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How does energy management AI technology innovation promote environmental mitigation?

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ABSTRACT

Given the escalating threat of climate change, the potential of artificial intelligence to revolutionize global sustainability efforts lies in its ability to optimize energy management and enhance energy efficiency, thereby paving the way for a greener future. This study investigates the impact of energy management artificial intelligence technology innovations (EMAITI) on environmental degradation. It examines a panel of 19 countries from 2010 to 2020 by applying the panel correlated standard errors regression model, along with the instrumental variable generalized method of moments for robustness checks. Firstly, the results show that EMAITI reduces environmental degradation, and these findings remain consistent even under robustness tests. The mediation analysis reveals that EMAITI reduces environmental degradation by decreasing energy intensity levels. Additionally, the moderating effects of research and development, as well as globalization, further strengthen the impact of EMAITI in reducing environmental degradation. Financial development, industrialization, and renewable energy consumption are found to reduce environmental degradation, whereas economic growth is associated with increased environmental degradation. However, a heterogeneity analysis reveals variations in effects between developed and developing countries, emphasizing the need for tailored environmental policies. The study emphasizes the significant role of energy management AI technology innovations in lowering energy intensity while highlighting the influences of research and development and globalization to inform effective environmental policies across diverse economies.

1. Introduction

Amidst the rapid escalation of climate change and growing environmental concerns, the urgency to shift towards sustainable energy practices has become increasingly imperative [1]. Central to this endeavor is the burgeoning field of energy management artificial intelligence (AI) technology innovation. AI technologies with advanced algorithms and data analytics capabilities hold immense potential to revolutionize energy management practices and drive significant reductions in environmental degradation [2]. Traditional energy management approaches often fail to address the complexities of modern energy systems and the urgent need for sustainability. Conventional methods often lack the agility and precision necessary to optimize energy consumption, mitigate waste, and minimize environmental impact effectively [3]. In contrast, AI-powered energy management systems offer unparalleled opportunities to enhance efficiency, streamline operations, and foster a more sustainable energy ecosystem [4]. By harnessing the power of big data, machine learning, and predictive analytics, AI technologies enable the real-time monitoring, analysis, and optimization of energy usage across various sectors, including manufacturing, transportation, and residential domains [5]. These systems can identify patterns, detect anomalies, and optimize energy consumption, leading to a significant reduction in greenhouse gas emissions, resource depletion, and environmental pollution.

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Moreover, AI-driven energy management solutions empower organizations and policymakers to make data-driven decisions, prioritize investments, and implement targeted interventions that promote sustainability [6]. From optimizing energy grids and smart buildings to enhancing the integration of renewable energy and electric vehicle infrastructure, AI technologies offer innovative solutions to address the complex challenges of environmental degradation. However, despite the promising potential of AI in energy management, several challenges and research gaps remain. Concerns related to data privacy, algorithmic bias, and ethical considerations necessitate scrutiny and thoughtful regulation [7]. Additionally, disparities in access to AI technologies and digital infrastructure may exacerbate existing inequalities, underscoring the importance of equitable deployment and inclusive policies [8].

Since traditional energy management practices often suffer from inefficiencies, limitations, and a lack of adaptability to dynamic environmental conditions, the advent of AI technologies presents a transformative opportunity to revolutionize energy management strategies and optimize resource utilization in ways previously unimaginable [8]. By leveraging AI's capabilities in data analytics, predictive modeling, and optimization algorithms, energy management systems can enhance efficiency, reduce waste, and minimize environmental footprint across various sectors. The policy relevance of this topic cannot be overstated. Effectively conducting energy management is crucial to achieving climate goals, as it is a vital aspect of mitigating greenhouse gas emissions [9]. By assessing the role of AI technology innovation in energy management, policymakers can gain valuable insights into the potential pathways for enhancing environmental sustainability and informing evidence-based policy interventions. To address the raised issues, this study explores several key questions. Firstly, it aims to evaluate the influence of AI technology innovations on energy management and their impact on environmental degradation. Secondly, the study examines potential mediating and moderating mechanisms through which energy management AI technology innovations may influence environmental degradation. Lastly, it aims to investigate how the relationship between AI technology innovations in energy management and environmental degradation varies across different levels of development.

In a landscape where the convergence of AI and environmental sustainability is increasingly drawing attention, this study establishes a distinct focus by meticulously examining the pioneering role of energy management AI technology innovation in mitigating environmental degradation. While previous literature has recognized the potential of traditional technological innovations and industrial robots across various domains to reduce environmental pollution [10], this research uniquely focuses on the specific impact of energy management AI technology innovations on ecological sustainability. This is achieved by analyzing patent applications granted in the field of energy management. By examining the specific impact of EMAITI on ecological sustainability, this study makes contributions to theoretical advancements in energy management, environmental economics, innovation studies, and technology management. Through its empirical analysis and theoretical framework, this research enhances our understanding of the intricate relationship between technological innovation, environmental impact, and sustainable development, thereby laying the groundwork for future research endeavors and theoretical refinement in this burgeoning area of inquiry. Moreover, this study enriches the existing literature by providing a comprehensive analysis of the mediating and moderating mechanisms. The mediation analysis sheds light on the role of energy intensity in influencing the reduction of environmental degradation through EMAITI. In contrast, the moderation analysis reveals the amplifying impact of research and development, as well as globalization. These insights provide a comprehensive perspective, bridging gaps in our understanding of the complex pathways through which EMAITI influences environmental outcomes.

The subsequent sections of this research include Section 2, which introduces the theoretical framework and outlines the research hypotheses. Section 3 provides a comprehensive overview of the data, models, and methodologies employed. Moving forward, Section 4 presents the empirical estimation results and engages in a discussion. Finally, Section 5 provides a concise summary of the research, presents pertinent policy recommendations, and acknowledges the study's limitations.

2. Literature review

Addressing the complex drivers of global environmental degradation requires a holistic economic approach that acknowledges the interconnected factors that strain ecosystems. The deterioration of our environment is a result of a complex web of economic, industrial, and social aspects, each contributing to the growing ecological crisis. Recent research highlights how diverse elements, including economic growth [11], financial development [12], industrialization [13], urbanization [14], population dynamics [14], renewable energy [15,16], energy intensity [17,18], research and development spending [19], and globalization [20] collectively shape environmental outcomes.

A growing body of research underscores the dynamic relationship between economic activity and environmental outcomes. For instance, Adekoya et al. [15] and Yusuf [11] observe that economic growth in resource-rich African nations tends to intensify environmental degradation in both the short and long run. Interestingly, Yusuf's findings also indicate a long-term reversal, where sustained growth eventually contributes to environmental improvement, highlighting the nonlinear dynamics between economic expansion and ecological well-being. Financial development also presents a nuanced picture. Ullah et al. [12] reported that an efficient financial structure can help reduce ecological footprints and mitigate environmental harm, particularly in Pakistan. In contrast, Saqib et al. [21] argue that despite being a driver of economic growth, financial development has adverse environmental implications in countries with high ecological footprints, indicating that the quality and direction of financial flows are crucial determinants of environmental impact. Industrialization remains a pivotal driver of environmental change. Opoku and Aluko [13] discovered that its effects vary across levels of development, with industrialization aggravating environmental degradation in lower quantiles but potentially reducing it in higher quantiles. They advocate for a transition to cleaner technologies in the manufacturing sector. Similarly, Luan et al. [22] suggested that when aligned with renewable energy strategies, industrialization can become a force for sustainable development.

Urbanization also plays a significant role in shaping environmental outcomes. Li and Zhang [14] found that increasing urbanization correlates with higher carbon emissions across Chinese provinces. Complementing this, Yusuf [11] highlighted that while urban growth exacerbates environmental damage in the long term, it may temporarily mitigate biodiversity loss, emphasizing its complex ecological implications. Population growth is another persistent factor influencing environmental quality. Appiah, Li et al. [23] demonstrated a strong link between population increases and environmental pollution in OECD countries. Li and Zhang [14] further emphasized that population size pressures are a primary driver of rising carbon emissions in Chinese provinces, suggesting that unchecked population growth may undermine environmental sustainability. Governance and institutional quality are also central to environmental management. Liu and Zhang [24] emphasized that effective governance plays a significant role in supporting green growth and reducing carbon emissions in BRICS economies. Similarly, Sadiq et al. [25] argued that robust institutions are crucial for lowering CO_2 emissions, as they enhance environmental regulations and align fiscal policies with sustainability goals. Renewable energy has shown promise in mitigating ecological harm. Adekoya et al. [15] reported that renewable energy consumption contributes to environmental improvement in both African and Asian contexts. They recommend that Asian countries adopt policies that support green innovations, such as hybrid vehicles, energy-efficient buildings, and smart energy grids, to promote sustainable energy use.

The role of energy intensity in environmental degradation has been well-documented. Baffour Gyau et al. [17,18], noted that higher energy intensity is associated with declining environmental quality in the Middle East and North Africa (MENA) region. Likewise, Li and Zhang [23] found that increased energy intensity leads to higher carbon emissions in Chinese provinces, potentially serving as a channel through which green ICT innovations influence environmental performance. Investment in research and development (R&D), and ICT, combined with globalization and financial expansion, offers further insight into environmental dynamics [26]. Azam Khan et al. [19] demonstrated that R&D spending, in conjunction with financial development and globalization, can mitigate environmental degradation by reducing CO_2 emissions in Asian economies. Dogan and Pata [27] similarly concluded that targeted R&D investment improves environmental quality in G7 countries and recommended directing such funds toward green ICT infrastructure. The environmental implications of globalization continue to be a subject of ongoing debate. Warsame et al. [20] found that globalization may exacerbate environmental degradation in the long run, although it contributes positively to environmental quality in the short term. Wen et al. [28] supported these findings, linking globalization to higher CO_2 emissions and environmental harm across several South Asian nations. These insights reinforce the importance of adopting strategic, context-sensitive approaches to leveraging globalization for sustainability. These findings indicate that sustainable development necessitates a balance between economic growth, industrialization, and urbanization, on the one hand, and the adoption of renewable energy, effective governance, and green innovation, on the other, to mitigate environmental degradation.

Within this broad context, the accelerating integration of AI into environmental management has opened new frontiers for mitigating ecological degradation, particularly through innovations that enhance energy efficiency and reduce reliance on carbon-intensive practices. Researchers have employed advanced AI techniques, including machine learning algorithms and deep learning models, to forecast environmental outcomes, demonstrating AI's potential in shaping a more sustainable future. Similarly, other scholars have explored the environmental implications of AI by focusing on the deployment of industrial robots, providing insight into how automation can intersect with ecological objectives [10,29].

For example, Xiang et al. [29] emphasize that advanced AI-driven approaches, such as Adaptive Intelligent Dynamic Water Resource Planning (AIDWRP), play a crucial role in maintaining sustainable water ecosystems in urban settings. Uriarte-Gallastegi et al. [30] highlight the transformative role of AI in energy management and sustainability, demonstrating that intelligent systems can optimize energy consumption while substantially reducing carbon emissions. Faiz et al. [31] concluded that advanced machine learning architectures, including Transformer Neural Networks and hybrid CNN-LSTM seq2seq models, exhibit superior performance in enhancing energy efficiency and maintaining thermal comfort within smart building energy management systems. Their findings suggest that these models outperform traditional standalone approaches, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, in optimizing environmental quality and energy management. Kumari and Pandey [32] argue that AI holds a pivotal position in the global push for environmental sustainability. Beyond its technological utility, AI is increasingly viewed as a strategic tool to address broad challenges, including poverty, food insecurity, and biodiversity loss. Its application ranges from intelligent energy systems with low carbon emissions to environmental domains like wildlife conservation, sustainable agriculture, pollution management, and circular waste systems. Importantly, their work highlights the need to develop environmentally conscious AI systems that cater to both current and future ecological needs. Mumtaz et al. [33] further assert that AI could usher in an era of "environmental intelligence" by 2030, thereby mitigating the adverse effects of urbanization, population expansion, and industrial growth, key drivers of environmental degradation.

In the context of AI applications through robotics, Liu [34] found that industrial robots have the potential to curb environmental pollution by stimulating green innovation and promoting higher-skilled employment structures in China. This led to recommendations for increased public and private investment in robotics to sustain these benefits. Extending this perspective globally, Chen et al. [35] demonstrated that industrial robots contribute to a reduction in the ecological footprint across 72 countries. Their findings attribute this impact to three core mechanisms: time-saving efficiencies, the emergence of green employment opportunities, and a shift toward cleaner energy sources. They advocate for proactive policy frameworks that encourage investments in human capital and clean energy transitions. Yao et al. [36] provided further evidence from OECD and BRICS nations, demonstrating that the adoption of industrial robots is associated with a significant decline in CO_2 emissions, particularly in contexts with higher emissions. The environmental benefits were most evident in advanced economies, particularly across OECD, European, and North American regions. However, not all outcomes are uniformly positive. Luan et al. [37] cautioned that increased robot usage could exacerbate air pollution and climate change. The logic is that higher productivity and energy efficiency, though seemingly beneficial, can lead to expanded production and consumption cycles. This rebound effect ultimately increases total energy demand, thereby offsetting the environmental gains and contributing to atmospheric degradation. These findings suggest that AI and industrial automation hold immense potential to drive environmental sustainability, but their actual impact hinges on mindful design, policy coherence, and systemic integration.

The existing literature has extensively explored the relationships between economic, demographic, industrial, governance factors, as well as artificial intelligence and environmental degradation, emphasizing the crucial need for effective energy management and efficiency to promote environmental sustainability. However, this study addresses several key gaps and introduces groundbreaking contributions to the understanding of how AI technology innovation, in conjunction with these socio-economic factors, impacts the environment. Unlike prior studies that rely on measures of AI, such as deep learning, machine learning algorithms, or industrial robots, this research adopts a more precise and policy-relevant approach by focusing on patent applications specifically related to energy management AI technologies. This targeted methodology provides a more accurate assessment of how AI innovation directly contributes to sustainable energy and efficiency solutions for ecological footprint. Moreover, this study extends beyond direct effects by examining the underlying mechanisms that shape the impact of energy management AI technology innovation on environmental degradation. Specifically, it explores the mediating role of energy intensity and the moderating effects of R&D and globalization. These insights reveal the conditions under which AI innovation is most effective in mitigating ecological damage. Lastly, the study conducts a heterogeneity analysis, distinguishing between developed and developing economies to assess how the effects of energy management AI technologies vary across different economic contexts. This novel approach is crucial for designing tailored policies that maximize the potential of AI in advancing global sustainability goals.

2.1. Theoretical basis and research hypotheses

The escalating concerns over environmental degradation and climate change have underscored the urgency of adopting innovative approaches to energy management. Energy management AI technology Innovation emerges as a promising solution to optimize energy consumption, reduce waste, and minimize environmental impact. This section aims to elucidate the theoretical mechanism through which EMAITI contributes to mitigating ecological footprint and environmental degradation. EMAITI facilitates the continuous, real-time monitoring, analysis, and optimization of energy consumption trends across industrial, residential, and commercial sectors [38]. Through machine learning algorithms and predictive analytics, AI systems identify energy-saving opportunities, optimize equipment performance, and minimize energy waste, thereby reducing the ecological footprint of energy production and consumption. AI technologies enhance the integration and management of renewable energy resources, including hydro, wind, and solar energy potential [39]. By forecasting renewable energy generation, optimizing grid operations, and managing energy storage systems, EMAITI facilitates the transition to a low-carbon energy mix, mitigating greenhouse gas emissions and environmental pollution. EMAITI contributes to behavioral change and consumer awareness by providing real-time feedback, insights, and incentives for energy conservation [40]. AI-driven energy management platforms empower individuals, businesses, and communities to make informed decisions, adopt sustainable practices, and reduce their environmental footprint through energy-saving behaviors. Therefore, the first hypothesis posits that increased adoption and integration of EMAITI will significantly reduce ecological footprint and environmental degradation.

Hypothesis 1. EMAITI reduces environmental degradation.

Energy intensity, defined as the amount of energy consumed per unit of economic output, is a crucial determinant of environmental impact [41]. High energy intensity levels are associated with greater resource depletion, pollution, and greenhouse gas emissions, exacerbating environmental degradation. EMAITI utilizes AI algorithms and data analytics to optimize energy usage, minimize waste, and enhance efficiency across various sectors [42]. By employing predictive modeling, real-time monitoring, and automated control systems, AI technologies identify inefficiencies and opportunities for energy conservation, thereby lowering energy intensity levels. AI-driven energy management systems provide dynamic feedback and adaptive control mechanisms, enabling the continuous optimization of energy-intensive processes [43]. Through machine learning algorithms, EMAITI learns from historical data and adjusts operational parameters in real time to minimize energy consumption while maintaining performance standards, resulting in sustained reductions in energy intensity. The adoption of EMAITI generates technological spillovers and systemic effects that extend beyond individual firms or sectors [44]. As AI technologies permeate energy management practices, best practices and efficiency gains are diffused across industries, contributing to economy-wide reductions in energy intensity and environmental impact. Thus, the second hypothesis posits that EMAITI reduces ecological footprint by decreasing energy intensity.

Hypothesis 2. EMITI reduces environmental degradation by decreasing energy intensity.

Investment in R&D stimulates the development of new technologies, including AI-driven solutions, that enhance energy efficiency, optimize resource utilization, and mitigate environmental impact [45]. R&D investments generate technological spillovers and facilitate knowledge transfer across sectors and industries [46]. Collaboration between academia, industry, and government in R&D initiatives accelerates the diffusion of EMAITI innovations, fostering a culture of innovation and enabling widespread adoption of energy-efficient technologies. R&D efforts contribute to the scalability and adaptability of EMAITI solutions, making them more suitable for diverse applications and contexts [47]. Continuous innovation and refinement of AI algorithms, sensor technologies, and data analytics capabilities enhance the precision, reliability, and effectiveness of EMAITI in addressing specific environmental challenges. Government support for R&D initiatives, through funding, incentives, and regulatory frameworks, plays a crucial role in advancing EMAITI development and deployment [48]. Policy interventions that promote collaboration, knowledge sharing, and technology transfer facilitate the translation of R&D investments into tangible environmental benefits. Therefore, the third hypothesis suggests that higher levels of R&D expenditure will strengthen the reduction effect of EMAITI on ecological footprint.

Hypothesis 3. R&D enhances the reduction effect of EMAITI on environmental degradation.

Globalization facilitates the diffusion of technology, knowledge, and best practices across borders, accelerating the adoption and deployment of innovative solutions, such as EMAITI [49,50]. International trade, investment, and collaboration enable countries to access advanced technologies and expertise, fostering the implementation of energy-efficient practices worldwide. Globalization expands access to global markets and resources, creating opportunities for disseminating and adopting EMAITI solutions on a broader scale [51]. Enhanced connectivity and integration enable firms to leverage AI technologies for energy management across supply chains, driving efficiency gains and environmental benefits. Globalization fosters knowledge exchange and collaborative innovation, enabling cross-border partnerships and networks that accelerate EMAITI development [52]. International research collaborations, technology transfer agreements, and joint ventures facilitate the sharing of expertise and resources, catalyzing advancements in energy management and environmental sustainability. Globalization encourages regulatory harmonization and policy alignment, creating a conducive environment for EMAITI adoption and implementation [53]. International agreements and standards promote uniformity in energy efficiency regulations, incentivizing firms to invest in AI-driven energy management solutions to comply with global norms and standards. Consequently, the fourth hypothesis proposes that higher levels of globalization will enhance the reduction effect of EMAITI on ecological footprint (see Fig. 1).

Hypothesis 4. Globalization enhances the reduction effect of EMAITI on environmental degradation.

3. Data, model, and methodology

3.1. Model

Building upon the insights from prior literature, this study endeavors to investigate the influence of energy management AI technology innovation, alongside other explanatory variables, on environmental degradation resulting from energy transition [10,14,54]. Drawing from earlier research, the current analysis employs the following econometric model:

$$EFP_{it} = \alpha_0 + \alpha_1 EMAITI_{it} + \beta CV_{it} + \varepsilon_{it} \tag{1}$$

In this equation, EFP_{it} represents environmental degradation, which is measured by the ecological footprint (EFP), while $EMAITI_{it}$ denotes energy management AI technology innovation. The variable CV_{it} comprises a range of control variables, including economic growth (GDP), financial development (FD), industrialization (IND), urbanization (URB), population growth (POPG), government regulations (GR), and renewable energy consumption (RE). The intercept term is denoted by α_0, and ε_{it} represents the error term, α_1 and β represent the coefficients for each variable that needs to be estimated. The subscript ″i″ represents the individual countries, amounting to 19 in the study, while the subscript ″t″ signifies the time span from 2010 to 2020.

The paper now delves into the internal mechanism through which EMAITI influences environmental degradation and will verify Hypothesis 2. Drawing on previous research on mediating effects, Li and Zhang [14], the subsequent equation for the mediating effect is formulated as follows:

$$M_{it} = \alpha_0 + \alpha_3 EMAITI_{it} + \beta CV_{it} + \varepsilon_{it} \tag{3}$$

$$EFP_{it} = \alpha_0 + \alpha_4 EMAITI_{it} + \phi M_{it} + \beta CV_{it} + \varepsilon_{it} \tag{4}$$

The equation above M_{it} represents the mediating variable, which is energy intensity (EI).

In order to assess the moderating influence of research and devel-

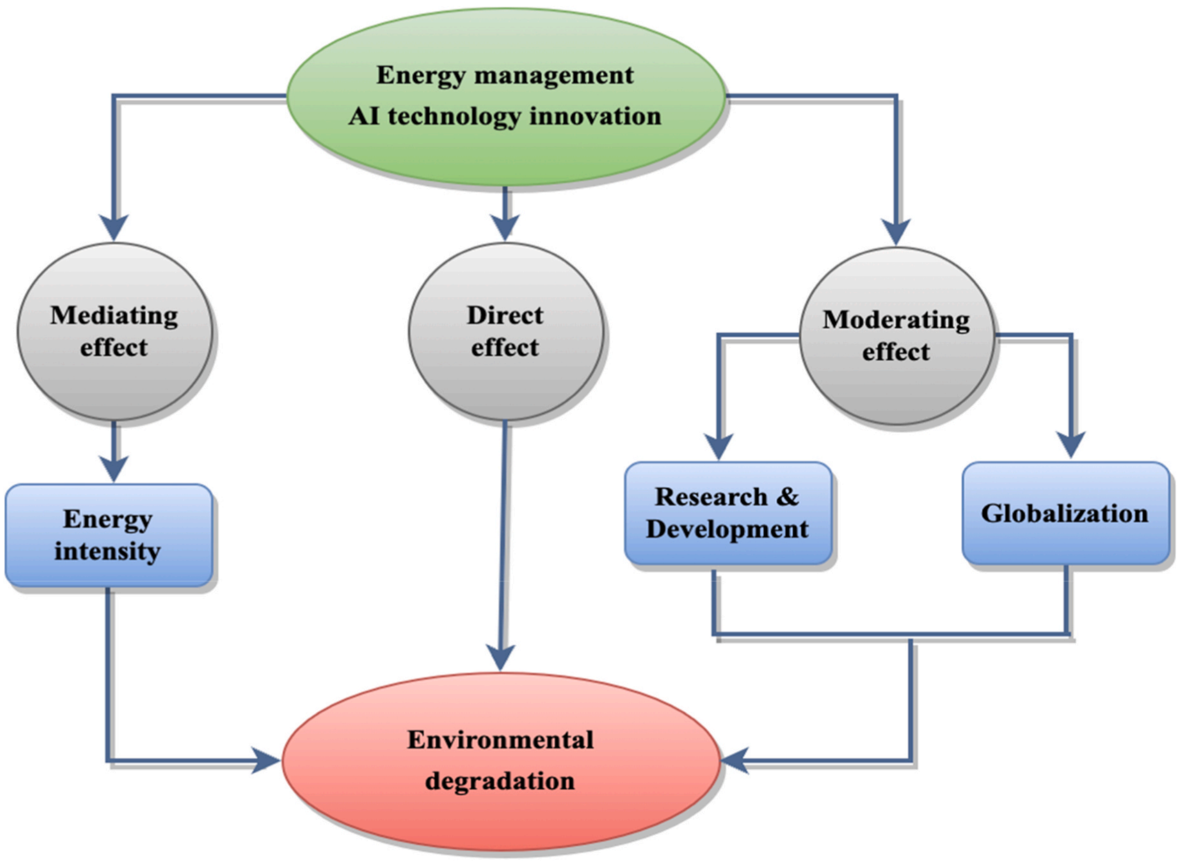

Fig. 1. Theoretical model.

opment and globalization and validate **Hypotheses 3** and **4**, we introduce the interaction terms of research and development (R&D) and globalization (GLOB) and EMAITI into equation (1). Following the framework outlined by Li and Zhang [14], we formulate the following equations to represent the moderating effect:

$$EFP_{it} = \alpha_0 + \alpha_3 EMAITI_{it} + \beta CV_{it} + \varphi R\&D_{it} + \gamma(EMAITI_{it} * R\&D_{it}) + \varepsilon_{it} \quad (5)$$

$$EFP_{it} = \alpha_0 + \alpha_3 EMAITI_{it} + \beta CV_{it} + \chi GLOB_{it} + \lambda(EMAITI_{it} * GLOB_{it}) + \varepsilon_{it} \quad (6)$$

The variables denoted as $R\&D_{it}$ and $GLOB_{it}$ serve as the moderating factors in equations (5) and (6) while γ and λ are the coefficients of the interactive terms to be estimated.

3.2. Methodology

The study initiates various diagnostic tests to evaluate regression equation (1) to determine the optimal estimating strategy for the given dataset. Firstly, a cross-sectional dependency (CSD) test is conducted to identify any dependency among cross-sectional units [55]. To achieve this, the study employs tests for cross-section independence proposed by Pesaran [56], Friedman [57], and Frees [58]. In the next step, the study utilizes the slope homogeneity (SH) test developed by Blomquist and Westerlund [59] to ascertain the presence or absence of heterogeneous slope coefficients in the panel data due to varying economic and demographic frameworks. Following the SH deduction, tests for heteroscedasticity and autocorrelation are performed to investigate evidence of these phenomena in the data. Modified Wald tests for groupwise heteroskedasticity and Born and Breitung [60] serial correlation test are chosen for their robustness and minimal assumptions [60,61]. The fourth step of the econometric methodology involves conducting a panel unit root test. To achieve this, the study employs the cross-sectional Augmented Dickey-Fuller (CADF) and cross-sectional Im Pesaran & Shin (CIPS) tests, which are second-generation panel stationarity tests proposed by Pesaran [62] to address CSD.

After completing the aforementioned analytical steps, the study employs the panel-corrected standard errors (PCSE) Approach. Recognizing that panel data may be affected by cross-sectional dependency, autocorrelation, and heteroscedasticity issues, traditional econometric techniques such as pooled ordinary least squares, fixed effects, and random effects may lead to incorrect conclusions. Therefore, the present study employs the PCSE approach, which provides robust and unbiased estimates in the presence of CSD, serial correlation, and heteroscedasticity [63]. Utilizing this methodology, more meaningful and valuable insights are derived from the panel data of 19 economies spanning the period from 2010 to 2020.

3.3. Data source and description

To explore the impact of innovation in energy management AI technology on mitigating environmental degradation, a panel dataset encompassing 19 countries spanning from 2010 to 2020 is utilized. The selection of these countries and the timeframe for the panel data is predicated on the availability of data on the variable of interest, namely energy management AI technology innovation (EMAITI) from the Center for Security and Emerging Technology (CSET) database published by Our World in Data. Furthermore, the study period is marked by the rapid adoption of AI technologies, particularly in energy management, amid growing concerns over climate change and environmental degradation. During this period, a global shift toward sustainable energy solutions, increased innovation in AI, and efforts to enhance energy efficiency emerged. The 19 countries selected for this study, including global leaders such as the United States, China, and Germany, are at the forefront of AI research and energy management AI technologies [64–66], while nations like Denmark, South Korea, and Japan are implementing advanced AI-driven energy strategies [67,68]. Countries with strong environmental policies, such as Germany, Denmark, and the UK, provide ideal contexts for studying the impact of energy management AI on environmental degradation [69–71]. Meanwhile, rapidly developing economies like Brazil, India, Russia, and Mexico offer valuable insights into the challenges of adopting AI for energy management [72,73]. Additionally, countries like Finland, South Korea, and Singapore, known for their technological advancements and smart city initiatives, demonstrate how AI can drive sustainable energy solutions [74], making them key to understanding the role of innovation in environmental sustainability. The description and measurement of the variables are outlined in Table 1. Energy management AI technology innovation data is sourced from the CSET, ecological footprint data from the Global Footprint Network (GFN), and data for the remaining variables is extracted from the World Bank (WB) database [75–77].

3.3.1. **Dependent variable:** *Ecological footprint*

The dependent variable in this study is the ecological footprint (EFP) representing environmental degradation. Ecological footprint is a metric that quantifies the human impact on nature and ecosystems. It specifically measures the amount of biologically productive land and water needed to produce the resources consumed and absorb the waste generated by a population or activity. It is a comprehensive indicator of environmental impact, encompassing resource consumption, waste generation, and environmental degradation [78]. In this study, the ecological footprint is the outcome variable that reflects the extent of environmental degradation resulting from human activities, including energy consumption and management practices. The global ecological footprint of countries is represented in Fig. 2, with most countries in our sample among the high ecological footprint exhibitors.

3.3.2. **Independent variable:** *Energy management AI technology innovation*

The independent variable of interest is energy management AI technology innovation (EMAITI), specifically assessed based on the number of patents that were granted in energy management. This variable represents the advancements in AI technology specifically tailored for energy management purposes, such as optimizing the use of energy and ensuring more sustainability by cutting down wastes in energy systems. Patent applications granted serve as a tangible indicator of technological innovation [17,18], and signify the growth and adoption

Table 1
Variables description.

Variable	Symbol	Measurement	Source
Environmental degradation	EFP	Ecological footprint: global hectares per person	GFN
Energy management artificial intelligence technology innovation	EMAITI	Patent applications granted - field: energy management	CSET
Economic growth	GDP	GDP (constant 2015 US$)	WB
Financial development	FD	Domestic credit to private sector (% of GDP)	WB
Industrialization	IND	Industry (including construction), value added (% of GDP)	WB
Urbanization	URB	Urban population (% of Total Population)	WB
Population growth	POPG	Annual %	WB
Government regulation	GR	Regulatory quality: estimate	WB
Renewable energy	RE	% of total final energy consumption	WB
Energy intensity	EI	Level of primary energy (MJ/ $2017 PPP GDP)	WB
Research & development	R&D	% of GDP	WB
Globalization	GLOB	Composite of foreign direct investment, net inflows (% of GDP) and trade (% of GDP)	WB

of AI-based solutions in the energy industry [80]. The distribution of granted AI patents in energy management is depicted in Fig. 3.

3.3.3. *Control variables*

Economic growth (GDP) is a control variable that accounts for a country's overall economic activity and development level [81]. A higher GDP implies greater industrialization, urbanization, and increased energy consumption, which can contribute to environmental degradation.

Financial development (FD), measured by domestic credit to the private sector as a percentage of GDP, reflects the availability of financial resources for investment and economic growth. It can impact energy infrastructure investment and technological innovation, thereby affecting environmental outcomes [82].

Industrialization (IND), represented by the value added in the industry sector as a percentage of GDP, indicates the contribution of industrial activities to the economy. Higher industrialization levels may increase energy consumption and pollution, thereby exacerbating environmental degradation [83].

Urbanization (URB), proxied by the percentage of the population residing in urban areas, reflects the concentration of economic activities and energy demand in urban centers. Urbanization can influence energy consumption patterns, infrastructure development, and environmental pressures [14].

Population growth (POPG) serves as a control variable to account for the demographic factor's influence on environmental degradation. Higher population growth rates can lead to increased energy demand, resource depletion, and environmental stress [23].

Government regulation (GR), representing the effectiveness and efficiency of government regulations, is included to assess the impact of regulatory frameworks on environmental outcomes. Stronger regulatory quality may lead to better enforcement of environmental policies and the mitigation of environmental degradation [84].

Renewable energy consumption (RE), the proportion of renewable energy consumption relative to total final energy consumption, is considered a control variable. A higher reliance on renewable energy sources can mitigate environmental degradation by reducing greenhouse gas emissions and decreasing dependence on fossil fuels [17,18].

3.3.4. **Mediating variable:** *energy intensity (EI)*

The mediating variable in this study is the energy intensity level of primary energy, measured in megajoules per unit of constant 2017 purchasing power parity (PPP) GDP. Energy intensity reflects the efficiency of energy use within an economy and is calculated as the ratio of total energy consumption to GDP [85,86]. A lower energy intensity level indicates higher energy efficiency and less environmental impact per unit of economic output. In the context of this study, the energy intensity level of primary energy serves as a mechanism through which energy management AI technology innovation influences the reduction of ecological footprint. AI-based energy management technologies can reduce energy intensity and environmental degradation by optimizing energy consumption and improving efficiency.

3.3.5. *Moderating variables*

Research and development (R&D) expenditure as a percentage of GDP is a moderating variable in this study. It reflects the investment in technological innovation and development, including AI-based energy management technologies. Higher R&D expenditure may enhance the development and adoption of innovative AI solutions, thereby amplifying the impact of energy management AI technology on reducing environmental degradation [87].

Globalization (GLOB), represented by a composite index of foreign direct investment net inflows as a percentage of GDP and trade as a percentage of GDP, is included as a moderating variable. Globalization can influence technology transfer, market integration, and resource access, thereby affecting the adoption and diffusion of energy

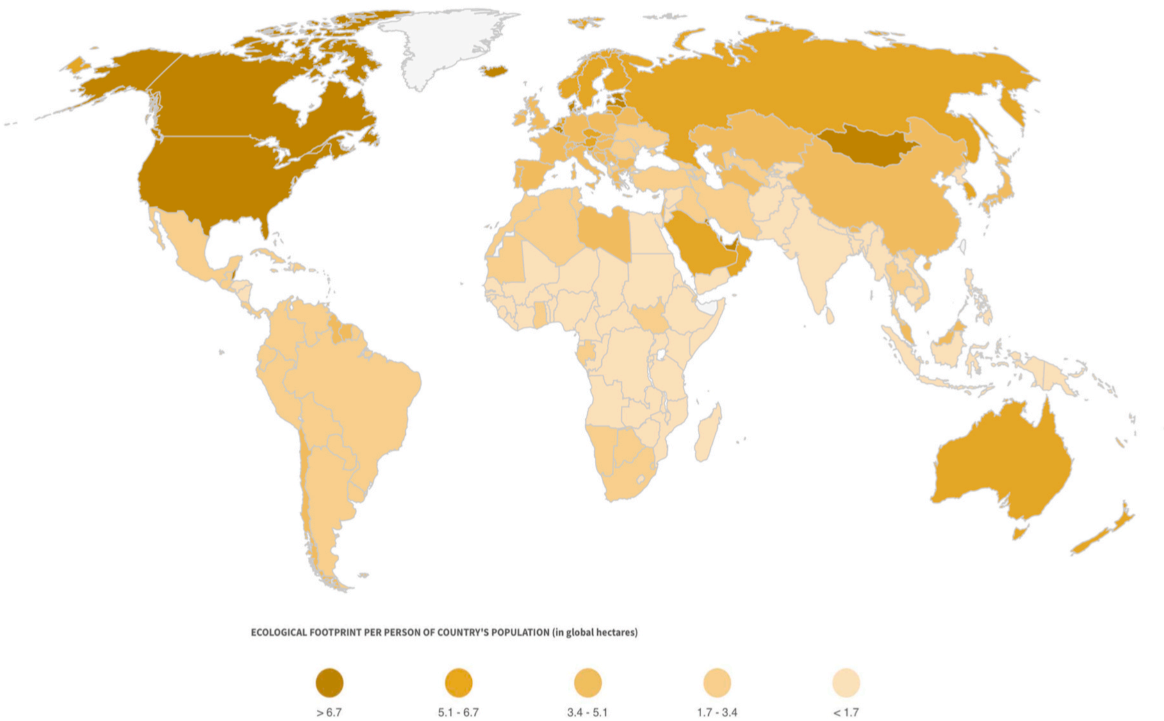

Fig. 2. Ecological footprint of countries from 1961 to 2022. Source: Global Footprint Network [79].

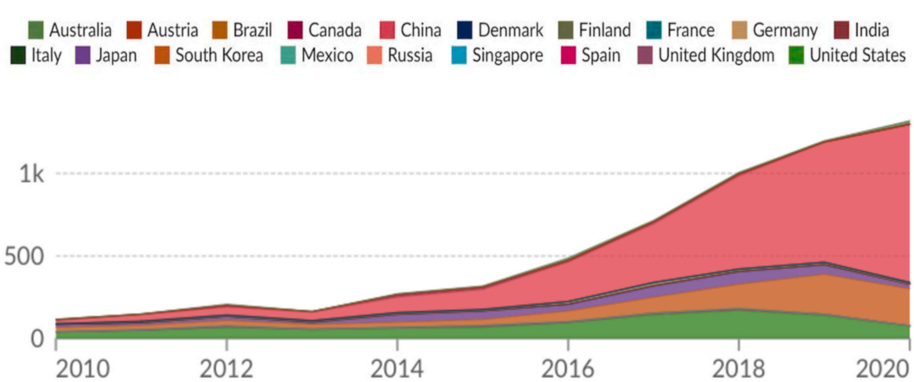

Fig. 3. The annual distribution of AI-granted patents in energy management from 2010 to 2020. Source: Center for Security and Emerging Technology [23].

Table 2
Descriptive statistics.

Variable	EFP	EMAITI	GDP	FD	IND	URB	POPG	GR	RE	EI	R&D	GLOB
Mean	5.512	28.44	3.03E+12	107.666	25.34	77.271	0.607	1.031	17.343	4.306	2.125	78.521
Std. Dev.	2.44	100.299	4.31E+12	45.53	6.134	14.622	0.551	0.809	13.329	1.747	0.975	71.536
Minimum	0.88	0	2.30E+11	22.324	16.786	30.93	−1.854	−0.58	0.47	1.96	0.284	24.041
Maximum	11.18	957	2.00E+13	215.778	46.529	100	2.453	2.252	50.05	8.93	4.796	396.695
Correlation statistics												
EFP	1											
EMAITI	−0.132	1										
GDP	0.188	0.525	1									
FD	0.356	0.335	0.487	1								
IND	−0.443	0.367	0.0831	−0.152	1							
URB	0.447	−0.141	−0.111	0.335	−0.356	1						
POPG	0.111	−0.0928	−0.0576	−0.180	0.0265	−0.0588	1					
GR	0.659	−0.206	−0.124	0.435	−0.455	0.590	0.0660	1				
RE	−0.135	−0.134	−0.230	−0.296	−0.249	−0.298	0.0551	−0.0907	1			
EI	−0.0131	0.235	0.236	−0.176	0.569	−0.259	0.0388	−0.411	−0.0926	1		
R&D	0.213	0.183	0.173	0.611	0.000579	0.310	−0.277	0.578	−0.0748	−0.0572	1	
GLOB	0.111	−0.132	−0.297	0.0221	−0.0271	0.351	0.226	0.406	−0.229	−0.318	0.0762	1

management AI technologies and their environmental impact [88].

4. Results and discussion

4.1. Preliminary tests

Table 2 provides a comprehensive overview of the variables used in the current analysis, including summary statistics and correlation analysis. According to the descriptive statistics, the mean value of the dependent variable, ecological footprint, is 5.512, with the highest and lowest values recorded at 11.18 and 0.88, respectively. Similarly, the average value for EMAITI stands at 28.44, with a minimum value of 0 and a maximum value of 957 observed in the selected sample. Furthermore, summary statistics for GDP, FD, IND, URB, population growth, government regulation, RE, EI, R&D, and globalization are presented in Table 2. The lower section of Table 2 displays the correlation analysis. This analysis reveals a negative correlation between EMAITI, urbanization, renewable energy consumption, and energy intensity with the ecological footprint. Conversely, economic growth, financial development, population growth, government regulation, research and development, and globalization exhibit a positive correlation with the ecological footprint. Notably, all the coefficients observed in the correlation analysis are below 0.70, indicating the presence of multicollinearity among the variables. Table 3 presents the results of numerous tests conducted to assess CSD, SH, heteroskedasticity, and autocorrelation within the dataset. These tests were implemented while assuming the null hypothesis of no CSD in the data, as proposed by Pesaran [56], Friedman [57], and Frees [58]. As indicated in Table 3, the outcomes indicate significant cross-sectional dependency among the countries. Moreover, the modified Wald and Born and Breitung [60] tests reveal the presence of both heteroskedasticity and serial correlation within the dataset. Additionally, the Blomquist and Westerlund [59] SH test results confirm the existence of slope heterogeneity, as presented in Table 3. The stationarity tests, as shown in Table 4, indicate that the variables exhibit stationary behavior at the first-difference level with a significance level of 1 %. These results lend credence to the argument that the variables such as GDP, FD, industrialization, urbanization, population growth, government regulation, RE, EI, R&D, globalization, ecological footprint, and EMAITI are stationary at the level and after the first difference. The outcomes suggest that the variables are integrated at orders I (0) and I (1). Based on the results of the pre-estimation tests, it is evident that cross-sectional dependency, heteroskedasticity, autocorrelation, and heterogeneity issues affect the data sourced for the present investigation. Consequently, the study uses the PCSE method of estimation, which offers robust estimates in the presence of these challenges.

4.2. Benchmark regression results

Table 5 displays the main outcomes of the benchmark estimation from equation (1) through a stepwise regression, from column (1) to (8), by progressively adding the variables. Examining the table reveals that in column (8), the EMAITI coefficient is −0.00233 and holds significance at the 5 % level. This implies that EMAITI contributes to the reduction of environmental degradation, thereby supporting Hypothesis 1. Energy management AI technology innovations are likely to focus on optimizing energy efficiency and reducing waste in energy systems [2]. By deploying AI-based algorithms and predictive analytics, industries can more effectively manage their energy usage, leading to lower emissions, reduced resource depletion, and less environmental harm overall. The development and adoption of EMAITI may also generate technological spillovers, leading to broader innovation and efficiency gains across the economy. As industries invest in AI-based energy management solutions, they may discover new techniques, processes, or technologies that can be applied to other environmental challenges, amplifying the overall positive impact on environmental degradation. The finding aligns with Liu et al. [89].

Table 3
CSD, SH, heteroscedasticity, and serial correlation tests.

Test	Statistics	Prob.
Pesaran's test of cross-sectional independence	4.043***	0.0001
Friedman's test of cross-sectional independence	28.842***	0.0000
Frees' test of cross-sectional independence	1.424***	0.0000
Slope homogeneity ($\tilde{\Delta}$)	−7.493***	0.0000
Slope homogeneity ($\tilde{\Delta}adj$)	−6.368***	0.0000
Modified Wald test for groupwise heteroskedasticity	3861.37***	0.0000
Born and Breitung serial correlation Q(p)-test	7.25**	0.027

Note: $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Stationarity tests.

Variables	CIPS Test		CADF Test	
	Level	First difference	Level	First difference
EFP	−2.069	−2.850[c]	−1.435[a]	−3.772[c]
EMAITI	−2.809[c]	−3.406[c]	−2.406[c]	−2.955[c]
GDP	−2.396[b]	−2.722[c]	−2.660[c]	−2.521[c]
FD	−1.249	−2.545[c]	−1.542	−2.781[c]
IND	−1.711	−2.306[a]	−2.611[c]	−2.004[b]
URB	−1.391	−4.828[c]	−1.391	−2.683[c]
POPG	−1.296	−2.406[b]	−2.203[b]	−2.422[c]
GR	−1.920	−2.904[c]	−1.262	−4.353[c]
RE	−2.126	−3.010[c]	−2.410[c]	−2.510[c]
EI	−2.387[b]	−3.497[c]	−2.387[c]	−3.497[c]
R&D	−1.123	−3.327[c]	−1.548	−2.473[c]
GLOB	−1.737	−2.507[b]	−1.826	−2.659[c]

Note.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Regarding the control variables, the coefficient for GDP is 2.17e-13, indicating a positive relationship between economic growth and environmental degradation, which is significant at the 1 % level. Economic growth often entails increased industrial activity, the extraction of natural resources, and the expansion of manufacturing sectors, which can lead to higher emissions, pollution, and habitat destruction [90]. As economies grow, there is typically an accompanying rise in energy use, mainly from fossil fuel-based sources. Higher energy consumption contributes to air and water pollution, greenhouse gas emissions, and ecosystem degradation [91,92]. Rapid economic growth often necessitates the construction of roads, buildings, and transportation networks, which can lead to habitat fragmentation, deforestation, and biodiversity loss. This observation aligns with the findings of Adekoya et al. [15] and Yusuf [11].

The coefficient for FD is −0.00638, suggesting a statistically significant negative correlation between financial development and ecological footprint, although it is not deemed necessary. Financial development often involves the availability of diverse financial instruments and services, including loans, investments, and insurance products. Companies and individuals in financially developed economies may have better access to capital for investing in environmentally sustainable practices, such as renewable energy projects, energy-efficient technologies, and pollution control measures. This investment in sustainability can lead to reduced environmental footprints over time. Financial development can facilitate technological innovation and adoption, including advancements in cleaner production methods, resource-efficient technologies, and environmental management systems [12]. Access to capital markets and financial resources enables firms to invest in sustainable R&D activities for reducing environmental impacts. As a result, greater financial development may lead to innovations that contribute to lower ecological footprints. This result contradicts the findings of Saqib et al. [21] and confirms the findings of

Table 5
Main regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EFP	EFP	EFP	EFP	EFP	EFP	EFP	EFP
EMAITI	−0.00320[b]	−0.00773[c]	−0.00875[c]	−0.00473[c]	−0.00432[c]	−0.00402[c]	−0.00257[c]	−0.00233[b]
	(-2.30)	(-3.61)	(-3.97)	(-4.54)	(-4.14)	(-3.92)	(-2.57)	(-2.28)
GDP		2.00e-13[c]	1.07e-13[b]	1.03e-13[c]	1.52e-13[c]	1.45e-13[c]	2.25e-13[c]	2.17e-13[c]
		(5.30)	(2.55)	(3.29)	(4.87)	(4.72)	(7.73)	(6.98)
FD			0.0206[c]	0.0150[c]	0.00749[a]	0.00920[b]	−0.00579[a]	−0.00638[a]
			(5.73)	(3.96)	(1.85)	(2.25)	(-1.73)	(-1.86)
IND				−0.137[c]	−0.107[c]	−0.109[c]	−0.0576[c]	−0.0686[c]
				(-6.58)	(-4.82)	(-4.88)	(-2.90)	(-3.51)
URB					0.0516[c]	0.0513[c]	0.0191[b]	0.0147[a]
					(5.43)	(4.94)	(2.17)	(1.80)
POPG						0.737[c]	0.336	0.338
						(3.11)	(1.49)	(1.52)
GR							1.795[c]	1.802[c]
							(8.52)	(8.97)
RE								−0.0113[a]
								(-1.86)
Constant	5.603[c]	5.124[c]	3.220[c]	7.190[c]	3.091[c]	2.534[b]	3.455[c]	4.341[c]
	(33.41)	(26.15)	(8.46)	(9.35)	(3.01)	(2.33)	(3.92)	(4.31)
Observations	209	209	209	209	209	209	209	209
R-squared	0.0173	0.108	0.220	0.312	0.381	0.408	0.566	0.569
Wald chi^2	5.31[b]	13.06[c]	48.49[c]	166.45[c]	230.61	216.97	298.38[c]	328.32[c]

Note.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$; *z* statistics in parentheses.

Ullah et al. [12].

Regarding IND, the coefficient is −0.0686, indicating a statistically significant negative correlation of 1 %, implying that industrialization may contribute to reducing environmental degradation. Industrialization often coincides with advancements in technology and production processes [93]. As industries become increasingly technologically advanced, they can adopt cleaner and more efficient production methods that reduce pollution and minimize their environmental impact. For example, industries may invest in pollution control technologies, implement waste management practices, or transition to cleaner energy sources. Additionally, through economies of scale, industries can invest in more efficient technologies, optimize resource utilization, and reduce waste generation, resulting in lower environmental degradation per unit of output. Nevertheless, it is crucial to acknowledge that the specific relationship between industrialization and environmental outcomes may vary depending on contextual factors, policy interventions, and industrial practices in different regions or countries. This discovery aligns with the research of Opoku and Aluko [13].

The coefficient of URB is 0.0147, with a significantly positive correlation at the 10 % level, indicating that urbanization has contributed to increased environmental degradation. Urbanization is often accompanied by rapid infrastructure expansion, encompassing the construction of buildings, roads, and transportation systems. These activities can result in habitat destruction, loss of green spaces, and disruption of natural ecosystems, thereby contributing to environmental degradation [94]. Cities tend to be centers of industrial and commercial activity, hosting manufacturing plants, factories, and other industrial facilities. These activities can release air, water, and soil pollutants, further exacerbating environmental problems. Urbanization is associated with an increased demand for transportation services, resulting in higher vehicular emissions and air pollution. Traffic congestion, vehicle exhaust, and emissions from public transportation systems contribute to poor air quality and environmental degradation in urban areas. Urbanization is associated with higher levels of waste generation due to increased consumption and population density. Municipal solid waste, industrial waste, and sewage disposal pose significant challenges to urban environments, leading to pollution of land, water, and air. The positive correlation between urbanization and environmental degradation emphasizes the importance of sustainable urban planning, effective resource management, and strategic environmental approaches in mitigating the adverse environmental impacts of urban growth. This finding corresponds with the outcomes reported by Li and Zhang [14].

The coefficient for POPG is 0.338, although insignificant, suggesting that an increase in population may lead to higher environmental degradation. As populations grow, demand for products and services tends to rise, leading to increased industrialization, urbanization, and higher resource consumption [94]. This surge in economic activity frequently leads to increased levels of environmental degradation, including pollution, habitat destruction, and depletion of natural resources. Increased energy consumption, transportation needs, and waste production contribute to environmental pressures. Moreover, rapid population growth can strain ecosystems and exacerbate environmental stresses, particularly in densely populated areas with more acute resource constraints. As more people compete for limited resources, such as water, land, and energy, the environmental footprint per capita is likely to increase, further intensifying environmental degradation. This result confirms the findings of Appiah, Li et al. [23].

Regarding GR, the coefficient is 1.802 and significant at a 1 % level, implying that a rise in regulations may exacerbate environmental degradation. During the initial phases of economic growth, regulatory frameworks, and enforcement mechanisms may be insufficient to mitigate environmental impacts effectively. Weak environmental governance can exacerbate ecological degradation that is often associated with economic growth. Stringent regulations may inadvertently incentivize firms to engage in regulatory arbitrage or "pollution havens" by relocating production to jurisdictions with lax environmental standards, where they can operate more cost-effectively but with potentially greater ecological impacts. This phenomenon can result in the displacement of pollution rather than its reduction, exacerbating environmental degradation on a global scale. This outcome contradicts the findings of Liu and Zhang [24].

Finally, the coefficient for RE is −0.0295, which is significant at a 10 % level, indicating that renewable energy consumption has a significant impact on reducing environmental degradation. Renewable energy sources, such as wind, hydropower, and solar, produce electricity with lower or no emissions of greenhouse gases and other pollutants compared to fossil fuels [95]. As a result, increased utilization of renewable energy reduces the emission of pollutants into the environment, improving air and water quality and mitigating environmental degradation. Utilizing renewable energy helps mitigate climate change by reducing the release of greenhouse gases, specifically carbon dioxide, a significant contributor to global warming and environmental degradation. Renewable energy technologies lessen the reliance on fossil fuels for energy production, thereby preventing the accumulation of greenhouse gases in the atmosphere. This helps mitigate the negative impacts of climate change on ecosystems and biodiversity. This finding aligns with the studies by Adekoya et al. [15], Satrovic et al. [96], and Ahakwa et al. [97].

4.3. Robustness test

To ensure the consistency of the main estimation findings, the study undertakes a robustness test by addressing endogeneity concerns and altering the measure of environmental degradation. The outcomes are presented in Table 6.

Various tests were conducted on the baseline regression to validate the model's reliability and robustness. Initially, potential endogeneity issues within the model were addressed. Given the possibility that EMAITI may reciprocally influence environmental degradation, we treated two lags of EMAITI as instrumental variables in the research model. We employed the instrumental variable generalized method of moments (IV-GMM) estimation. The regression outcomes, depicted in column 1 of Table 6, validate the effectiveness of this approach. Firstly, the Kleibergen-Paap rk LM statistic attains a value of 7.293, which is significant at the 5 % critical value, thereby rejecting the null hypothesis of unidentifiable instrumental variables. Secondly, the p-values of the Cragg-Donald Wald F statistic (1526.336) and Kleibergen-Paap rk Wald F statistic (333.515) are above the Stock-Yogo IV critical value of 10, rejecting the null hypothesis of weak instruments. Thirdly, the insignificant Hansen J statistics (0.055) reject the null hypothesis of the overidentification test of all instruments. The direction and significance of each coefficient are consistent with the baseline estimations, reaffirming the model's robustness.

Furthermore, the dependent variable was replaced to validate the baseline findings. The ecological footprint variable was replaced with CO_2 emissions measured in kilograms per 2017 PPP $ of GDP. The results in column 2 indicate that, even with this change in measurement methodology, the EMAITI coefficient remains significantly negative, thus ensuring the ongoing validity of the results.

Table 6
Robustness test results.

Variables	(1)	(2)
	IV-GMM	CO_2
EMAITI	−0.00246[a]	−0.000131[c]
	(-1.83)	(-2.78)
Constant	4.005[c]	−0.0698[a]
	(3.55)	(-2.01)
Control variables	YES	YES
Observations	171	209
R-squared	0.560	0.680
F statistics/Wald chi^2	30.94[c]	815.95[c]
Kleibergen-Paap rk LM statistic	7.293[b]	
Cragg-Donald Wald F statistic	1526.336	
Kleibergen-Paap rk Wald F statistic	333.515	
Hansen J statistic	0.055	

Note.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$; z statistics in parentheses.

Table 7
Mediating effect results.

Variables	(1)	(2)	(3)
	EFP	EI	EFP
EMAITI	−0.00233[b]	−0.00129[b]	−0.00153[a]
	(-2.28)	(-2.37)	(-1.87)
EI			0.615[c]
			(10.15)
Constant	4.341[c]	−0.272	4.508[c]
	(4.31)	(-0.37)	(4.49)
Control variables	YES	YES	YES
Observations	209	209	209
R-squared	0.569	0.420	0.681
Wald chi^2	328.32[c]	345.57[c]	871.05[c]

Note.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$; z statistics in parentheses.

4.4. Mediation effect

Table 7 presents the findings from the mediating effect test regarding energy intensity. The procedure involves several steps outlined below, followed by an analysis of the estimated results. In the initial step, attention is drawn to column (1) of Table 5. Notably, the coefficient for EMAITI exhibits a negative trend at the 5 % significance level, indicating that EMAITI contributes to a reduction in ecological footprint. Subsequently, the second step involves sequentially testing equations (3) and (4). The outcomes depicted in column (2) reveal that augmenting EMAITI results in a decline in the energy intensity of each country. Moving on to column (3), the analysis indicates a significantly positive coefficient for energy intensity at the 1 % level. This signifies the indirect impact of energy intensity. Moreover, the coefficient for EMAITI remains negative and significant, suggesting that energy intensity partially mediates the reduction of environmental degradation. As a result, Hypothesis 2 is substantiated. In other words, while EMAITI directly reduces environmental degradation by improving energy efficiency, its indirect effect, mediated through changes in energy intensity, also contributes to the overall reduction in environmental impact. This highlights the complex interplay between technological innovation, energy use, and environmental outcomes, emphasizing the importance of considering multiple pathways and mechanisms in understanding the effects of EMAITI on sustainability.

4.5. Moderation effect

Table 8 displays the findings from the analysis of the moderation effect. In column (2) of Table 8, the introduction of the moderating variable "research and development" reveals a negative coefficient for EMAITI at the 1 % significance level, confirming the baseline findings. Moving to column (3), where the interaction term between EMAITI and R&D is included based on column (2), the results indicate a 1 % significant negative coefficient for the interaction term. Notably, the coefficient sign of the interaction term mirrors that of EMAITI, suggesting that R&D has a positive moderating effect on the impact of EMAITI on ecological footprint across different countries. Increased investment in R&D enhances the development and refinement of AI-based energy management technologies, leading to more effective solutions for environmental sustainability [98]. R&D expenditure may facilitate the optimization and diffusion of EMAITI innovations, thereby augmenting their positive influence on reducing environmental degradation. Therefore, there is empirical substantiation for Hypothesis 3. Additionally, in Table 8, when considering column (4), incorporating the moderating variable "globalization" showcases a negative coefficient for EMAITI, reaching a 10 % significance level, which aligns with the baseline findings. Progressing to column (5), where the interaction

Table 8
Moderating effects results.

Variables	(1)	(2)	(3)	(4)	(5)
	EFP	EFP	EFP	EFP	EFP
EMAITI	−0.00233[b]	−0.00222[c]	−0.0131[b]	−0.00199[a]	−0.0262[c]
	(-2.28)	(-3.48)	(-2.53)	(-1.77)	(-4.24)
R&D		−0.921[c]	−0.563[c]		
		(-4.99)	(-2.61)		
EMAITI[a]R&D			−0.00629[c]		
			(-2.80)		
GLOB				−0.00499[c]	−0.00594[c]
				(-3.17)	(-4.14)
EMAITI[a]GLOB					−0.000713[c]
					(-4.32)
Constant	4.341[c]	3.129[c]	3.418[c]	4.348[c]	3.551[c]
	(4.31)	(3.14)	(3.55)	(4.27)	(3.82)
Control variables	YES	YES	YES	YES	YES
Observations	209	209	209	209	209
R-squared	0.569	0.613	0.630	0.582	0.651
Wald chi^2	328.32[c]	444.52[c]	456.83[c]	355.61[c]	427.66[c]

Note.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$; *z* statistics in parentheses.

between EMAITI and GLOB is introduced based on column (4), the outcomes reveal a significant negative coefficient for the interaction term at the 1 % level. Notably, the sign of the coefficient of the interaction term mirrors that of EMAITI, indicating that globalization positively magnifies the influence of EMAITI on environmental degradation across diverse countries. Globalization facilitates the diffusion of technology, knowledge, and best practices across borders, enabling the more widespread adoption and implementation of EMAITI innovations [99]. Increased globalization may lead to greater access to markets, resources, and expertise, thereby enhancing the effectiveness of EMAITI in addressing environmental challenges on a global scale. These findings emphasize the significance of contextual factors, including R&D expenditure and globalization, in influencing the effectiveness of EMAITI in mitigating environmental degradation. Hence, Hypothesis 4 receives empirical validation.

4.6. Heterogeneity analysis

Considering the diverse economic development levels across the countries in our sample, categorized by the World Bank, we utilized gross national income (GNI) to distinguish between developed and developing nations. According to the World Bank's categorization, countries with a GNI of $12,696 or more are classified as high-income, while those with a GNI below this threshold are designated as developing [100]. Applying these criteria, our sample was stratified into fourteen developed and five developing countries. The regression outcomes for both developed and developing countries are outlined in Table 9. In column (2), the explanatory variable displays statistical significance at the 5 % level, with a coefficient of −0.00681. Similarly, in column (3), the coefficient retains statistical significance at the 10 % level, with a precise coefficient of −0.000674. However, the effect is smaller among developing countries. In developed countries, where infrastructure, technology, and regulatory frameworks are generally more advanced, adopting and implementing energy management AI technologies will likely be more efficient and effective [4]. These countries often have higher levels of investment in research and development, greater access to capital and technological resources, and more robust institutional support for innovation. As a result, the impact of EMAITI on reducing environmental degradation may be more pronounced, leading to a larger coefficient estimate in the regression analysis. Conversely, in developing countries, several factors may hinder the full realization of the potential benefits of EMAITI. Limited financial resources, technological infrastructure, and institutional capacity may constrain the adoption and deployment of AI-based energy management solutions. Additionally, socio-economic challenges such as poverty, inequality, and political instability may divert attention and resources away from environmental sustainability initiatives [101]. Consequently, while EMAITI may still have a statistically significant effect on reducing environmental degradation in developing countries, the magnitude of this effect may be smaller compared to developed countries due to these constraints and challenges.

Table 9
Heterogeneity analysis results.

Variables	(1)	(2)	(3)
	EFP	EFP	EFP
	Full sample	Developed countries	Developing countries
EMAITI	−0.00233[b]	−0.00681[b]	−0.000674[a]
	(-2.28)	(-2.42)	(-1.80)
Constant	4.341[c]	5.405[c]	4.043[c]
	(4.31)	(3.05)	(3.58)
Control variables	YES	YES	YES
Observations	209	154	55
R-squared	0.569	0.670	0.843
Wald chi^2	328.32[c]	47.04[c]	192.45[c]

Note.
[a] $p < 0.10$.
[b] $p < 0.05$.
[c] $p < 0.01$; *z* statistics in parentheses.

5. Conclusion, policy implications, and limitations

This study examines the impact of energy management AI technology innovations on environmental degradation. It utilizes panel data from 19 countries globally, covering the period from 2010 to 2020. The analysis employs the PCSE regression model, with IV-GMM used for robustness checks. The main regression analysis indicates a significant negative relationship between EMAITI and environmental degradation. This finding suggests that advancements in AI technology tailored for energy management contribute to reducing environmental degradation. Economic growth exhibits a positive association, indicating that it is linked to increased environmental degradation. In contrast, financial development, industrialization, and renewable energy consumption show negative correlations with the ecological footprint. Conversely, urbanization and government regulation exhibit positive relationships with environmental degradation. Robustness tests validate the main regression findings, addressing concerns about endogeneity and confirming the model's reliability. Mediation analysis demonstrates that energy intensity partially mediates the nexus between EMAITI and environmental degradation, and the moderation analysis reveals that both R&D and globalization positively amplify the impact of EMAITI on ecological footprint. Furthermore, heterogeneity analysis indicates variations in the effects of EMAITI between developed and developing countries, highlighting the importance of considering economic development levels in environmental policy formulation. The research findings provide significant theoretical and empirical insights into the nexus between energy management, AI technology innovation, and environmental degradation.

According to the study's empirical results, several policy implications emerge to harness the potential of energy management artificial intelligence technology innovation in reducing environmental degradation. First, policymakers should prioritize initiatives to foster the adoption and integration of energy management artificial intelligence technology innovation across various sectors, particularly in industries with high energy consumption. This could include providing financial incentives, tax breaks, or grants to organizations investing in AI-based energy management solutions. Second, governments should enact and strengthen regulatory frameworks to incentivize the development and deployment of EMAITI while ensuring environmental protection. Regulations could include mandates for energy efficiency standards, emissions reductions, and requirements for AI-enabled energy management systems in new constructions or industrial facilities. Third, increasing R&D investment is crucial, particularly in energy management AI technologies. Governments, businesses, and research institutions should collaborate to fund R&D projects focused on enhancing the efficiency, effectiveness, and scalability of EMAITI solutions. Fourth, policymakers should prioritize initiatives to build the capacity and skills to adopt and effectively utilize EMAITI. This could involve investing in education and training programs to ensure a workforce with the technical expertise to develop, implement, and manage AI-based energy management systems. Fifth, international collaboration and knowledge sharing are essential, given the global nature of environmental challenges. Governments, multilateral organizations, and industry stakeholders should collaborate to share best practices, experiences, and technological innovations related to the adoption of EMAITI and environmental sustainability. Sixth, urbanization trends highlight the importance of incorporating EMAITI into sustainable urban planning and development strategies. Cities should leverage AI technology to optimize energy use, enhance resource efficiency, and mitigate environmental impacts, promoting sustainable urbanization. Seventh, public awareness and engagement are critical for driving demand for EMAITI solutions and fostering a culture of sustainability. Governments, businesses, and civil society organizations should engage in public outreach campaigns, educational programs, and community initiatives to raise awareness about the benefits of AI-enabled energy management and environmental conservation. By implementing these policy recommendations, policymakers can capitalize on the potential of EMAITI to contribute to environmental sustainability, mitigate climate change, and foster a transition toward a more resilient and resource-efficient economy.

Despite the findings mentioned earlier, the research has a few limitations. Firstly, the study covers the period from 2010 to 2020 due to the unavailability of the dataset. Subsequent research could expand the dataset to include more recent years or conduct a more detailed analysis to capture subtle changes, variations, and emerging trends. Secondly, the study utilizes two robust methods; nevertheless, further advanced methodologies or alternative econometric techniques could offer supplementary insights. Lastly, future research can explore other factors, such as environmental regulations and institutional quality, that influence the relationship between AI and the environment.

Authors' contributions

Emmanuel Baffour Gyau: Conceptualization, data curation, and analysis; Yaya Li: Introduction and literature; Michael Appiah: Conceptualization and analysis; Bright Akwasi Gyamfi: Analysis, policy framework; Stephen Taiwo Onifade: Interpretations, policy framework and supervision.

Availability of data and materials

The data for this present study are sourced from the database of the World Development Indicators (https://data.worldbank.org), the Global Footprint Network (GFN) (https://data.footprintnetwork.org/#/countryTrends?cn=5001&type=BCpc,EFCpc), and CSET: Country Activity Tracker (CAT): Artificial Intelligence "Energy Management". (https://cat.eto.tech/?expanded=Summary+metrics&dataset=Patent&patentField=Energy+Management)

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The authors wish to disclose here that there are no potential conflicts of interest at any level of this study.

Data availability

Data will be made available on request.

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