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Artificial intelligence and sustainable development during urbanization: Perspectives on AI R&D innovation, AI infrastructure, and AI market advantage

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Abstract

This study explores the impact of artificial intelligence (AI) on sustainable development across 51 countries during urbanization. Using panel data, the study examines AI's effects on sustainable development through three dimensions: R&D innovation, infrastructure, and market advantage. The results demonstrate that AI promotes sustainable development, with AI R&D innovation exerting the strongest influence, followed by AI infrastructure, whereas AI market advantage has the smallest impact. Additionally, the study uncovers regional heterogeneity in AI's impacts. In countries with upper middle sustainable development levels (60%–70% quantiles), AI's promoting effect is the strongest. Moreover, urbanization plays a threshold role in the relationship between AI and sustainable development. When urbanization is below the threshold, AI infrastructure and R&D innovation promote sustainable development, whereas AI market advantage inhibit it. Conversely, when urbanization exceeds this threshold, AI infrastructure inhibits sustainable development, the impact of AI R&D innovation becomes insignificant, and AI market advantage begin to promote sustainable development. This study recommends governments should consider the level of urbanization and sustainable development when crafting sustainable development policies utilizing AI.

KEYWORDS
artificial intelligence, green growth, R&D, sustainable development, urbanization

1 | INTRODUCTION

As global development accelerates, issues such as climate change, economic inequality, and resource depletion are intensifying. These challenges threaten human survival and development, necessitating the international community's formulation of more comprehensive development strategies (Biermann et al., 2022). Following the Millennium Development Goals (MDGs), the United Nations introduced the Sustainable Development Goals (SDGs) in 2015, aiming to achieve a more equitable and sustainable world by 2030 (UN, 2015). These goals provide an integrative framework encompassing the economic, social, and environmental dimensions, addressing environmental protection, economic growth, and social equity. Countries worldwide are actively working towards these goals, aiming to improve human well-being and protect the earth (Van Zanten & van Tulder, 2021). To effectively monitor progress towards the SDGs, it is essential to establish reliable measurement indicators (Razzaq et al., 2023). The Global Green Growth Index (GGGI), which benchmarks against the SDGs, utilizes a composite index to assess the sustainable development performance of nations (GGGI, 2024). This index incorporates indicators from four dimensions: efficient and sustainable resource use, natural capital protection, green economic opportunities, and social inclusiveness. Launched in 2019, the GGGI is subject to periodic reviews and updates to expand its scope of SDGs indicators, thereby

Global Green Growth Index

Dimension	Indicator Description	SDGs
Efficient and sustainable resource use	Ratio of total primary energy supply to GDP	SDG 7.3
	Share of renewable to total final energy consumption	SDG 7.2
	Water use efficiency	SDG 6.4
	Share of freshwater withdrawal to available freshwater resources	SDG 6.4
	Sustainable fisheries as a proportion of GDP	SDG 14.7
	Domestic material consumption per unit of GDP	SDG 8.4, SDG 12.2
	Total material footprint per capita population	SDG 8.4
	Share of food loss to production and food waste to consumption	SDG 12.3

Dimension	Indicator Description	SDGs
Natural capital protection	$PM_{2.5}$ air pollution, mean annual population-weighted exposure	SDG 3.9
	DALY rate due to unsafe water sources	SDG 12.4
	Municipal solid waste generation per capita	SDG 9.4
	Ratio of CO_2 emissions to population, including AFOLU	SDG 13.2
	Ratio of non-CO_2 emissions to population, excluding AFOLU to population	SDG 13.2
	Ratio of non-CO_2 emissions in agriculture and LUCF to population	SDG 14.5
	Proportion of KBAs covered by protected areas	SDG 15.1,15.4
	Share of forest area to total land area	SDG 15.1
	Above-ground biomass in forest	SDG 15.2
	Red List Index	SDG 15.5
	Share of terrestrial and marine protected areas to total territorial areas	SDG 14.5

Dimension	Indicator Description	SDGs
Green economic opportunities	Degree of integrated water resources management implementation, financing	SDG 6.5
	Total amount of funding to promote environmentally sound technologies per GDP	SDG17.7
	Share of green employment in total manufacturing	SDG9.2.2
	Employed population below international poverty line	SDG1.1
	Installed renewable energy-generating capacity (Watts per capita)	SDG7.b

Dimension	Indicator Description	SDGs
Social inclusion	Population with access to basic services	SDG 6.1, 6.2, 7.1
	Prevalence of undernourishment	SDG 2.1
	Proportion of seats held by women in national parliaments	SDG 5.5
	Gender ratio of an account at a financial institution or mobile-money-service	SDG 8.10
	Population with access to basic services by urban/rural, i.e., electricity	SDG 17.1
	Share of youth not in education, employment or training	SDG 8.6
	Proportion of population above statutory pensionable age receiving pension	SDG 1.3
	Universal health coverage service coverage index	SDG 3.6
	Proportion of urban population living in slums	SDG 11.1

FIGURE 1 Correspondence between Global Green Growth Index indicators and SDGs.

providing a comprehensive tool for evaluating the sustainable development achievements of countries. The correspondence of the GGGI indicators with the SDGs is demonstrated in Figure 1.

In recent years, artificial intelligence (AI) has developed rapidly (Wang et al., 2023). The application of AI has significantly improved efficiency and optimized resource utilization in the production field and demonstrated unprecedented potential in many fields, such as education, medical care, and public safety (Vinuesa et al., 2020). Economically, AI technologies have significantly enhanced production efficiencies by automating and optimizing processes (Kulkov et al., 2023). Moreover, although AI has catalyzed employment growth in several sectors, it has concurrently automated lower-skilled jobs, leading to profound structural shifts within the labor market (Abulibdeh et al., 2024). Socially, AI's integration into sectors like education, healthcare, and public safety has significantly elevated the quality and accessibility of services (Leimanis & Palkova, 2021). However, its proliferation could intensify the digital divide and undermine efforts towards social inclusivity (Truby, 2020). With the increasing integration of AI into personal life, issues concerning data privacy and the security of user information have become more pronounced (Tomašev et al., 2020). Environmentally, while AI contributes positively by optimizing energy use and conserving resources in heavy industries, it also demands considerable energy, especially in training extensive machine learning models, presenting a paradox in its environmental impact (Ahmad et al., 2021). Although AI holds significant transformative potential, its inherent risks, such as exacerbating the digital divide and contributing to unemployment, complicate its impact on sustainable development. However, this complexity has not been sufficiently highlighted in existing academic literature. Thus, examining the relationship between AI and sustainable development is crucial for capitalizing on AI's advantages to foster sustainable growth. A comprehensive and in-depth understanding of AI's impacts will enable policymakers to develop informed strategies that advance sustainable development, ensuring that AI advancements contribute positively to societal progress without compromising equity or environmental sustainability.

The nexus between the AI and urbanization is noteworthy. As concentrated hubs of human activity, urban areas inherently provide the optimal conditions conducive to AI advancements. They equip AI with necessary infrastructures and applications such as public transportation, construction planning, and intelligent power networks (Petrescu et al., 2022), significantly advancing the proliferation of smart cities (Wang & Ma, 2024). As AI technology becomes more widespread and integrated, it has profoundly transformed urban industrial structures, employment patterns, and lifestyles (Balsalobre-Lorente et al., 2023). This transformation is characterized by the decline of traditional industries and the rise of new sectors, which have introduced new economic growth points to cities. Furthermore, the aggregation of AI-driven innovations and activities within urban settings has expedited the evolution of functional divisions within urban value chains (Haefner et al., 2021), fostering the development of knowledge-centric cities, which holds promise for their sustainable development (Goi, 2017).

Despite these advancements, the nexus between AI, urbanization, and sustainable development has not been thoroughly examined, which this study aims to address. This investigation focuses on three critical questions: (1) what is the impact of AI on sustainable development? (2) Does this impact vary among countries with differing levels of sustainable development? (3) How does urbanization affect the relationship between AI and sustainable development? To answer these questions, we constructed a panel dataset for 51 countries and employed a series of econometric techniques, including Fully Modified Ordinary Least Squares (FMOLS), Generalized Method of Moments (GMM), Panel Quantile Regression (PQR), and Dynamic Panel Threshold Moldel (DPTM) to conduct the following work. First, we quantify the impact of AI on sustainable development by employing the AI Index and the GGGI as proxy variables. Second, we examine the asymmetric impact of AI on sustainable development, revealing heterogeneous effects in different sustainable development contexts. Finally, we use urbanization as a threshold variable to explore the impact of urbanization on the nexus between AI and sustainable development.

The contributions of this study are as follows. First, this study introduces a comprehensive assessment framework for AI, which incorporates 10 evaluation indexes across three dimensions: AI R&D innovation, AI infrastructure, and AI market advantage. This framework was applied to conduct a quantitative analysis of AI progress in 51 nations, yielding data foundations for a global evaluation of AI. Second, this study follows rigorous estimation procedures to investigate the impact of AI on sustainable development. It precisely identifies how AI's three dimensions affect sustainable development and reveals the heterogeneous impacts of these dimensions in countries at various sustainable development stages. This insight is valuable for global governments to craft precise policies leveraging AI to effectively enhance sustainable development. Third, by identifying thresholds where urbanization modifies the nexus between AI and sustainable development, this study contributes to understanding urbanization's role in this nexus, providing strategic insights that enable policymakers to craft integrated strategies for sustainable development that consider both AI and urbanization factors.

The remaining sections of this study are organized as follows: Section 2 provides a comprehensive literature review on AI, urbanization, and sustainable development. Section 3 discusses theoretical analyses and hypotheses. Section 4 introduces the methodologies and data utilized in this study. Section 5 presents the model results and discussions. Finally, Section 6 offers conclusions and policy implications derived from the findings.

2 | LITERATURE REVIEW

2.1 | AI and sustainable development

As an emergent technology, AI has catalyzed transformative shifts in modes of production (Graetz & Michaels, 2015). With the continuous advancement of AI technologies, AI plays a pivotal role in global actions towards sustainable development (Cowls et al., 2021). Kehayov et al. argue that, in contrast to other sustainability tools like carbon capture and storage or the use of renewable energy, AI is not confined to endpoint applications but enables diverse applications across the entire industrial chain (Kehayov et al., 2022). A systemic dynamics model examining the influence of AI on the SDGs for the period 2022–2030 highlighted that while AI positively affects SDGs 1, 3, and 5, it has less impact on SDGs 10, 12, and 14, 15 (Nahar, 2024).

From a multi-dimensional perspective on sustainable development, AI technologies enhance environmental process integration and bolster green supply chain collaborations at the economic level, thus driving improvements in supply chain synergy and green growth (Benzidia et al., 2021). Data from 1993 to 2019 reveals that Industry 4.0 initiatives, involving industrial robots, have promoted green technology innovations in manufacturing across 34 countries (Lee et al., 2022). The World Economic Forum forecasts that by 2030, AI will drive a 14% increase in global GDP, amounting to $15.7 trillion, surpassing the combined economies of China and India (WEF, 2023a). AI's potential to automate tasks, optimize processes, and enhance decision-making could yield an annual economic value of $3.5–$5.8 trillion across various sectors (Truong & Papagiannidis, 2022). On the social front, through online learning platforms, adaptive learning systems, and intelligent tutoring systems, AI technologies can cater to diverse learning needs, offering personalized assessments, feedback, and real-time instruction. This innovation also achieves inclusive and equitable education, supports learners with disabilities, and provides educational opportunities to underserved and remote areas (Lammers et al., 2022). Environmentally, many scholars utilize industrial robot data to explore the impact of AI (Wang, Li, et al., 2024). Integrating advanced control systems and robotic technologies enhances industrial automation within manufacturing systems. However, effectively integrating control and robotic technologies into sustainable manufacturing systems remains challenging (Kovalenko et al., 2024). Additionally, an empirical analysis of data from the International Federation of Robotics and Chinese enterprises shows that AI applications enhance energy and resource efficiency (Li et al., 2023). A study conducted in 10 forefront industrial AI countries—namely Singapore, South Korea, Japan, Germany, Sweden, Denmark, the United States, China, France, and Italy—has indicated that industrial robots contribute to sustainable development by reducing the ecological footprints in varying data quantiles across these nations. The findings provide essential policy guidance for balancing industrial expansion with environmental sustainability in the era dominated by AI technologies (Liu et al., 2024). Furthermore, a detailed assessment carried out across 38 countries and 17 manufacturing sectors have established that using industrial robots markedly improves the energy efficiency of manufacturing processes. This enhancement in energy efficiency underscores the transformative impact of robotics on the sustainability of manufacturing operations (Wang et al., 2022).

2.2 | Urbanization and sustainable development

The nexus between urbanization and sustainable development is an essential focus of contemporary global discourse (Balsalobre-Lorente et al., 2023). Globally, urbanization is acknowledged as a pivotal factor in realizing of the SDGs (Xu et al., 2022). A recent study has provided a comprehensive analysis of the relationship between urbanization and the SDGs, revealing that urbanization aligns positively with 151 of the SDGs, accounting for approximately 89% synergy. Conversely, the study identifies conflicts with 66 goals (39%), including 31 goals (18%) where the trade-offs are pronounced (Chen et al., 2022).

Considering the various dimensions of sustainable development, economically, energy is recognized as the primary driver of economic advancement. Urbanization contributes to this dynamic by broadening the scale of energy utilization and enhancing consumer demographics, stimulating economic growth (Voumik et al., 2023). Additionally, urbanization fosters the rapid development of critical infrastructure, including transportation, communication, public health, and educational facilities. The enhancement of such infrastructure bolsters economic development and significantly elevates the quality of life. Conversely, this urban-centric growth often results in the relative underdevelopment of rural areas, primarily due to labor migration (Saner et al., 2021). Moreover, urban environments provide a rich pool of technological and educational resources, thereby facilitating scientific and technological innovation and the growth of high-tech industries, which contribute to the economy's modernization and diversification (Heikkila & Xu, 2022). In terms of social dimension, urban areas offer superior employment prospects, higher income levels, and enhanced access to educational and health resources compared to rural areas (Kalhor & Emaminejad, 2019). Urbanization improves residents' health and life expectancy by promoting health awareness, expanding medical resources, refining health insurance systems, and investing in public health infrastructure (Almulhim & Cobbinah, 2023). Nonetheless, the accelerated migration from rural to urban areas often leads to profound urbanization challenges, including traffic congestion, an increased prevalence of infectious diseases, and a strained urban medical and public health infrastructure, all of which pose significant threats to urban public health (Brueckner, 2019). Furthermore, recent studies highlight that China's approach to new urbanization is critical in advancing sustainable development, particularly for vulnerable populations (Zhao, 2022). In the environmental dimension, heightened population density and urbanization correlate with reduced energy consumption and carbon emissions in developed nations (Anochiwa et al., 2022). Additionally, Wang et al. utilized spatial models to assess the impact of urbanization on carbon emissions, finding that enhancing urbanization quality contributes to decarbonization (Wang et al., 2019). Additionally, Zimmerer et al. examined the dynamic relationship between urbanization and agricultural biodiversity, emphasizing its importance as a burgeoning focus in sustainable development research (Zimmerer et al., 2021). In a separate study, Raggad employed the ARDL method with structural breaks to investigate the interplay between TC, GDP, energy consumption, and urbanization in Saudi Arabia from 1971 to 2014, concluding that urban development does not entail heightened environmental pressure (Raggad, 2018).

According to the literature review, we have the following findings. On the one hand, most of the studies were conducted from a single perspective of technological innovation or application when evaluating AI, resulting in the measurement of only one aspect of AI and the lack of a comprehensive measurement of AI in multiple dimensions. On the other hand, the impacts of AI and urbanization on sustainable development are often studied in separate contexts. However, with the increasing convergence of urbanization and intelligence, it is essential to integrate AI, urbanization, and sustainable development into a unified research framework.

3 | THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

This study interprets the relationship between AI and sustainable development through direct impact, asymmetric impact, and threshold effect (as shown in Figure 2).

3.1 | Direct impact

Direct impact refers to the immediate influence of AI on sustainable development. AI's contributions to sustainable development are multifaceted. On the positive side, AI optimizes energy and water use and enhances supply chain efficiencies, thereby aiding in the sustainable management of resources and the protection of the environment (Wang et al, 2024). AI's role in promoting the development and deployment of green technologies also leads to improved efficiencies in renewable energy production and waste recycling, which are essential for the economic shift towards reduced carbon emissions (Yigitcanlar & Cugurullo, 2020). Socially, AI contributes to reducing disparities by providing customized solutions in education and healthcare, enhancing the inclusiveness of societies (Sætra, 2021). On the negative side, the operation of AI systems and data centers requires significant energy consumption, potentially exacerbating carbon emissions and thus conflicting with environmental sustainability targets (Nishant et al., 2020). Moreover, the uneven distribution of AI technologies can increase economic and technological divides, particularly between resource-abundant and resource-scarce regions globally (Bloomfield et al., 2021). Therefore, we propose hypothesis 1.

> **Hypothesis 1.** AI has a significant direct impact on sustainable development.

3.2 | Asymmetric impact

This study identifies regional heterogeneity in the impact of AI on sustainable development by exploring asymmetric impacts. Recognizing regional heterogeneity is crucial, as emphasized repeatedly by international organizations. The United Nations, through its 2030 Agenda for Sustainable Development, specifically in Goals 9 and 17, advocates for the adaptation of technological innovations like AI to meet global development challenges and encourages international cooperation to

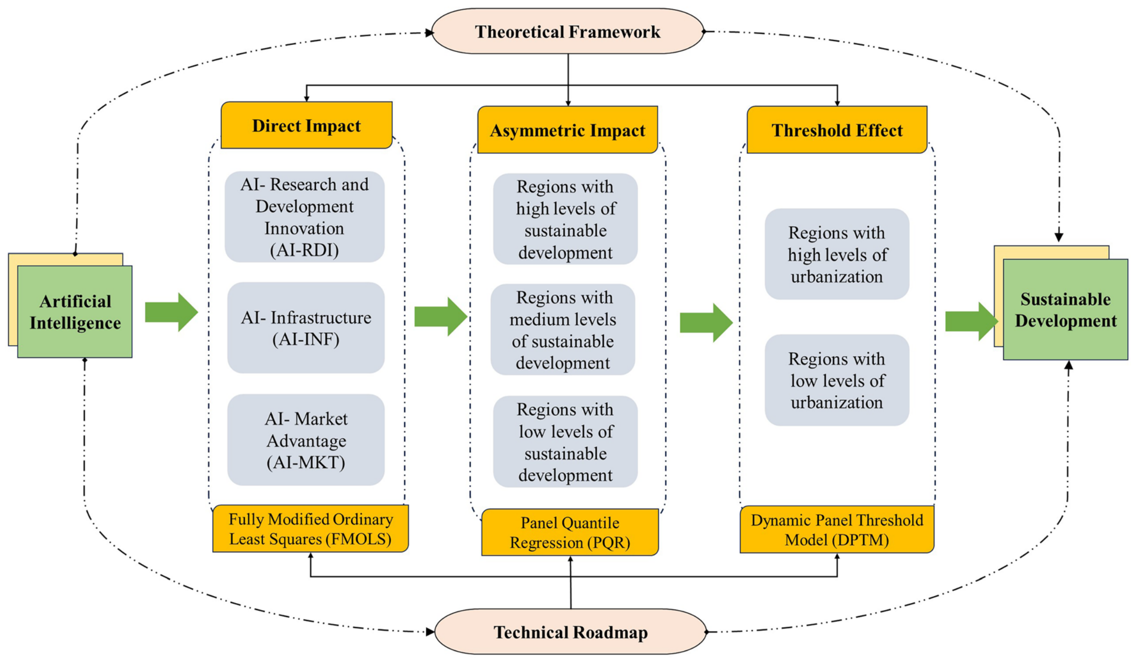

FIGURE 2 Theoretical framework of the relationship between artificial intelligence and sustainable development.

share these technologies with developing countries (Nations, 2015). Similarly, the World Economic Forum highlights the need for inclusive policies that ensure the benefits of AI are globally shared, mainly focusing on enhancing access to technology and building capacity in developing regions (WEF, 2023b). Understanding the regional heterogeneity of AI's impacts on sustainable development is essential for tailoring AI development to regional needs, ensuring the achievement of SDGs. Therefore, we propose hypothesis 2.

> **Hypothesis 2.** AI has an asymmetric impact on sustainable development.

3.3 | Threshold effect

Threshold effect is characterized by significant changes in the relationship or intensity between variables when one variable exceeds a certain level. This study posits that urbanization levels are critical in determining how AI influences sustainable development. According to the theory of technology absorption, larger urban areas typically exhibit enhanced capabilities for technology adoption and innovation, influencing the efficiency of AI applications in sustainable development endeavors (Ismail, 2023). Additionally, from the perspective of network externalities, increased urban scale contributes to greater data volume and diversity, which enriches the data pool available for AI, thereby enhancing its functionality in areas such as traffic management, energy distribution, and public safety (Mitlin & Satterthwaite, 2014). Using a DPTM, this study investigates how urbanization levels might modify the intensity or direction of AI's contributions to sustainable development. This exploration aims to understand how AI can be optimally leveraged in the urbanization process to foster sustainable development. Therefore, we propose hypothesis 3.

> **Hypothesis 3.** The relationship between AI and sustainable development is affected by urbanization.

4 | MODEL AND DATA

4.1 | Econometric modeling

This study employs an econometric model to assess the impact of AI on sustainable development. In this model, AI is the independent variable, while sustainable development is the dependent variable. Additionally, we have incorporated a range of control variables that might influence sustainable development, aiming to mitigate potential biases arising from omitted variables and related endogeneity issues. Equation (1) specifies the baseline regression model:

$$\mathrm{SD}_{it} = \beta_0 + \beta_1 \mathrm{AI}_{it} + \beta_2 X_{it} + \varepsilon_{it}. \quad (1)$$

In the model, i represents countries and t denotes the year. AI_{it} stands for AI, and X_{it} encompasses a set of control variables, including $\mathrm{IND}_{it}, \mathrm{TRD}_{it}, FDI_{it}$, which are industrialization, trade openness and foreign investment respectively. The term ε_{it} denotes the stochastic error component. The constant term is represented by β_0, while β_1 and β_2 are the parameters to be estimated.

In addition, we explore the asymmetric impact of AI on sustainable development at different levels of sustainable development by

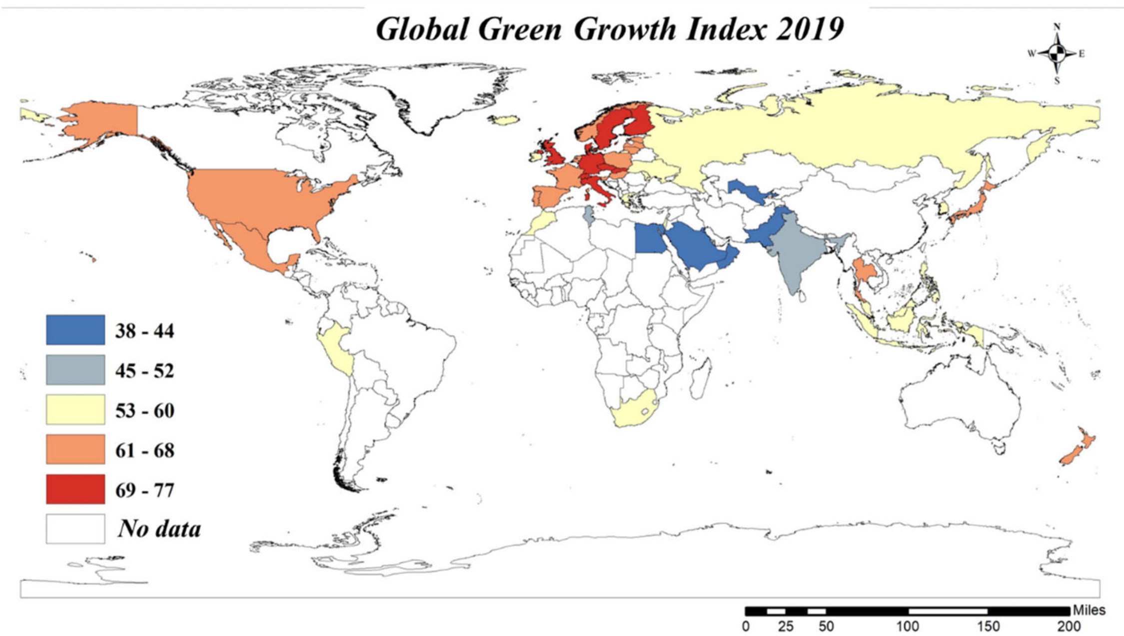

FIGURE 3 Geographical distribution of the 2019 Global Green Growth Index.

using panel quantile regressions. The specific test equation is shown in Equation (2):

$$Q_\tau(\mathrm{SD}_{it}) = \alpha_{0\tau} + \alpha_\tau \mathrm{AI}_{i,t} + \varepsilon_{i,t}, \tag{2}$$

$Q_\tau(\mathrm{SD}_{it})$ represents the τth quantile. α_τ denote the estimated coefficients of the variables at the τth quantile level.

To further identify the impact of urbanization on the relationship between AI and sustainable development, we reference the DPTM proposed by (Seo & Shin, 2016). The equation constructed is as follows, designated as Equation (3):

$$\begin{aligned}\mathrm{SD}_{it} = {} & \alpha_0 + \alpha_1 \mathrm{SD}_{it-1} + \beta_1 \mathrm{AI}_{it} + \beta_2 \mathrm{URB}_{it} + \delta_1 \mathrm{AI}_{it} I(\mathrm{URB}_{it} > \gamma) \\ & + \delta_2 \mathrm{URB}_{it} I(\mathrm{URB}_{it} > \gamma) + \varphi_{it} + e_{it},\end{aligned} \tag{3}$$

URB_{it} represents the threshold variable, and γ is the corresponding threshold value. Throughout all estimation results, particular attention is given to δ_1 and δ_2. These parameters capture the changes in the coefficients of AI_{it} and URB_{it} when URB_{it} exceeds the threshold γ. The sign of these parameters determines the direction of their impact.

4.2 | Variable description

4.2.1 | Dependent variable

In this study, sustainable development is the dependent variable, with the GGGI as its proxy. This index is a mode of development aimed at achieving environmentally sustainable and socially inclusive economic growth. It seeks opportunities for low-carbon and climate-resilient economic expansion, prevention or management of pollution, maintenance of healthy and productive ecosystems, creation of green job opportunities, reduction of poverty, and enhancement of social inclusion (GGGI, 2024). The GGGI is scored on a scale from 1 to 100 to measure a country's performance in achieving these sustainability objectives; higher scores indicate superior performance in reaching these sustainable goals. Figure 3 illustrates the GGGI across various countries.

4.2.2 | Independent variable

AI is the independent variable in this study. Numerous existing studies have relies on a single indicator to assess AI development, such as industrial robots and AI patents, which presents significant limitations (Giczy et al., 2022; Liu et al., 2020; Pantano & Pizzi, 2020; Wang et al., 2024; Wang, Liu, et al., 2023). For instance, early industrial robots operated according to predefined patterns and programs, which are far different from contemporary AI technologies. Moreover, while the quantity of AI patents may indicate the extent of technological innovation, it does not comprehensively capture the AI development. To overcome this limitation, we measure AI by constructing an AI index. In the prior studies, Ding et al. constructed an AI index by selecting nine indicators from three dimensions, namely, innovation support, innovation vitality and innovation benefits (Ding et al., 2023). Wang et al. constructed an AI index by selecting 15 indicators from the four dimensions of AI-related technologies, network infrastructure, international competitiveness and government support, realizing a comprehensive measurement of AI (Wang, Sun, & Li, 2023). Building on these methodologies, this investigation has extensively gathered

TABLE 1 Indicator system for measuring artificial intelligence (AI).

Dimension	Symbol	Indicator	Calculation	Source	Attribute
AI-Research and Development Innovation	AI_RDI	AI patent	Annual number of AI patents (Patent search uses AI IPC codes provided by the World Intellectual Property Organization, detailed in Table A2)	WIPO (2024)	Positive
		AI paper	Annual number of AI papers	SJR (2024)	Positive
		Industrial robot	Operational stock	IFR (2020)	Positive
AI-Infrastructure	AI_IFR	Fixed broadband subscriptions	Per 100 people	WDI (2023)	Positive
		Secure Internet servers	Per 1 million people	WDI (2023)	Positive
		Individuals using the Internet	Percentage of population	WDI (2023)	Positive
		Mobile cellular subscriptions	Per 100 people	WDI (2023)	Positive
AI-Market Advantage	AI_MKT	ICT service exports	Percentage of service exports, BoP	WDI (2023)	Positive
		ICT goods exports	Percentage of total goods exports	WDI (2023)	Positive
		High-technology exports	Percentage of manufactured exports	WDI (2023)	Positive

TABLE 2 Definitions and descriptions of variables.

Variable	Symbol	Description	Units	Data sources
Dependent variable	SD	Sustainable development	Index	GGGI (2024)
Independent variables	AI	AI	Index	Calculated (see Section 4.2.2 for details)
	AI_RDI	AI R&D Innovation	Index	
	AI_IFR	AI Infrastructure	Index	
	AI_MKT	AI Market Advantage	Index	
Threshold variable	URB	Urban population (% of total population)	Ratio	WDI (2023)
Control variables	FDI	Foreign direct investment, net inflows (% of GDP)	Ratio	WDI (2023)
	IND	Industry (including construction) value added (% of GDP)	Ratio	WDI (2023)
	TRD	Trade (% of GDP)	Ratio	WDI (2023)

AI-related data and formulated a multidimensional AI index. This index aims to evaluate AI development levels accurately by incorporating three dimensions: research and development innovation, infrastructure, and market advantage, detailed through 10 specific indicators. The composition and data sources of this index are elaborated in Table 1. Additionally, the entropy method is employed to quantitatively assess the development of AI and its constituent dimensions within each country, with the calculation steps shown in Appendix B. The index scores range from 0 to 1 and serve as indicators of AI development levels, where higher scores signify greater development.

4.2.3 | Threshold variable

This study selects urbanization as a threshold variable to explore its impact on the relationship between AI and sustainable development. There is a close correlation between urbanization and AI. The advancement of urbanization creates ample opportunities and practical scenarios for AI applications and influences the interaction between AI and sustainable development. Consistent with most existing research, this study uses the proportion of the urban population to the total population as a proxy variable for urbanization (Dempsey et al., 2011; Rodrigues & Franco, 2020).

4.2.4 | Control variables

This study incorporates three control variables: (1) Foreign Direct Investment (FDI). FDI impacts the host country's industrial structure and environmental management levels through technology transfer, financial support, and strategic industry selection influencing sustainable development (Gallagher & Zarsky, 2012). (2) Industrialization (IND). The transformation within industrial structures, shifts in energy consumption patterns, and variations in environmental pollutant emissions during industrialization significantly affect environmental quality. These changes are directly associated with realizing and sustaining

TABLE 3 Descriptive statistics of variables.

Variables	Mean	Median	Max	Min	Std. dev.	Obs
SD	5.8322	6.0075	7.6750	3.6570	1.0313	510
AI	0.0946	0.0749	0.7008	0.0084	0.0902	510
AI_RDI	0.0544	0.0103	0.9280	0.0001	0.1313	510
AI_IFR	0.1276	0.1193	0.9748	0.0014	0.0913	510
AI_MKT	0.1871	0.1597	0.8087	0.0000	0.1378	510
FDI	0.4123	0.2069	10.2315	−4.0086	1.0378	510
IND	2.8299	2.5263	7.4812	0.0000	1.1336	510
TRD	9.8331	8.3986	37.9099	2.4702	6.1667	510
URB	7.1873	7.3795	10.0000	3.0930	1.6745	510

sustainable development (Barbieri et al., 2020). (3) Trade Openness (TRD). Trade openness affects green growth by influencing international trade, technology exchange, and resource allocation, which impacts national environmental policies, industrial structures, and the adoption of green technologies (Xu et al., 2020).

4.3 | Data sources

Considering data accessibility, this study utilizes a panel dataset that spans 10 years (2010–2019) and includes 51 countries, with specific country samples detailed in Table A1. In 2022, these 51 countries accounted for 64% of the global GDP, reflecting their pivotal status in the global economy. Moreover, the development levels of these countries in AI show significant differences. For example, the United States' AI index in 2019 was as high as 0.7, while Pakistan's AI index in 2010 was only 0.01. Incorporating these samples into the panel data allows for a thorough consideration of individual variations, thereby enhancing the generalizability and applicability of the research findings. Definitions and descriptions of all variables are displayed in Table 2, and descriptive statistics are provided in Table 3.

5 | RESULTS AND DISCUSSIONS

5.1 | Measurement results of AI

The AI index of each country during the study period is shown in Figure 4. The countries are ordered from lowest to highest based on the average annual AI index, displayed sequentially from panels (a) to (d) of Figure 4. The United States, Japan, and South Korea are ranked among the top three, underscoring their dominant positions in the global AI landscape. In contrast, countries such as Peru, Pakistan, and Uzbekistan exhibit lower AI index indicating that AI development in these nations is still at an early stage. Additionally, we present the development across three dimensions of AI. As illustrated in Figure 5, there has been a significant growth in AI_INF over time, indicating an increasing focus on ICT infrastructure development among nations. Moreover, countries with higher AI index tend to possess elevated AI_RDI, demonstrating that R&D innovation in AI technology is crucial for the overall development of AI.

5.2 | Baseline regression results

This study employs the FMOLS to examine the impact of AI on sustainable development. The results are shown in Table 4. The analytical framework comprises four regression models that assess the contributions of AI and its specific dimensions to sustainable development.

The first results, as depicted in column (1), show a significant positive coefficient for AI (1.2632) at the 1% level after accounting for control variables, affirming AI's positive contribution to sustainable development. This result confirms that Hypothesis 1 is valid. Further, results from columns (2) to (4) indicate that AI_RDI, AI_INF, and AI_MKT exhibit significant positive coefficients, valued at 0.7880, 0.5675, and 0.1595, respectively. Notably, the coefficient for AI_RDI is the highest, indicating that R&D innovation is the most crucial factor in driving sustainable development within various aspects of AI. AI_RDI includes the development of new AI algorithms and models, which optimize resource use and enhance energy efficiency, thereby promoting environmental sustainability (Vinuesa et al., 2020). The impact of AI_INF on sustainable development, though second to AI_RDI, is also substantial. Infrastructure construction provides the necessary hardware and network support, enabling the extensive application of AI technologies across various sectors. For instance, AI's capability to process remote sensing data and monitor environmental conditions in real time facilitates the prediction of natural disasters and the prompt response to climate change challenges (Nchofoung & Asongu, 2022). Additionally, a robust ICT infrastructure boosts societal connectivity and supports the free flow of information, promoting sustainable social development. Although the coefficient for AI_MKT is smaller, it significantly enhances sustainable development. AI market advantages highlight the capacity of a country or region to export AI products globally. This result shows that such cross-border technology and knowledge transfers drive economic growth and environmental preservation and improve social welfare, achieving sustainable development's three pillars: environmental, economic, and social harmony.

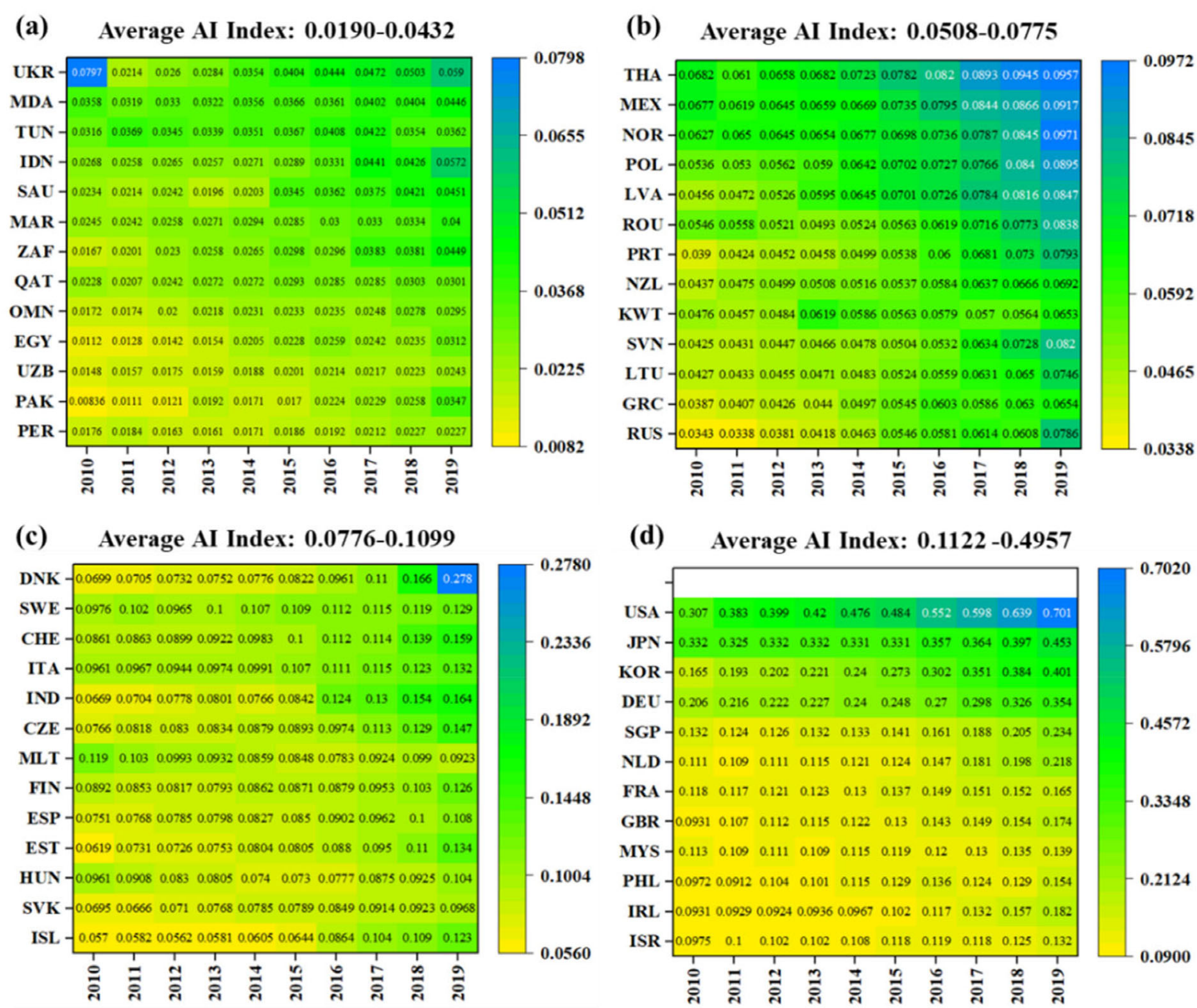

FIGURE 4 Comparative artificial intelligence (AI) index of various countries (2010–2019).

5.3 | Treatment of endogeneity

To ensure the robustness of baseline regression results, this study addresses the endogeneity problems caused by omitted variables, reverse causality, and measurement errors prevalent in prior models by employing the Instrumental Variable (IV) method. Drawing from prior studies (Moteng et al., 2023; Nepal et al., 2021), we utilized the Two-Stage Least Squares (2SLS) technique to achieve this. The lagged values of the independent variables were chosen as IV. The results are shown in Table 5, where columns (1), (3), (5), and (7) present the first-stage regression results, and columns (2), (4), (6), and (8) present the second-stage regression results. In the first-stage regression results, the coefficients of the lagged terms of AI, AI_RDI, AI_INF, and AI_MKT are significantly positive, indicating a strong positive correlation between the IV and the explanatory variables. Furthermore, the F-statistics are above 10 and significant, suggesting that the selection of IV is appropriate. Consequently, we proceed with these IVs for the second-stage analysis. According to the second-stage regression results, AI, AI_RDI, AI_INF, and AI_MKT all significantly promote sustainable development, which is consistent with the baseline regression results. Therefore, it can be confirmed that endogeneity issues do not affect the validity of the baseline regression results.

5.4 | Robustness test

This study conducted two robustness tests to ensure the robustness of empirical findings. First, given the GMM estimation's proficiency in addressing endogeneity and complex model structures, we utilized GMM estimation to affirm the stability of our results, as delineated in Table 6. The p value for AR(1) is below 1, whereas the p value for AR(2) exceeded 1, implying the absence of second-order autocorrelation. Besides, the p value for the Hansen test is over 1, indicating the absence of over-identification problems with the IV, thereby confirming the accuracy of the GMM results. According to these results, AI, AI_RDI, AI_INF, and AI_MKT still have a significant positive impact on sustainable development, consistent with the baseline regression results.

Second, this study employed a dependent variable substitution method to test the robustness of the results. We replaced the proxy

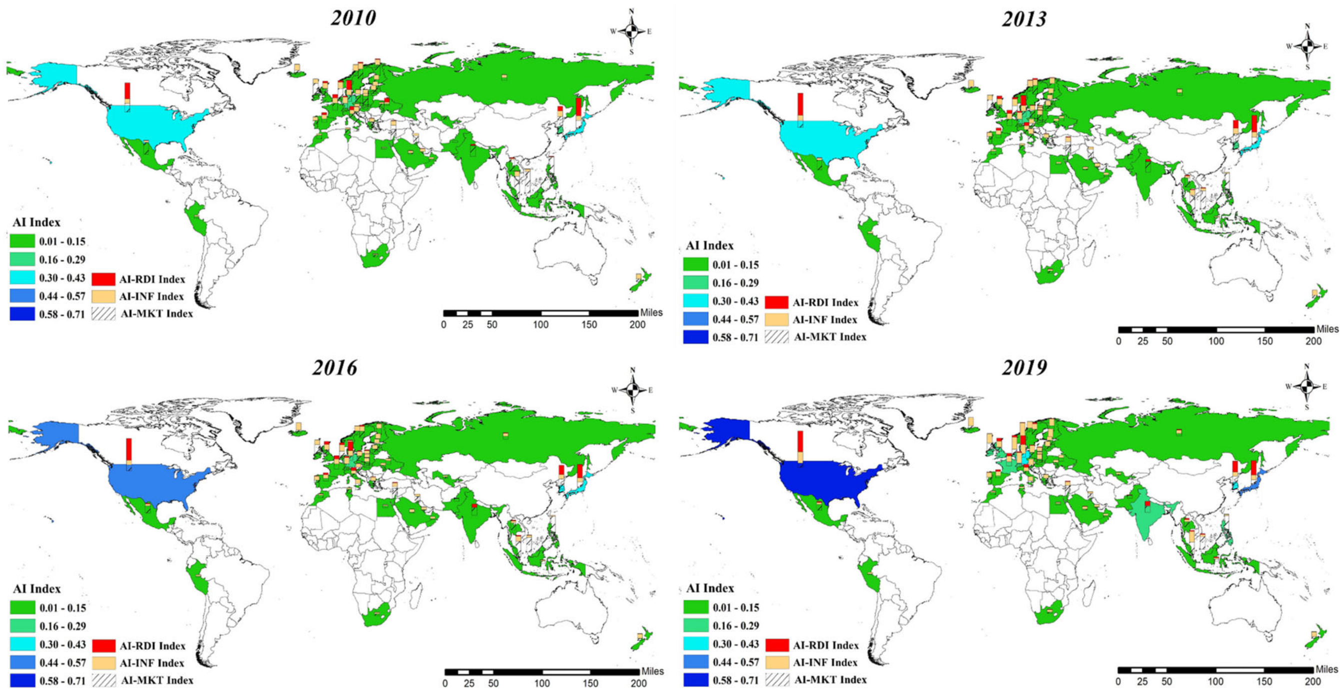

FIGURE 5 Spatial distribution of artificial intelligence (AI) and its three dimensions.

TABLE 4 Artificial intelligence (AI) and sustainable development: Fully Modified Ordinary Least Squares model.

	(1)	(2)	(3)	(4)
AI	1.2632***			
	(0.0770)			
AI_RDI		0.7880***		
		(0.0686)		
AI_INF			0.5675***	
			(0.0346)	
AI_MKT				0.1595***
				(0.0382)
FDI	−0.0103***	−0.0132***	−0.0054*	−0.0070
	(0.0027)	(0.0026)	(0.0028)	(0.0525)
IND	−0.0342***	−0.0395***	−0.0306***	0.0019
	(0.0081)	(0.0077)	(0.0082)	(0.0246)
TRD	−0.0110***	−0.0105***	−0.0158***	−0.0561***
	(0.0030)	(0.0028)	(0.0030)	(0.0203)
R^2	0.9916	0.9911	0.9917	0.9899

Note: Standard errors in parentheses. Significance: ***1%, **5%, and *10%.

variable for sustainable development with resource utilization sustainability. The results in Table 7 show that the coefficients for AI, AI_RDI, AI_INF, and AI_MKT are all significantly positive, indicating that AI and its three aspects significantly enhance the sustainability of resource utilization, consistent with the baseline regression findings. Therefore, our results are robust.

5.5 | Asymmetric impact results

To investigate the asymmetric effects of AI on sustainable development, this study utilized a PQR model to assess AI's impact across varying quantiles of sustainable development. The results of the PQR are presented in Table 8, while Figure 6 graphically depicts the variations in AI's impact across these quantiles. First, our findings indicate a significant positive influence of AI on sustainable development across the 10%–80% quantiles, with the impact peaking between the 60% and 70% quantiles. Therefore, Hypothesis 2 is valid. Second, a deeper analysis of different aspects of AI demonstrated that AI_RDI substantially fostered sustainable development at the 10% to 50% and 80% to 90% quantiles. This promotional effect was most pronounced in countries with lower levels of sustainable development. In contrast, AI_INF exerted a positive impact on sustainable development across all quantiles, with a more significant effect in countries that already exhibit higher levels of sustainable development. However, it is critical to highlight that AI_MKT had a positive impact on sustainable development within the 10%–30% quantiles but displayed a negative effect at the 60%–70% quantiles. This finding shows that different aspects of AI can play different roles at different stages of achieving sustainable development.

5.6 | Threshold effect results

The results of the DPTM are presented in Table 9. The model outputs two sets of coefficients labeled as β and δ. According to the DPTM equation, β represents the regression coefficients for variables before

TABLE 5 Artificial intelligence (AI) and sustainable development: 2SLS model.

Dependent variable	(1) AI	(2) SD	(3) AI_RDI	(4) SD	(5) AI_INF	(6) SD	(7) AI_MKT	(8) SD
L.AI	1.0807***							
	(0.0054)							
L. AI_RDI			1.0668***					
			(0.0044)					
L. AI_INF					1.2817***			
					(0.0172)			
L. AI_MKT							1.0095***	
							(0.0075	
AI		2.4971***						
		(0.4897)						
AI_RDI				1.1496***				
				(0.2723)				
AI_INF						5.1341***		
						(0.7653		
AI_MKT								0.6397**
								(0.2654)
TRD	−0.0001	0.0139	−0.0001	0.0191	−0.0002	−0.1410	−0.0004**	0.0062
	(0.0001)	(0.0114)	(0.0001)	(0.0121)	(0.0002)	(0.0100)	(0.0002)	(0.0113)
IND	−0.0001	−0.3546***	0.0003	−0.3769***	0.002*	−0.2698***	0.0009	−0.3928***
	(0.0004)	(0.0318)	(0.0005)	(0.0317)	(0.0010)	(0.0340)	(0.0008)	(0.0309)
FDI	−0.0007	−0.1396**	0.0003	−0.1427**	−0.0002	−0.0658	−0.0009	−0.1407**
	(0.0005)	(0.0599)	(0.0006)	(0.0610)	(0.0013)	(0.5374)	(0.0011)	(0.0604)
Constant	−0.0006	6.5213***	0.0006	6.7111***	−0.0224***	6.091***	0.0006	6.8277***
	(0.0016)	(0.1618)	(0.0018)	(0.1539)	(0.0043)	(0.1675)	(0.0030)	(0.1422)
F statistic	39677***		57825***		5552***		18289***	
R^2	0.9892	0.2372	0.9928	0.2095	0.9375	0.3177	0.9809	0.1955

Note: Standard errors in parentheses. Significance: ***1%, **5%, and *10%.

reaching the threshold, denoted as "Lower range" in Table 9. δ represents the change in the regression coefficients after surpassing the threshold compared to before the threshold, which we denote as "Difference." Therefore, to obtain the regression coefficient of the variable after exceeding the threshold, it is necessary to add the lower range group coefficient to the difference coefficient. We show the result in Figure 7. All four regressions passed the nonlinear test and obtained significant threshold values. Therefore, Hypothesis 3 is valid.

First, urbanization impacts AI and sustainable development at a threshold of 7.5582 (equivalent to an urbanization rate of 75.58%). Below this urbanization rate, AI has a significant coefficient of −2.8440. Beyond this urbanization rate, AI's coefficient increased to 1.4837, both significant at the 1% level. This result indicates that the impact of AI on sustainable development shifts from inhibitory to promotive as urbanization increases. The explanation for this finding could be as follows: At lower urbanization stages, due to insufficient infrastructure and technological penetration, the application of AI might be limited, preventing it from fully realizing its potential (Onifade et al., 2021). For example, a lack of adequate data processing capabilities or network connectivity might restrict the efficiency of intelligent systems (Bibri et al., 2024; Leal Filho et al., 2023). In highly urbanized areas, AI plays a crucial role in fostering sustainable development by improving resource allocation and enhancing environmental monitoring capabilities, achieved through sophisticated analytics and efficient data management.

Second, the impact of AI_RDI on sustainable development varies with urbanization, establishing 7.9455 (corresponding to an urbanization rate of 79.46%) as a threshold. Under this urbanization rate, AI_RDI positively affects sustainable development, with a regression coefficient of 1.5059, statistically significant at the 1% level. Beyond this urbanization rate, the impact of AI_RDI on sustainable development is not statistically significant. This indicates that AI_RDI has a promoting effect on sustainable development in countries with lower urbanization levels. This observation can be interpreted through the lifecycle theory of technological innovation, which posits that technology undergoes stages of introduction, growth, maturity, and decline,

TABLE 6 Artificial intelligence (AI) and sustainable development: Generalized Method of Moments model.

	(1)	(2)	(3)	(4)
L.SD	0.7867***	0.8577***	0.8218***	0.6109***
	(0.0420)			
AI	0.8680***			
	(0.1400)			
AI_RDI		0.7783***		
		(0.2403)		
AI_INF			0.3563***	
			(0.0698)	
AI_MKT				1.7157***
				(0.1822)
FDI	0.0034	0.0023	0.0017	−0.0117***
	(0.0026)	(0.0029)	(0.0027)	(0.0018)
IND	0.1204***	0.0789***	0.1295***	−0.0483***
	(0.0142)	(0.0128)	(0.0214)	(0.0174)
TRD	−0.0337***	−0.0244***	−0.0367***	−0.0124***
	(0.0054)	(0.0043)	(0.0060)	(0.0031)
AR(1)	−2.4561**	−2.5608**	−2.4220**	−2.3206**
AR(2)	0.6856	1.1717	0.5164	0.7000
Hansen test	41.5215	44.0600	40.6157	43.3795

Note: Standard errors in parentheses. Significance: ***1%, **5%, and *10%.

TABLE 7 Artificial intelligence (AI) and sustainable development: resource utilization sustainability as dependent variable.

	(1)	(2)	(3)	(4)
AI	1.5029***			
	(0.0755)			
AI_RDI		0.5756***		
		(0.0704)		
AI_INF			1.1631***	
			(0.0423)	
AI_MKT				0.8413***
				(0.0389)
FDI	0.0140***	0.0079***	0.0251***	−0.1842***
	(0.0025)	(0.0027)	(0.0027)	(0.0530)
IND	−0.0119	−0.0187**	−0.0034	−0.1653***
	(0.0074)	(0.0080)	(0.0079)	(0.0248)
TRD	0.0034	0.0010	−0.0009	0.3534***
	(0.0027)	(0.0029)	(0.0029)	(0.0204)
R^2	0.9939	0.9935	0.9946	0.9543

Note: Standard errors in parentheses. Significance: ***1%, **5%, and *10%.

each impacting society and the economy differently (Onifade & Alola, 2022). At lower levels of urbanization, introducing technological innovations such as AI can rapidly improve infrastructure and optimize resource usage. These enhancements lead to significant improvements in energy efficiency and environmental friendliness, thus substantially impacting sustainable development. Conversely, at higher urbanization levels where infrastructure and technological applications are more developed, the marginal benefits of new innovations tend to diminish, as these systems struggle to produce effects on the same scale (Goralski & Tan, 2020). This finding highlights the critical role of early technological adoption in promoting sustainable development. In the context of promoting sustainable development through AI technological innovations, it is essential to prioritize the introduction of AI innovations that significantly enhance resource efficiency and environmental protection, particularly in the early stages of urbanization (Kavya et al., 2023). Such innovations include developing intelligent systems for energy management, traffic optimization, and wastewater treatment, which could offer substantial benefits (Niu & Feng, 2021).

Third, the threshold analysis of the relationship between AI_INF and sustainable development shows that the urbanization threshold is 6.3315, equivalent to an urbanization rate of 63.32%. After exceeding this threshold, the AI_INF coefficient changes from 2.1266 to −0.1447, both significant at the 1% level. This change shows that the role of AI_INF on sustainable development changes from promotion to inhibition as urbanization increases. This finding highlights a critical, often overlooked aspect of sustainable development. In the early phases of urbanization, establishing AI infrastructure significantly contributes to efficiency and resource optimization, thus fostering sustainable development (Gyamfi, Onifade, & Ofori, 2023). This perspective has been mentioned in a previous study (Balsalobre-Lorente et al., 2023). However, as urbanization progresses, the demands on

TABLE 8 Artificial intelligence (AI) and sustainable development: Panel Quantile Regression (PQR) model.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	4.0591***	3.6786***	2.3384***	1.8861***	1.6247***	4.7307***	4.9661***	4.1688***	5.8839
	(0.2819)	(0.4757)	(0.3969)	(0.4080)	(0.4134)	(1.3389)	(1.2767)	(1.2182)	(4.4720)
C	3.9139***	4.3031***	5.3320***	5.6239***	5.7740***	5.8780***	6.0105***	6.2712***	6.3726***
	(0.0606)	(0.1127)	(0.0918)	(0.0720)	(0.0687)	(0.1134)	(0.1187)	(0.1261)	(0.3818)
AI_RDI	2.4846***	2.0418***	1.1854***	0.9749***	0.6945***	0.3097	0.9041	1.9654**	1.2842*
	(0.1861)	(0.2558)	(0.1925)	(0.2003)	(0.2005)	(0.1922)	(2.9592)	(0.9340)	(0.7652)
C	4.1058***	4.5712***	5.4724***	5.7346***	5.9305***	6.2106***	6.4508***	6.5829***	6.9313***
	(0.0688)	(0.1084)	(0.0774)	(0.0623)	(0.0581)	(0.0544)	(0.1046)	(0.0658)	(0.0702)
AI_INF	4.3392***	6.2414***	6.5642***	5.6957***	5.7625***	5.6786***	6.4469***	7.5130***	9.6137***
	(0.7074)	(0.7563)	(1.2108)	(0.7414)	(0.6977)	(0.7051)	(0.8029)	(0.9558)	(1.0881)
C	3.7870***	4.0269***	4.6781***	5.2397***	5.4073***	5.5571***	5.5752***	5.5806***	5.5671***
	(0.0738)	(0.1203)	(0.1956)	(0.1015)	(0.0906)	(0.0893)	(0.0954)	(0.1047)	(0.1121)
AI_MKT	1.2021***	1.8918***	0.5662**	0.2624	−0.2390	−0.6668**	−0.6786**	1.0411	0.3066
	(0.3029)	(0.3241)	(0.2538)	(0.2636)	(0.2828)	(0.2872)	(0.3116)	(1.1618)	(1.6675)
C	3.9126***	4.4229***	5.4452***	5.7055***	6.1262***	6.3753***	6.5700***	6.4954***	6.9949***
	(0.0789)	(0.1510)	(0.1045)	(0.0902)	(0.0818)	(0.0837)	(0.0827)	(0.1993)	(0.3394)

Note: Standard errors in parentheses. Significance: ***1%, **5%, and *10%.

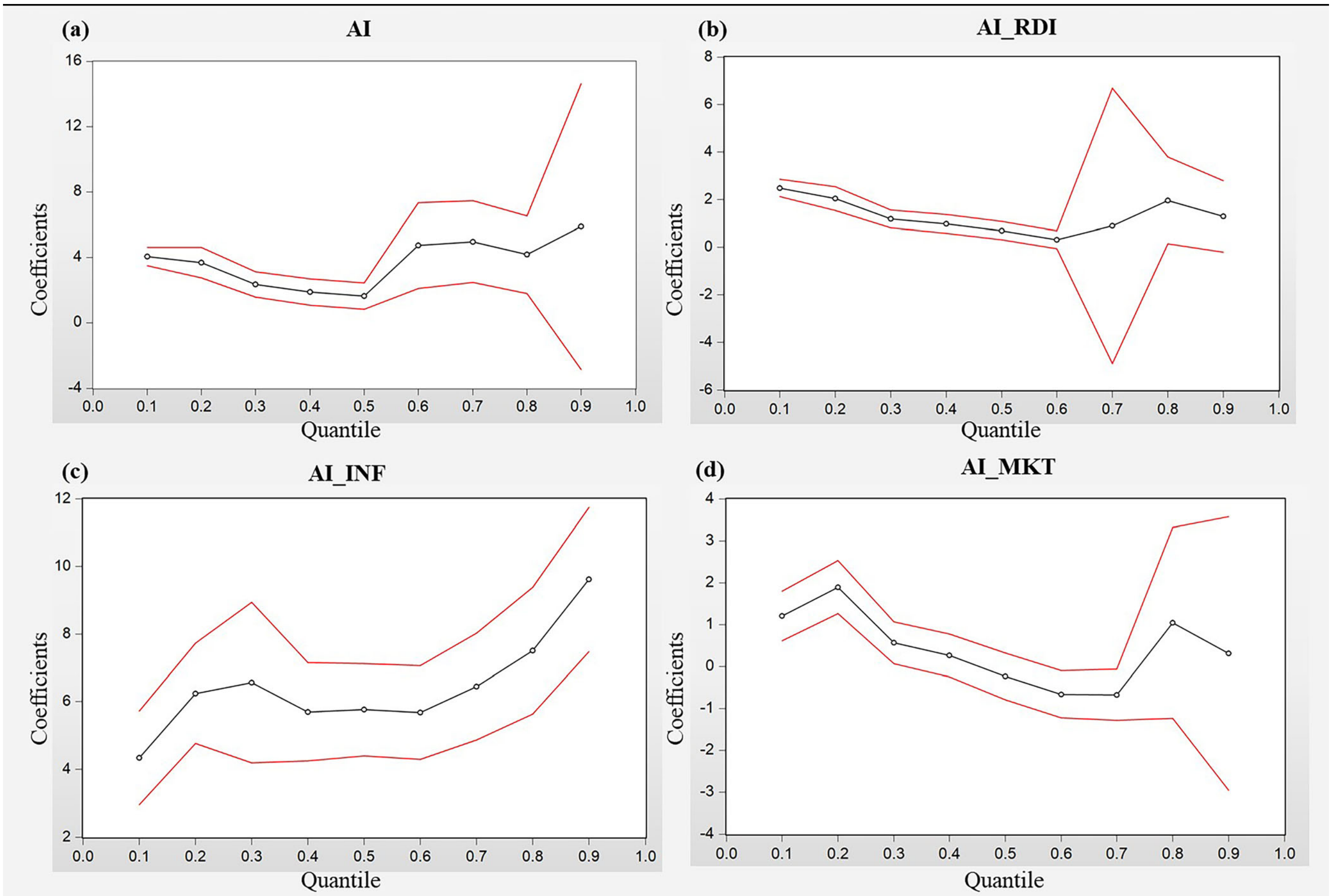

FIGURE 6 Asymmetric impacts of artificial intelligence (AI) and sustainable development.

TABLE 9 Artificial intelligence (AI) and sustainable development: Dynamic Panel Threshold Model (DPTM).

	(1)		(2)		(3)		(4)	
	Lower range	Difference	Lower range	Difference	Lower range	Difference	Lower range	Difference
L.SD	0.3124***	0.6291***	0.9019***	0.1229***	0.5723***	−0.1232*	0.1781**	0.8641***
	(0.0809)	(0.0587)	(0.0635)	(0.0277)	(0.0724)	(0.0747)	(0.0801)	(0.0808)
AI	−2.8440***	4.3277***						
	(0.4720)	(0.4813)						
AI_RDI			1.5059***	−0.0632				
			(0.4714)	(0.6028)				
AI_INF					2.1266***	−2.2713***		
					(0.1364)	(0.1385)		
AI_MKT							−2.8925***	4.0861***
							(0.2014)	(0.1170)
URB	1.0090***	−1.7931***	0.2183*	−0.1630	−0.8972***	1.2311***	0.3915***	−0.6467***
	(0.1191)	(0.2275)	(0.1281)	(0.1720)	(0.1489)	(0.1840)	(0.0854)	(0.1260)
C		10.1321***		0.1512		−6.5061***		−2.1828***
		(1.7807)		(0.1281)		(1.0918)		(0.9713)
Threshold value (γ)	7.5582***		7.9455***		6.3315***		7.0739***	

Note: Standard errors in (); ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively. The results are obtained through command "xthenreg" of Stata 16. The value of bootstrap is set as 300.

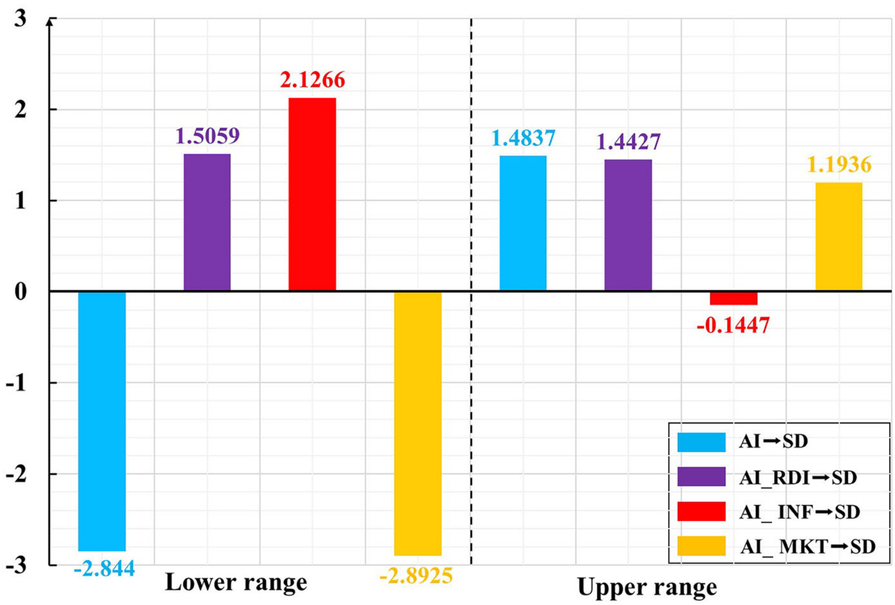

FIGURE 7 Dynamic Panel Threshold Model (DPTM) results of artificial intelligence (AI)'s impact on sustainable development.

these infrastructures increase, particularly in sectors like data centers and sensor networks that require significant electrical power and cooling resources, potentially leading to adverse environmental impacts (Truby, 2020). Moreover, the development and utilization of AI infrastructure can exacerbate social inequalities. The benefits of such technologies are often disproportionately accrued to economically more affluent regions or social strata, leaving poorer or marginalized groups without comparable advantages (Van Wynsberghe, 2021). These inequities can indirectly hinder sustainable development by limiting access to environmental benefits and sustainable resources.

Fourth, regarding the impact of AI_MKT on sustainable development, an urbanization threshold of 7.0739, corresponding to a 70.74% urbanization rate, was identified. Notably, the coefficient of AI_MKT shifted from −2.8925 to 1.1936 as urbanization surpassed this threshold. These results are statistically significant at the 1% level. This indicates that the impact of AI market dominance on sustainable development shifts from inhibition to promotion with higher urbanization. In this study, the AI_MKT is assessed through the export levels of high-tech products and ICT goods and services. This finding can be contextualized within the Heckscher-Ohlin model from international trade theory, which asserts that trade patterns and flows among countries are primarily determined by differences in national factor endowments (Leamer, 1995). With the advancement of urbanization, nations progressively transition from producing and exporting low-value-added products to high-tech products and services. This shift bolsters competitiveness in the global market and enhances the domestic adoption and application of these advanced technological solutions, thereby facilitating sustainable development (Gyamfi, Agozie, et al., 2023).

6 | CONCLUSIONS AND POLICY IMPLICATIONS

This study investigates the impact of AI on sustainable development using data from 51 countries globally from 2010 to 2019. There are three main conclusions.

First, baseline regression results confirm that AI has a positive impact on sustainable development. Among the three dimensions of AI, AI research and development innovation is the biggest driver of sustainable development, followed by AI infrastructure. Conversely, the AI market advantage has the least impact on sustainable development.

Second, the role of AI in promoting sustainable development is asymmetric. Specifically, AI significantly promotes sustainable development only when it lies in the quartile range of 10% to 80%. Furthermore, AI's promotion effect is greatest at the 60%–70% quartile level of sustainable development.

Third, the impact of AI on sustainable development is influenced by urbanization. Specifically, as urbanization exceeds 75.58%, the role of AI shifts from inhibiting to promoting sustainable development. In addition, the impact of three dimensions of AI on sustainable development is also affected by urbanization. Specifically, the threshold values for urbanization are 63.32% for AI infrastructure, 79.46% for AI research and development innovation, and 70.74% for AI market advantage. When urbanization falls below these thresholds, AI infrastructure and R&D innovation promote sustainable development, whereas AI market advantage exerts an inhibition effect. Conversely, when urbanization exceeds these thresholds, the promotive impact of AI infrastructure turns inhibitory, the promotive impact of AI R&D innovation turns insignificant, and the influence of AI market advantages becomes beneficial to sustainable development.

Based on the above conclusions, we propose the following policy implications. First, regional differences in sustainable development levels should be considered when integrating AI into sustainable development policy frameworks. Specifically, for countries with lower levels of sustainable development, it is advisable to increase investments in AI research and technological innovation and to provide trade facilitation measures for AI-related technological products, thereby swiftly enhancing their sustainable development. For countries that have already reached medium to high levels of sustainable development, the focus should be intensified on optimizing AI infrastructure. Second, we suggest adjusting AI strategies based on urbanization rates to ensure maximum facilitation of sustainable development. In countries with a low proportion of urban population, such as India, Pakistan, and the Philippines, the emphasis should be on supporting AI applications in infrastructure and R&D innovation. There should be strategic implementations aimed at enhancing intelligent agriculture and stimulating rural revitalization, utilizing AI to boost agricultural productivity and efficiency, such as through the application of drones and satellite imagery for land analysis and automated irrigation systems tailored to weather predictions and soil conditions. Developing digital services in rural areas, including telemedicine and online education, will also be vital for advancing social welfare and economic development. In countries with a high proportion of urban population, like Singapore, Malta, and Iceland, suggests simplifying the import and export procedures of ICT products and reducing trade barriers. Strengthen exchanges and cooperation with the international market, promote the country's AI technology and products, attract foreign investment in the domestic AI industry, and fully realize the potential positive effects of the export trade of AI products on sustainable development.

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CONFLICT OF INTEREST STATEMENT

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

DATA AVAILABILITY STATEMENT

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

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APPENDIX A

TABLE A1 List of sample countries.

	Country code	Country name
1	CHE	Switzerland
2	CZE	Czechia
3	DEU	Germany
4	DNK	Denmark
5	EST	Estonia
6	EGY	Egypt, Arab Rep.
7	ESP	Spain
8	FIN	Finland
9	FRA	France
10	GRC	Greece
11	HUN	Hungary
12	ISL	Iceland
13	IDN	Indonesia
14	IRL	Ireland
15	ISR	Israel
16	IND	India
17	ITA	Italy
18	JPN	Japan
19	KOR	Korea, Rep.
20	KWT	Kuwait
21	LTU	Lithuania
22	LVA	Latvia
23	MAR	Morocco
24	MDA	Moldova
25	MLT	Malta
26	MEX	Mexico
27	MYS	Malaysia
28	NLD	Netherlands
29	NOR	Norway
30	NZL	New Zealand
31	OMN	Oman
32	PER	Peru
33	PHL	Philippines
34	PAK	Pakistan
35	POL	Poland
36	PRT	Portugal
37	QAT	Qatar
38	ROU	Romania
39	RUS	Russian Federation
40	SAU	Saudi Arabia
41	SWE	Sweden
42	SGP	Singapore
43	SVK	Slovak Republic

(Continues)

TABLE A1 (Continued)

	Country code	Country name
44	SVN	Slovenia
45	THA	Thailand
46	TUN	Tunisia
47	UKR	Ukraine
48	GBR	United Kingdom
49	USA	United States
50	UZB	Uzbekistan
51	ZAF	South Africa

TABLE A2 Artificial intelligence index search code.

PATENTSCOPE query	Key phrases	IPC symbols
AI	artific intelligen, computation intelligen, neural network, neuralnetwork, bayes network, bayesiannetwork, chatbot, data mining, decision model, deep learning, deeplearning, genetic algorithm, inductive logic programm, machine learning, machinelearning, natural language generation, natural language processing, reinforcement learning, supervised learning, supervised training, supervisedlearning, swarm intelligen, swarmintelligen, unsupervised learning, unsupervised training, unsupervisedlearning, semi-supervised learning, semi-supervised training, semisupervised learning, semisupervised training, semi supervisedlearning, semisupervisedlearning, connectionis, expert system, transfer learning, transferlearning, learning algorithm, learning model, support vector machine, random forest, decision tree, gradient tree boosting, xgboost, adaboost, rankboost, logistic regression, stochastic gradient descent, multilayer perceptron, latent semantic analysis, latent dirichlet allocation, multi-agent system, hidden markov model, clustering, combinatorial explosion, comput creativity, deep blue, descriptive model, inductive reasoning, overfitting, predictive analytics, predictive model, target function, test data set, training data set, validation data set, backpropagation, self learning, selflearning, objective function, feature selection, embedding, active learning, regression model, stochastic approach, stochastic technique, stochastic method, stochastic algorithm, probabilist technique, probabilist approach, probabilist method, probabilist algorithm, recommend systemrobot, autonomous system, medical imag, healthcare, virtual assist, personali medic, precision medic, genomic screening, drug discover, medical diagnos, drug creation, medication manag, autonomous vehicle, transportation, driverless, smart car, smart cars, smart city, smart grid, automotive, agriculture, irrigation system, fintech, banking, finance, economics, text analysis, speech analysis, hand writing analysis, handwriting analysis, facial analysis, face, text analytic, speech analytic, hand writing analytic, handwriting analytic, facial analytic, face analytic, text recognition, speech recognition, hand writing recognition, handwriting recognition, facial recognition, face recognition, cybersecurity, predictive analysis, predictive analytic, predictive purchas, marketing analytic, video game	A61B5/00, A63F13/67, B23K31/00, B25J9/16, B29C65/00, B60W30/06, B60W30/10, B60W30/14, B62D15/02, B64G1/24, E21B41/00, F02D41/14, F03D7/04, F16H61/00, G01N29/44, G01N33/00, G01R31/28, G01R31/36, G01S7/41, G05B13/02, G05D1/00, G06E1/00, G06E3/00, G06F9/44, G06F11/14, G06F11/22, G06F15/00, G06F17/00, G06F19/00, G06G7/00, G06J1/00, G06K7/14, G06K9/00, G06N3/00, G06N5/00, G06N7/00, G06N99/00, G06T1/20, G06T1/40, G06T3/40, G06T7/00, G06T9/00, G08B29/18, G10L13/00, G10L15/00, G10L17/00, G10L25/00, G10L99/00, G11B20/10, G16H50/20, H01M8/04992, H02H1/00, H02P21/00, H02P23/00, H03H17/02, H04L12/24, H04L12/70, H04L12/751, H04L25/02, H04L25/03, H04N21/466, H04R25/00

Note: This table follows the same classification as in the WIPO Technology Trends Report: Artificial Intelligence.

APPENDIX B

The detailed procedure of the Entropy Weight Method is as follows:

Step 1: Standardization of the original values of the indicators.

For positive indicators:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{max(X_j) - \min(X_j)}. \tag{B1}$$

For negative indicators:

$$X'_{ij} = \frac{\max(X_j) - X_{ij}}{\max(X_j) - \min(X_j)}, \tag{B2}$$

where X_{ij} is the original value of the *i*th evaluation object on the j-th indicator, X'_{ij} is the standardized value, $\min(X_j)$ is the minimum value, and $\max(X_j)$ is the maximum value.

Step 2: Calculate the proportion of the *i*th evaluation object on the j-th indicator:

$$Y_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{m} X'_{ij}}. \tag{B3}$$

Step 3: Define the entropy of each evaluation indicator:

$$e_j = -k\sum_{i=1}^{m} (Y_{ij} \times \ln Y_{ij}) Y_{ij} > 0, \tag{B4}$$

where $k = 1/lnm$，m is the number of samples.

Step 4: Calculate the redundancy of the entropy:

$$d_j = 1 - e_j. \tag{B5}$$

Step 5: Determine the entropy weight of each evaluation indicator:

$$w_j = d_j / \sum_{j=1}^{n} d_j. \tag{B6}$$

Finally, compute the comprehensive score of the indicators using the following formula:

$$AI_i = \sum_{j=1}^{n} I_{ij} \times w_j, \tag{B7}$$

where AI_i represents the Artificial Intelligence Index, n is the number of indicators, I_{ij} represents the value of the j-th indicator in the i-th unit, and w_j represents the weight of each indicator.