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

Citation: Pimenow, S.; Pimenowa, O.; Prus, P. Challenges of Artificial Intelligence Development in the Context of Energy Consumption and Impact on Climate Change. *Energies* **2024**, *17*, 5965. https://doi.org/10.3390/en17235965

Academic Editors: Joanna Rosak-Szyrocka and Radosław Wolniak

Received: 30 October 2024
Revised: 20 November 2024
Accepted: 25 November 2024
Published: 27 November 2024

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.

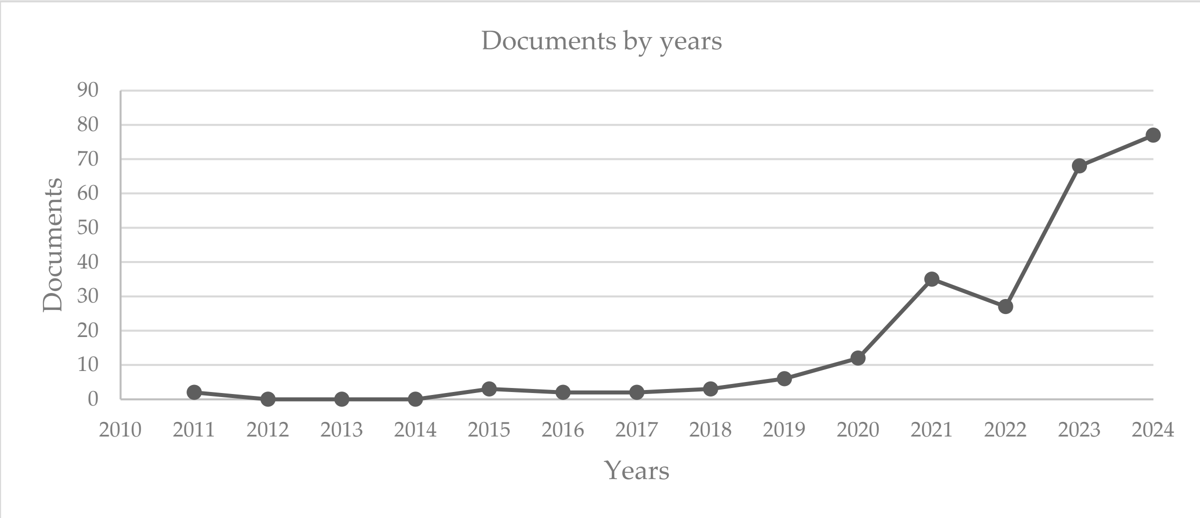

Figure 1. Distribution of documents by years. Source: compiled by authors.

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.

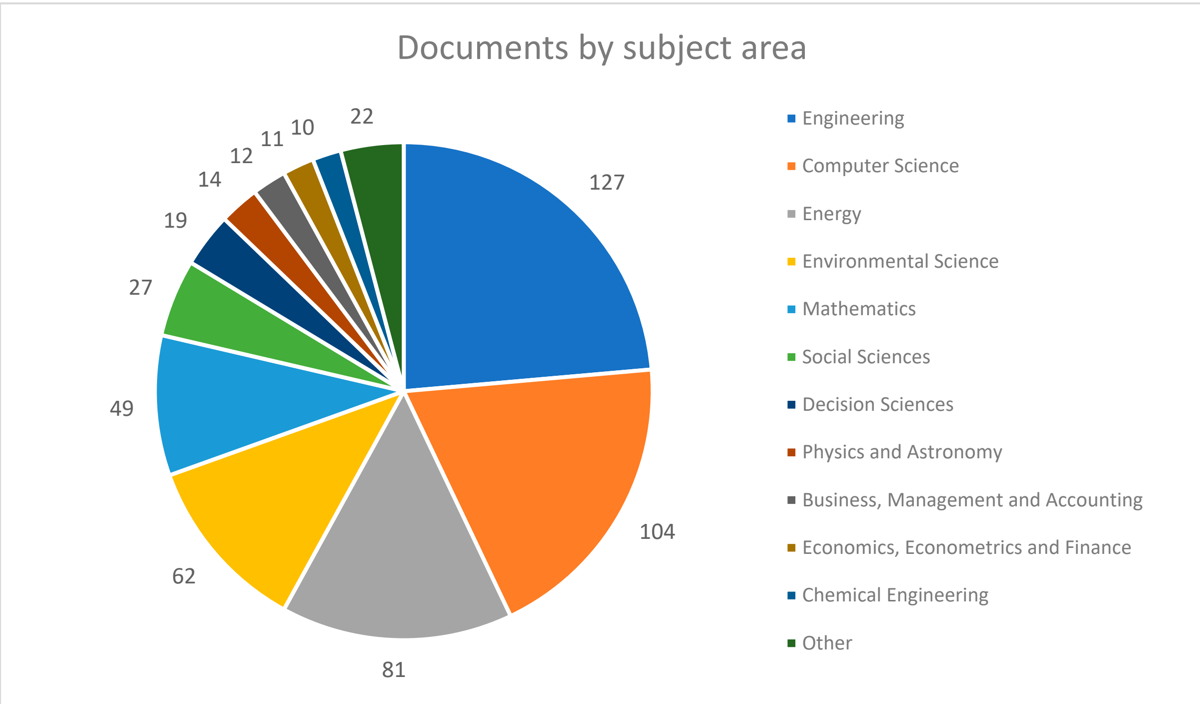

Figure 2. Distribution of documents by industries. Source: compiled by authors.

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).

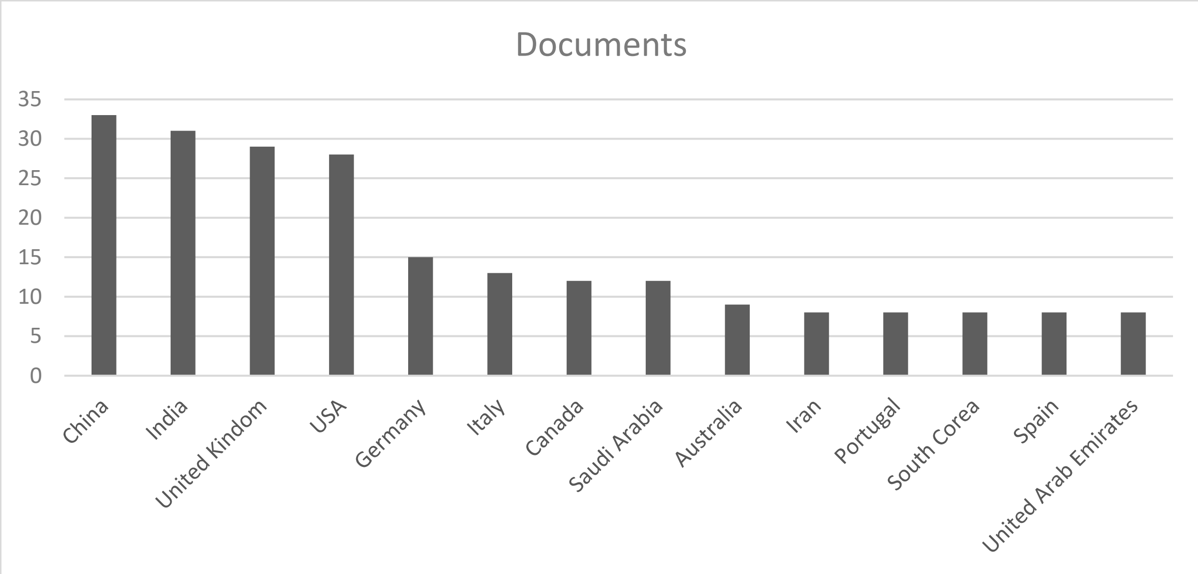

Figure 3. Distribution of documents by countries. Source: compiled by authors.

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).

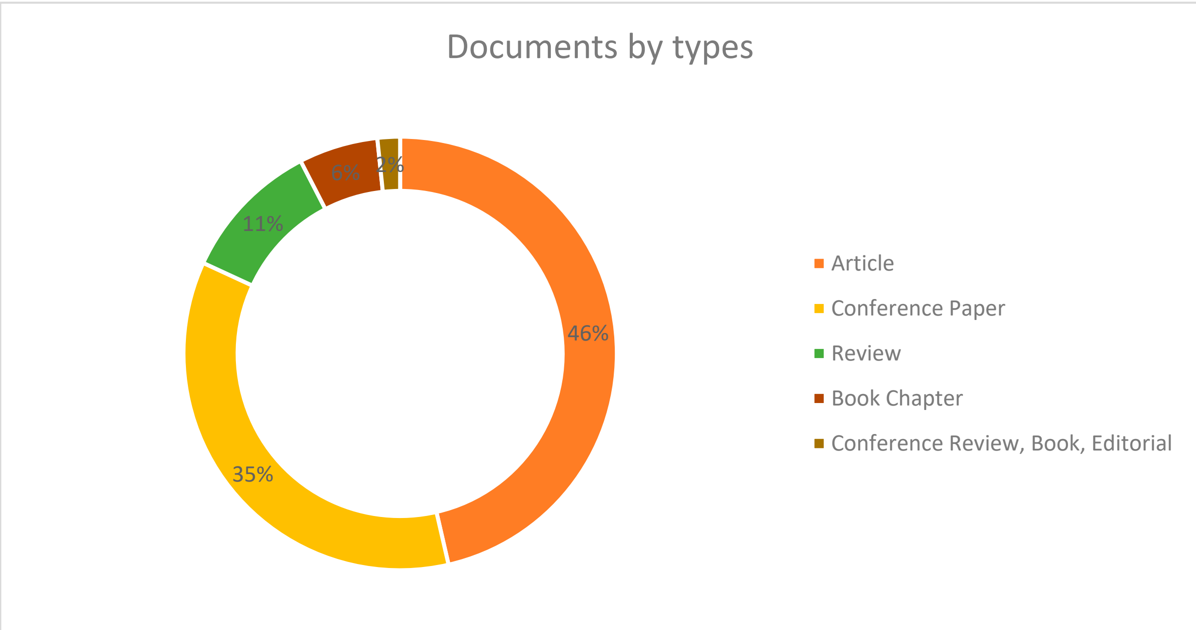

Figure 4. Distribution of documents by types. Source: compiled by authors.

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.

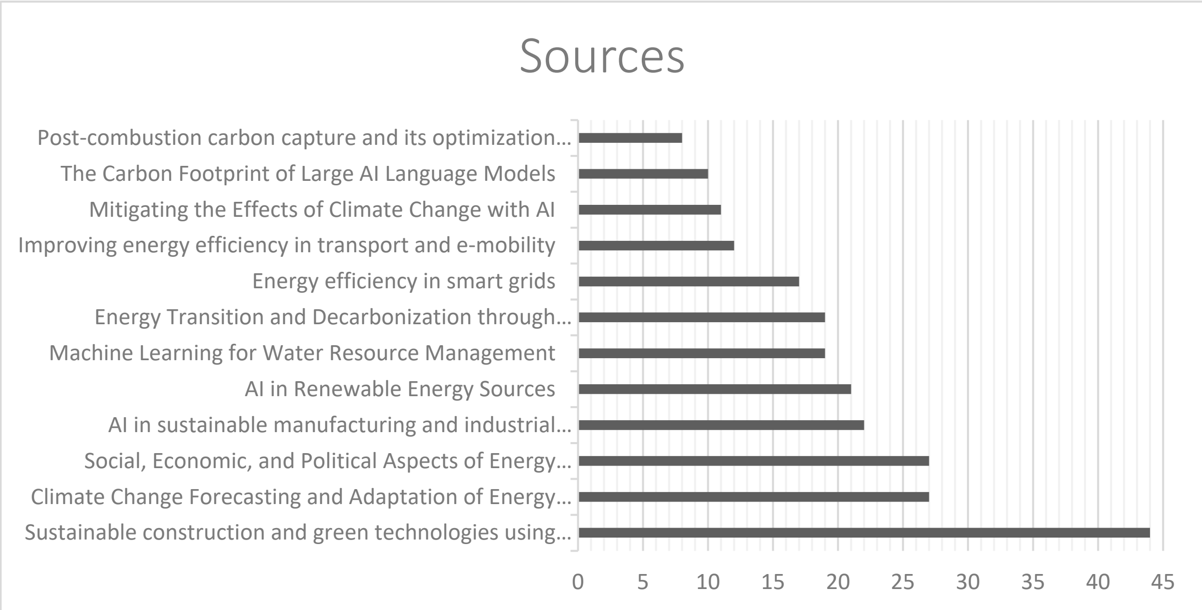

Figure 5. Distribution of topics by number of references in sources. Source: compiled by authors.

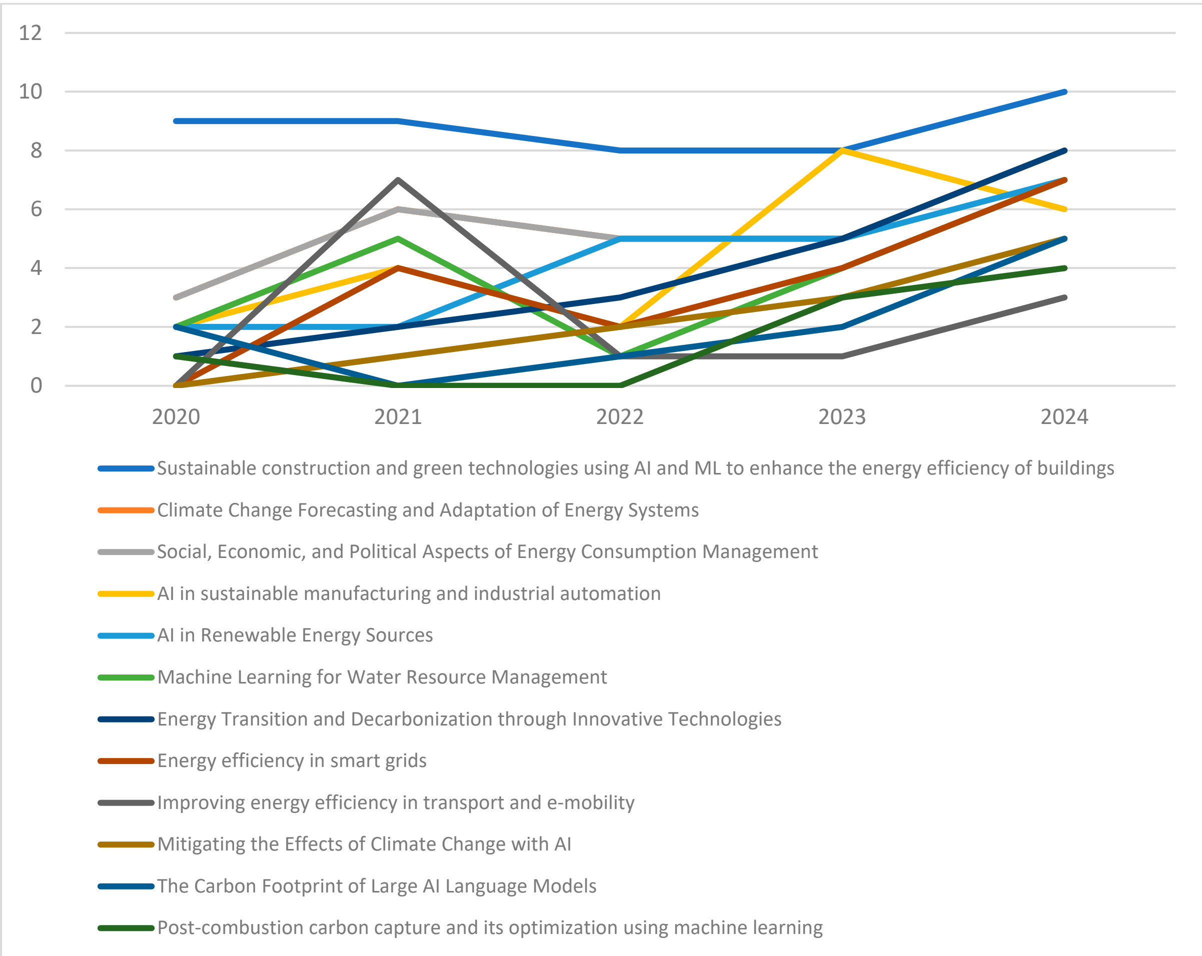

Figure 6. Dynamics of changes in interest in the topics over the last years. Source: compiled by authors.

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.

Author Contributions: Conceptualization, S.P., O.P. and P.P.; methodology, S.P., O.P. and P.P.; software, S.P., O.P. and P.P.; investigation, S.P., O.P. and P.P.; data curation and analyzed the results, S.P., O.P. and P.P.; validation, P.P., S.P. and O.P.; formal analysis, S.P., O.P. and P.P.; writing—original draft preparation, O.P., S.P. and P.P.; writing—review and editing, project administration, O.P., S.P. and P.P.; supervision, S.P., P.P. and O.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare that they do not have any competing financial, professional or personal interests from other parties.

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