AI FOR SUSTAINABILITY: BIBLIOMETRIC REVIEW OF POWER-SAVING ALGORITHMS IN IOT AND EDGE SYSTEMS

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ABSTRACT

Objective: This research aims to explore the global trends, challenges, and future opportunities in the development of energy-efficient AI technology in the context of IoT, edge computing, and its potential to synergize with quantum computing.

Research Design & Methods: This study uses a bibliometric-based systematic literature review approach to 113 documents from the Scopus database published in the 2021-2025 period. The analysis used VOSviewer to map keyword co-occurrence, collaboration between countries, topic trends, and citations.

Findings: The research focus is expanding from basic topics of power efficiency to integrating AI with edge systems, adaptive communication protocols (such as BLE and LoRaWAN), and ML-based predictive models for smart home and agriculture. Countries like China, the United States, and India are central to global collaboration. The research also revealed the lack of studies on integrating quantum-inspired optimization in energy-efficient AI edge architectures.

Implications & Recommendations: The findings indicate that further research directions are needed in the development of adaptive, efficient, and environmentally friendly AI architectures and that strengthening collaboration between countries is important. This research also supports strategies for developing low-emission and power-efficient digital technologies to support the global sustainability agenda.

Contribution & Value Added: This research provides an important contribution in the form of current literature mapping and a scientific synthesis framework to formulate a research agenda and policy for sustainable AI technology in IoT and edge computing systems.

Keywords: Internet of Things, Edge Computing, Sustainable, energy efficient.

JEL codes: C88, Q42, D83
Article type: research paper

INTRODUCTION

The emergence of Artificial Intelligence (AI) has revolutionized contemporary enterprise systems by enabling automation, predictive analysis, and data-driven decision-making (Nalini, 2024). However, this rapid technological advancement is accompanied by high energy consumption (Lee and Yan, 2024). AI models, especially during the training and inference phases, require significant computational resources, leading to increased energy requirements that contribute to increased operational costs and environmental concerns, especially in enterprise-wide implementations (Dash, 2025; Shang et al., 2024). Over the past decade, AI has become a key technology driving innovation across various sectors, including industry, transportation, healthcare, and smart cities (Zhang et al., 2018). Additionally, the Internet of Things (IoT) and edge computing ecosystems are experiencing exponential growth, leading to a significant increase in local computing demand and real-time AI usage in power-constrained devices (Shi et al., 2016). However, integration of AI in edge and IoT systems also poses major challenges regarding energy consumption, given that most modern AI algorithms, such as deep learning, are computationally intensive (Strubell et al., 2020). As sustainability increasingly emerges as a strategic priority, there is an urgent demand for AI optimization methods that efficiently minimize energy use while maintaining superior model performance (Tosin et al., 2024).

The energy efficiency issue is becoming increasingly important as inefficient use of AI can lead to significant energy wastage and worsen the carbon footprint, contradicting the global sustainability agenda (Schwartz et al., 2020). Therefore, there's an urgent need to develop power-efficient and computationally efficient AI algorithms to enable their widespread deployment on edge devices and IoT sensors without compromising performance or accuracy (Sze et al., 2017). Various approaches, such as compression models, pruning, and quantization techniques, have been proposed to overcome power limitations in AI execution in edge environments (Choi et al., 2016).

Furthermore, the advent of quantum computing offers transformational potential in addressing these energy efficiency challenges. Quantum computing enables large-scale data processing more efficiently than classical computing architectures (Preskill, 2018). Within this context, the collaboration between AI and quantum computing, known as Quantum Machine Learning (QML), opens up new opportunities to create AI systems that are not only faster but also more power-efficient and environmentally friendly (Biamonte et al., 2017). Potential synergies between AI, edge computing, and quantum computing are key to future systems that are efficient, sustainable, and adaptive to low-energy demands (Assis et al., 2021).

This research is designed to discover the direction and urgency of developing energy-efficient AI technologies. First, it is important to know how the global research trend on power-efficient AI is evolving, especially in the context of IoT and edge computing, which demand high efficiency in energy consumption. Second, along with the advancement of quantum computing technology, it is necessary to examine the role of this technology in strengthening AI efficiency in data processing and algorithm optimization. Third, identifying gaps and research opportunities from the available literature is an important foundation for developing future research directions.

This study aims to bibliometrically analyze the literature map on energy-efficient AI and sustainability based on data from the Scopus database. With this approach, trends in research development and patterns of global collaboration that support green technology innovation can be identified. In addition, this study also seeks to develop recommendations for future research directions, especially for the synergistic integration of AI, edge computing, and quantum computing in achieving energy efficiency and sustainability. The main contribution of this study is to provide an up-to-date scientific mapping of research trends and directions in the field of energy-efficient AI, and to offer a synthesis of academic and industrial collaborations in driving sustainable innovation based on innovative technology. Thus, this study is expected to serve as a strategic reference for researchers, policy makers, and technology developers in directing investment and research towards solutions that are not only advanced but also environmentally friendly.

LITERATURE REVIEW

According to Basuki, (2011), in Kurnia et al. (2023), bibliometrics is an approach that aims to explain the process of written communication in the scientific domain. This approach involves quantifying and descriptively analyzing the various aspects of communication that occur in scientific literature or works. The aim is to reveal the characteristics and direction of development of scientific communication through quantitative data contained in these works. In an increasingly connected digital age, artificial intelligence (AI) is central in realizing energy efficiency, sustainability, and integrating advanced technologies such as quantum computing and edge computing. One significant contribution of AI to energy efficiency is realized by developing power-efficient models that can be implemented on resource-constrained devices such as IoT and edge devices. According to Lee et al. (2013), the Internet of Things (IoT) is a concept in which various physical objects with unique identification can communicate and interact with their surrounding environment through the Internet network or related infrastructure. IoT allows these objects to collect and share data and perform relevant actions without direct human involvement. IoT refers to a concept where physical objects such as electronic devices, vehicles, sensors, and other equipment are connected and communicate through the internet (Gavalas et al., 2020).

Techniques such as pruning and quantization have been shown to significantly lower power consumption without sacrificing accuracy. For example, developing a cross-layer framework for efficient and secure Edge AI systems, integrating pruning, quantization, and approximation techniques at both hardware and software scales to improve overall efficiency (Shafique et al., 2021). A similar approach was applied by Zawish et al. (2023), who utilized deep reinforcement learning to perform adaptive pruning on CNN models based on energy availability from edge energy management systems, resulting in high efficiency for intermittent energy-based IoT devices. In a real application context, the combination of pruning and 8-bit quantization on the YOLOv3 model resulted in 29.41% energy savings and 22.72% improvement in inference latency, without significant accuracy loss (Naveen and Kounte, 2024). Other research has confirmed the effectiveness of this approach through hands-on experiments on Arduino devices, demonstrating optimal performance in low-energy visual classification (Zhen, 2025).

AI also plays an important role in sustainability, primarily through its integration with renewable energy systems and intelligent load management. Edge AI is comprehensively used in the Internet of Energy (IoE), supporting real-time analytics, adaptive consumption management, and cost efficiency in modern innovative grid systems (Himeur et al., 2024). For example, the implementation and demonstration of the utilization of federated learning and distributed inference for edge AI systems, which not only saves energy but also maintains the privacy and security of user data in smart home systems (Tamanampudi, 2024).

METHODS

This research uses a systematic bibliometric-based literature review approach to explore global trends, scientific collaborations, and innovation directions in energy-efficient Artificial Intelligence (AI), especially in the context of Internet of Things (IoT), edge computing, and its potential synergy with quantum computing. This review aims to map the development of scientific knowledge and identify important contributions to the development of AI-based green technologies.

The research data were obtained from the Scopus database, which has a wide and reliable coverage of multidisciplinary scientific literature. The search process was conducted using the following structured keywords: "AI" AND ("energy efficiency" OR "low-power" OR "green AI") AND ("IoT" OR "Edge Computing") AND ("Quantum Computing" OR "QML"). From the initial search results, 1,631 scientific documents relevant to the topic were found and published between 2010 and 2025. However, to focus on recent developments and representation of the latest trends, this study filtered the data again based on the last five-year period (2021-2025). It produced 113 scientific documents that became the main object of analysis.

The next step is metadata extraction. The metadata was downloaded in CSV format, and then data cleaning and normalization were performed to ensure consistency of terms, such as the unification of different keyword variations, but referring to the same concept. For data analysis and visualization, this research uses VOSviewer software. Co-occurrence keyword mapping was analyzed to identify keywords that often appear together in a document and show the dominant thematic focus, as well as citation analysis to measure the influence of a publication in the scientific community. In addition, topic trends and evolution of publications by year of publication were analyzed and collaboration analysis between authors, institutions, and countries to understand the network of scientific cooperation in this field.

The visualization results in bibliometric maps are then interpreted narratively to identify key thematic patterns, research clusters, and relationships between important topics such as energy efficiency, low-power AI, IoT, edge computing, and quantum computing. These interpretations were also used to uncover research gaps and make strategic recommendations on future research directions. With this approach, the research can provide a comprehensive and in-depth picture of the development of science and its contribution to sustainable technological development in the digital era.

RESULT

Analysis of publication trends from 2010 to 2025 shows a significant increase in research related to Artificial Intelligence (AI) for energy efficiency in IoT, edge computing, and quantum computing, as awareness of the importance of energy efficiency in intelligent computing systems grows. A drastic surge occurred since 2020, characterized by a sharp yearly increase: 133 documents in 2020, peaking in 2024 with 386 documents. This shows that integrating AI in low-power systems has become a significant research agenda, in line with the global push towards sustainable and environmentally friendly technologies. The year 2025 has already recorded 126 documents by mid-year, indicating the continuation of this research trend into the future. This surge emphasizes the urgency and relevance of the topic in addressing power consumption challenges in an increasingly connected digital age.

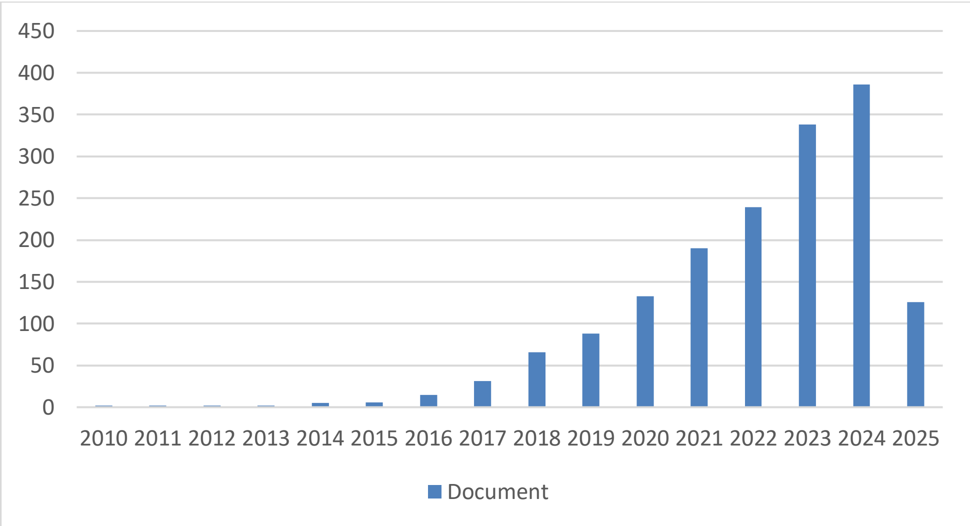

Figure 1. Research publication trends

Based on bibliometric analysis using VOSviewer, research topics on the Internet of Things (IoT) are grouped into several main clusters based on the interrelationships between keywords in the indexed scientific literature. The most dominant clusters reflect the technical aspects of IoT, security, industrial applications, and supporting technologies used in its development. The first cluster, which deals with IoT technology and infrastructure, shows the dominance of keywords such as Internet of Things, Cloud Computing, Big Data, and Wireless Sensor Networks. This indicates that research in IoT still focuses heavily on technical aspects and technology integration, particularly in big data processing and cloud computing to support complex and distributed IoT systems. The second cluster deals with security and privacy in IoT, with keywords often appearing, such as Security, Privacy, Blockchain, and Authentication. This shows that security issues are a major challenge in IoT deployment, especially ensuring data protection and user privacy. Increasing cybersecurity threats are also driving research focused on data encryption, identity management, and the implementation of blockchain technology to improve the security of IoT systems. Meanwhile, the third cluster highlights IoT applications in various sectors, with key keywords such as Smart Cities, Smart Homes, Healthcare, and Industry 4.0. The application of IoT in innovative city management and smart home systems is increasingly becoming a significant focus of research, reflecting the global trend in optimizing technology-based services to improve people's efficiency and quality of life. Additionally, the implementation of IoT in healthcare and the Manufacturing industry is also showing a significant increase, especially in the context of automation and digitization of business processes. The fourth cluster relates to IoT-enabling technologies, where buzzwords such as Machine Learning, Artificial Intelligence, and Edge Computing often appear together. This trend shows that AI and machine learning are increasingly used in IoT to improve data analysis and system efficiency. Edge computing is also emerging as an important solution to reduce latency in IoT data processing, which supports real-time computing needs in resource-constrained IoT devices.

Although various topics have become the main focus of IoT research, this analysis also reveals some potential research gaps. One aspect that has received less attention is sustainability and energy efficiency in IoT, which are crucial issues in developing environmentally friendly technologies. In addition, the relationship between IoT and Environmental, Social, and Governance (ESG) concept is still not widely explored in the scientific literature. Studies that focus more on the sustainability and social impact aspects of IoT implementation have the potential to significantly contribute to this field.

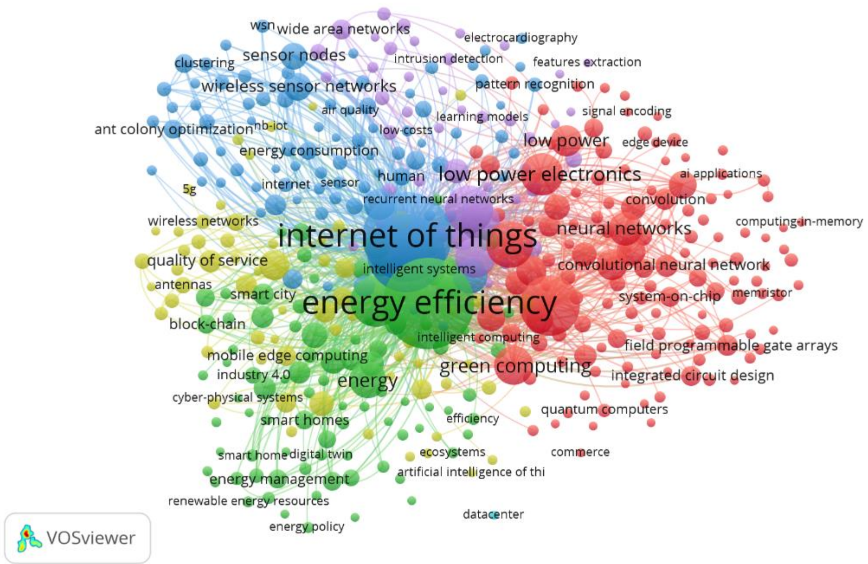

Figure 2. Visualization of bibliometric maps using VOSviewer

Based on the analysis of co-authorship data by country, it can be seen that international collaboration in Artificial Intelligence (AI) and energy efficiency research shows a strong and organized pattern. Countries such as China, the United States, India, the United Kingdom, and Germany are the dominant centers of collaboration, with many co-publications with partners from various regions. China, for example, collaborates heavily with countries in Southeast Asia and Europe, reflecting its position as one of the global leaders in developing energy-efficient innovative technologies.

The United States also plays an important role in building global research networks, especially with Western European and East Asian countries. These collaborations involve the development of power-efficient AI models, integration of edge computing technologies, and early exploration of synergies with quantum computing. In addition, India and countries such as South Korea and Japan are showing an increasing participation trend in cross-border research, especially in the context of IoT applications for energy efficiency in the industrial and residential sectors.

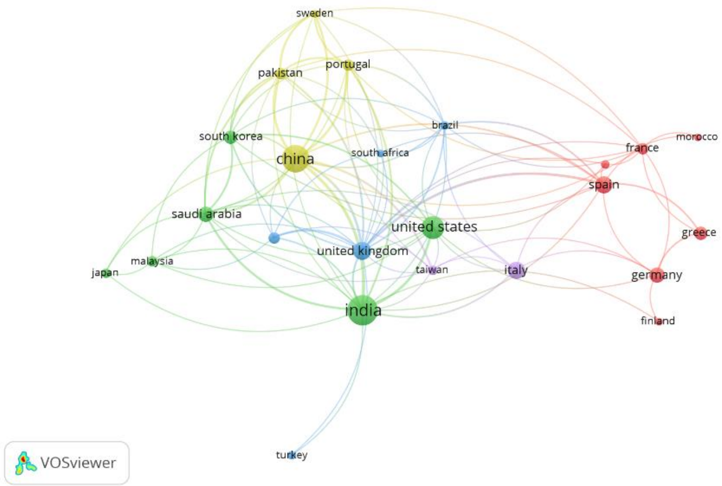

Figure 3. International collaboration network on AI and energy efficiency research

The collaboration map reflects that research in this field is growing not only in quantity but also in quality through cross-border strategic partnerships. Strong international collaborations encourage knowledge exchange, broader utilization of research infrastructure, and acceleration of technological innovations relevant to the global sustainability agenda. Therefore, strengthening the network of cross-border collaborations is one of the important strategies in accelerating innovative and sustainable energy transformation in the future.

DISCUSSION

Integrating AI and Edge for Energy Efficiency

Integrating Artificial Intelligence (AI) and edge computing technology in Internet of Things (IoT) systems plays a crucial role in driving energy efficiency, especially in devices with limited power. Recent studies have shown that combining AI and edge computing can not only optimize data processing locally but also significantly reduce power consumption and improve system performance in real-time environments. Research by Lu et al. (2025) shows that integrating various machine learning approaches, such as supervised learning, reinforcement learning, ensemble learning, and deep learning, into the IoT service composition mechanism can improve the efficiency of system adaptation to the dynamic context at the edge. By utilizing AI capabilities to compose more responsive and efficient service orchestrations, IoT systems become more power-efficient and able to adaptively handle device diversity and operational scenarios.

Furthermore, the research on the RIOT-ML toolkit introduces a real solution to address the challenge of efficiently updating AI models in edge devices with low power consumption (Huang et al., 2025). The toolkit combines a power-efficient operating system, a universal transpiler, and a secure over-the-air (OTA) protocol, enabling massive and efficient testing and deployment of TinyML on a wide variety of microcontrollers. With RIOT-ML, the process of integrating AI in edge computing becomes easier, safer, and more energy-efficient, while accelerating the process of innovation and field testing for IoT developers and researchers. Another significant contribution comes from the implementation of AIoT in human motion classification. Systems designed using Arduino Nano 33 BLE Sense and LoRaWAN proved that by performing data processing directly at the edge device, as well as adaptively adjusting communication parameters (such as bandwidth and spreading factor), energy consumption can be reduced by 40% without compromising signal quality or classification accuracy, which reached 95.32% (Ganesha et al., 2025). This shows the great potential of the combination of edge AI and energy-efficient wireless communication in healthcare and rehabilitation applications.

Additionally, AI approaches for intelligent irrigation systems based on the EWDO-LSSVM model confirmed the importance of machine learning-based prediction for energy efficiency in agriculture. With the ability to accurately predict temperature, air humidity, and soil, the system is able to reduce the frequency of irrigation pump activation, saving up to 30% energy. Integration with the power-efficient LoRaWAN further strengthens the system's effectiveness in supporting sustainable precision agriculture (Khalifeh et al., 2025). The findings from these four studies show that the integration of AI with edge computing can significantly address the energy consumption challenges in IoT systems. Through model optimization, wireless communication adaptation, and efficient system updates, this approach paves the way for developing more innovative, power-efficient, and applicable IoT technologies in sectors ranging from healthcare to agriculture.

In IoT and Edge AI ecosystems, energy optimization is a major challenge due to edge devices' limited computing power and capacity (Lu et al., 2025). As the number of IoT devices increases, demanding localized data processing to reduce latency and bandwidth consumption, the need for energy-efficient Edge AI systems is becoming more pressing. One of the main approaches that has been widely researched is model optimization techniques. According to a comprehensive survey by Sze et al. (2017), strategies such as pruning, quantization, and knowledge distillation have reduced model complexity without significantly degrading performance. Pruning works by removing unimportant neurons, while quantization lowers the numerical precision of model parameters to reduce computational burden and memory consumption. Meanwhile, knowledge distillation enables the training of lightweight models that remain accurate by emulating large models.

Energy optimization is not limited only to the AI model side. It requires a holistic approach that includes efficient hardware selection and system architecture design. Using accelerators such as TPUs and NPUs is considered effective for power-efficient model execution, while system architectures that support dynamic offloading strategies are increasingly relevant (She et al., 2024). The system is supported by a multi-objective literative optimization algorithm that considers not only energy efficiency, but also throughput and latency. The pairing process between users and workload offloading is efficiently performed to balance the load on the edge network and cloud, which can improve system performance while significantly reducing energy consumption. With real-time network and device workload conditions, the system can decide when and how tasks should be offloaded to edge servers or the cloud. This approach can reduce energy consumption by up to 30% compared to static offloading methods, while maintaining service quality (Zhao and Lu, 2024). Furthermore, the Configurable Model Deployment Architecture (CMDA) approach is also key in addressing energy efficiency needs in industrial applications (Zhang et al., 2023). This allows customization of energy and latency without compromising inference accuracy.

Communication Optimization and Energy-Efficient Network Protocols

Communication optimization and energy-efficient network protocols are crucial elements in developing sustainable IoT and Edge AI systems. Recent approaches have shown that energy efficiency can be achieved through the adaptation of communication parameters and intelligent protocol design. One concrete implementation is seen in the study of an Energy-Efficient LoRa-based AIoT system for hand gesture classification. In the system, the Convolutional Neural Network (CNN) algorithm is implemented on the edge device (Arduino Nano 33 BLE Sense Rev2) without dependency on the cloud, thus reducing bandwidth and latency requirements. In addition, LoRa parameter settings such as Spreading Factor (SF) and Bandwidth (BW) are dynamically adjusted to the environmental conditions (obstructed or free), resulting in up to 40% reduction in radio power consumption while maintaining signal quality through optimal SNR and RSSI values (Ganesha et al., 2025).

Furthermore, communication efficiency is also applied in the intelligent irrigation system based on the Enhanced Wind-Driven Optimization-Least Squares Support Vector Machine (EWDO-LSSVM) algorithm. The algorithm can predict environmental parameters with a high accuracy of up to 87.5%, which contributes to actuator energy savings by reducing the duration and frequency of irrigation pump work by 30%. Using LoRaWAN in this system facilitates efficient transmission of environmental data to the cloud with low communication overhead, reinforcing the role of energy-efficient wireless networks in precision agriculture and green irrigation systems (Khalifeh et al., 2025).

The development of the Bluetooth Low Energy (BLE) standard version 6.0 also contributes to energy efficiency in IoT (Koulouras et al., 2025). Features like LE Power Control and Isochronous Channels allow the device to adjust transmission power based on distance, saving up to 15% energy. In addition, enhancements to security through encryption and mesh topology support provide reliability and low latency, which are critical for edge AI applications. Integrating lightweight machine learning capabilities in BLE, such as audio and object detection, expands its potential applications in energy-efficient and intelligent smart homes.

Furthermore, AI-based routing protocols, such as Energy Aware Parent Load (EA-EPL), show high effectiveness in balanced network traffic distribution (Rahman et al., 2025). Considering node load metrics and residual energy in parent node selection in the RPL protocol, the energy consumption of nodes near the sink is reduced by 30%. This not only extends the life of the network but also improves topology stability and network security, as seen from the 15% increase in packet delivery ratio compared to conventional methods. This approach is an important foundation in developing adaptive and power-efficient smart home IoT networks. Various studies have focused on developing energy-efficient communication protocols and optimizing adaptive routing mechanisms. These studies provide an important foundation for improving the endurance of edge devices and extending the overall network lifespan. A summary of some of the other key findings from the literature can be seen in Table 1.

Table 1. Energy-efficient network Protocol research

No	Title & Year	Contribution	Details of Findings	Source
1	*Energy-Efficient Communication Protocols for IoT Devices* (2024)	Establishing energy-efficient communication protocols for IoT	Development and evaluation of adaptive protocols capable of adapting energy usage to network conditions, increasing device lifespan, and lowering carbon footprints.	(Rahamathunnisa et al., 2024)
2	*AI-enhanced context-aware optimization of RPL routing protocol for IoT environments* (2023)	RPL routing protocol optimization with machine learning	Uses network context (node energy, link quality, mobility) with reinforcement learning to dynamically adjust routing metrics; reduces energy consumption and improves topology stability.	(Wakili et al., 2023)
3	*AI-Based Energy-Efficient Routing Protocol for Intelligent Transportation System* (2022)	DAI implementation for routing efficiency in intelligent transportation	An intra-cluster approach using a neural network and SOM (Self-Organizing Map) reduces transmission energy and accelerates network response for an autonomous transportation system.	(Goswami et al., 2022)
4	*AI-Enhanced Routing Protocols for Efficient Data Transmission* in Wireless Networks (2024)	Position-based routing and Deep Reinforcement Learning	Combining node positions with AI predictions for optimal routing: reduced energy consumption by 15%, latency decreased by 35%, PDR increased by 23% compared to the AODV/DSR protocol.	(Anitha V et al., 2024)
5	*Hybrid Quantum Classical Optimization for Low-Carbon Sustainable Edge Architecture in RIS-Assisted AIoT Healthcare Systems* (2024)	Energy-efficient RF access protocol based on deep learning and hybrid optimization	Developed fingerprint-based protocol for edge device access with high efficiency; 99% identification accuracy, suitable for a continuous health IoT system.	(Yu et al., 2024)

No	Title & Year	Contribution	Details of Findings	Source
6	*Communication-Efficient Edge AI Inference Over Wireless Networks* (2020)	Distribution-based edge inference optimization and wireless collaboration	Provides a distributed inference framework and collaborative transmission between edge devices with significantly reduced power consumption for real-time applications.	(Yang et al., 2020)
7	*Energy-Efficient Federated Edge Learning with Joint Communication and Computation Design* (2020)	Federated learning is energy-efficient on the edge	Optimized allocation of transmission power and local CPU speed for federated learning; drastically reduced energy consumption while maintaining training accuracy.	(Mo and Xu, 2021)

Sustainable Building and Infrastructure Systems

Regarding the utilization of sustainable materials, a study by Ranesi et al. (2022) showed that biomass waste of the invasive plant Acacia dealbata can be processed into additives in gypsum mortars, resulting in improved mechanical and thermal properties such as compressive strength and reduced density. Using this waste not only improves the technical performance of the material but also supports the circular economy through the utilization of local resources that were previously unproductive, even damaging to the ecosystem. This approach demonstrates how waste-based material innovation can support sustainability in the construction industry.

More broadly, there is a need for integration between economic and technological analysis in order to achieve the Sustainable Development Goals (SDGs). Although this study does not directly address buildings and infrastructure, its approach is highly relevant to the construction sector regarding cost efficiency, technological innovation, and simultaneous calculation of environmental impacts (Managi et al., 2022). The importance of using quantitative data and performance indicators in assessing progress towards sustainability is in line with the application of Life Cycle Assessment (LCA) in infrastructure assessment (Managi et al., 2022). Additionally, policy and governance support is an important foundation, especially regulations that encourage energy efficiency, sustainable design, and the use of low-carbon materials.

Sustainable development in context of building systems and infrastructure has been the main focus of many studies in order to reduce the environmental impacts caused by conventional construction approaches. One important approach studied is the application of circular economy principles, which emphasizes redesign strategies, selection of environmentally friendly materials, and management of construction waste recycling to reduce carbon emissions (Timm et al., 2023). This has been shown to improve resource efficiency and overall environmental performance of buildings.

Correspondingly, LCA is also an important tool in evaluating the sustainability of buildings, as it covers all phases of their lifecycle, from raw material extraction to demolition (Abouhamad and Abu-Hamd, 2021). Through LCA, project designers and managers can identify critical phases that have the greatest environmental impact and make strategic decisions for mitigation. The development of an LCA framework for evaluating the embodied environmental impacts of building construction systems, covering the entire building life cycle and enabling the selection of more sustainable design alternatives. This approach is considered highly relevant in the planning of ecologically and economically efficient buildings. Furthermore, the governance dimension is also a crucial aspect in the transition to sustainable infrastructure, as it emphasizes the importance of integration between public policies, collaboration between stakeholders, and the adoption of green technologies (Ahn and Baldwin, 2024). They emphasize that success depends not only on technological sophistication but also on adaptive policies and active community involvement in decision-making.

Continuing from the previous discussion, digital transformation through the integration of advanced technologies such as artificial intelligence (AI), machine learning (ML), and Internet of

Things (IoT) has opened up new opportunities in the development of sustainable building systems and infrastructure. The application of AI and ML in LoRaWAN networks can significantly improve the energy efficiency and communication performance of IoT networks, by enabling dynamic adjustment of communication parameters, which in turn reduces power consumption and extends the battery life of devices, especially in agriculture, smart cities, and environmental monitoring applications (Alkhayyal and Mostafa, 2024).

Furthermore, digitalization's contribution to sustainability is developing a digital twin-based energy storage system powered by AI and IoT for electric vehicles. The integration of AI in the digital twin framework enables high-accuracy state of charge (SOC) estimation through the combination of TS-GAN networks and LSTM algorithms, which has a direct impact on improving battery operational efficiency and reducing the risk of premature degradation (Pooyandeh and Sohn, 2023). EV energy management system based on deep reinforcement learning and digital twin, resulting in more than 7% energy efficiency and 25% reduction in battery degradation (Ye et al., 2024). Even at the smart city scale, the use of AI-enhanced digital twins has been proven to increase the efficiency of electricity-based transportation by up to 18% and reduce carbon emissions by 20% (Li, 2025). Therefore, digital twin technology plays a crucial role in supporting the transition to sustainable transportation by improving energy efficiency and extending the life of power storage systems in electric vehicles.

Energy-based Tools, Frameworks, and CI/CD / The Role of AI in Energy Management for Smart Homes

The evolution of Bluetooth Low Energy (BLE), as reviewed in the first article, confirms the important role of BLE as a low-power wireless communication protocol that is highly relevant in smart home IoT architectures (Koulouras et al., 2025). BLE version 6.0 brings new features such as LE Power Control and Isochronous Channels that not only improve device power efficiency but also expand support for edge AI applications through mesh networking capabilities and lightweight machine learning integration. BLE's ability to perform audio processing and object detection locally at edge devices makes it a key element in supporting energy-efficient smart home systems in line with the Sustainable Development Goals (SDGs).

Meanwhile, the implementation of the AI-based parent node selection strategy developed in the second study shows how communication management at the network protocol layer (RPL) can be significantly optimized. This approach targets a classic problem in IoT topologies, namely the imbalance of traffic load and energy consumption at nodes near the sink. By combining energy and load metrics in a new objective function (EA-EPL), the system successfully distributes network load more fairly, reduces energy drainage, and improves network stability and security with increased packet delivery ratio. This concept is highly relevant as part of a network tool or module in CI/CD architecture that supports runtime adaptivity to smart home network conditions (Rahman et al., 2025).

In social and user behavior, the third study provides important insights into the non-technical dimensions of successful smart home implementation, particularly in the framework of energy decentralization and carbon reduction (Lazaroiu et al., 2024). Public awareness of energy efficiency and digitalization is increasing along with the integration of smart home devices equipped with AI and IoT-based monitoring capabilities. The research confirms that achieving energy savings in smart homes depends not only on technology but also on social readiness, the digital divide, and demographic factors such as education and income levels. Therefore, AI-based smart home energy system design needs to consider aspects of inclusivity and personalization so that energy-saving strategies can be widely accepted by all levels of society (Lazaroiu et al., 2024). Efficient energy management in smart home systems has become a strategic issue in the development of AI-based technologies and IoT, as the number of interconnected household devices increases. AI-based solutions are not only focused on automating control of energy consumption but also on optimizing operational efficiency through load prediction, real-time adaptation, and integration into continuous integration and delivery (CI/CD) systems.

One leading framework offered can design cloud-based AI systems for smart homes with a focus on energy efficiency. The system is capable of predicting energy consumption with ±5% accuracy, resulting in peak hour energy savings of up to 20% and a response time of only 0.1 seconds on value-added tasks (Gowda et al., 2024). A multi-agent approach based on deep reinforcement learning proved effective in balancing energy efficiency, cost, and comfort with adaptation to changing energy load patterns, through the collaboration of AI agents in dynamic decision-making (Abishu et al., 2024). An artificial neural network (ANN) control system developed to regulate four main household devices based on priority and time of use is able to produce significant energy efficiency without disturbing occupants' comfort (Ijala et al., 2024). On the digital systems development side, integration of AI into DevOps and CI/CD practices provides tangible benefits in resource requirement prediction, deployment automation, and real-time anomaly monitoring and mitigation in cloud-native smart home systems (Ganesan, 2023). Utilizing AI in CI/CD pipelines also accelerates the innovative energy system integration process with high accuracy through features such as automatic bug detection, predictive project management, and resource savings in iterative development.

Additionally, incorporating renewable energy into a HEMS (Home Energy Management System) system with AI and IoT control enables optimal regulation between supply from solar panels, battery storage, and household loads. This approach uses a multi-objective optimization strategy that successfully lowers operational costs while maximizing clean energy utilization without sacrificing user comfort (Rochd et al., 2021). Smart home energy management is not just about device automation, but also about building a digital infrastructure that is efficient, resilient, and connected to users' real behaviors and needs.

Future Challenges and Opportunities

Recent research in the field of artificial intelligence (AI) for sustainability and energy efficiency reveals both great potential and profound challenges in applying this technology in various domains, particularly the Internet of Things (IoT), edge computing, smart buildings, and cloud-edge systems.

Table 2. Future challenges and opportunities of applying AI for energy efficiency

No	Main Challenges	Future Opportunities	Source
1	Research limitations on ML integration and IoT service composition, as well as interoperability and dynamic adaptation, are still complex.	ML integration (supervised, RL, DL) can support adaptive and energy-efficient orchestration of IoT services.	(Lu et al., 2025)
2	There aren't many energy-efficient CI/CD toolkits for TinyML; cross-platform evaluation challenges.	RIOT-ML, as an open-source framework, supports scalable and efficient AI edge development.	(Huang et al., 2025)
3	Optimal adjustment of communication parameters depends on dynamic environmental conditions.	LoRa + CNN adaptive parameters can reduce power consumption by 40% with high accuracy.	(Ganesha et al., 2025)
4	Challenges in adopting advanced technologies in farming systems with limited infrastructure.	The EWDO-LSSVM predictive model improves environmental prediction accuracy and saves up to 30% of irrigation pump energy.	(Khalifeh et al., 2025)
5	Data fragmentation and manual methods in extensive facility management.	Digital Twin + AI + BIM integration can cut energy consumption by 20% and maintenance costs by 25%.	(Abdelalim et al., 2025)
6	LoRaWAN still faces issues of network stability and intelligent traffic management.	AI/ML on LoRaWAN enables dynamic resource management and improves the efficiency of IoT networks.	(Alkhayyal and Mostafa, 2024)
7	Complexity of multi-objective optimization and AI processing with heterogeneous hardware.	NOMA-MEC + CPU-NPU enables edge AI to be more energy efficient through optimal workload regulation.	(She et al., 2024)

No	Main Challenges	Future Opportunities	Source
8	Challenges of distributed energy integration and real-time control in prefabricated buildings.	The AI + IoT framework improves energy management, power quality, and building operational efficiency.	(J. Shi et al., 2025)
9	Predictive maintenance is rarely automated.	Digital Twin drives proactive AI-based maintenance and reduces critical system downtime.	(Abdelalim et al., 2025)
10	Edge AI requires efficient, lightweight algorithms that can run on limited devices.	Integration of quantum-inspired algorithms drives low-power AI and cloud-edge end-to-end automation.	(She et al., 2024)

Contribution to the Global Sustainability Agenda

The contribution of research and development of AI technology for energy efficiency in IoT and edge computing systems is directly in line with global efforts to achieve Sustainable Development Goals (SDGs), especially SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), and SDG 13 (Climate Action). The application of AI in this context not only creates technical efficiency but also forms an important foundation for sustainable development across sectors. One tangible contribution to the global sustainability agenda is AI's ability to optimize energy consumption in infrastructure systems such as smart buildings, smart homes, and electric vehicles. For example, digital twin systems combined with IoT and AI can improve the energy efficiency of electric vehicles by up to 15% and extend battery life through real-time data-based performance prediction, while reducing carbon emissions from the transportation sector (Lakshmi and Sarma, 2025). In buildings, the development of AI-based decision support systems such as the IBIS ECO Platform is demonstrating the ability to proactively monitor and manage energy, thereby reducing power consumption while improving occupant comfort and quality of life (Cardinale et al., 2024).

Besides technical contributions, the development of smart home systems that integrate AI, LoRaWAN, and BLE also encourages people to be more aware and involved in managing their own energy consumption. This supports the transition to a low-carbon society and encourages social participation in achieving decarbonization goals (Lazaroiu et al., 2024). Technologies such as BLE 6.0, which is equipped with power-saving features, mesh networking, and on-device processing integration, are also expanding the scope of green technology adoption at the individual and community scale. At the macro scale, the efficiency offered by AI in energy management contributes to reducing the capacity requirements of conventional power generation, which still relies heavily on fossil fuels. When widely deployed, AI-based power-saving and smart management technologies can help countries reduce reliance on non-renewable energy and accelerate the transition to clean energy, a key aspect of global commitments to the Paris Agreement and the global climate agenda.

Importantly, research and development in this field also reinforces the principles of equity and inclusion in the sustainability agenda. Low-power and edge AI technologies enable affordable and easy-to-implement solutions in developing countries, remote areas, or communities with limited infrastructure. Thus, AI is not just a tool for energy efficiency in developed countries, but a bridge for technological transformation that is globally equitable. AI research for energy efficiency plays a crucial role in shaping the digital infrastructure and ecosystem that supports a green economy and sustainable society. Contributions to the global sustainability agenda are not only technological but also encompass social, economic, and environmental aspects, making AI a key catalyst in the collective effort towards a more equitable and climate-resilient future.

CONCLUSION

The research concludes that the global trend in the development of Artificial Intelligence (AI) for energy efficiency in the context of the Internet of Things (IoT), edge computing, and quantum computing has shown a significant increase in the past five years. This is driven by the urgency for energy-efficient innovative technology solutions as the number of interconnected smart devices grows. Through a bibliometric approach to 113 selected publications from the Scopus database, it was found that the research focus falls into several dominant clusters, namely IoT technology development, system security, industrial and household applications, and AI and edge computing integration. Global collaboration was also shown to play an important role in accelerating cross-border innovation, with dominant contributions from countries such as China, the United States, India, and European countries.

The analysis results show that the integration of AI and edge computing can reduce energy consumption by up to 40%, improving the operational efficiency of systems such as smart irrigation, smart home, and AIoT-based rehabilitation systems. Approaches such as pruning, quantization, and knowledge distillation prove effective in optimizing AI models for limited devices, while dynamic offloading strategies and flexible deployment architectures support system adaptivity to changing workload and network conditions. In addition, the development of energy-efficient communication protocols such as LoRaWAN, BLE 6.0, and AI-based intelligent routing algorithms strengthens the sustainability of AI edge networks and smart homes.

The implications of this study are multidimensional. First, practically, the results of this study serve as a basis for the development of more adaptive, efficient, and inclusive low-power technology systems for various sectors. Second, strategically, this study recommends the importance of expanding the focus to sustainability and ESG aspects in future AI and IoT studies. Third, the contribution to the global sustainability agenda is strengthened through the adoption of intelligent systems that support carbon emission reduction, energy efficiency improvement, and equitable digital transformation. Therefore, AI is not only a technical tool but also a key driver in achieving sustainable development goals and a more environmentally friendly and socially inclusive future.

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