye et al., 2017). Using 1990 as a baseline year, the UK can track its progress towards these targets and monitor its success in reducing its contribution to global greenhouse gas emissions.

We suspect the natural variation recorded between 2009 and 2013 is part of the response to the measures preceding this period, including the first Kyoto Protocol commitment, which could normalise as part of the baseline. However, the Second Kyoto Protocol commitment and several other efforts introduced a shift from the baseline in 2013, leading to caused variation, as seen on the control chart.

Correlating the UK government's known carbon reduction/energy policies and emissions-related events with the out-of-control periods

The control chart's out-of-control periods (i.e., the shaded region) show correlations with the most significant UK carbon reduction and energy efficiency commitments and plans and events relating to carbon emissions over the years. To demonstrate that the approach in this paper can identify where carbon-related policies and events within the UK may impact its usual carbon emission process, we have identified carbon-related policies and events recorded within the shaded periods. Significant carbon reduction policies and events in the UK that correlate with the shaded regions in the control chart have been presented as follows:

1982–1984

a While no carbon reduction policy or legislation was directly established by the UK government within this period, an earlier policy, such as the UK Energy Conservation Act 1981 (Legislation.gov.uk, 1981), could have affected the CO2 emissions within this period. The Act required energy audits and efficiency measures for public sector buildings and large companies. Its goal was to reduce energy consumption, improve energy efficiency, and promote sustainable development in the UK. Data published by the UK National Infrastructure Commission shows that total inland coal consumption in the UK decreased from 1981 to 1982 by 6.25%.[1]
b A major event within this period, which could impact UK carbon emissions, was the UK miners' strike (from March 84 to March 85) (Adeney & Lloyd, 2021), which led to the closure of many coal mines in the UK. This closure could decrease carbon emissions around this period since coal significantly contributes to carbon emissions. Mamurekli demonstrated that as well as the reduction in the

[1] https://nic.org.uk/app/uploads/Historical-Energy-Data-Final-Dataset.xlsx

UK's coal supply between 1984 and 1985, the UK's coal consumption reduced from 34.6% of the total energy consumption in 1978 to 25% in 1984–85 (Mamurekli, 2010).

1995–2009

a The liberalisation of the energy market in the UK began in the late 1990s (Stanford, 1998) and paved the way for competition in the generation and supply of electricity. The subsequent "dash for gas" in the 1990s saw a significant increase in the use of natural gas for power generation (Spooner, 1995). This refers to a transition among newly privatised electricity companies in the UK towards generating electricity using natural gas. The "dash for gas" caused a decrease in gas prices, a substantial increase in gas-fired power generation capacity, significant improvements in the average efficiency of gas-fired power plants, and a corresponding rise in total gas-fired electricity generation from 4 TWh in 1990 to 140 TWh in 2003 (Graus et al., 2007). Richardson and Chanwai confirm that the "dash for gas" contributed to reducing the UK's carbon emissions within this period (Richardson & Chanwai, 2003).

b The UK government levies a fee on the energy used by industry, farms, and the governmental sector. This fee is known as the Climate Change Levy (CCL) (Pearce, 2006). The programme was first implemented in 2001 to promote energy efficiency and lower greenhouse gas pollution, with plans to cut annual emissions significantly by 2010. Since then, it has incentivised businesses to reduce energy consumption, increase the use of renewable energy, and generate government revenue, but it has also increased costs for businesses. Data is needed to conclude how much this scheme contributed to the variability in the UK's carbon emissions at the outset before it became part of the baseline.

c In 2005, the European Union created the EU Emissions Trading System (EU ETS) as a cap-and-trade programme to lower greenhouse gas emissions from industrial areas (Action, 2013). It limits the overall quantity of emissions that industries can release and covers all EU members, including the UK before it leaves the EU. Companies included in the programme are given permits to cover their emissions. They can purchase or trade these allowances on the market to generate revenue, providing an incentive to cut emissions. Similar to the situation with the CCL, data is needed to conclude how much this scheme contributed to the variability in the UK's carbon emissions at the outset before it became part of the baseline.

d Energy Performance Certificates (EPCs) were introduced in the UK in 2007 (Watts et al., 2011), a significant move towards increasing building energy efficiency and lowering carbon pollution. EPCs offer details on a building's energy efficiency and suggestions for development, assisting in spreading knowledge about energy efficiency and encouraging homeowners and sellers to invest in energy-saving technologies.

e Following the Climate Change Act of 2008, the UK government ratified the Kyoto Protocol and committed to reducing greenhouse gas pollution significantly by 2050 (Skiba et al., 2012). In response, the UK has taken measures to support the use of renewable energy, improve the energy economy, and promote low-carbon transit to meet this goal. For example, the UK has established legally binding carbon budgets, passed the Climate Change Act, and committed to providing international climate finance to support developing countries' climate action. These were targeted at reducing UK's greenhouse gas emissions by 12.5% below 1990 levels by 2008–2012, a target it had exceeded in 2014 (of Energy & Change, 2015).

f A carbon budget, or cap on the amount of greenhouse emissions the UK can release over five years, was established by the Carbon Budgets Order 2009 (UK Government, 2023a) as a piece of UK law. The UK government adopted policies and steps to decrease emissions and provide regular updates on its progress towards achieving these goals.

2013–2021

a To promote energy efficiency and lower greenhouse gas pollution, the UK passed the Energy Act 2013 into legislation (UK Government, 2023b). It consists of several measures, including the Carbon Price Floor, Electricity Market Reform, Green Deal, Minimum Energy Efficiency Standards, and Renewable Heat Incentives. These regulations seek to advance the use of low-carbon technologies, foster the growth of green energy sources, and improve the energy economy of residential and commercial buildings.

b The Carbon Reduction Commitment(CRC) Energy Efficiency Scheme was a mandatory UK government initiative introduced in 2010 to improve energy efficiency and reduce carbon emissions (Committee on Climate Change, 2010; UK Department of Energy and Climate Change, 2010). However, the CRC Energy Efficiency Scheme was criticised for its complexity, which made compliance challenging and expensive. The scheme was reformed in 2013 to simplify the process, focus on energy efficiency and introduce a performance league table to encourage transparency and improvements. It was later replaced by the Streamlined Energy and Carbon Reporting (SECR) framework in 2019 (UK Government, 2021b).

c The UK government launched the Clean Growth Strategy in 2017 to promote economic growth while reducing greenhouse gas emissions and addressing climate change (Ward & Matikainen, 2018). The strategy outlines various measures to achieve this, including improving energy efficiency in homes and businesses, encouraging the use of low-emission vehicles and investing in infrastructure, supporting the development of low-carbon industries, investing in research and development for new low-carbon technologies, and incentivising businesses to reduce their carbon footprint.

d The UK government and the offshore wind industry launched the offshore wind sector deal in 2019 to significantly increase offshore wind power generation (BEIS, 2019). Its goal is to increase the UK's offshore wind capacity by 2030 and expand the number of jobs in the sector while contributing to efforts to combat climate change and reduce greenhouse gas emissions. The deal includes strategies such as investment in new offshore wind farms, improvements to supply chains and infrastructure, and support for innovation and research and development.

e The UK government committed in 2019 to achieve net zero carbon emissions by 2050, aiming to limit global warming to 1.5°C above pre-industrial levels and prevent the worst impacts of climate change (UK Government, 2021a). This target is enshrined in law, making the UK the first major economy in the world to commit to net zero carbon emissions by 2050. Strategies include increasing renewable energy generation, phasing out petrol and diesel cars, improving energy efficiency in buildings, and investing in new technologies.

f The COVID-19 pandemic significantly impacted worldwide carbon emissions (Mehlig et al., 2021). With lockdowns and travel restrictions, energy demand was significantly decreased, particularly from transportation and industry. As a result, carbon emissions in the UK fell to their lowest levels in decades, with a 13% reduction compared to the previous year.

g The UK government introduced the Sixth Carbon Budget in December 2020, aiming to achieve the country's net zero emissions objective by 2050 by lowering greenhouse gas emissions by 78% by 2035 compared to 1990 (UK Government, 2021c). The plan outlines sector-specific emissions reduction goals and methods for achieving them, including growing renewable energy sources, enhancing the energy economy, and utilising fewer fossil fuels for transportation. The UK government accepted the Committee on Climate Change's proposals and plans to propose legislation to formalise the goals.

Conclusions and recommendations

This research demonstrates the application of a hybrid technology comprising deep learning and statistical process control in monitoring the impact of the government's carbon reduction policy on carbon emissions within the UK economy. We first developed the surrogate model of the carbon emissions process of the UK and computed the deviation of out-of-sample measured data from the model. I-MR was employed to identify regions of special cause variations, which we demonstrated to correlate with significant carbon reduction policies of the UK government and known events, such as COVID-19, that can impact UK carbon emissions. However, there are still aspects of this work that warrant future research. For example, it can be challenging to identify each policy's or event's contributions to an out-of-control region. Also, we cannot demonstrate whether the responses on the control charts emanated from the long-term or short-term effects of policies. Solving these problems will make it possible to investigate the impact of individual policies and how long they take to reflect on the process. In our future related work, we aim to explore explainable AI applications on this task, leveraging explicit dummies to understand better the influence of policies of interest on carbon emissions data. This paper considers the government's carbon reduction policies and events such as COVID-19; however, several other events can impact carbon emissions. These activities include economic development, technology, agriculture, and imports. Investigating the impact of changes in the actions within these activities will be a valuable further contribution to knowledge. Although our method cannot recommend future climate policies, when used in combination with a qualitative approach it can be helpful in identifying the impact of existing policies and determining which ones to reinforce for more effective CO2 emissions control.

Author contributions Chinedu Pascal Ezenkwu worked on the study's conceptualisation, developing the methodology, implementing the research, and writing the manuscript. San Cannon provided a critical review of the work, contributing to the content relating to the UK government's carbon reduction commitments and providing suggestions for improvement in the manuscript. Ebuka Ibeke contributed to the workflow of the study, including the statistical analysis and data interpretation, and also provided a critical review of the technical content of the paper.

Data availability The data source for this research has been cited in this paper; it is publicly available on 'Our World In Data' https://ourworldindata.org/co2/country/united-kingdom.

Declarations

Ethics approval All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Author" as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Conflict of interest The authors declare no competing interests.

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Artificial intelligence and the environment: ethical challenges and strategic opportunities for organizations

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ABSTRACT

In this viewpoint article, our goal is to raise awareness and spark debate in the Information Systems (IS) community regarding a prominent concern that has important strategic and ethical implications: the environmental impact of the increasing use of generative artificial intelligence (GAI). We examine several specific issues, beginning with GAI's heavy consumption of natural resources and electricity. We then move to assessing how the rich and the Global North gain via GAI, while the poor and the Global South must deal with its adverse effects. We then move to assessing GAI's impact on underrepresented communities and countries in the Global South; while GAI contributes to global warming, this affects people unevenly, because it is mostly rich people and the Global North that make intensive use of these technologies. After suggesting that more local and global laws are needed to regulate the sustainable use of AI, we report on how organizations can perform *AI strategizing*, for instance to control emissions in smart cities and improve weather forecasting. We conclude with a research agenda that aims to encourage IS scholars to focus on the environmental impact of AI, its ethical implications for organizations, and how GAI can be used strategically to benefit all.

Introduction

Artificial intelligence (AI) has been around for several decades. However, only since the 2010s have we witnessed AI's widespread diffusion, in large part due to the big data revolution (McAfee and Brynjolfsson 2012) and the increased capabilities of contemporary computers. AI, and its most recent development generative AI (GAI), has the potential to benefit a cornucopia of activities such as automation (decision-making processes, robotics industry), online content creation and moderation, customer-facing processes (chatbots), and e-commerce website management (and nudging). With these strategic opportunities, ethical challenges surface (Marabelli and Davison 2025). For instance, biased systems (e.g., hiring/firing systems, AI supporting juridical systems) can lead to discrimination and privacy concerns, such as how GAI employs user prompts (among other data sources) to train its algorithms.

While these AI issues are well-known and broadly discussed by IS scholars, AI's impacts on the environment are significantly understudied. Focusing on AI's impacts on the environment is, however, important because AI is "resource hungry[1]" and contributes to greenhouse gas emissions. For instance, the data centers powering AI already account for up to 2 % of global energy demand, a figure that is close to what is currently consumed by the airline industry. The continuous rise in AI use will cause this figure to surpass 20 % of

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[1] https://www.nytimes.com/2024/07/11/climate/artificial-intelligence-energy-usage.html.

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the global energy demand by 2030, according to a recent MIT report (Stackpole 2025). The reason for this vast consumption of power relates to the fact that new AI models, notably GAI, require constant training (even when the systems are "in production") and thus a considerable amount of processing power. In addition, rigorous measures of GAI's impact on the environment are still unavailable (Luccioni and Hernandez-Garcia, 2023). This represents an important departure from more traditional AI systems, for instance those used to automate routine processes such as inventory management, which require less in the way of "constant" training. Given the current pace of global warming due to the increased emission of greenhouse gases and given that global warming impacts are not distributed evenly across communities worldwide, we need to ask and obtain answers to the following questions:

- *What is the actual impact of GAI on the environment?*
- *Why is GAI so resource demanding?*
- *What can we do to mitigate GAI's negative impacts on the environment, especially when climate changes affect communities unevenly?*
- *What are the strategic opportunities for organizations and government concerning the use of GAI to mitigate global warming and address climate changes issues?*

The goal of this viewpoint article is to discuss the above questions and create awareness in the IS (information systems) community regarding the ethical challenges and strategic opportunities associated with GAI that concern the environment. A discussion around technologies and the environment constitutes a sociotechnical topic that will, we believe, appeal to IS scholars, and is something that *JSIS* has historically supported, for instance with respect to sustainable IT and green IS (cf. Bengtsson and Ågerfalk 2011; Butler 2011; Dao et al., 2011; Petrini and Pozzebon 2009). GAI, like most technologies, has a bright and a dark side (Bohnsack et al., 2022). For instance, and related to the environment, the recent push to adopt electric vehicles to reduce the short-term release of greenhouse gases poses long term challenges associated with the disposal of batteries. Similarly, the widespread deployment of GAI focusing on automating routine tasks poses environmental concerns stemming from these systems' demand to be constantly trained with large datasets. This training indirectly requires considerable amounts of natural resources (primarily water) and electricity. In sum, GAI training leads to the release of greenhouse gases, and the use of huge quantities of water. Meanwhile, global warming is a direct consequence of greenhouse gas emissions.

Global warming contributes to such extreme climate events as storms/hurricanes/cyclones, droughts, wildfires and floods. What is more, global warming unevenly affects communities worldwide. For instance, in rural, hot, less-developed areas, heat waves disproportionately affect the poor who need to work either outdoors (agriculture, construction) or in factories and mills without air conditioning systems and who cannot afford cooling systems in their own homes. However, GAI is mostly produced and consumed in urban, rich areas where residents are more likely to have air conditioning systems both at home and in the workplace. Thus, while global warming affects everyone, AI producers and consumers (where AI-related pollution originates) suffer fewer consequences associated with global warming than those who are not (and might never be) AI producers or consumers. Consequently, the uncontrolled use of GAI by organizations has the potential to generate *social injustices*, specifically penalizing marginalized populations and poor countries.

It is however important to note that, in the last few years, GAI was used, strategically, to mitigate the release of greenhouse gases and respond to our fast-changing climate. For instance, organizations and government institutions have started to design systems supporting smart cities (e.g., to reduce traffic, and therefore pollution), aiding agricultural systems (e.g., to optimize harvesting techniques), and improving weather forecasting (Fang et al., 2023; Musa 2016). Nuclear power, a source of energy that involves the release of minimal amounts of greenhouse gases, is used to generate electricity in limited amounts. For instance, in 2024 nuclear power provided roughly only 9 % of the world's electricity from 440 power reactors.[2] But GAI's widespread diffusion and the demand to power these systems with green sources of energy might boost the development of nuclear plants worldwide. For instance, Google is leading important initiatives related to nuclear power and partnering with Kairos Power aimed at "accelerat[ing] a new technology to meet energy needs cleanly and reliably, and unlock the full potential of AI for everyone."[3] Clearly, regulations at the local and global level will play an important role enabling (or constraining) GAI-based innovations, together with disciplining organizations' behaviors with respect to the (mis)use of these technologies with respect to environmental impacts.

In sum, technologies can serve the goal of addressing grand challenges such as global warming (Nambisan and George 2024) and implementing the application of cutting edge innovations to environmental sustainability (George et al., 2021). However, in our opinion, current IS research has focused mostly on the apparently positive impacts of technologies on the environment. In this viewpoint article, we aim to lay out our concerns regarding the increased use of GAI, while acknowledging its potential to benefit the environment (or at least to not generate more harm). Fig. 1 below portrays a roadmap of our viewpoint of AI and the environment, which reflects how the rest of the paper unfolds.

Next, following our roadmap, we provide an overview of GAI's impact on the environment and explain why GAI needs so much more natural resources and electricity than traditional information systems. We then move to the ethical challenges and focus on the AI value chain (all actors involved from design to use) because AI systems require significant resources throughout their lifecycle. To this end, an important issue we discuss concerns the lack of rigorous and transparent ways to assess AI's potentially negative effects on the environment. We further provide examples of how AI might create social injustice due to its unequal effects on the environment and reflect on what institutions could do to regulate the industry.

[2] https://world-nuclear.org/information-library/current-and-future-generation/nuclear-power-in-the-world-today.

[3] https://blog.google/outreach-initiatives/sustainability/google-kairos-power-nuclear-energy-agreement/.

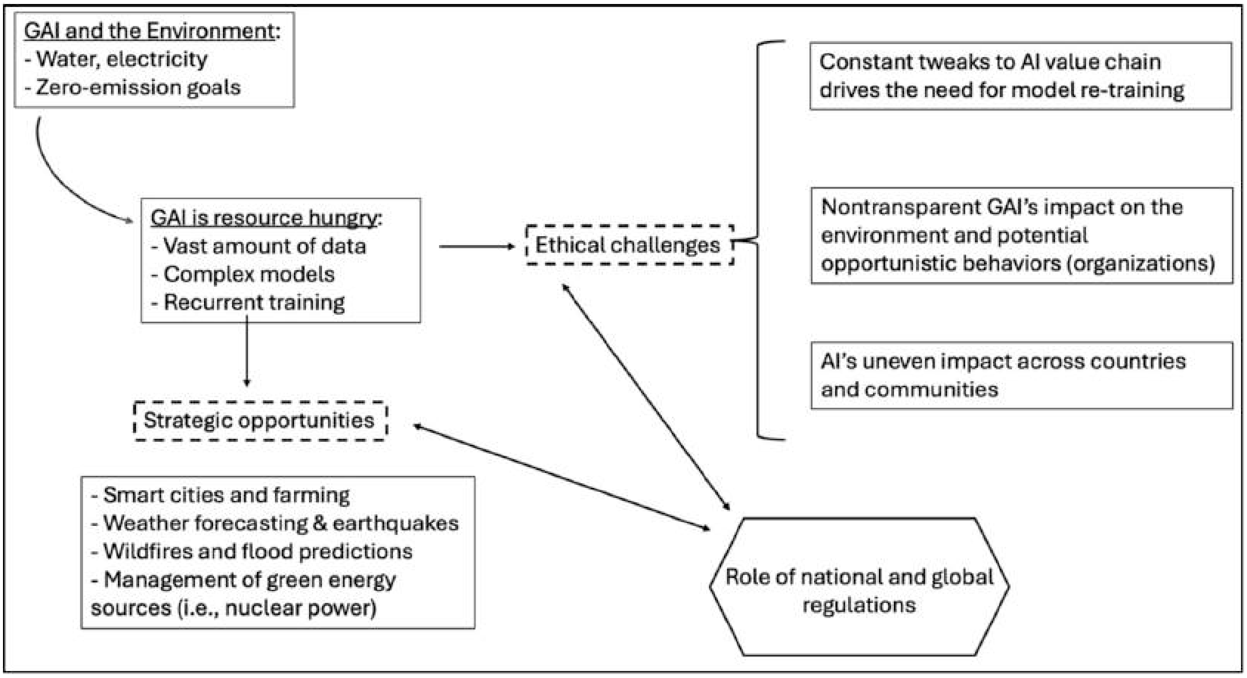

Fig. 1. AI and the environment: a roadmap.

Finally, we move to the potential benefits of AI, which include the creation of smart cities (to reduce traffic, and therefore greenhouse gas emissions), smart agriculture, weather forecasting systems and so on. The outcome of our roadmap consists of reflections on the strategic use of AI to address climate changes and advice for IS scholars on potential avenues of further research and theorizing around AI and the environment, with the goal to advance knowledge and insight on this important topic in our field and beyond – for instance computer science, management, and other scientific disciplines that study earth phenomena.

Overview of GAI's Relationship with the Environment

GAI is a significant consumer of both natural resources, which may be in short supply, and electricity, which in many countries is prevalently generated in coal-fired power stations that also emit significant volumes of greenhouse gases (Li et al., 2023b). In fact, compared with "traditional" AI, GAI models require far higher volumes of natural resources and electricity, because their models need to be constantly trained, as in the case of cf. for instance large language models (LLMs) used by GAI such as ChatGPT.

Natural resources primarily refer to water to cool down the systems that run the intense processing activities that training GAI models requires. Electricity powers and keeps AI systems up and running 24/7. The demand for these resources to train GAI models in data centers is destined to increase exponentially over time.[4] What is more, GAI applications need to be trained for their entire lifecycle (Chandhiramowuli et al., 2023). For these reasons, organizations that use GAI intensively face challenges with meeting so-called net-zero emissions, a goal for businesses such as Google,[5] one of the most prominent AI organizations. Net-zero emissions means that the amount of emissions added to the environment should not exceed the amount taken away by the same organization or entity. Emissions refer to greenhouse gases released into the atmosphere, which trap heat and contribute to global warming, a trend we've witnessed for the past century at least.[6] These gases include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases (all these gases are collectively referred to as greenhouse gases). Carbon footprints are measured in tons of greenhouse gas emissions, which are converted into carbon dioxide equivalent (CO_2e), a standard unit for measuring carbon footprint. Pushing organizations to achieve net-zero emissions has unfortunately also led to greenwashing,[7] a phenomenon that we discuss later in this paper.

[4] https://www.goldmansachs.com/insights/articles/AI-poised-to-drive-160-increase-in-power-demand.
[5] https://sustainability.google/operating-sustainably/net-zero-carbon/.
[6] https://earthobservatory.nasa.gov/world-of-change/global-temperatures.
[7] https://www.un.org/en/climatechange/science/climate-issues/greenwashing.

GAI is resource hungry

GAI is resource hungry.[8] Hugging Face, a US organization based in New York that develops AI applications in collaboration with researchers at Carnegie Mellon University, found that it takes as much electricity to fully charge a smartphone as it does to generate an image using GAI (Luccioni et al., 2023). Moreover, the use of these applications is widespread and available free of charge on online platforms, which means that individuals can access these systems at all times and "play" with GAI. These systems benefit from receiving countless prompts, all of which contribute to training. However, this crowd-based *constant training* increases the demand for natural resources and electricity.

GAI is resource hungry because in order to be trained it needs a vast amount of data, generally obtained by scraping the web and by analyzing users' prompts. Resources also refers to the natural resources, such as rare earth metals (e.g., Gallium and Germanium) needed to fabricate chips, but also, more importantly, water, a scarce resource in many countries yet one that is essential to cool down high-speed computers. Some water can be reused, and some is discharged (in the environment), but a considerable amount evaporates.[9]

For instance, Spain is a country that, on average, experiences very high temperatures in the summer with only mild temperatures in winter, yet that has limited precipitation. In 2022, Spain struggled with drought to the point that local authorities recommended that residents should use water parsimoniously and not water their gardens. Along with a high risk of wildfires (Pausas and Keeley 2021), as a direct consequence of this drought the Castilla La Mancha region, which produces a quarter of all Spanish grain, was expected to lose up to 90 % of its 2023 harvest. Nevertheless, in 2023, Meta announced plans to build a US$1.1 billion data center in Talavera de la Reina, a city in central Spain, that would likely use around 176 million gallons of water/year for cooling.[10] Similarly, Microsoft uses water in Arizona (US) (a state where the average daytime temperature in its summer nears 100 °F/38 °C) to cool down AI servers.[11] Li et al. (2023a) suggest that global AI demand could cause data centers to consume 1.1 trillion to 1.7 trillion gallons of water by 2027.

Researchers at the University of California who studied water footprint related to AI, found that GPT-3, a LLM that OpenAI released in 2020, consumes roughly one liter of water to cool down a computer for every 40–100 responses. GPT-4 consumes even more (Li et al., 2023a). In 2022, Google and Microsoft combined, consumed 8.5 billion gallons of water, mostly in their data centers, which is equal to how much water 700,000 people in a rich country consume annually.[12] Projections about future water use to cool down AI systems are not encouraging: by 2027, the global demand for water for AI could be half that of the UK's annual consumption (Wu et al., 2022).

It is debatable whether Western countries should promote investments by large organizations such as Meta at the expense of their own citizens' water needs. But the fact that water is such a key resource makes it even more problematic for organizations to use these systems in the Global South, where even residential properties often lack running water. This creates an unfair situation: Global South countries, where water is often scarce, have less potential to create and use AI systems internally (let alone the possibility to become profitable venues to host data centers from Global North countries). For instance, and solely referring to Africa, the United Nations considers Chad, Comoros, Djibouti, Eritrea, Ethiopia, Liberia, Libya, Madagascar, Niger, Sierra Leone, Somalia, South Sudan, and Sudan as "water insecure" countries.[13]

Along with natural resources such as water, most AI systems need a considerable amount of electricity for everyday use/training. For instance, while a rack of web or mail servers generally runs on 7 kW of electricity, AI racks need up to 100 kW. The situation becomes more serious when it comes to GAI. For instance, it costs OpenAI more than 50 GW-hours of electricity to train GPT-4, more than 50 times more electricity than training its predecessor, GPT-3, required. In 2022, worldwide data centers, including Amazon's cloud and Google's search engine, used about 1 to 1.3 percent of the world's electricity.[14] However, GAI-based tasks such as creating an image from a prompt can be performed routinely, free of charge, on several onlinxe platforms that offer GAI. A 2023 report by the International Energy Agency projects that the growth of AI will cause energy consumption in data centers to double by 2026.[15] Because of the lack of specific applications to measure AI's negative impact on the environment, it is hard to make long-term predictions. Nevertheless, optimistic reports from the United Nations predict that by 2030 AI will be able to substantially support the environment by "optimiz[ing] grids and increase[ing] the efficiency of renewable sources.[16]

In summary, GAI's resource-hungry nature calls for a reflection on how organizations currently use and will use AI systems. This poses three issues that involve ethical considerations. The first concerns time. Organizations train AI models not only during the design phase; these models, in ordet to provide timely answers and improve their response quality constantly need training. This means that

[8] https://www.nytimes.com/2023/10/10/climate/ai-could-soon-need-as-much-electricity-as-an-entire-country.html.

[9] https://dgtlinfra.com/data-center-water-usage/.

[10] https://www.bloomberg.com/news/articles/2023-07-26/extreme-heat-drought-drive-opposition-to-ai-data-centers.

[11] https://www.theatlantic.com/technology/archive/2024/03/ai-water-climate-microsoft/677602.

[12] https://www.economist.com/technology-quarterly/2024/01/29/data-centres-improved-greatly-in-energy-efficiency-as-they-grew-massively-larger.

[13] Water security refers to "the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability".(https://www.unwater.org/publications/what-water-security-infographic).

[14] https://www.iea.org/energy-system/buildings/data-centres-and-data-transmission-networks.

[15] https://iea.blob.core.windows.net/assets/6b2fd954-2017-408e-bf08-952fdd62118a/Electricity2024-Analysisandforecastto2026.pdf.

[16] https://news.un.org/en/story/2023/11/1143187.

they demand resources in the long term, substantially affecting GAI's *value chain*. The second concerns the extent to which it is possible to assess AI's *direct and indirect impact* on the environment; we recognize that our ability to assess impact is currently limited. The third concerns *social justice*, and the uneven negative effects that AI has on the environment; AI's contribution to global warming affects worldwide populations in different ways. We outline these three ethical concerns next.

GAI's value chain and constant training

As we noted above, training AI models represents a major challenge for the environment because their computational capabilities require significant resources. But it is important to note that training is not a one-off process. Models are initially trained during/after the design phase to test their potential for deployment, the so-called "production" phase. Nevertheless, once an AI model operates in the real world, the value chain of AI needs constant tweaks that humans supervise during the whole AI lifecycle (Chandhiramowuli and Chaudhuri, 2023). Accordingly, the nature of AI models leads to two important ethical implications. First, the "automated" part of this constant training will intensely and continuously use precious resources (i.e., water and electricity). Second, organizations often outsource the "manual" part to contractors and gig workers in the Global South. These people, located in countries like India, Pakistan and Venezuela, are often egregiously exploited. For instance, minors are often recruited to perform microtasks to train AI systems for little pay over long shifts and in unhealthy work conditions.[17] Thus, we can see that other ethical considerations involving exploited Global South workers compound AI's ethical implications for the environment.

The fact that GAI systems need constant training has important ethical consequences affecting its value chain, which seems to generate value only for some actors in the chain (i.e., the high-tech organizations that produce and use these systems at the expense of contractors in their lifecycle and end users). A focus on end users here is important because AI systems also affect consumer spending via so-called online nudging practices, which e-commerce websites use to subtly persuade users to purchase what they don't need (Mirbabaie et al., 2023). For instance, Amazon pushes customers to purchase several items, often located in different warehouses with options such as "same day" or "two-hour" delivery, which helps to support a gig economy that comprises workers who drive long hours day and night to deliver items.

The practices described above regarding the gig economy lead to unnecessary emissions and extra maintenance costs, e.g., from using private vehicles more often. In addition, ground transportation has its own issues, regardless of whether gig workers use their own vehicles or company-provided vehicles (cf. Amazon trucks); producing and using tires creates environmental hazards. The manufacture of tires requires both nonreusable components and electricity, while the use of tires releases tire wear particles from abrasion that become especially dangerous when entering aquatic environments (Tamis et al., 2021; Trudsø et al., 2022). Furthermore, this example of AI-powered nudging on websites, with side effects associated not just with ethical implications concerning nudging but also with ethical implications concerning more driving (including potential fuel consumption and the plastic materials used to package items), represents just one among many examples involving secondhand effects of AI. We suggest that studying the environmental implications of pervasive and invasive AI use should also account for indirect effects. We are aware that it is generally difficult to quantify a phenomenon's indirect effects. In the case of AI and the environment, even direct effects that might turn into an ethical issue are difficult to quantify as we explain next.

AI assessments and ambiguities

While it is well known that AI systems require a considerable amount of resources, we lack rigorous ways to measure AI's actual carbon footprints. This nontransparent aspect of GAI's impact on the environment creates opportunities for organizations to pursue environmentally-unfriendly initiatives with poor vetting from institutions and the general public. Opportunistic behaviors associated with environmentally-unfriendly initiatives in general terms are particularly prone to occur within the global tech industry and account for as much as 3.9 % of worldwide greenhouse gas emissions, with AI representing a significant fraction of that number. However, it is not clear how much AI and GAI specifically (notably the resources required to train models) contributes to the carbon footprint, and scholars have suggested creating a centralized repository to report and track AI-related emissions (Luccioni and Hernandez-Garcia, 2023). For instance, according to Luccioni et al. (2023), between 2017 and 2021, the volume of electricity that four organizations (Meta, Amazon, Microsoft, and Google) used doubled, and global data center electricity consumption has grown by up to 40 % annually in recent years. It now accounts for almost 2 % of global electricity consumption and contributed 1 % of energy-related greenhouse gas emissions in 2022 (Stackpole 2025). However, to what extent AI specifically contributes to these figures remains unclear. It is nevertheless credible to suggest that AI's contribution to greenhouse gas emissions will grow in the near future, because of the race to build powerful GAI systems (MIT News 2025).

Dodge et al. (2022) built a framework to measure the carbon footprint of AI applications that run in the cloud. They also noted that organizations that act strategically with respect to where they build data centers (i.e., their physical locations) can reduce AI's carbon footprint. Picking strategic locations to build data centers involves building facilities in regions with a colder climate (e.g. in higher latitudes or altitudes). This can reduce how much water or electricity they use. Needless to say, systems trained in areas where energy production relies more heavily on fossil fuels are more prone to releasing more greenhouse gases (cf. also Kirkpatrick 2023).

While organizations such as Microsoft have attempted to release accurate information on greenhouse gas emissions, it is much more

[17] https://www.wired.com/story/artificial-intelligence-data-labeling-children/.

difficult to obtain similar information with respect to the supply and value chains (Joppa et al., 2021). In addition, organizations developing AI models do not have specific incentives to share quantitative data on resources used to build and run such models. In fact, in many countries, no laws mandate organizations to report on their carbon footprint. This echoes longstanding problems associated with the same (high-tech) organizations not being willing to share internal research findings, e.g., on the potential issues associated with social media issues (addiction, etc.) and damages to adolescents. A good example from the near past is Instagram, where only thanks to a whistleblower was the public made aware of the platform's negative effects on young people with eating disorders (Marabelli and Newell 2023).

Assuming that organizations will be required to share their AI carbon footprint (or will decide to do so for marketing purposes, i.e., to look good to the general public), they may anyway attempt to game the system through greenwashing practices, encouraged by the lack of objective and precise measurement of greenhouse gas emissions. For instance, a large study by the European Union (EU) concerning organizations across EU member countries[18] found that, in 2022, 53 % of green claims published by organizations gave vague, misleading, or unfounded information while 40 % of claims had no supporting evidence. But even when organizations report precise data on their green claims, they can still purchase carbon offsets without changing their behavior. Carbon offsetting, according to earth.org, refers to "a process through which organizations or individuals compensate for their greenhouse gas emissions by investing in an equivalent removal of such emissions from the atmosphere. This offsetting occurs through projects like reforestation, renewable energy, methane combustion/collection, and energy conservation.[19]" Carbon offsetting gives organizations credits in the form of tokens that they use to account for net climate benefits from one entity to another; entities can trade these credits once a certified authority approves them.

Organizations keen on pursuing environmentally unfriendly or unsustainable AI-related projects might purchase credits by giving money to initiatives, e.g., to preserve forests in South America, while keeping up with intensive GAI training and with this achieving net-zero emissions, because the purchase of credits offsets the release of pollution generated by their computers. This practice is, in our opinion, both dangerous and disingenuous: it avoids the need to consider how to create long-term solutions for developing AI systems in a sustainable manner and, more importantly, does not address issues associated with the uneven distribution of negative consequences stemming from global warming, a topic that we discuss in the next section.

AI and social justice

AI's impact on the environment is not evenly distributed across countries and populations. A 2017 United Nations study systematically analyzed climate change with respect to social justice and concluded that "*initial* inequality causes the disadvantaged groups to suffer *disproportionately* from the adverse effects of climate change, resulting in greater *subsequent* inequality" (Islam and Winkler 2017 emphasis in original). There are numerous examples of such situations. For instance, Meta and Amazon are known to have shown interest in building data centers in Spain and in the US state of Arizona state respectively (both regions being prone to drought). These examples of Global North countries add to the list of similar practices happening in the Global South, where the consequences of climate changes are more likely to affect citizens. For instance, Amazon (among other organizations) is building data centers in Huechuraba (Chile), a district with ongoing drought problems. Amazon's spokespersons reported that the organization is "DIA (Declaration of Environmental Impact) compliant[20]", yet this begs the question as to whether organizations realize that legal compliance does not equate with being ethical.

In a similar way, in January 2025, Alibaba (a Chinese multinational technology company specializing in e-commerce, retail, Internet, and technology) opened a data center in Querétaro, Mexico, allegedly to bring "world-class cloud technology to support local businesses[21]". Here too we wonder about the extent to which local communities will be penalized, as data centers are water and electricity demanding and Mexico is already a country where both resources are scarce. Amazon, Microsoft and Google together make up 65 % of the world's cloud service market and are the leaders in data centers in Africa, with operations mainly concentrating in South Africa.[22] The IEA[23] (International Energy Agency) forecasts that the US and China, the world's two top greenhouse gas polluters, could consume a lot more electricity by 2027. In addition to large providers wanting to build data centers in the Global South, local organizations are also building their own data center infrastructures. For instance, in Nigeria, organizations are building their own data centers, which represent affordable alternatives for local communities, if compared to large providers.[24] While on the one hand one might suggest that large providers take advantage of weak economies in the Global South, on the other hand, it is arguable that if a data center has to be built in a weak economy, larger providers could be better positioned to use more energy-efficient hardware (when compared with local providers that may not be able to invest in energy-efficient equipment) and offer more capabilities to benefit the region or country.

All the above evidence is worrying, given that countries that intensely use AI to foster automation release a disproportionally higher level of AI-related pollution to the environment as compared with countries that minimally use AI. However, the impact of AI on the

18 https://environment.ec.europa.eu/topics/circular-economy/green-claims_en.
19 https://earth.org/is-carbon-offset-a-form-of-greenwashing/.
20 https://restofworld.org/2024/data-centers-environmental-issues/.
21 https://www.scmp.com/tech/big-tech/article/3299333/alibaba-opens-first-data-centre-mexico-ramping-ai-infrastructure-expansion
22 https://www.canalys.com/newsroom/worldwide-cloud-services-q2-2024.
23 https://www.iea.org.
24 https://restofworld.org/2025/aws-google-cloud-nigeria-alternatives/.

environment is felt globally. For instance, India (which has nearly 18 % of the world's population) generates just 3 % of the world's air pollution but pays a high price due to global warming (e.g., it recorded temperatures as high as 110 °F/43.3 °C in June and July 2022[25]). In June 2023, temperatures in India reached the "limits of 'survivability'[26]" with 116 °F/47 °C recorded in Uttar Pradesh, affecting 220 million people, and causing nearly 50 additional deaths. In the same period, Phoenix, Arizona, US (where Microsoft has built data centers), reached temperatures over 109 °F/42.7 °C. But Arizona and Uttar Pradesh differ substantially. Most residents in Arizona can adequately deal with hot temperature; more than 90 % of urban homes have air conditioning systems.[27] Meanwhile, in Uttar Pradesh very few people have air conditioning systems.[28] However, only 8–10 % of Indian households have air conditioning systems, and the electricity itself is often subject to outages[29] (Pavanello et al., 2021).

Overall, the Global North generates more heat, and its residents deal with it by fighting high temperatures using resources that, in turn, contribute to global warming. On the other hand, the Global South contributes far less to global warming but suffers more because it generally does not have the resources to deal with it, and air conditioning systems make matters even worse because they consume yet more electricity. This reflects evidence that countries and populations that contribute the least to global warming pay the highest price. In 2023, *The Guardian* conducted a study with Oxfam[30] and the Stockholm Environment Institute[31] (among others) called *The Great Carbon Divide* in which they studied causes and consequences of carbon inequalities and the disproportionate impact of rich individuals and countries (named "the polluter elite"). According to the study, it would take 1,500 years for someone in the bottom 99 % of the world's population to produce as much CO_2 as the richest billionaires do in one year.

The 2023 AI global index[32] benchmarks 62 countries based on their AI investment, innovation, and implementation. The US, China, and the UK top the list, while Kenya, Nigeria, and Pakistan are the bottom three. As the deployment of GAI becomes prevalent, AI's role in global warming will also increase, further penalizing countries that don't use this technology. If we focus on local contexts, the benefits of using AI are remarkable. For instance, consider smart cities (which we discuss later in this article): regulating traffic could lower CO_2 emissions to a degree that more than compensates for the emissions that result from running AI models that calculate how to regulate traffic. However, by definition, global warming is a "global" issue. Therefore, the logic that relies on AI's cost-benefit analysis should shift from a local to a global perspective. Is it ethical to reduce the pollution in San Francisco with advanced (and resource demanding) GAI models, if doing so means releasing greenhouse gases contributing to global warming, and thereby penalizing other regions in the world with little to no means to cope with rising temperatures, such as the previously mentioned example in India? We argue that it is dangerous to try to measure AI pros and cons locally, because this (typically Western) approach ignores (local) Global South realities where AI is seldom used, and where populations experience only the negative consequences of the mass adoption of innovations (including AI) generating greenhouse gases.

National and global regulations: protecting (or not) the environment from AI use

The emergence of algorithmic-based data collector systems, associated with the massive use of AI (and more recently GAI) have increasingly become the focus of government regulations (see the EU's General Data Protection Regulation[33] (GDPR) and AI Act,[34] China's Personal Information Protection Law[35] (PIPL), and the US' Blueprint for an AI Bill of Rights[36]). These regulations focus mainly on data privacy (cf. GDPR and PIPL), something now very relevant to AI, if we consider that the level of confidentiality with which prompts from users are treated is unclear (cf. EU AI Act and US AI Bill of Rights). However, most countries lack specific regulations on how organizations should (or should not) use AI in a sustainable fashion. For instance, the EU's AI Act mentions that "This regulation aims to ensure that fundamental rights, democracy, the rule of law and environmental sustainability are protected from high-risk AI", but it does not specify what kind of high-risk activities qualify as dangerous for the environment. The AI Act distinguishes between low, medium, and high risk (of using AI) based on the extent to which humans are directly affected by the consequences of using AI.[37] For instance, an AI that prioritizes access to an important vaccine would be defined as high risk because its outputs are close to humans (and a problematic algorithm would impact them directly), whereas an AI that serves as a videogame engine or that manages an antispam system would be defined as low risk. The problem here is about invisible connections between, e.g., training a LLM and the consequent harm to humans. In addition, the EU's framework doesn't account for the secondhand environmental implications of using AI. For instance, how much greenhouse gas production does programming and using videogames cause? AI and videogames are

[25] https://www.technologyreview.com/2022/07/05/1055436/download-india-deadly-heatwaves-climate-change-carbon-removal/.
[26] https://www.cnn.com/2023/06/26/india/india-heatwave-extreme-weather-rain-intl-hnk/index.html.
[27] https://www.theguardian.com/us-news/2022/jan/27/phoenix-arizona-hottest-city-cooling-technologies.
[28] https://www.npr.org/sections/goatsandsoda/2022/08/02/1114354904/opinion-life-hacks-from-india-on-how-to-stay-cool-without-an-air-conditioner.
[29] https://www.theguardian.com/world/2023/dec/05/india-unstoppable-need-air-conditioners.
[30] https://www.oxfamamerica.org.
[31] https://www.sei.org.
[32] https://intersog.com/blog/ai-dominant-players-and-aspiring-challengers/ (raw dataset of this study available here: https://www.kaggle.com/datasets/katerynameleshenko/ai-index).
[33] https://gdpr-info.eu.
[34] https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence.
[35] http://en.npc.gov.cn.cdurl.cn/2021-12/29/c_694559.htm.
[36] https://www.whitehouse.gov/ostp/ai-bill-of-rights/.
[37] https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai.

considered low risk because the EU framework is blind when it comes to proxy effects.

In the US, the AI Bill of Rights focuses on sustainability in an even more indirect way. It primarily concentrates on unwanted consequences of AI (and automated systems in general) such as biases that can lead to discrimination and privacy issues (e.g., personal data being used without consent and intellectual property issues in reference to how GAI is trained with Internet data). What is more, the US AI Bill of Rights is nonbinding, which means that, at present, it contains only unenforceable recommendations. Linking an imperfect algorithm to an environmental problem will be even harder than is the case with the EU regulations. Interestingly, on February 1, 2024, Senator Edward J. Markey of Massachusetts introduced the Artificial Intelligence Environmental Impacts Act to regulate how organizations measure and report AI's environmental impacts.[38] This Act represented an important policy step, especially given the notoriously poor extent to which the US has engaged with environmental issues (Marabelli 2024). However, in 2025, the Trump administration has reverted most AI-related protections for end users. For instance, the January 23, 2025 presidential executive order titled "Removing Barriers to American Leadership in Artificial Intelligence" Section 5 officially revoked the 2023 executive order 14,110 "Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence", essentially allowing companies to develop GAI systems with very few guardrails, including environmental considerations.

China's PIPL doesn't contain environmental recommendations and is more focused on data privacy, even if its impact on GAI is and will be substantial, especially with respect to how this technology leverages user prompts to train its algorithms. Nevertheless, China lately has taken strong actions to force organizations to reduce their carbon emissions, and AI seems to contribute positively to that reduction. For instance, several AI initiatives in China contribute to reduce carbon emissions by improving industrial and information structures and enhancing innovations that support green technology (e.g., innovations focused on smart cities) (Chen et al., 2022). Other examples in China that focus on the environment include initiatives to build underwater data centers.[39] The underwater setting naturally cools the hardware, which saves electricity and fresh water while also preserving land space.[40]

Overall, most jurisdictions lack legislation that considers the impact of AI on the environment. Therefore, more such legislation is required to ensure that organizations take advantage of AI systems ethically, i.e., with environmental considerations kept firmly in mind. The greenhouse gas emissions associated with GAI use currently constitute a relatively small fraction of the total volume of emissions. However, AI continues to grow at a fast pace and as result the fraction will increase in size. It is our opinion that legislation should be promulgated globally to promote its ethical use. Overall, organizations are revenue-driven and very few of them will adopt environmental-friendly policies if these policies penalize their bottom line, unless they are legally mandated to do so.

Strategic use of AI for the environment

Environmentalist movements that push organizations to behave ethically, together with newly enacted laws and regulations (companies are generally responsive to both due to profits/reputation and compliance issues, respectively), have led to AI initiatives that address ethical AI issues that relate to the environment and specifically global warming. For these reasons, a number of initiatives have emerged in recent times which aim to take advantage of the potential of AI to mitigate threats posed by climate changes, and the associated global warming issues such as extreme weather conditions such as storms/hurricanes/cyclones, droughts, wildfires, and floods. Organizations, public administrations and governments have the opportunity to use AI strategically, and the duty to do so ethically, in order to positively affect climate changes thereby showcasing ethical behavior and conduct.

We next lay out ways in which organizations can pursue AI strategizing, in the context of climate change. While the list below is not meant to be comprehensive, we believe that it is a good start to bring awareness of the fact that AI, along with its environmental pitfalls, can nevertheless be used ethically and strategically, to address climate changes.

Smart cities: This refers to cities designed with embedded technologies that provide automated services to citizens and minimize natural resource use. These cities can use data that AI systems collect via sensor technologies to engage in such activities as: improving traffic flow, optimizing water supplies, handling waste, investigating criminal activity, and performing other community services (Musa 2016). Digital twin technologies can help redesign key city operations (such as traffic) as in Barcelona, which has begun to create its digital twin. Sensors around the city collect real-time data to help decision makers make AI understand how to analyze and predict traffic and energy usage. In a 2024 interview with the *Financial Times*,[41] Jordi Cirera Gonzalez, director of the Knowledge Society at Barcelona City Council, said that "Thanks to AI, we can answer questions about what is going to happen without knowing exactly the law that drives the system… but you need good data. Without it, you cannot train an artificial intelligence system." This surfaces a potential ethical issue concerning how much data from private citizens must be collected to build a digital twin to develop smart cities. For instance, residents wanting to access "smart parking" might need to accept being monitored (via a GPS-equipped car's onboard devices). Only wealthy people will be able to buy their privacy by paying for more expensive parking spaces.

Smart farming: also known as digital (or e-) agriculture, smart farming concerns farmers' ability to collect and analyze data (including with AI systems) on various harvesting-related activities. The United Nations considers smart farming a digital revolution in

[38] https://www.markey.senate.gov/news/press-releases/markey-heinrich-eshoo-beyer-introduce-legislation-to-investigate-measure-environmental-impacts-of-artificial-intelligence.

[39] https://www.scmp.com/news/china/science/article/3299313/chinas-subsea-data-centre-could-power-7000-deepseek-conversations-second-report.

[40] https://circleid.com/posts/20231205-china-launches-worlds-first-underwater-data-center.

[41] https://www.ft.com/content/45737bf0-8f69-46da-bd0b-98986be74a00.

the agriculture field.[42] For instance, an ML regression algorithm can determine the required water resource level for farming a particular crop in a specific season or at certain temperatures (Akkem et al., 2023). Smart farming probably represents one of the most advanced, localized AI applications, yet with global reach. For instance, increasing a particular crop's production in one region via AI could benefit (or harm) other, less advantaged regions due to supply/demand effects on sale prices.

Weather forecasting: AI-based weather forecasting systems represent another way in which one can use AI technology for good. For instance, recent developments into 3D neural networks have offered substantial improvements to current forecasting models (Bi et al., 2023). The World Economic Forum explains[43] how AI can outperform mainstream weather forecasting systems with specific reference to GraphCast, Google DeepMind's AI weather forecasting model which Google has trained with 40 years of historical weather data.[44] Advanced systems that can predict weather in the longer-term (weeks rather than days) can be used globally to deliver timely aids to regions hit by heat waves or floods and to alert people in areas that face potential extreme weather conditions, where imprecise forecasting might lead to more casualties.[45] Thus, more accurate forecasting could help save lives. Weather-related predictions have recently involved the forecasting of dust and sandstorms, a very common (and property-damaging and life-threatening) phenomenon in countries such as China, Saudi Arabia and Pakistan. Local researchers have recently applied AI models to better predict dust and sand storms, potentially saving money and lives in these regions (You 2024).

AI and earthquakes: Until recently, predicting the location, depth and intensity of earthquakes seemed to be an impossible task. However, an ongoing project funded by the European Commission called TECTONIC[46] seems to have the potential to leverage AI to predict earthquakes with a degree of precision that will outperform traditional systems based on historical seismic activities, strain accumulation in rocks, and changes in ground elevation.[47]

AI and wildfires: According to space.com (UK), AI is developing the ability to predict wildfires, a phenomenon that has become increasingly common worldwide, because of rising temperatures and droughts.[48] Geostatic satellites already do a good job in mapping the earth's "hot spots", i.e., those more prone than other areas to wildfires. AI can analyze factors including the emergence of smoke, the incidence of fires and the disturbance of vegetation, and relate them with other parameters such as vegetation type, climate, landscape, fire susceptibility mapping, and soil deposits in order to identify wildfires patterns (Ahmad et al., 2024). The constant evolution of AI applications to aid firefighters managing wildfires is documented by a March 2025 report in the Wall Street Journal, which describes techniques such that "AI bots that now serve as digital fire-lookouts and crucial eyes …" and are able to spot wildfires via camera sensors before they spread.[49]

AI and floods: Floods are one of the most common natural disasters which disproportionately affect the Global South, where countries often lack dense streamflow gauge networks (Rentschler et al., 2022). A recent Nature study (Nearing et al., 2024) documented how AI can improve predictions concerning floods by using long short-term memory (LSTM) networks (Hochreiter and Schmidhuber 1997) to predict daily streamflow through a 7-day forecast horizon. While strong winds due to storms/hurricanes/cyclones lead to structural damages (buildings, infrastructures, trees), the associated floods are the main cause of loss of lives.

AI and nuclear power: Microsoft recently launched an initiative[50] to use nuclear power (CO_2 emission-free technology) to boost AI systems, which however poses regulatory issues, at least in the US. Nuclear power received attention during the 2023 COP28, the United Nations' annual climate conference. Using nuclear power to supply energy-demanding systems has long been a contentious/controversial subject (e.g., due to the environmental challenges associated with dumping radioactive waste and the hazards associated with nuclear accidents). Nevertheless, the possibility of using nuclear power to boost AI systems is worth studying, because nuclear power has the potential to be a zero-emission clean energy source, if managed correctly.

Along with the above initiatives, the Stanford 2024 AI index report[51] mentions several areas where AI can be used to benefit the environment. These include the management of thermal energy storage systems (Olabi et al., 2023), improving waste management (Fang et al., 2023), improving efficiency of cooling systems in buildings (Luo et al., 2022), and enhancing urban air quality (Shams et al., 2021). However, because we lack accurate means to measure the negative impact of AI on the environment, it is challenging to say whether the benefits of AI for the environment outweigh the pitfalls associated with global warming.

Overall, the ethical challenges associated with AI use and the environment may be balanced by strategic opportunities for organizations as well as public administrations and governments. Importantly, as we illustrate above, some grey areas prevent full assessment of the risks AI poses to the environment. These concern what it really means for an organization to achieve "zero-net" emissions, the (so far) impossibility of accurately quantifying AI's carbon footprint, and the lack of laws and regulations, locally and globally, around the use of natural resources and energy to support AI systems. Table 1 summarizes these insights.

[42] https://www.fao.org/3/ca4887en/ca4887en.pdf.
[43] https://www.weforum.org/agenda/2023/12/ai-weather-forecasting-climate-crisis/.
[44] https://www.science.org/content/article/ai-churns-out-lightning-fast-forecasts-good-weather-agencies.
[45] https://www.fastcompany.com/90923189/weather-forecast-heat-wave-accuracy-life-and-death.
[46] https://cordis.europa.eu/project/id/835012.
[47] https://www.usgs.gov/faqs/can-you-predict-earthquakes.
[48] https://www.space.com/how-scientists-are-using-artificial-intelligence-to-predict-wildfires.
[49] https://www.wsj.com/tech/ai/these-ai-cameras-detect-wildfires-before-they-spread-6b6e3229.
[50] https://www.wsj.com/tech/ai/microsoft-targets-nuclear-to-power-ai-operations-e10ff798.
[51] https://aiindex.stanford.edu/wp-content/uploads/2024/04/HAI_AI-Index-Report-2024.pdf.

Table 1
AI and the Environment.

Situations	Challenges	Opportunities	Call for actions for IS scholars
– Current AI models require massive datasets – AI is increasingly becoming resources hungry – AI organizations need to build large, cost-efficient data center	– Reducing the size of AI training data – Identifying various"green" resources – Limiting offshoring of data centers	– Designing smart cities and farming – Improving weather forecasting – Improving timely alert systems for earthquakes	– Building on topics such as green IT and sustainability to more specific topics on AI and the environment – Creating opportunities for topical discussions (i.e., panels, tracks) at IS conferences – Promoting cross-disciplinary research involving natural and applied science and computer science scholars, for instance
– AI uses hold "hidden" negative effects, e.g., on gig workers	– Considering indirect effects of intense use AI	– Increasing prediction of wildfire spreads	– Considering the key role of institutional theories in framing country-level and global issues associated with AI's impact on the environment
– AI's supply chain involve intense use of human capital	– Avoiding exploitation of workforce	– Using nuclear power to power AI (and more)	

Looking forward: practical solutions and a research agenda for IS scholarship

At the present time, considerable uncertainty surrounds the development of AI, and especially GAI, whose LLMs are very resource hungry. Nevertheless, we foresee practical solutions as well as important research opportunities for IS practitioners and scholars engaged in the strategic use of emerging technologies such as AI (i.e., AI strategizing) to deal with, and contrast climate change.

Practical solutions to address global warming with GAI

With respect to practical solutions, we argue that there are two main ways AI's resource-demanding nature could be addressed. The first concerns exploring techniques that can train models with relatively small datasets including models that can be trained with as few as 10,000 data points, which would substantially reduce energy demand. This is supported by research suggesting that, in circumstances where outcomes are known, neural networks (AI computer systems modeled on the human brain and nervous system) may require only minimal amounts of training data (so-called shallow neural networks). One major limitation of this approach is that small datasets can be used only in specific settings, and can be hardly applied to GAI (Ng 2021). It is also worth noting that using small datasets, along with addressing environmental issues, can help deal with risks associated with AI being trained with its own data, a phenomenon known as AI cannibalism (Marabelli 2024). In fact, GAI outputs are increasingly populating online platforms and discussion groups. Nina Schick from Yahoo Finance projected that, by 2025, nearly 90 % of online content could be created by GAI.[52] Deepseek, a Chinese GAI organization headquartered in Hangzhou, Zhejiang, is currently developing LLMs whose training costs are dramatically lower than those of other organizations such as OpenAI. This process, known as "distillation", aims at creating models that are cheaper (and less energy demanding) to produce and less expensive for organizations to adopt.[53] On paper, Deepseek has the potential to positively affect GAI's impact on the environment. However, some argue that when AI models become cheaper and therefore more accessible to organizations, then they also become more widespread, partially offsetting the benefits associated with distillation.

The second way to address AI's resource-demanding nature concerns using renewable (green) energy sources to power this technology, given that in some instances natural resource-demanding LLMs *must* be employed. However, these resources are scarce and should be used in tandem with strategies concerning how and where data centers are built; for instance, it is important to identify locations with cooler climates while minimizing the disruption of local sites and landscapes, or even to build data centers underwater (Periola et al., 2022).For instance, along with underwater data centers previously mentioned in China, Microsoft is undertaking a large scale project (Project Natick) that concerns building underwater data centers near some of the US's coastal cities.[54] Additional ideas (perhaps premature, yet worth mentioning for completeness of information) concerning strategic locations where to build data centers include outer space. In fact, in March 2025, Lonestar,[55] a US-based data storage and recovery organization explored opportunities to store data in outer space. Outer space provides unlimited access to solar power; it is possible to radiate excess heat in space, according to Damien Dumestier, a space systems architect at the European aerospace conglomerate Thales Alenia Space.[56]

While GAI benefits not related to the environment go beyond the scope of this viewpoint article, it is important to mention potential GAI strategic uses in a variety of contexts. Examples include healthcare/disease prevention, educational settings to assist people with disabilities and promote inclusion in schooling, disaster management and the streamlining of production processes for the faster distribution of life-saving resources.[57] These are just a few examples of the bright side of GAI. But we wonder if, looking forward, all these GAI benefits shouldn't be put on hold, at least in part, as an unlivable environment will prevent the mass diffusion of positive AI-

52 https://finance.yahoo.com/news/90-of-online-content-could-be-generated-by-ai-by-2025-expert-says-201023872.html.
53 https://www.ft.com/content/c117e853-d2a6-4e7c-aea9-e88c7226c31f.
54 https://natick.research.microsoft.com.
55 https://www.lonestarlunar.com.
56 https://www.technologyreview.com/2025/03/03/1112758/should-we-be-moving-data-centers-to-space/.
57 https://insights.fusemachines.com/possibilities-for-ai-driven-growth-in-underserved-countries/.

related innovations, and thus render nugatory all these potential strategic positives.

A research agenda for IS scholars engaged in topics concerning AI and the environment

Given the increasing relevance of sustainable AI for policymakers, organizations, and society, we believe that IS scholars should take this issue seriously. Yet, words are not enough: *what actions can we actually take to make a difference?* Despite a few exemplary contributions on sustainable AI (Nishant et al., 2020; Schoormann et al., 2023) or, more generally, digital sustainability (Dao et al., 2011; Kotlarsky et al., 2023), the IS field has yet to delve into the topic, even though it very much concerns sociotechnical systems and the ethical implications of the design and use of technologies, two key, interwoven subjects that should be central to an IS research agenda. For instance, recent articles discussing digital approaches to "Societal Grand Challenges" (i.e., Nambisan and George 2024) do not see AI as a threat for the environment at all. Instead, and in line with mainstream views of technology, they only see the potential for AI to solve some grand challenges. Interestingly, Nambisan and George (2024), drawing on Ostrom (2010), elaborate on the concept of common-pool resources (the environment being one). This provides opportunities to take relevant IS research further and theorize on how emerging technologies should (or should not) contribute to managing "commons" such as the air we breathe or the atmosphere in which we live.

Our community, the AIS (Association for Information Systems), appears to be increasingly sensitive to technologies and sustainability, which sends good signals to related scholarship. Two recent conferences witnessed firstly a panel on the role of IS in (technology-related) sustainability (Ixmeier et al., 2024), and secondly a track on "Societal impacts of IS[58]". Thus, sustainability-related topics, albeit not specific to AI and the environment, were addressed. Although these efforts may seem paltry, not least because they do not focus on the environment specifically, they are at least steps in the right direction. We recognize that studying the environmental impacts of AI requires competences that might go beyond the knowledge of most IS scholars. We therefore advocate for an interdisciplinary approach that crosses the sociotechnical axis of our field (cf Sarker et al., 2019). This interdisciplinary approach should involve both technical as well as behavioral sciences appealing to IS scholars, especially since we view the current and future developments of GAI as strategic (and challenging) for organizations, communities, governments/institutions etc. It is not unusual for IS researchers to build on the strategy literature. For instance, Nambisan and George (2024) discussion of digital sustainability draws on the strategy literature.

In the same vein, strategy scholars will have to borrow insights from the IS literature to highlight GAI characteristics that can be key to competitiveness while using this technology in a way that is not detrimental to the environment. Given the interweaving relevance of GAI across the two disciplines (IS and Strategy), it is both difficult and of questionable value to separate the two literatures. Indeed, we should arguably avoid working in silos and instead aim at cross-fertilization and mutual exchange of knowledge and insights. What is however important, in our opinion, is to ensure that GAI is not solely viewed as a strategic asset that can be leveraged to bring economic value to the organization. GAI must also be viewed as a technology that has the potential to be detrimental to non-economic indicators, including the sociocultural values of humans and the imperative that we respect and conserve the natural environment.

A noninclusive list of potential areas (and associated research questions) that IS scholars engaged in AI strategizing should explore are the following:

Concerning AI being "resource hungry":

– What are the alternative strategies that avoid broad web scraping practices and could be enacted to train complex models, and what is the associated need for computing capacity to process all these data? What are the risks and benefits of using small and synthetic datasets? Here, IS scholars could benefit from collaborations with computer science academics and practitioners whose research focuses on small-size AI models and datasets. Computer scientist Andrew Ng, one of the pioneers of AI, suggests that it is possible to reduce datasets to as few as 10,000 examples, "a sort of threshold where the engineer can basically look at every example and design it themselves and then make a decision" (Hao 2021). How could these (technical) insights be incorporated into (and contribute to) relevant IS literature?

Concerning the AI value chain:

– How is it possible to control and limit hidden practices such as the offshoring of labeling processes which add to the already prominent ethical issues concerning sustainable AI? Is sustainable AI only an environmental concern, or does the way AI is used in practice involve other aspects of sustainability, such as the exploitation of Global South workers through unethical offshoring? The IS strategic literature on offshoring is very rich and was pioneered by *JSIS* (cf. Abbott et al., 2013; Kranz 2021; Schermann et al., 2016); we believe that scholars can build on this body of research to theorize around environmental issues associated with the AI value chain across countries and continents. At the interdisciplinary level, this requires IS scholars to work strategically with colleagues in HR (Human Resources) and even Sociology as we explore impacts of AI in other domains.

Concerning measuring AI's impact on the environment:

58 https://icis2024.aisconferences.org/submissions/track-descriptions/#toggle-id-5.

- How is it possible to account for (and measure) secondhand environmental effects of AI? These second-hand effects concern online nudging that leads to more (unnecessary) purchases but also to gig workers being asked to perform almost real-time deliveries. Almost real-time delivery may include extra trips to the same customer or in the same neighborhood. What are other secondhand environmental effects of AI? Allied disciplines here could include Computer Science, Remote Sensing (i.e. use of satellite data), Transportation Science, and Operations Research. Here, interdisciplinary research can be pursued by seeking collaborations with communities such as the FAccT (Fairness, Accountability, and Transparency) community,[59] that studies social phenomena concerning AI such as environmental concerns (cf. Dodge et al., 2022) using a sociotechnical lens, but with a strong technical background.

Concerning AI and social justice:

- How is it possible to empower Global South countries and make sure that they too benefit from AI advances? Niche IS communities such as ICT4D (Information and Communication Technologies for Development) should play a relevant role in shedding light on the societal impacts of environmental changes due to intense use of AI (even in the Global South). For instance, adverse digital incorporation (Heeks 2022) is a notion that theorizes around the detrimental impact for countries, societies and cultures that are incorporated into digital systems. These issues are prominent in the ICT4D community; in a global environment characterized by adverse digital incorporation, the ICT4D research agenda is positioned within the debate on social inclusion in the broader spectrum of critical data studies, a field which views data as immersed in their social and political context (Dalton et al., 2016; Masiero 2022).

Concerning policymakers:

- How should governments require organizations to provide AI data in ways that would clearly assess organizations' standing with respect to their actual use of natural resources and electricity? What are the challenges of doing so when global organizations can opportunistically move their operations to countries where controls to this end are lacking? Here, it is important that IS scholars partner with fellow legal scholars to delve into local as well as global jurisprudence with the goal of advising policymakers in order to incorporate AI into comprehensive international initiatives such as the Kyoto Protocol[60] and the Paris Agreement.[61] We believe that the IS community could effectively leverage institutional theories (Powell and DiMaggio 1991; Scott 2008) – already widely applied in technology contexts (Currie 2009; Currie and Swanson 2009) and even used to support progress towards building and implementing sustainable systems strategically (Butler 2011), to shed light on coercive, mimetic, and normative dynamics between governments and organizations and within organizations.

In summary, IS scholars can contribute to solving problems concerning AI and the environment in several ways, spanning from technical to more processual and policy-focused aspects of the issue at hand (cf. Sarker et al., 2019). It is possible to identify positive aspects of AI concerning global warming. We therefore believe that it is already and will continue to be strategic for organizations to generate business models aimed at leveraging AI capabilities to reduce greenhouse gas emissions, thereby offsetting AI's demands for electricity and natural resources. For instance, in a study involving 31 high-tech startups, Böttcher et al. (2024) found that sustainable startups were able to leverage digital technologies to create ecological sustainable value propositions without compromising revenue streams.

Being environmentally wise should be an ethical principle. In turn, marketing and reputation along with the possibility to pursue sustainable business models should encourage organizations to employ AI systems in ways that account for environmental concerns. Activists worldwide are already sensitive to environmental problems caused by AI (and associated technologies). For instance, when in 2023 it became official that Google planned to build a large data center in Uruguay, the Movement for a Sustainable Uruguay[62] (MOVUS) became extremely vocal in expressing concerns over potential exploitation of the country's natural resources. Our community is increasingly becoming sensitive to ethical and societal issues, especially in the aftermath of the COVID-19 pandemic, when the AIS decided to hold most conferences in hybrid mode, both so as to promote inclusiveness and to reduce the environmental impact associated with travel (Ahuja 2024; Marabelli et al., 2023). In turn, we, as a community, cannot just watch what is happening with AI and how our planet's livability is increasingly compromised on a daily basis (in part, because of unethical use of AI). While AI can (and will) positively affect the environment (as we outlined above), we need to make sure that the benefits of AI advances outweigh the societal costs, which are distributed unevenly, often penalizing people in the Global South.

Conclusions

AI is nowadays associated with ethical concerns. Its negative effects on the environment are largely overlooked, but will increasingly become relevant. Many factors contribute to global warming, not least humankind's unethical behavior in using our

[59] https://facctconference.org.
[60] https://unfccc.int/kyoto_protocol.
[61] https://unfccc.int/process-and-meetings/the-paris-agreement.
[62] https://movusuruguay.blogspot.com.

planet's resources. AI (so far) accounts for a small part of overall greenhouse gas emissions, the main source of global warming. However, AI will likely become increasingly widespread and more resource hungry, especially because of the advent of GAI, which needs nearly infinite datasets. The IS community has the moral obligation to conduct research and engage with practitioners and policymakers regarding whether AI is and will be used ethically (or not) with respect to the environment. However, there are also many benefits of AI. It can be used strategically to reduce pollution from traffic in large urban areas (smart cities) and also to improve weather forecasting. Nevertheless, it is our opinion that more regulations and global agreements to limit AI's impact on global warming are needed. AI's impact on global warming currently affects people and populations unevenly. Furthermore, we believe that research should consider the indirect effects that AI can have on the environment, such as via web nudging. Ethical issues associated with AI's effects on the environment, along with the strategic opportunities for organizations to use AI "for good", represent a novel research avenue for *JSIS* authors and readers and, more generally, for IS scholars engaged in topics at the intersection of technology, ethics, and the health of our planet.

CRediT authorship contribution statement

Marco Marabelli: Project administration, Investigation, Conceptualization. **Robert M. Davison:** Project administration, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Artificial intelligence in sustainable food design: Technological, ethical consideration, and future

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A R T I C L E I N F O

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A B S T R A C T

Background: Addressing pressing global challenges such as climate change, resource depletion, and food insecurity necessitates innovative approaches to sustainable food design. Artificial intelligence (AI) is emerging as a transformative technology with the potential to significantly enhance sustainability across the food system.
Scope and approach: This review comprehensively examines the integration of AI into sustainable food design. It explores technological innovations including AI-driven precision farming, smart food processing, and the development of alternative proteins. The paper further investigates AI's role in optimizing food supply chains through predictive analytics and blockchain. Crucially, it also delves into the ethical considerations, environmental and social impacts, and the evolving regulatory landscape surrounding AI in food systems, identifying future prospects and inherent challenges.
Key findings and conclusions: AI offers profound capabilities to revolutionize food production, distribution, and consumption, driving efficiency and reducing environmental footprints. However, realizing its full potential hinges on addressing critical ethical concerns like algorithmic bias, data privacy, and social equity, alongside mitigating AI's own environmental impact. A multi-stakeholder, collaborative approach, underpinned by robust ethical frameworks and transparent policies, is imperative to ensure the responsible and equitable deployment of AI, ultimately fostering a resilient and sustainable global food system for future generations.

1. Introduction

The advent of artificial intelligence (AI) has heralded unprecedented transformations across numerous sectors, including food design and production. As we venture into an era characterized by rapid technological advancements, it is imperative to examine the intersection of AI, ethics, and sustainability within the context of food systems. Food consumption plays a pivotal role in the politics of sustainable consumption and production due to its significant impact on the environment, individual and public health, social cohesion, and the economy (Hotta et al., 2021). The sustainability of food systems and our capacity to ensure adequate food and nutrition for present and future generations are threatened by population growth, climate change, resource depletion, and pollution (Camaréna, 2020). The current agricultural and supply chain systems significantly contribute to the issues at hand. To transition to sustainable food systems that can support nearly 10 billion people within the next 30 years, we need transformational change rather than incremental adjustments.

Sustainable food design is an interdisciplinary approach that seeks to create food systems capable of meeting the nutritional needs of current

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and future populations without compromising the health of the environment, economic viability, and social equity (Gustafson et al., 2016). This concept encompasses a holistic view of food production, processing, distribution, consumption, and waste management. It aims to integrate sustainable practices at every stage of the food chain to mitigate adverse environmental impacts, enhance food security, promote public health, and foster social cohesion (Varzakas & Antoniadou, 2024). At its core, sustainable food design focuses on reducing resource consumption, minimizing waste, and preserving biodiversity. Sustainable food design addresses the economic aspects by promoting fair trade, supporting local economies, and ensuring equitable access to food resources (McClements, 2020). The scope of sustainable food design extends to technological innovations, policy frameworks, and ethical considerations.

The rapid advancements in AI offer transformative potential for sustainable food design. AI technologies, including robotics, predictive analytics, and machine learning (ML), are enhancing precision agriculture by optimizing resource use and increasing crop yields (Gul & Banday, 2024). AI can analyze vast amounts of data, AI can monitor crop health, predict pest outbreaks, and provide tailored recommendations to farmers, reducing environmental impact. Additionally, AI is revolutionizing food processing and manufacturing through automation and quality control, ensuring consistency and safety (Karanth et al., 2022). In supply chain management, AI enhances transparency and traceability, improving food safety and reducing waste. This integration of AI within food systems directly contributes to the objectives of sustainable food design by fostering resource efficiency, minimizing waste, and enhancing overall system resilience.

However, the effective and equitable deployment of AI in food systems necessitates a strong emphasis on ethical considerations and sustainability (Craigon et al., 2022). Ethical aspects such as fairness in algorithms, safeguarding personal data, and ensuring equal access to technological benefits are crucial to guarantee that AI advancements are shared equitably and with clarity (Cumming et al., 2024) Moreover, incorporating sustainable practices into the creation and deployment of AI technologies is essential to ensure the enduring viability and strength of food systems (Iqbal et al., 2024). While existing literature extensively discusses the individual aspects of AI in food systems and sustainable food design, a critical gap remains in the comprehensive, integrated analysis of their multifaceted relationship, particularly focusing on the intricate ethical and sustainability implications of AI integration within food systems. Previous works often address either the technological advancements of AI or the principles of sustainable food systems in isolation, or they touch upon ethical concerns without a deep, systemic examination of their interplay with sustainability goals within this specific domain. This review distinguishes itself by providing a holistic examination of how AI not only drives sustainable food design but also introduces novel ethical and sustainability challenges that demand systematic consideration. Our work specifically bridges this gap by offering a critical synthesis of current applications, while rigorously scrutinizing the ethical pitfalls and long-term sustainability implications, thereby offering a more nuanced and integrated perspective. This paper is structured as follows: it begins by providing a comprehensive overview of sustainable food design principles and practices. Subsequently, it delves into the current applications and transformative potential of AI across various stages of the food supply chain. Following this, it critically examines the ethical considerations and sustainability challenges associated with AI deployment in food systems. Finally, the paper offers concluding remarks and outlines future research directions in this critical area. Priority was given to peer-reviewed journal articles, reputable conference proceedings, and authoritative review papers published within the last decade, with a focus on interdisciplinary research that directly addressed the intersection of AI, ethics, and sustainability in food contexts.

2. Technological innovations in sustainable food design

The convergence of advanced technologies and sustainable practices is paving the way for transformative changes in food systems. As the global demand for food continues to rise, driven by population growth and changing dietary preferences, there is an urgent need for innovative solutions that ensure food security while minimizing environmental impact (Van Dijk et al., 2021). The present agricultural landscape demands resilience, stability, and heightened productivity to address the escalating needs posed by population growth, climate change, transboundary pests, and crop diseases. Meeting these challenges is essential to ensure a sustainable and secure food supply for current and future generations. The application of AI in agriculture, also known as precision farming, has revolutionized traditional farming practices (Ghosh et al., 2024, pp. 67–77). AI-powered tools and systems assist farmers in making informed decisions, utilizing resources efficiently, and improving crop productivity, with advancements in AI-based agriculture and precision farming outlined in Table 1. By leveraging ML algorithms and predictive analytics, precision farming can monitor soil health, predict pest outbreaks, and provide real-time recommendations for irrigation and fertilization (Elango et al., 2024). This not only boosts productivity but also reduces the environmental footprint of agriculture by minimizing water and chemical usage.

Technological advancements in food processing are crucial for enhancing efficiency, ensuring quality, and reducing waste. Smart food processing technologies, such as AI-powered robotics and computer vision, streamline operations and maintain product consistency (Jambrak et al., 2021). Fuzzy logic techniques have been used in the food business for food modeling, control, and classification as well as for solving food-related issues, they could analyze factors like temperature fluctuations during transport, humidity, and ethylene levels to predict the remaining shelf life of fruits and vegetables more accurately than traditional methods (Mavani et al., 2021). These innovations enable real-time monitoring and quality control, ensuring that food products meet safety standards. AI-powered cucumber harvesting robots equipped with advanced computer vision systems and sophisticated

Table 1
Technological innovations in AI-driven agriculture and precision farming.

Technological innovations	Description	Benefits	Reference
AI driven management system	Integration of AI for data collection, analysis and decision making in crop health and management.	Enhanced efficiency and precision in resource utilization.	Potluri et al. (2024)
Crop monitoring and management	Use of AI to monitor crop health, predict harvest and optimize input like fertilizers and pesticides.	Increase crop productivity and reduce environmental impacts.	Naresh et al. (2020)
Deep learning for pest management	Control pest infestation.	Early detection and control of pests, minimizing crop losses.	Benos et al. (2021)
Data collection devices	Collect data on light, temperature, humidity, rainfall and fertilizer concentrations.	Comprehensive environmental monitoring for optimal growth conditions.	George et al. (2020)
Satellites and imagery drones	Real time monitoring of agriculture lands.	Improved accuracy in crop health assessment and resource allocation.	Dagur et al. (2024)
Predictive analysis	Potential issues like pest outbreaks and abiotic stress factors.	Proactive management and mitigation of risk.	Linaza et al. (2021)
Optimization of resources	Optimize the use of water, pesticides and fertilizers	Reduced waste and enhance sustainability.	Sharma et al. (2020)

hardware, including autonomous vehicles, manipulators, and end-effectors, have been engineered (Nath et al., 2024). These innovative robotic systems possess the capability to accurately detect and image the ripeness of cucumbers, thus enhancing the efficiency and precision of the harvesting process. Additionally, AI-driven predictive maintenance can prevent equipment failures and reduce downtime. Innovations in waste reduction, including the use of AI to predict and manage food surplus, contribute to more sustainable food systems by minimizing waste at every stage of the supply chain (Kumar et al., 2021). As concerns over the environmental impact of conventional animal agriculture grow, alternative protein sources such as plant-based and cultured meats offer promising solutions. The development of alternative proteins and lab-grown foods represents a significant leap toward sustainable food systems (De Oliveira Padilha et al., 2022) These innovations not only reduce the reliance on resource-intensive livestock farming but also address issues related to animal welfare and food security. AI plays a critical role in optimizing the production processes of these alternative proteins, from formulation to manufacturing, ensuring that they are both sustainable and scalable (Nikkhah et al., 2023). The application of AI in food industry in discussed in Table 2. The significant advancements in AI application across agriculture, food processing, alternative proteins, and waste reduction highlight its overarching potential to enhance efficiency and sustainability within food systems. These diverse applications collectively underscore how AI is not merely optimizing individual stages but is also poised to revolutionize the entire food supply chain, a topic further explored in the subsequent section.

3. AI in food supply chain optimization

The efficient and sustainable delivery of food from producers to consumers hinges on the optimization of food supply chains (Anwar et al., 2023). AI offers transformative capabilities in this domain, encompassing predictive analytics for demand and supply management, blockchain for transparency and traceability, and AI-powered logistics and distribution efficiency (Abaku et al., 2024). These integrated technologies are crucial for enhancing the resilience, responsiveness, and sustainability of modern food supply chains, thereby directly contributing to the broader goals of sustainable food design discussed previously. AI-driven predictive analytics plays a pivotal role in managing the dynamic nature of food supply and demand (Elufioye et al., 2024). By analyzing vast datasets from various sources such as historical sales, market trends, weather patterns, and consumer behavior, AI algorithms can forecast demand with high accuracy (Zong & Guan, 2024). These precise predictions enable producers, distributors, and retailers to make informed decisions regarding inventory management, production planning, and resource allocation (Zatsu et al., 2024). The immediate benefits include minimized food wastage due to overproduction or spoilage, reduced stockouts that disrupt consumer access, and an overall improvement in supply chain efficiency. The ability to anticipate fluctuations in demand also allows for better coordination and timely adjustments, ensuring that food reaches consumers when and where it is needed most, aligning with the principles of food security and resource optimization. Transparency and traceability are essential components of a sustainable food supply chain, fostering trust and accountability (Khan et al., 2020). While blockchain technology itself creates a decentralized and immutable ledger of transactions, ensuring that every step in the supply chain is recorded and verifiable (Raparthi et al., 2021), the integration of AI significantly enhances this capability AI's role is not merely to facilitate a blockchain system but to elevate its utility. AI algorithms analyze the vast amount of data stored on the blockchain for anomalies, potential fraud, and inefficiencies that might not be immediately apparent through raw ledger entries. This intelligent analysis allows for a more proactive and comprehensive understanding of the supply chain. The combined use of blockchain and AI facilitates end-to-end traceability, enabling stakeholders to track the origin, journey, and quality of food products with unprecedented detail (Tsolakis et al., 2022). The silent feature of blockchain technology for supply chain is given in Table 3 blockchain provides the secure, transparent, and immutable foundation for data recording. AI then acts as an intelligent layer on top of this foundation, extracting deeper insights, enabling more sophisticated automation, and improving overall system efficiency. They are complementary technologies, but not mutually dependent for basic functionality. This enhanced transparency empowers consumers with increased confidence in food safety and authenticity, while producers and retailers can swiftly address any issues related to contamination or recalls, mitigating risks and ensuring product integrity (Dedeoglu et al., 2023). Therefore, AI acts as an intelligent layer on top of blockchain, transforming raw data into actionable insights for improved traceability and transparency. The logistics and distribution segments of the food supply chain are critical for ensuring timely and cost-effective delivery of products. AI-powered systems optimize these processes by using real-time data and ML algorithms to enhance route planning, fleet management, and warehouse operations. For instance, AI can dynamically adjust delivery routes based on traffic conditions, weather forecasts, and delivery schedules, significantly reducing fuel consumption and transit times, which directly lowers the environmental footprint. In warehouses, AI-driven robotics and automation streamline sorting, packing, and inventory management, increasing throughput and accuracy. These advancements contribute to reduced operational costs, lower environmental impact, and improved service levels. The integration of AI technologies in food supply chain optimization presents significant opportunities for enhancing efficiency, sustainability, and transparency. Predictive analytics, blockchain, and AI-powered logistics collectively enable a responsive and resilient supply chain capable of meeting the growing demands of a global population. By leveraging these innovations, stakeholders can build a food system that is both economically viable and environmentally responsible, directly contributing to the overarching goals of sustainable food design. This seamless integration of AI throughout the food supply chain is a critical step towards achieving a truly sustainable global food system.

Table 2
Application of AI in food industry.

Food industries	Application	AI used	Reference
Dairy	Controlling the spoilage of milk Lactose removal from the milk	Fuzzy logic and artificial neural network	Negash et al. (2018) Balieiro et al. (2016)
Soft drink and beverage	Nutrient content of the beverages	Convolutional neural network	Hafiz et al. (2020)
Fruit and vegetable	Sorting, grading of vegetables and yield assessment	Feed forward neural networks and photometric camera	Zhang et al. (2016) Patil et al. (2021)
Food packaging	Cost management and packaging design	ML and robotics	U. Ahmad et al. (2022)
New product development	Formulations and grocery delivery	AI based astrograph system	Taneja et al. (2023)
Food adulteration detection	Detection of food adulterants	Artificial neural network, deep learning and stratified cross validation.	Meng et al. (2022) Zhang et al. (2022) Cardoso and Poppi (2021)
Quality control and food image	Chemical composition, phenolic and flavonoid	Artificial neural network	Nath et al. (2024)

4. Ethical considerations in AI-driven food systems

Food security is a multifaceted issue encompassing the availability,

Table 3
Key features of blockchain technology for enhancing food supply chain efficiency.

Features	Descriptions	Benefits for food supply chain optimizations
Transparency	All interaction between supply chain stakeholders is managed by the blockchain, offering visibility to all involved parties.	Enhanced visibility and trust among stakeholders; easy tracking of food products.
Immutability	The write once ledger prevents any modification of stored data.	Ensure data integrity and reliability; prevents fraud and tempering in food supply chain
Timestamped transactions	All transaction is recorded with timestamps, allowing verification of the order of events.	Accurate tracking of product history and timeline; improves accountability.
Robustness	Many nodes collectively manage operations, ensuring system stability even if some nodes fail.	Maintain operation continuity; ensure reliability of the supply chain network.
Decentralized control	Digital operations are managed by distributed nodes, without a single controlling nodes entity.	Increase system resilience; eliminates single point of failures.
Improved privacy	Privacy preserving mechanisms protect sensitive data from competitors.	Safeguard propriety information; enhances stakeholder confidence in data security.
Automation through smart contracts	Smart contracts execute within the blockchain network, automating operation like payment transfers.	Streamline processes, reduce manual interventions ensure transparency in transaction executions.
AI powdered predictive analysis	AI analyses data to forecast demand and supply optimizing inventory and resource allocations.	Reduces food wastage; improve supply chain efficiency; match supply with demand accurately.
Blockchain enhanced traceability	Blockchain records location, quality and certification information ensuring product traceability.	Enhances food safety and quality control increases consumer confidence in product origin
AI driven logistic and distribution	AI optimizes route plaining and fleet management enhancing logistics efficiency.	Reduce transportation cost; minimize environmental impact ensures timely delivery.

access, utilization, and stability of food systems. AI-driven food systems have the potential to address these challenges by optimizing agricultural practices, improving supply chain efficiencies, and enhancing food distribution networks (Ahmad et al., 2024). However, the integration of AI must be approached with critical ethical considerations to ensure equitable access to food resources and avoid exacerbating existing inequalities.

The ethical implications of AI in food systems are complex and manifest at various stages of design, application, and outcome. One of the most critical aspects is algorithmic bias, which can stem from incomplete, unrepresentative, or skewed datasets used to train AI models (Belenguer, 2022). For instance, an AI algorithm designed to optimize food distribution might inadvertently prioritize areas with more readily available historical data (e.g., urban centers) over marginalized rural communities, leading to unfair resource allocation (Mayuravaani et al., 2024). Similarly, AI in agricultural decision-making, such as predicting optimal fertilizer use or crop yields, could be biased if trained predominantly on data from large-scale, technologically advanced farms, thus failing to accurately serve the needs of smallholder farmers or diverse agricultural practices (McLennon et al., 2021). This bias can lead to unequal outcomes, where technological benefits disproportionately favor certain groups, compromising the goal of equitable food security (Siddiqui, 2024). Addressing this requires a comprehensive approach, including meticulous data curation to ensure diversity, the development of robust data auditing mechanisms, and the promotion of diverse and inclusive development teams to mitigate inherent human biases in algorithm design. Beyond bias, ethical concerns also vary with different types of AI applications:

- **Predictive Analytics and Machine Learning:** While powerful for early detection of disease outbreaks, risk prediction, and monitoring of foodborne pathogens (Qian et al., 2022), these systems heavily rely on vast amounts of data, raising significant data privacy and security concerns. The collection and analysis of consumer data, for instance, necessitates strict adherence to regulations like GDPR (European Union, 2018) and the implementation of robust cybersecurity measures to maintain consumer trust. The potential for misuse or unauthorized access to sensitive agricultural or consumer data is a critical ethical challenge.
- **Robotics and Automation:** AI-powered robotics in harvesting (Nath et al., 2024) or smart processing facilities (Jambrak et al., 2021) introduce ethical questions related to job displacement and the need for just transition strategies for agricultural laborers. While increasing efficiency, the social impact on livelihoods must be carefully managed to prevent exacerbating socio-economic disparities within the food system.
- **Computer Vision and IoT:** These technologies, used for monitoring crop health or predicting shelf life (Mavani et al., 2021), generate vast quantities of data. The ownership and control of this data become critical ethical issues, particularly for farmers who may find their proprietary information used by larger corporations without equitable benefit or consent.

Central to mitigating these ethical challenges is the establishment of robust accountability and transparency frameworks. Accountability, conceptualized as a policy framework encompassing principles of trust, inclusivity, transparency, and verification (Kraak et al., 2014), ensures that stakeholders are held responsible for the design, deployment, and outcomes of AI systems. This includes clear lines of responsibility for AI failures or biased outputs. Transparency in data practices, coupled with explainable AI models, is crucial for fostering trust among consumers, farmers, and industry stakeholders. While proprietary information must be protected, a balance is needed to ensure that the logic and decision-making processes of AI systems are understandable, allowing for scrutiny and correction. Enhancing supply chain transparency, for example, necessitates reducing information asymmetry and promoting less opaque decision-making processes, particularly where algorithmic bias could privilege one group over another (Manning et al., 2022). AI holds immense promise for enhancing food safety and security, its deployment must be rigorously guided by ethical principles. Addressing bias in design, considering the varying ethical issues across different AI applications, and establishing strong frameworks for data privacy, accountability, and transparency are paramount. Critically examining and mitigating these ethical challenges is essential to ensure that AI-driven food systems contribute to a more secure, equitable, and sustainable food future for all. The pervasive issue of bias, in particular, warrants continued investigation and proactive mitigation strategies in future research endeavors.

The successful integration of AI into food systems is fundamentally tied to addressing complex ethical considerations, particularly concerning bias, data privacy, and accountability. These ethical considerations directly underpin the broader environmental and social impact of AI in food design. While AI offers immense potential for enhancing sustainability and efficiency, its deployment also carries significant implications for ecological well-being and social equity, which must be proactively managed to achieve genuinely sustainable food systems.

5. Environmental and social impact of AI in food design

The environmental impact of AI in food design is a dual-edged sword. On one hand, AI offers powerful tools for minimizing the environmental footprint of food production and consumption. Precision agriculture, powered by AI, optimizes resource use by precisely managing irrigation, fertilizers, and pesticides, thereby reducing water consumption, chemical runoff, and greenhouse gas emissions. This directly contributes to a reduced Ecological Footprint (EFP) in life cycle analysis, encompassing a broad spectrum of products and services, thereby representing the ecological assets required by a community and the natural resources utilized for the production of essential goods and services, as well as for the absorption or disposal of waste and by-products. In the context of global warming and anthropogenic emissions, EFP—encompassing all components such as water and biodiversity—serves as a key indicator of greenhouse gas emissions associated with the production of goods and services (Więk & Tkacz, 2013). When converted to carbon equivalent, the EFP provides a comprehensive measure of environmental impact across the entire life cycle of a product or service. The Carbon Footprint, a consolidated numerical value encompassing components like Land Footprint, Water Footprint, Biodiversity Footprint, Resource Footprint, and Food Footprint, is extensively used to identify mitigation and adaptation strategies for global climate change (Lal, 2022). Agriculture and the food system constitute a large component of the total carbon footprint, especially in developing countries like India, China, Japan, and South Korea, highlighting the urgency of reduction strategies (Fig. 1 outlines five pillars for Carbon Footprint reduction). AI has the potential to significantly reduce the carbon footprint of food systems by optimizing various stages. By streamlining supply chains, AI can minimize transportation emissions and improve resource allocation Precision agriculture, powered by AI, enables farmers to make data-driven decisions that enhance productivity while reducing environmental impact (Blasch et al., 2020). AI-driven tools can predict optimal growth conditions, monitor plant health, and detect pests and diseases, leading to more efficient use of resources and lower emissions (Pathan et al., 2020). Furthermore, advancements in automation, such as harvesting robots and food processing robots, enhance environmental sustainability by reducing food waste, a significant environmental challenge (Van Der Burg et al., 2022). Beyond production and processing, sustainable packaging solutions are crucial for reducing the environmental impact of food. Innovations like biodegradable, compostable, and edible packaging offer alternatives to traditional plastics (Sokka et al., 2024).

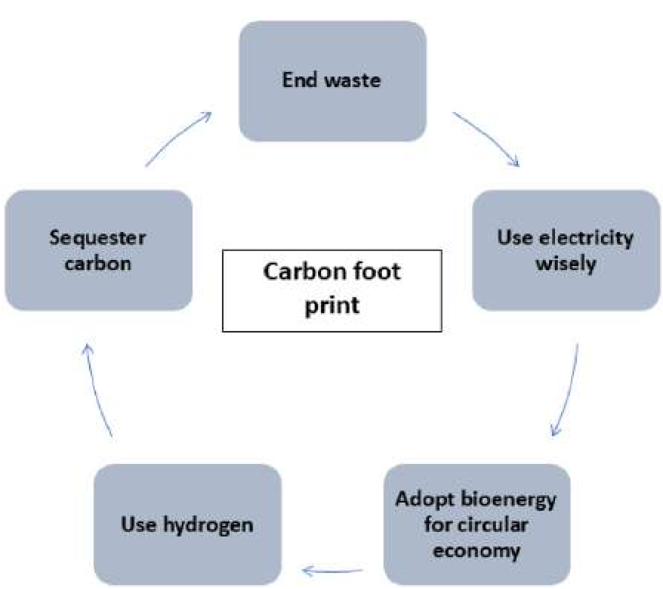

Fig. 1. Pillars to reduce Carbon Footprint.

Innovations in packaging technology, such as biodegradable and compostable materials, offer alternatives to traditional plastics. Edible packaging, made from natural, plant-based sources, can be consumed or biodegraded rapidly, reducing waste. Smart tags, a term introduced by researchers, denote a unique integration of intelligent packaging technologies, characterized by visible electronic markers equipped with environmental sensing capabilities and augmented by software intelligence (Htun et al., 2023). These tags incorporate machine vision, user information, and location tracking, facilitating real-time monitoring and enhanced communication within the supply chain. Smart labels, equipped with sensors, can monitor product conditions in real-time, ensuring freshness and reducing food waste (Gligoric et al., 2019). These technologies not only enhance product safety but also contribute to a greener future. However, the development and operation of AI systems themselves have an environmental cost. The massive computational power required for training and running complex AI models consumes substantial energy, often derived from fossil fuels, contributing to carbon emissions. Data centers, which house AI infrastructure, also require significant water for cooling and generate electronic waste from discarded hardware (United Nations Environment Programme, 2024). While the environmental benefits of AI applications in food systems are often emphasized, it is crucial to conduct life cycle assessments of AI technologies to ensure that the environmental benefits outweigh their operational footprint. This demands a focus on developing energy-efficient AI algorithms and hardware, promoting renewable energy sources for data centers, and establishing responsible e-waste management practices.

Concurrently, the social impact of AI in food design is profound and requires careful attention, building upon the ethical issues discussed previously. The social acceptance and public perception of AI in food design are influenced by various factors. While AI offers numerous benefits, such as improved efficiency and sustainability, concerns about job displacement and data privacy remain prevalent. Public education and transparent communication about the benefits and limitations of AI can help build trust and acceptance. Engaging stakeholders in the development and implementation of AI technologies can also foster a positive perception and ensure that AI solutions are aligned with societal values and needs. The ethical issue of algorithmic bias, as discussed, can have direct social consequences, potentially exacerbating existing inequalities in food access or resource allocation if not properly addressed through diverse development teams, transparent AI practices, and continuous auditing. AI has the potential to revolutionize food systems by significantly reducing carbon footprints, enhancing packaging sustainability, contributing to a greener future. Simultaneously, it holds the key to improving public perception through education and engagement, fostering social acceptance. (Zatsu et al., 2024). AI continues to evolve, it is essential to proactively address both its environmental footprint and its social challenges to ensure a sustainable and equitable future for all. Recognizing these complex interdependencies, the next section will explore the regulatory and policy landscape necessary to guide the responsible development and deployment of AI in food design, ensuring its benefits are maximized while mitigating its risks for both the environment and society.

6. Regulatory and policy landscape

The integration of AI in food production is subject to a growing body of global regulations aimed at ensuring safety, quality, and ethical standards. Regulatory bodies such as the Food and Drug Administration in the United States and the European Food Safety Authority in Europe have established guidelines that food companies must adhere to when employing AI technologies. These regulations address various aspects, including data privacy, cybersecurity, and product liability, to mitigate risks associated with AI applications in the food industry. Ethical AI frameworks are paramount for guiding the responsible development and deployment of AI technologies within the food industry, emphasizing principles such as transparency, accountability, fairness, and human oversight. For instance, the European Union's AI Act mandates clear communication regarding AI system capabilities and limitations, ensuring user awareness during AI interactions. Moreover, these frameworks advocate for inclusive AI development processes to prevent biases and discrimination. The Engineering and Physical Sciences Research Council's Framework for Responsible Innovation, which employs anticipation, reflection, engagement, and action, offers a structured methodology for evaluating the ethical implications and practical applications of AI. This approach was utilized to conceptualize a fictional data trust leveraging AI for data sharing and decision-making within the food supply chain (Craigon et al., 2022), demonstrating how stakeholder engagement and diverse perspectives can lead to ethically sound and practically viable AI solutions.

Governments and institutions play a pivotal role in shaping the regulatory environment for AI in the food industry. Initiatives like the India AI Mission are dedicated to establishing a robust AI ecosystem founded on principles of safe and trusted AI (Choudhary et al., 2024). These efforts include the development of indigenous tools for bias mitigation, algorithm auditing, and ethical certifications. By fostering collaboration among stakeholders and implementing comprehensive regulatory frameworks, governments can ensure the responsible development and utilization of AI technologies for societal benefit.

While global efforts are underway, the regulatory and policy landscape specifically within Sri Lanka regarding AI in food production remains nascent. The Sri Lanka Association for Artificial Intelligence, primarily functioning as an AI research group, is actively involved in promoting public awareness, enhancing AI education and research, and fostering industry-academia collaborations for real-world AI applications (Chamara et al., 2020). The Sri Lanka Association for Artificial Intelligences activities, including promotional programs, short courses, research promotion, and an annual AI conference, are crucial for building foundational knowledge and capacity. However, the current focus is predominantly on research and advocacy rather than the direct formulation and implementation of specific regulatory policies governing AI in the food sector. This highlights a significant gap in the Sri Lankan context, where the transition from general AI promotion to sector-specific regulation for food production is yet to be fully realized. This necessitates further development of national policies and frameworks to ensure the safe, ethical, and transparent adoption of AI within Sri Lanka's food industry, aligning with international best practices and safeguarding consumer interests. The preceding discussion underscores the nascent stage of regulatory development for AI in Sri Lanka's food sector, contrasting with more established global frameworks. This gap presents both significant challenges and opportunities as the nation looks towards the future. The future integration of AI in food production hinges on addressing several critical aspects, ranging from policy formulation to technological infrastructure and human capital development.

7. Future prospects and challenges

The integration of AI in the food industry is a transformative force, fundamentally reshaping sustainable food innovation. This paradigm shift is evident in the emergence of precision fermentation, an advancement made possible by the convergence of AI, bioinformatics, and computational biology. AI technologies are enabling the development of hyper-personalized meals, eco-conscious consumption, and real-time consumer data analysis. These innovations are reshaping the food and beverage sector, allowing companies to identify trends, test new concepts, and bring products to market more rapidly than ever before. Key drivers of this transformation include the need for personalized experiences, the use of technology to enhance food interactions, and a growing focus on eco-friendly practices. AI is also being utilized to create faster, more personalized, and sustainable products by analyzing vast amounts of consumer data and gaining real-time insights into changing preferences.

The advent of "Food Industry 4.0″ breakthroughs has paved the way for novel food product development. Industry 4.0 represents a multifaceted paradigm that seamlessly integrates physical, digital, and biological realms (Hassoun et al., 2022). Within the agriculture and food sectors, this framework leverages cutting-edge technologies such as AI, the Internet of Things, advanced smart sensors, robotics, and innovative 3D printing methods. These synergistic technologies collectively modernize and enhance agricultural practices and food production, contributing to a more efficient, sustainable, and responsive industry. A prime example of sustainable strategies within this context is enzymatic hydrolysis, which offers a promising avenue for recovering value-added compounds from food waste and by-products (Hassoun et al., 2022, Bekhit, et al., 2022). These Industry 4.0 technologies collectively facilitate the modernization and enhancement of agricultural practices and food production, contributing to a more efficient, sustainable, and responsive industry. Emerging trends in food industry is given in Fig. 2.

Beyond process optimization, AI is instrumental in developing new food ingredients and products. Wang et al. (2022) reported that algae could be a functional ingredient which has high amounts of essential amino acids. These algae can be an alternative source of protein rather than the traditional available sources. Davies et al. (2021) reported that ML can develop the information regarding the nutritional composition of the packed foods. Furthermore, 3D printing offers significant potential to reduce carbon foot print and minimize raw materials useage in food production. Portanguen et al. (2019) stated that textured and appealing meat products can be produced which have high nutrition values and convenient for people. Despite the numerous benefits, the application of AI in food design is not without challenges.

A primary concern is the potential for inherent bias in AI algorithms, which can lead to unintended and potentially inequitable consequences in food production and distribution. For instance, if training data for an AI system reflects existing dietary biases or socioeconomic disparities, the AI might perpetuate or even amplify these issues in its recommendations or optimized processes. The increasing reliance on AI technology also raises critical questions regarding data privacy and security, given the sensitive nature of consumer preferences and supply chain data. The intrinsic complexity of many AI systems can further result in a lack of transparency, making it difficult for stakeholders to comprehend and trust the decision-making processes. This "black box" phenomenon can hinder accountability and ethical oversight. Moreover, the ethical implications of AI in food design extend to potential labor displacement, particularly impacting small-scale farmers and producers who may struggle to adapt to AI-driven automation without adequate support and policy interventions. The socio-economic impacts on these vulnerable groups warrant careful consideration to ensure that AI adoption benefits all stakeholders within the food system.

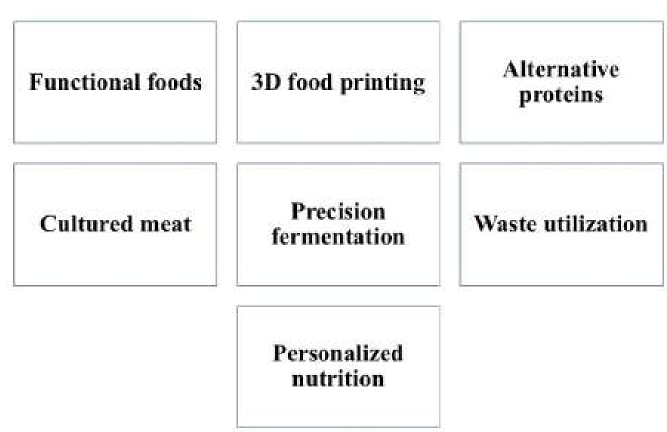

Fig. 2. Emerging trends in food industry.

To realize the full potential of AI in the food industry, it is essential to develop a comprehensive roadmap is essential, one that meticulously addresses both sustainability and ethical considerations. This roadmap should prioritize the development of transparent and unbiased AI algorithms, ensuring that AI-driven solutions are equitable and inclusive. This means not only technical solutions for bias detection and mitigation but also diverse representation in AI development teams. Investment in robust education and training programs is crucial to equip all stakeholders, from farmers to food scientists and policymakers, with the necessary skills to effectively implement and manage AI technologies. Additionally, collaboration between governments, industry, and academia is vital to establish regulatory frameworks that promote the ethical use of AI in food systems. By fostering innovation while safeguarding ethical standards, it is possible to create a sustainable and resilient AI-driven food system that delivers equitable benefits to all members of society.

8. Conclusion

The integration of AI into sustainable food design represents a pivotal frontier in addressing some of the most pressing global challenges of our time, including climate change, resource depletion, and pervasive food insecurity. As this review has demonstrated, AI's transformative potential extends across various facets of the food system, from enabling hyper-precision agriculture that minimizes waste and optimizes resource allocation to streamlining complex supply chains for enhanced efficiency and reduced environmental footprint. Furthermore, AI is a catalyst for disruptive innovations such as the advancement of lab-grown foods and the development of intelligent, sustainable packaging solutions. These technological leaps are poised to revolutionize food production, distribution, and consumption patterns, moving us towards a more resilient and environmentally benign food system. However, this technological paradigm shift is not without its complexities and inherent risks. For AI to truly serve as a force for good in sustainable food design, its deployment must be meticulously guided by robust ethical frameworks and inclusive policy instruments. As highlighted, critical concerns such as algorithmic bias, potential privacy breaches of sensitive consumer and agricultural data, and the exacerbation of social inequities demand proactive and comprehensive mitigation strategies. The environmental footprint of AI itself, encompassing energy consumption for data centers and hardware manufacturing, also necessitates careful consideration within the broader sustainability discourse. Moreover, the socio-economic impacts, particularly the potential for labor displacement within traditional agricultural and food processing sectors, underscore the imperative for just transition strategies and continuous workforce upskilling. Ensuring the successful and equitable integration of AI in food systems hinges on core principles of transparency, accountability, and meaningful public engagement. Stakeholders, from policymakers and industry leaders to farmers and consumers, must have a clear understanding of AI's capabilities, limitations, and decision-making processes. As the regulatory landscape continues to evolve globally, a concerted effort towards international collaboration will be absolutely essential to harmonize standards, share best practices, and foster responsible AI adoption that transcends national borders.

Looking ahead, the trajectory of sustainable food design is fundamentally intertwined with our ability to judiciously balance rapid technological advancements with unwavering ethical considerations. The imperative is to foster continuous innovation while simultaneously safeguarding planetary health and promoting social equity. This ambitious vision necessitates a multi-stakeholder, collaborative approach that brings together governments, industry, academia, and civil society. Only through such unified efforts can we effectively navigate the complexities of AI integration, harness its immense potential, and ultimately realize a sustainable, AI-driven food system capable of meeting the nutritional needs and environmental responsibilities of both present and future generations. The challenges are significant, but the potential rewards of a truly optimized, sustainable, and equitable global food system, powered by responsible AI, are profound and achievable through concerted action.

Author contributions

S.H. writing—original draft. D.K. Conceptualization; data curation; visualization; writing—original draft. P. R. and A.K. writing—original draft. C. P. writing—review and editing; data curation. F. O. writing—review and editing; conceptualization. M. K. Conceptualization; data curation; visualization; writing—review and editing, N.K. and C. K. R. writing—review and editing.

Data availability statement

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Data availability

Data will be made available on request.

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Is AI a functional equivalent to expertise in organizations and decision-making? Opportunities and pitfalls for AI in the context of just transitions

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The urgency of addressing climate change and achieving a just transition to sustainability has never been greater, as the world approaches critical environmental thresholds. While artificial intelligence (AI) presents both opportunities and challenges in this context, its role in organizational decision-making and expertise remains underexplored. This paper examines the interplay between AI and human expertise within organizations, focusing on how AI can complement or substitute traditional expertise across factual, temporal, and social dimensions. Drawing on Social Systems Theory, we argue that while AI excels in data processing and rapid decision-making, it falls short in contextual adaptation, long-term strategic thinking, and social legitimacy—areas where human expertise remains indispensable. And this is, we observe, particularly evident in problems connected with climate change and sustainability more broadly, where the tensions for organizational decision-making -and governance become even denser as much in the factual, temporal and social dimensions, making them into very complex, 'super-wicked', problem situations. Thus, there is a need to think more in detail about possible hybrid approaches, integrating AI's computational strengths with human interpretive and adaptive capabilities, which may offer promising pathways for advancing organizational decision-making in the overly complex, wicked decision-making scenarios characteristic of just transitions. However, this requires careful consideration of power dynamics, trust-building, and the ethical implications of AI adoption. By moving beyond techno-optimism, this study highlights the need for a nuanced understanding of AI's functional and social plausibility in organizational settings, offering insights for fostering equitable and sustainable transitions in an increasingly complex world.

KEYWORDS

intelligence, expertise, organizations, just transitions, complexity, science-policy, interface

Introduction

With the world on the verge of surpassing the 1.5°C threshold set by the Paris Agreement and exceeding multiple planetary boundaries, the urgency of transitioning to sustainable development has never been greater. While past efforts have been insufficient, a profound transformation in production, consumption, and societal organization is imperative to achieve carbon neutrality and environmental sustainability.

Yet, sustainability is not merely about reducing emissions and pollution; it must also be just and inclusive. A just transition ensures that the burdens and benefits of change are equitably distributed, leaving no one behind. In this context, artificial intelligence (AI) emerges as both a potential catalyst and a challenge. On one hand, AI offers new efficiencies in production, energy management, and resource tracking, but on the other, its ecological footprint and disruptive effects on employment raise pressing concerns. AI itself is a driver of transition, particularly in reshaping labor and decision-making structures, making it crucial to examine how this shift can be made equitable.

The rapid evolution of AI—outpacing regulatory capacities—has fueled both optimism and anxiety. While some view it as a technological leap toward a better future, others warn of unregulated risks. The 2024 "Global Digital Compact," established at the UN Summit for the Future in New York, represents an initial effort to harness AI's potential while mitigating its threats in the pursuit of sustainability and equity.

However, meaningful action requires moving beyond hype to a deeper understanding of AI's real impact on society and the conditions for a just transition. Much of the existing literature focuses on AI's technical dimensions, often neglecting the broader socio-technical dynamics at play. Transformative shifts—particularly those that redefine production, consumption, and development paradigms—cannot be understood solely as technological processes. They are embedded within complex networks of science, regulation, industry, economics, and social expectations, unfolding through gradual, multi-scalar, and non-linear dynamics.[1] In this sense, promoting a just transition—as well as tackling climate change and sustainability more generally- is at its core a matter of decision-making and governance (Agrawal et al., 2022; Underdal, 2010; Billi et al., 2021). And in modern society, a good part of decision-making and governance is made in, through or between organizations (Luhmann, 2018; Willke, 2006) so that understanding if and how AI development can impact—positively or negatively—organizational decision-making is very relevant for the research o just, sustainable and zero-carbon transitions.

This paper contributes to this discussion by examining the relationship between AI and expertise within organizations and reflecting on the implications—opportunities and challenges—it can bring to decision-making relating to climate change and sustainability. We argue that understanding expertise's historical de-humanization within organizations is key to assessing AI's role in a just transition. Using Social Systems Theory, we provide a sociological and historical perspective to counter the oversimplifications often present in AI debates, particularly the tendency to "over-humanize" both organizations and AI itself. Then, we look at how sustainability challenges may require rethinking the dichotomy between AI and human expertise, moving towards more 'hybrid' approaches and thus pushing forward the need of more research on how to design and implement effective and just forms of human-AI expertise hybridization.

The paper is structured as follows: Section II reviews dominant theories on technological singularity and AI's impact on expertise within organizations. Section III draws on Social Systems Theory to contextualize the evolution of expertise and the pressures toward its de-humanization, while Section IV explores whether AI can functionally replace expertise in organizations, identifying its limits. With this theoretical background, Section V turns to the central question: what are AI's opportunities and challenges in fostering a just transition to sustainability? Finally, Section VI offers concluding reflections and directions for future research.

Artificial intelligence, expertise and organizational decision-making: a brief summary

The term *Artificial Intelligence* broadly encompasses various technologies, though most current applications revolve around machine learning—algorithms that refine performance through exposure to data without explicit programming. Since the 1950s, AI development has oscillated between phases of optimism ("AI springs") and stagnation ("AI winters"), constrained by computing power, labor-intensive data preparation, and the brittleness of early systems (Schraagen and van Diggelen, 2021). A turning point arrived in the 2010s with big data and deep learning, which allowed neural networks to autonomously process vast datasets, reducing human intervention while introducing new challenges such as data dependence and opaque decision-making mechanisms (Jiang et al., 2022).

This progress has fueled a resurgence of speculation about AI's long-term trajectory, including debates over superintelligence and technological singularity (Krüger, 2021). Perspectives vary widely: skeptics argue that AI's advancement is overhyped and that true singularity remains a distant or unattainable goal, while proponents—including transhumanists—view it as an imminent and beneficial breakthrough. Meanwhile, critics warn of potential risks, ranging from job displacement to existential threats (Hoffmann, 2023). Although some foresee rapid progress, others highlight persistent limitations such as the finite availability of high-quality data and the growing computational costs of scaling AI models (Walsh, 2017).

AI's role in decision-making has evolved in parallel. The first significant applications emerged in the 1980s with expert systems, which sought to encode human knowledge into structured AI models. These systems, however, proved limited in their application, leading to the refinement of knowledge-based systems and, later, the resurgence of AI-driven decision-making through deep learning (Duan et al., 2019). Despite these advances, concerns persist over AI's capacity to replace human labor and the risks associated with autonomous decision-making, particularly in high-stakes areas such as healthcare, security, and governance (Pilling and Coulton, 2019).

In response, contemporary approaches increasingly emphasize hybrid models that integrate human expertise with AI capabilities. Many organizational decisions involve uncertainty, complexity, and ethical considerations, where AI's analytical strengths can complement human intuition, experience, and contextual understanding (Trunk et al., 2020). This shift aligns with a broader redefinition of expertise,

1 Admittedly, these kind of considerations have a much broader application than sustainability or climate change issues. Readers may find these arguments interesting also for other topics of research. However, in this paper we decided to focus on this particular framing as questions of IA and expertise in organization and decision-making tend not to be sufficiently considered in sustainability and climate change literature, and we believe our approach may provide useful insights for this field, as is discussed at length below.

moving beyond static domain-specific knowledge to incorporate adaptive intelligence, intuitive reasoning, and interdisciplinary competencies (Carbonell and Dailey-Hebert, 2021).

Consequently, scholars and practitioners increasingly advocate for AI-human hybridization that acknowledges elements of singularity debates while preserving the unique strengths of human intelligence. As with past waves of automation, AI may not eliminate jobs outright but rather transform labor markets, reshaping the nature of expertise and the skills required for emerging roles (Jarrahi, 2018). While AI's impact remains uncertain, its integration into organizational decision-making suggests a shift not toward full automation but toward redefining human labor and intelligence in an evolving technological landscape (Labraña and Bill, 2015).

Organizations as social systems and the role of expertise

Niklas Luhmann's Social Systems Theory offers a sociological framework for analyzing modern society as a system of communication (Luhmann, 2013). Rather than focusing on individuals or actions, this theory conceives society as constituted by communication. Within this framework, organizations are understood not as aggregates of persons or goals, but as specific types of social systems defined by their ability to produce decisions. From this perspective, organizations are forms of social systems that emerge to manage complexity and reduce uncertainty in modern, functionally differentiated societies. Unlike interaction systems or broader societal function systems—such as politics, economy, or education—organizations are problem-oriented systems that establish structured ways of coordinating communications through decisions. While organizations are not defined by a specific binary code, as function systems are, their operations depend on the continuous generation and stabilization of decisions, which in turn create their internal coherence against their environment (Luhmann, 2013). This approach has been extensively used to analyze the structural and operational logic of organizations, highlighting how decisions function as a mechanism of systemic closure and continuity (Andersen, 2003).

This focus on decision-making underlines the fundamental problem organizations face: the necessity of addressing and reducing overwhelming complexity while maintaining its coherence in a dynamic environment (Seidl and Becker, 2005). Decisions, as selective mechanisms, serve to filter possibilities by determining what aspects are included in communication and what is excluded. This ongoing process of selectivity underscores the fragility of organizational coherence, as every decision, by simplifying complexity, simultaneously excludes alternatives, thereby generating risks that in turn demand further decisions in a self-producing cycle of further decisions. In this sense, organizations are not stable entities, but dynamic systems whose continuity depends on their capacity to recursively produce decisions (Nassehi, 2005; Seidl and Mormann, 2014; Luhmann, 2020).

Expertise must be understood within this broader context as a phenomenon that does not represent an inherent feature of organizations or their initial development. In pre-modern societies, coordination within pre-organizational forms—such as guilds, religious orders, or early bureaucracies—relied heavily on tradition, charisma, or personal authority, which tied decision-making and knowledge systems to individual actors and culturally embedded norms (Weber, 1978). However, as societal complexity increased, these mechanisms proved insufficient to address the demands of more differentiated and dynamic environments. Expertise emerged as an institutionalized resource in early modernity, serving as a response to this growing challenge, decoupling decision-making from individual authority and anchoring it in specialized systems of knowledge (Meyer and Rowan, 1977). This shift not only allowed organizations to manage complexity more effectively, in a way less context-dependent, but also contributed to the de-humanization of organizational dynamics, as the reliance on personal relationships and intuitive authority was replaced by impersonal, procedural, and often automated frameworks of knowledge production and decision-making (Warner, 2007). Expertise thus became embedded within roles, credentials, and institutional structures, transforming organizations into systems increasingly oriented towards predictability, while subordinating interpersonal or traditional forms of coordination to the authority of specialized knowledge systems that claimed a better understanding of their respective environments (Collins, 1979).

Functional differentiation—the process by which society becomes segmented into autonomous subsystems, each with its own rationality, language and rules, such as law, economy, education, and science (Luhmann, 1982)—has been pivotal in shaping the relationship between expertise and the emergence of modern organizations. As each subsystem developed its own distinct operational logic, organizations emerged as mediating structures tasked with interpreting and implementing these logics in context-specific ways (Labraña et al., 2025). Financial institutions, for example, became critical to the economy by operationalizing financial transactions and managing economic flows, while schools aligned themselves with the education system by translating pedagogical theories into structured learning practices, and courts embedded within the legal system transformed legal norms into decisions on concrete cases. In each of these instances, organizations required specialized expertise to bridge the gap between the abstract, often self-referential operations of societal subsystems and the concrete, practical demands of their environments. Expertise thus became indispensable, enabling individuals within organizations to fulfill their expected roles while allowing organizations to adapt and coordinate in response to the increasingly abstract and complex demands arising from the expansion of functionally differentiated systems (Zald and Lounsbury, 2010; Labraña and Vanderstraeten, 2020).

Expertise thus became the primary mechanism through which organizations structured their relationships with the broader societal systems they were embedded in (Luhmann, 2013). By doing so, expertise enables organizations to achieve operational stability by systematically reducing complexity across the three key dimensions of meaning: factual, temporal, and social. In the factual dimension, expertise allows organizations to presuppose a stable and predictable reality by providing specialized knowledge that delineates domains of relevance, framing problems and solutions within bounded contexts. This stabilization of communication reduces the need for continuous renegotiation of facts, creating a foundation for shared understandings among organizational members (Simon, 1991; Weick, 1995). For instance, in engineering firms, expertise defines technical parameters, enabling clear problem identification and reliable solutions (Bucciarelli, 1994). Similarly, in medical organizations, expertise grounds diagnoses and treatments in evidence-based practices, fostering a common understanding of health and disease that shapes operational decisions (Berg, 1997). Lastly, in schools, expertise establishes pedagogical frameworks that stabilize teaching methodologies, fostering shared educational goals among educators and students (Shulman, 1987). Through these mechanisms, expertise aligns organizational practices with the complex demands of the societal systems they are embedded in, ensuring that responses are not only legitimate but also help reduce environmental complexity in ways that are both effective and socially convincing.

In the temporal dimension, expertise operates as a dynamic and continuously evolving resource for organizational decisions, distinguishing itself from forms of knowledge that often claim timeless validity. Its relevance lies in its ability to adapt to changing circumstances, functioning as a self-substitutive order that perpetually renews itself through the ongoing refinement of the theories and methodologies upon which it is ultimately based (Luhmann, 1990). For instance, legal expertise evolves to integrate new regulations and precedents, while technological expertise advances alongside innovations in tools and systems to retain its social effectiveness (Teubner, 1987). Central to this process is professional training within educational institutions, which serves as the primary mechanism for the continual updating and refinement of expertise. Schools and universities, especially, play a crucial role by establishing standardized frameworks and methodologies designed to equip individuals with the knowledge needed to operate as experts in their respective fields, ensuring that expertise remains a relevant, adaptive, and useful resource in complex organizational environments (Brown, 2001).

In the social dimension, expertise legitimizes decision-making processes within organizations by establishing hierarchies of knowledge and authority, where the ability to decide is not solely based on possessing specialized knowledge but also on being recognized as having the authority to do so (Luhmann, 2000). This recognition functions as a legitimizing mechanism that is not merely an objective reflection of competence but also a socially constructed attribution of authority (Stichweh, 1994; Eyal, 2019). In this sense, legitimacy is not derived from expertise alone but from the institutional and communicative processes that attribute trustworthiness and decision rights to certain roles or individuals. In turn, this recognition creates distinctions between experts and non-experts, facilitating the coordination of decisions and reducing complexity within organizations. Based upon this, expertise fosters trust and accountability by enabling the delegation of responsibilities and the implementation of decisions within a framework of legitimacy, reinforcing organizational coherence and ensuring the effective allocation of tasks and resources toward shared objectives (Bunz, 2014). For example, in hospitals, the expertise of doctors and nurses—validated through certification and training—ensures that medical decisions are both credible and authoritative, maintaining trust among organizational members and external stakeholders (Freidson, 1970). Likewise, in educational institutions, the expertise of teachers and administrators—validated through formal qualifications and professional development—provides a foundation for decision-making processes that guide curriculum design, student assessment, and resource allocation (Hoyle and Wallace, 2005). By clearly defining roles and responsibilities based on expertise, organizations reduce uncertainty, minimize conflicts over who has authority to decide on which topics, and establish a framework for achieving their goals, reinforcing their capacity to respond to internal and external changes.

Artificial intelligence as a (partial) functional equivalent of expertise in organizational decision-making

The increasing adoption of AI in organizational settings has prompted debates about whether it can serve as a functional equivalent to human expertise. As explored in the previous section, expertise has historically emerged as a mechanism to reduce complexity in organizations, addressing uncertainty through the factual, temporal, and social dimensions. AI, with its capacity for data analysis, pattern recognition, and automation, appears to replicate certain functions of expertise. However, when examined in light of a sociologically-grounded understanding of expertise as outlined earlier, AI reveals limitations that challenge its ability to serve as an equally comprehensive substitute.[2]

In the factual dimension, human expertise combines generalization and specificity to address organizational challenges within bounded contexts. This capacity for contextual adaptation allows experts to frame problems in ways that are both precise and actionable, drawing on abstract principles and practical experience. By contrast, AI systems focus on generalizable patterns derived from vast datasets (LeCun et al., 2015). As already discussed above, in the first eras of AI, this training often made these systems overfitted to specific problem-situation, completely losing any ability to translate knowledge from one domain to the other (i.e., they only had a very restricted domain expertise, with no general expertise). This was called 'brittleness'. While contemporary approaches to AI, and particularly deep learning, have overcome some of these limitations thanks to the use of a much broader base of data and parameters, they fundamentally still rely on the learning of specific 'rules' and patterns, as opposed to what human experts do by assigning a 'meaning' to data which can actively connect one domain of knowledge and learning with others through higher-level cognitive architectures, that these systems lack. The deep learning approach thus excels in identifying trends or optimizing routine processes, but it often fails to account for the specificities that arise in complex or novel situations. For example, a financial algorithm may efficiently detect fraudulent transactions by analyzing patterns across thousands of data points but may struggle to account for contextual nuances, such as the socio-economic conditions influencing certain behaviors (O'Neil, 2016). Similarly, in the healthcare sector, AI tools may accurately flag anomalies in diagnostic imaging; however, they often fail to integrate this

2 Of course, this 'equivalence' between AI and human expertise is only partial, and contingent to specific contexts (e.g., specific topics or functions, 'tactical' instead than strategic decisions, 'hard' instead than 'soft' skills and so on). That is in part what the discussion between 'specific' AI and 'general' AI (AGI) (Emmert-Streib, 2024): the long-waited—or feared—promise of AGI is that it can substitute human expertise across the whole spectrum, and flexibly through different fields or decision-making situations. But all forms of AI, from search-aid chat-bots to 'expert systems' to enhanced reality to autonomous driving- are in some way a form of substituting 'some' kind of expertise in 'some' decision-making situation, and one of the main objectives of AI development has been indeed to expand the scope and reduce the 'brittleness' (that is, the lack of flexibility and generalizability) of AI in ever-more complex and broader decision-making situations.

information with patient histories, physician observations, or the socio-cultural contexts that influence care—unless explicitly trained to do so (Obermeyer and Emanuel, 2016). Even more relevant, in the field of artistic creation, AI demonstrates the ability to generate texts that give the impression of creativity. However, these outputs often lack the deeper contextual awareness and intentionality that has historically defined proper human artistic expression.

This emphasis on generalization limits AI's ability to generate the context-sensitive relevance required for effective organizational decision-making. Expertise, in contrast, goes beyond merely providing answers; it involves identifying the limitations of existing knowledge and bridging these gaps through experiential insights. AI's reliance on large-scale datasets creates a dependency fundamentally distinct from the contingency-responsive and adaptive qualities inherent in human expertise (Stinson and Vlaad, 2024). As discussed in Section III, expertise reduces complexity in organizational operations by presupposing a relatively stable world and integrating theoretical knowledge with practical experience to frame and address relevant issues. AI, however, lacks such foundational presuppositions, making it highly susceptible to incomplete, biased, or poorly contextualized data —a vulnerability that has garnered growing attention (Zou and Schiebinger, 2018). As a result, the insights generated by AI risk being not only irrelevant but also potentially counterproductive to organizational decision-making anytime the decision involves this kind of context-specificity, or higher degrees of general expertise as compared to domain expertise, undermining its capacity to address context-specific challenges and ensure the relevance and effectiveness of its actions.

Furthermore, AI's reliance on external inputs highlights its inability to autonomously delineate and prioritize relevance within complex organizational environments. This dependency renders AI incapable of independently addressing ambiguity or adapting to contexts where information is incomplete, conflicting, or fluid, as it is increasingly evident in organizational decision-making (Kahneman and Klein, 2009). Unlike human expertise, which leverages experiential insights and reflection to discern relevance and establish priorities, AI systems are entirely constrained by the quality, scope, and structure of the data they are provided. This reliance not only limits their capacity to make judgments but also prevents them from accounting for variables that lie outside predefined parameters, reducing their effectiveness in new and unpredictable scenarios. Similarly, it also makes them strongly subject to underlying biases in the data, something very visible in the different forms of 'automated discrimination' that AIs inherit from their data (Heinrichs, 2022).

In the temporal dimension, AI clearly surpasses human expertise any time a very quick decision needs to be made considering a large amount of new information, that humans would not be able to process. But in organizations, expertise is not only a mechanism to make quick decisions; rather, and much more importantly, it serves to reduce complexity by fostering trust in human judgment, particularly in uncertain contexts. Unlike AI, which operates within predefined parameters, human expertise is inherently dynamic and adaptive, drawing on interpretive processes that integrate past experiences with plausible anticipations of the future. This ability to contextualize decisions temporally enables expertise to address immediate challenges while considering their broader implications for future scenarios. By aligning present actions with long-term objectives and strategies, expertise equips organizations to confront uncertainty with confidence, ensuring that decisions are guided by both historical insights and forward-looking perspectives. In contrast, AI operates through a logic of sufficiency rather than interpretive anticipation. While machine learning systems can adapt by incorporating new data, this process is fundamentally reactive, relying on existing patterns and inputs. As a result, AI lacks the critical proactive capacity to assess emerging or unforeseen conditions (Dreyfus and Dreyfus, 2005).

Equally important, trust in expertise is deeply rooted in its capacity to justify decisions and respond effectively to unanticipated developments. Experts do not merely predict outcomes; they provide explanations that frame uncertainty in meaningful ways, fostering confidence and enabling contingency planning. In contrast, AI systems, while capable of producing statistically robust outputs, often lack the interpretive depth necessary to contextualize their recommendations. The opacity of many algorithms—the so-called "black box" problem (Bathaee, 2018)—further erodes trust by concealing the reasoning behind their conclusions. This lack of transparency poses significant challenges for organizations, particularly in high-stakes contexts where accountability, adaptability, and a clear rationale for decisions are critical. Without the ability to articulate why a specific course of action is recommended, AI systems risk being perceived as unreliable, limiting their utility in contexts requiring rather explicit interpretive insights (Ananny and Crawford, 2018). In this sense, AI systems are somewhat more similar to 'intuitive' expertise, or 'gut feeling', which while broadly used in decision-making (and arguably, one of the most significant components of human expertise) also shares this lack of clear explain ability. However, even intuitive expertise can ultimately be explained, understood and even predicted (and abundantly subject to measurement and testing, see Section 2) based on identifiable sets of human characteristics, which makes it possible to anticipate that some 'person' will be likely more expert than another in certain tasks, as well as to foster and nurture expertise, both in the education system and within organizations. This is not the case with IA: while AI 'learns', and AIs with more parameters or more data allegedly learn more and faster, there are still not clearly defined attributes that can help an observer know beforehand which AI will be more expert at what, and even, whether all times the same AI will be called -each of this is, in some way, a new individual 'expert' that learns from the specific interaction but cannot be replicated in future interactions- it will always show the same expertise. Steps are being done in this direction, and prompt engineering' may somewhat solve this, but still strongly relying on human intervention.

Additionally, the institutional trust-building mechanisms underpinning human expertise is fundamentally absent in AI systems. Expertise is deeply embedded within professional networks, credentialing processes, and institutional frameworks that collectively establish its legitimacy and ensure its accountability (Brint, 1994). These structures not only validate and update expert knowledge but also create mechanisms for holding experts responsible for their decisions, thereby fostering confidence in their guidance. AI, by contrast, functions as a technical artifact, disconnected from these institutional connections, which makes it significantly more challenging to perceive its outputs as a reliable foundation for long-term decision-making. While AI excels at optimizing specific tasks within well-defined parameters under quick-answer problem situations, its inability to participate in the broader dynamics of social trust highlights a limitation in its capacity to replace human expertise in longer-term contexts that require a broader picture (Pasquale, 2015).

In the social dimension, expertise serves not only as a repository of specialized knowledge but also as a legitimizing mechanism within organizational hierarchies. It gains recognition and validation through the distinction between experts and non-experts, creating a structured framework for trust, authority, and accountability. This distinction is essential for organizational operations, as it facilitates the delegation of decision-making and the establishment of clear lines of responsibility. AI, however, disrupts this social framework. As a non-human system, it lacks the relational and institutional positioning that underpins human expertise, making it incapable of occupying the role of an "expert" in the traditional sense. While advanced AI systems such as ChatGPT can simulate dialogue, offer justifications, and respond to challenges to some extent, these interactions remain only partially embedded in the social and institutional contexts necessary for conferring legitimacy. As noted, legitimacy arises not merely from functional outputs but from the social attribution of trust, responsibility, and accountability—dimensions that AI is not capable of fulfilling autonomously. It therefore continues to function as a tool whose outputs require human interpretation and mediation (Binns, 2018).

A key issue in this regard is the indeterminacy of AI's "unmarked side." Expertise relies on clearly defined boundaries between what is known and what remains unknown, along with the ability to articulate those boundaries transparently. Human experts do not simply provide answers; they also inevitably communicate the limitations of their knowledge, making the scope and constraints of their expertise explicit. In contrast, AI operates without such transparency. The already mentioned "black box" nature of many AI systems obscures the assumptions underlying their outputs and makes it difficult to identify the limits of their knowledge. This opacity disrupts the traditional distinction between experts and laypersons, creating uncertainty about AI's appropriate role within organizational hierarchies and how its outputs should be evaluated (Ananny and Crawford, 2018). That is: AI is both an extremely knowledgeable specialist and a stupid advisor.

Moreover, the social dynamics of expertise involve more than the validation of knowledge—they also encompass the coordination of diverse perspectives within organizations. Human experts play a critical role as mediators, integrating insights from various domains to facilitate collaboration, alignment, and consensus-building. They do so not only by 'knowing' (and being expert) at all the domains, but even more importantly, engaging in team work, creative collaboration and knowledge sharing with other areas. In contrast, AI systems lack this capacity. While they can generate highly individualized information, AI systems do not engage in the processes that harmonize knowledge with organizational objectives or resolve conflicting perspectives, limiting their effectiveness in multi-stakeholder environments and resulting in less legitimate outcomes (Jarrahi, 2018).

Organizational decision-making in the face of sustainability and climate change: the promise of AI

Having understood to what extent and with which caveats can AI complement or integrate with traditional human expertise in organizational decision-making, we now turn to the central question of the manuscript: *what challenges and opportunities does this imply for sustainability and climate change?* In particular, how—to which degree and in which direction—the expansion and potential hybridization of expertise may have an effect on the (organizational) decision-making dilemmas related to the attempt to steer and accelerate sustainable transitions in our societal, technological and ecological environments? In previous works (Billi et al., 2020; Billi et al., 2024a,b), we have performed a deep reflection on these dilemmas, using an analytical framework very similar to the one we have discussed so far. In these reflections, we have employed the term 'governance' to refer to the whole array of decision-making processes related to sustainable transitions, including both decisions that are taken in the domain of traditional for-profit and non-for-profit organizations, in the public arena (by State and public organizations, as well as political institutions) and in the different emerging realms of network-like quasi-organizations that often populate the field of sustainability. This implies broadening the scope of analysis to a broader meaning of organization and decision-making, which however can learn a lot from all that has been studied in terms of expertise, and its relationship with AI, in the narrower setting of conventional organizations.

In these studies, we have argued that decision-making related to sustainability transitions and climate change mitigation or adaptation, and thus expertise related to said decisions, is fundamentally faced with three dilemmas, each of which implies a specific 'tension' that decisions and expertise need to navigate, related to the same three dimensions discussed above: factually, in terms of the tension between the universality and specificity of the problem and knowledge on which decisions need to be made; temporally, the tension between long-term and short-term horizons of decision, and related to this, between the continuity of drive between decisions taken at different times and the need to adjust to changing circumstances; and socially, the tension between the coordination of decisions taken by different actors, and thus, also the possibility of some actors of restricting or steering decisions of others, and the need to maintain a degree of agency and autonomy of each individual decision maker (and thus, take advantage of their specific expertise).

In particular, our claim was that the quest for sustainability transitions applies an increasing pressure on both sides of the spectrum of each of these decision-making tensions, and thus the problem of governance (but also of expertise) becomes how to balance between them in these growingly complex conditions. This is, for many, one of the core issues that requires facing in order to face problems related to climate change -and sustainability more broadly: linear, structured, problem-solving thinking is not enough to fathom -let alone solve them. In fact, it can often lead to worsening them or creating new ones (Gupta, 2016; Lazarus, 2008; Voss et al., 2006). And it is also why, while the COVID-19 pandemics, despite its tragedy and impact, could be mostly 'solved' in less than 2 years, while climate change has still no clear 'solution' in sight despite knowledge of it having been around for more than a century, and counting (Billi et al., 2024b).

In the factual dimension, decisions regarding just transition oriented to sustainability and climate change require specificity because they relate to multiple and different domains, systems, scales, each implying its own kind of expertise. For instance, a transition in the 'energy system' requires to consider economical, technical, ecological, socio-cultural, legal and political factors, as they accrue as much at the global level, as at the national and subnational ones (Klein, 2020; Saruchera, 2025). No single set of decisions will be the best one to push forward transitions across all these contexts, different variables and knowledges need to be balanced, and this deeply challenges the cognitive limitations of human experts, which tend to have a limited grasp of the knowledge required in each of these domains, and are likely expert at most in a subset of them.

However, at the same time, these decisions need also to be able to transcend their contexts, because of the high interdependence of actions taken in each domain and scale: impacts on one sector can generate chain effects on others; measures that respond to current challenges at some scale could generate counterproductive consequences in other scales and actions that are appropriate for a certain group or sector may be negative for others. Even improved as it is, AI remains too brittle to be able to deeply tackle these interdependencies, and it lacks access to a meaning-making mechanism that can allow it to interpret and understand how these different decisions may interact with each other in different contexts. However, it can provide a vast access to data and knowledge which can help human experts to make sense of this complexity. Here, a hybridization of human (both intuitive and rational) general and context-sensitive expertise and artificial domain-specific expertise could be beneficial in that it may be able to expand the cognitive span of decision-making systems beyond the traditional limitations and thus capture as much domain knowledge as needed while also retaining the ability to read between domains, much similar to the hope that was once upon a time invested in the development of 'expert systems'. However, for that to happen, the human expert should remain in charge and at the drive, resisting the temptation of taking for granted patterns and suggestions made by AI systems, and instead guiding the search for new and more reflexive ways of understanding the complexity and making connections. In this framework, AI should primarily serve as a tool and an assistant to human expertise, augmenting rather than replacing the interpretive strengths of human decision-makers.

In the temporal dimension, decisions regarding just transitions imply a high degree of anticipation, long-term perspective and tolerance to uncertainty. Not only sustainability and climate change imply slow-moving variables, so that their causes and effects require to take into account decades- and often centuries-long timeframes. But also, transitions required to tackle them may require decades to happen, needs to nidify strategies into strategies and anticipate future scenarios which are unclear in their probability and even in the assumptions that are made to create them (sometimes referred to as 'deep uncertainty' Haas et al., 2023). Even more crucially, transitions are ill-structured problem situations, or "wicked problems" as they tend to often be called (Termeer et al., 2015) -or even "super-wicked," in the case of climate change (Gilligan and Vandenbergh, 2020). AI is not well equipped to deal with these kinds of problems, and truth be said, not all humans are. In fact, it is often implied that these problems require reframing our way of thinking, deepening our critical reflexivity, inter and transdisciplinary attitude and advancing new form of collaboration and leadership (Earle and Leyva-de la Hiz, 2021). Expertise, particularly adaptive expertise, must then be nurtured to face these problems, requiring not only human decisions, but decisions that are trained and sensitivities to open up to these new forms of thinking. But at the same time, just transitions also require short-term decisions, and in fact, it requires to quicken and multiply decision-making power to be able to adjust almost in real time to changing scenarios and conditions, in a way and pace which humans cannot readily adopt. For instance, optimizing energy efficiency, or water use, or organizing circular economy structures and so on, requires very fast and broad-spanning decisions on multiple contexts and places at once. This does not necessarily require long-term thinking, but rather rapid data processing and memory, qualities in which AI systems excel (Haider et al., 2024; Zejjari and Benhayoun, 2024). So in the temporal dimension, hybridization should take at the same time the role of human expertise enhancement through AI, providing scenarios, data exploration and management tools to foster future-thinking, and replacing of humans by AI in routinary, quick-thinking tasks but with the possibility of overriding these when intuitive expertise tells otherwise.

Finally, in the social dimension, sustainability and climate change problems face not only a multiplicity of decision-makers, as they often require actions to be taken in a coherent and collaborative manners between public institutions, private enterprises, community members and so on, but also inherent and sometimes unsurpassable trade-offs, 'hard choices', contrasting values and worldviews, and no-size-fits-it-all solutions, that make all decision-making situation in this context inherently controversial and open-ended (O'Brien et al., 2009; Sapiains et al., 2020). Thus, the problem is how to include multiple perspectives, so that decisions not only make sense but also ensure their legitimacy and ownership by these different groups, while at the same time allowing that actors are able to coordinate and act in a timely and relatively orderly manner, in the face of joint problems and (limited) common resources.

In this context, AI is not up to the task, not alone at least. Replacing human decisions for AI systems may seem an attractive way out to some, removing the alleged 'bias' of human decisions to specific factions or worldviews, but what it ultimately does, is promoting a cold, context- and socially-insensitive form of technocracy. As discussed above, while AI does exude some sense of authority or legitimacy because of its perceived 'objectivity', this does not apply in overtly conflicted situations in which attention to subjectivity and controversies is fundamental for decisions to be considered legitimate. Moreover, as also discussed above, excessive trust on the objectivity of AI may also be misguided, as AI systems ultimately take in the inputs that they receive and derive patterns from them, without any ability to identify potential biases or discriminations that these may hide (either unintentionally or deliberately). On the other hand, AI systems can have a role here in expanding the accessibility of knowledge and expertise. As also discussed in the factual dimension, in complex problem-situations, not everybody can have access to all the knowledge needed to make a decision, and particularly, most people will probably have no training on most of the technical aspects of a decision, making human-only approach prone either to technocratic exclusion, or to populist rhetoric, e.g., oversimplifying myths and post-truths. In fact, even after decades of scientific and political work over this, many people still do not get a deep understanding of sustainability and climate change processes, and climate skepticism remains rampant (Dunlap, 2013). AI can here help by translating and making rapidly accessible deeper forms of knowledge to people that go beyond their individual sphere of expertise, so they can engage in more productive and informed dialogue and deliberation with their peers. However, this would require incorporating more explicitly training in use of AI -and also, in critical appraisal of AI 'truths' into both higher education and adult specialization curricula, which would also help in shifting capacities required to support inclusive and just transition processes.

Conclusion

This paper examined the opportunities and challenges of AI in shaping a just transition to sustainability, particularly regarding its role as a partial alternative to human expertise within organizations. We have argued that expertise functions as a key mechanism for reducing complexity in decision-making, defining problems and solutions, adapting to change, and legitimizing decisions. AI, while useful in processing data, identifying patterns, and facilitating accessibility, cannot fully replace human expertise due to technical and social plausibility limitations. Effective AI integration requires developing new forms of collaboration between AI and human decision-makers—ranging from assistance to hybridization and supervised substitution—while simultaneously advancing human expertise to address the growing complexities of the world and support just transitions.

As discussed in the previous section, hybridization is required to respond to the growing complexity, rapidity, uncertainty and policontextuality of decision-making challenges, which becomes even more relevant in the frame of super-wicked problems such as climate change and other sustainability issues. Combining human and IA expertise would bring in this case not only a way of fostering the compatibility between human and AI expertise in organization, but also ways to harness this in the context of the green transition and adaptation strategies required by climate change and other sustainability issues.

However, as already noted, hybridization between human and artificial intelligence can take multiple forms—ranging from context-dependent procedures such as the interactive division of tasks, to AI-enhanced access to information, delegation of routine responsibilities, and more integrated workflows that enable the co-construction of knowledge and joint task execution. These models vary in their effectiveness and feasibility across different settings, highlighting the need for further research into the specific forms of hybridization most conducive to promoting just and sustainable transitions. Crucially, all such approaches require a rethinking of how current and future workforces are trained. This is particularly pressing in the context of green transitions, where occupational reorientation toward climate-compatible roles is rapidly becoming a central challenge. While our analysis highlights the limitations of AI in replicating the social and interpretive dimensions of human expertise, we also acknowledge that in certain well-structured, high-volume decision environments, AI systems may achieve a degree of autonomy or functional legitimacy—especially when supported by robust validation procedures, transparency protocols, and effective human oversight. Future research should critically investigate these scenarios to understand the institutional, technical, and social conditions under which AI might reliably assume roles traditionally reserved for human experts, without compromising trust, accountability, or ethical integrity.

Similarly, future research should explore how different organizations incorporate AI to advance just transitions, particularly in human-centric fields like education and healthcare, where ethical judgment and empathy remain irreplaceable. Another critical issue is trust—AI adoption depends not only on technical proficiency but also on its perceived legitimacy. Skepticism persists, warranting further study on whether it stems from AI's limitations, its perceived inferiority to human expertise, or broader societal concerns. Additionally, the power dynamics of AI implementation must be further examined, as AI can either reinforce hierarchical structures or democratize access to expertise, impacting equity and justice in sustainability transitions.

The discourse on AI is often steeped in grand expectations or dramatic concerns, where lofty aspirations and dystopian fears outpace reality. Organizations stand at the crossroads of these ambitions, translating ideals into practice of day-to-day work and workforce management. In this context, however, insufficient attention has been put so far on the role, opportunities and challenges that the incorporation of AI-assisted decision and the hybridization of human and AI expertise can have on fostering more grounded and informed decisions in the context of complex, (super-)wicked problems such as climate change and sustainability. This study moves beyond promises, anchoring the conversation in functionality and plausibility—what AI can truly offer, rather than what it merely envisions. In this pursuit, innovation alone is not enough; a deeper understanding of the social, cultural, and political landscapes in which AI unfolds is essential. Only by acknowledging these complexities can AI's role in sustainability and climate change transcend rhetoric and become a force for meaningful transformation.

To advance in this direction, it is essential to foster interdisciplinary collaboration among computer scientists, organizational theorists, and sustainability scholars to develop context-sensitive frameworks for human–AI interaction. Practical experimentation through pilot initiatives—particularly in sectors such as urban planning, renewable energy, and climate governance—holds particular promise and can yield valuable insights into how hybrid systems function in real-world decision-making environments. In parallel, policy-oriented research should examine the regulatory, institutional, and normative infrastructures needed to ensure that AI implementation is consistent with democratic values, social inclusion, and environmental priorities. Addressing these challenges requires more than technical innovation; it demands a fundamental transformation in professional cultures, organizational learning, higher education, and accountability frameworks. Only through such integrated and reflexive efforts can AI serve as a meaningful contributor to just, sustainable and climate-neutral transitions.

Author contributions

MB: Conceptualization, Writing – original draft, Writing – review & editing. JL: Conceptualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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