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Artificial Intelligence and Sustainable Development: The Role of Human Development in Global Cross-Country Disparities

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Abstract

Artificial intelligence (AI) is increasingly regarded as a technology that could accelerate progress towards the Sustainable Development Goals (SDGs), yet its contribution may depend on broader development conditions. This study examines the relationship between AI capacity, sustainable development, and human development across 167 countries. The analysis combines the Government AI Readiness Index, SDG Index, Human Development Index (HDI), and urbanization data. Ordinary Least Squares (OLS) regression is used to estimate nested models, complemented by Pearson correlation across four HDI groups. In the basic model, AI Infrastructure is positively and significantly associated with the SDG Index, while Development & Diffusion makes no statistically significant independent contribution. The model explains 63.1% of the variance in SDG performance. After HDI and urbanization are introduced, explanatory power increases to 82.2% while the AI Infrastructure coefficient becomes small and statistically insignificant. HDI shows the strongest standardized association with the SDG Index ($\beta = 0.908$), although this relationship should be interpreted in light of the conceptual overlap between the two composite indices. Urbanization is negatively associated with SDG performance in the expanded model. AI Infrastructure–SDG correlations are positive and statistically significant across all HDI groups, but differences in correlation strength are not statistically significant. By distinguishing the bivariate association between AI infrastructure and SDG performance from its association conditional on broader development characteristics, this study provides a more nuanced cross-country assessment of the relationship between AI readiness and sustainable development.

Keywords: artificial intelligence; sustainable development; sustainable development goals; human development; urbanization; cross-country disparities

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1. Introduction

Artificial intelligence (AI) has become an increasingly important component of technological and economic development, with applications ranging from energy systems and environmental monitoring to healthcare, agriculture, and public administration. Its growing capacity to process large volumes of data and support complex decision-making has led to increasing expectations that AI could contribute to progress towards the Sustainable Development Goals (SDGs). At the same time, AI is developing unevenly across countries, raising an important question: does greater national AI capacity contribute to better sustainable development outcomes, or does the observed relationship mainly reflect

differences in countries' levels of development? This question is particularly relevant as the 2030 Agenda approaches its final years and progress towards many SDG targets remains uneven. AI is often presented as a technology that could accelerate progress, but its benefits are unlikely to depend on technological capacity alone. Countries differ substantially in digital infrastructure and access to technological resources [1], as well as in human capital and the availability of skills needed for development [2]. These differences may determine not only whether AI can be developed and adopted, but also whether its potential can be translated into development outcomes.

Although relatively recent, this research question has attracted growing scholarly attention, with existing studies highlighting both the potential and the challenges of AI for sustainable development [3–5]. The rapid advancement of AI appears promising, both for the green transition and for economic growth and social development, but increasingly, experts are also issuing warnings, particularly concerning the environmental challenges associated with AI Infrastructure. Huang and Abe [6] argue that AI holds significant potential to advance the SDGs, but realizing this potential is not automatic and it depends on overcoming ethical, resource, and regulatory challenges through robust governance and requires coordinated investment and participation from governments, international organizations, the private sector, and civil society to ensure its benefits are shared inclusively. Gosselink et al. [7] similarly show that AI has enormous potential to contribute to progress towards the SDGs, and this potential is expected to increase over time, while, on the other hand, numerous studies discuss the role of AI in widening global inequalities, governance deficits, and security instability [8,9]. A comprehensive review identifies key challenges in AI-for-sustainability research, including data limitations, uncertain impacts, cybersecurity risks, and measurement difficulties, and calls for more integrated approaches to ensure sustainable outcomes [10,11]. More specifically, it has been estimated that AI could facilitate progress towards 128 of the 169 SDG targets, while simultaneously inhibiting 58 targets, and that its contribution is significant but not uniform [11,12]. Although evidence of AI applications in specific sustainability domains is growing, the aggregate relationship between national AI capacity and sustainable development remains less clear [13–15].

Empirical evidence demonstrates that the contribution of AI is particularly evident in sectors where complex systems require continuous optimization and large-scale data processing. The strongest evidence comes from the energy sector, where AI improves renewable energy integration, electricity demand forecasting, grid stability, storage management, and energy efficiency [12]. Cross-country evidence from 67 countries indicates that AI is associated with lower ecological footprints, lower carbon emissions, and a stronger energy transition, with the largest effects observed in renewable energy systems [16]. Previous research suggests that AI adoption could reduce energy consumption and carbon emissions by 8–19% by 2050, with the potential for much larger reductions when combined with supportive energy policies and low-carbon power generation [17]. AI applications have been investigated across several sustainability-related sectors, including energy, agriculture, environmental monitoring, healthcare, and climate adaptation [18–20].

Despite many benefits, AI's own energy consumption, particularly that of large language models, remains an important environmental concern, so there is a need for more energy-efficient computing and algorithms [21]. The environmental impacts of AI are substantial and context-dependent, with energy demand, hardware emissions, and electricity mix being key determinants of its carbon footprint. This highlights the need for a system-level approach to sustainable AI that integrates energy and carbon constraints into AI design and deployment [22]. In parallel, AI raises important social and governance concerns, including algorithmic bias, labor displacement, privacy risks, unequal access to technology, and the concentration of benefits among already developed countries [14,23].

Regulation, transparency, accountability, and international cooperation are increasingly regarded as essential prerequisites for ensuring that AI contributes positively to sustainable development [11,12,16,20]. This also has an important theoretical implication. AI can be understood as a general-purpose technology whose potential benefits depend on complementary economic, technological, and institutional capacities [10,24]. AI Infrastructure provides the technological foundation for developing and deploying AI applications, but translating this capacity into outcomes relevant to the SDGs may also depend on education, digital skills, institutional support, and economic resources. Countries with higher AI readiness may therefore also possess stronger development capacities that facilitate both the adoption of AI and progress towards the SDGs. Consequently, a positive cross-country association between AI readiness and SDG performance may partly reflect differences in human development rather than an independent association with AI capacity itself. This distinction is particularly important because the HDI and the SDG Index overlap conceptually, especially in their coverage of health, education, and living standards, which may contribute to their observed statistical association. The key empirical question is therefore whether the association between AI Infrastructure and SDG performance remains after accounting for differences in human development and urbanization.

Research on the impact of AI on sustainable development at the national level remains only partially explored, and here too there are substantial differences between countries in their ability to measure and monitor these relationships. Existing studies have primarily examined individual countries, specific regions, or particular sectors rather than global patterns of sustainable development. AI significantly contributes to SDG achievement in China, particularly in economic development and climate action, with these effects mediated by technological innovation and human capital, while also varying across regions and exhibiting significant spatial spillovers [25]. AI–SDG research is rapidly expanding but remains thematically fragmented, with India leading in publication output and Malaysia and Saudi Arabia showing high levels of international collaboration, while challenges remain in research coherence, ethical integration, and translating knowledge into actionable sustainability outcomes [26]. Other studies report that AI investments stimulate renewable energy production, AI readiness promotes green energy consumption, and AI activity improves environmental performance, although these relationships often exhibit non-linear patterns and vary across countries with different levels of economic development [27–29]. The uneven diffusion of AI across countries reflects a persistent digital divide, with substantially higher adoption in high-income countries and marked regional disparities, highlighting the need for more equitable AI development [30,31].

Despite the growing body of work on AI and sustainable development, an important empirical question remains insufficiently addressed: whether the cross-country association between national AI capacity and aggregate SDG performance persists after accounting for broader development conditions. Previous comparative studies have established associations between AI-related indicators and sustainable development outcomes, but differences in analytical approaches and model specifications limit the extent to which these findings clarify the independent statistical association of AI capacity with SDG performance. This study addresses this gap in three ways. First, it uses nested regression models to examine how the association between AI Infrastructure and the SDG Index changes after accounting for human development and urbanization. Second, it distinguishes between AI Infrastructure and Development & Diffusion, thereby examining whether different dimensions of national AI capacity exhibit different associations with SDG performance. Third, it investigates the AI Infrastructure–SDG relationship within four human development groups and formally tests whether the observed correlations differ across these groups. The contribution of the study therefore lies not only in its broad cross-country coverage, but also

in combining conditional regression analysis with a development-group comparison to provide a more qualified assessment of the relationship between national AI capacity and sustainable development.

To address these gaps, this study investigates the relationship between national AI capacity and sustainable development across a global sample of countries. Three questions guide the analysis:

1. Is AI infrastructure associated with SDG performance at the global level?
2. Does this association remain after accounting for human development and urbanization?
3. Does the strength of the AI Infrastructure–SDG relationship differ across countries at different levels of human development?

The analysis combines the Government AI Readiness Index with the SDG Index, Human Development Index, and urbanization data. By using nested regression models and a subgroup analysis across four HDI categories, the study distinguishes between the AI–SDG association and the extent to which this association remains after development differences are considered.

2. Materials and Methods

Previous studies have used different methods to examine the relationship between AI and sustainable development. One common approach is to use composite indices that measure a country's AI capacity and readiness. Some of the most commonly used measures include the AI Preparedness Index (AIPI) [32], the Oxford Insights AI Readiness Index [33], the Government AI Readiness Index [31,34–36], and UNESCO's AI Readiness Assessment Methodology (RAM) [37]. AI readiness measures differ in their scope and purpose. While some indices focus on the broader preparedness of countries to develop and adopt AI, the Government AI Readiness Index specifically examines the role of governments in enabling, adopting, and governing AI for public benefit. UNESCO's AI Readiness Assessment Methodology, in contrast, focuses on countries' preparedness to develop and govern AI ethically and responsibly. The Government AI Readiness Index was selected for this study because its country-level framework provides comparable indicators of AI-related capacities across a broad international sample. The analysis focuses on its AI Infrastructure and Development & Diffusion dimensions to distinguish infrastructural capacity from the maturity and diffusion of AI-related activity. Most empirical analyses are based on panel data and econometric methods such as fixed-effects and random-effects models [29,38]. Studies conducted at the subnational level often use entropy weighting methods combined with two-way fixed-effects models [25].

This study adopts a cross-sectional design to examine the association between national AI capacity and sustainable development performance across countries. For each indicator, the latest available data were used to provide the most recent possible cross-country assessment, rather than to analyze changes over time. This temporal mismatch may introduce some uncertainty because country conditions may have changed between the respective reference years. However, the analysis is designed to examine cross-country associations rather than changes over time. The Government AI Readiness Index was analyzed, and the SDG Index and percentage of urban population were obtained for 2025, whereas the HDI values refer to 2023, as reported in the 2025 Human Development Report. The results should therefore be interpreted as relationships among the latest available country-level indicators, with the difference in reference years acknowledged as a limitation. The study examines the relationship between AI development and sustainable development in a global sample of 167 countries, while also accounting for socio-economic conditions through HDI and urbanization. Data were collected from several international organizations in order to ensure

comparability between countries. The main variables and their sources are summarized in Table 1.

Table 1. Overview of variables and data sources.

Variable	Indicator	Reference Year	Source
Dependent	SDG Index	2025	[39]
Independent	AI Infrastructure	2025	[40]
Independent	Development & Diffusion	2025	[40]
Control	HDI	2023	[41]
Control	Urban population (%)	2025	[42]
Additional analysis	Policy Capacity	2025	[40]

The selected indicators cover several aspects that are important for understanding the relationship between AI and sustainable development, including technological capacity, digital infrastructure, and socio-economic development. This allows the analysis to compare countries using the same type of data, while also taking into account factors that may influence sustainable development. The SDG Index was obtained from the Sustainable Development Report [39] and used as the main measure of a country's progress in social, economic, and environmental sustainability. AI capacity is represented by the AI Infrastructure and Development and diffusion dimensions [40]. Socio-economic development is measured using the Human Development Index (HDI) for 2023 [41], which combines indicators of health, education, and income. The share of the urban population [42] is included to account for differences in the spatial structure of development, while institutional capacity is represented by the Policy capacity indicator [40], which reflects the ability of public institutions to manage and support AI adoption.

Based on the theoretical framework, the following hypotheses are proposed:

H1. *National AI capacity, represented by AI Infrastructure and Development & Diffusion, is positively associated with SDG performance.*

H2. *AI Infrastructure is positively associated with SDG performance when examined separately from other dimensions of national AI capacity.*

H3. *Higher human development is positively associated with SDG performance.*

H4. *A higher share of the population living in urban areas is positively associated with SDG performance.*

H5. *The strength of the association between AI Infrastructure and SDG performance differs across countries at different levels of human development.*

The empirical analysis is based on Ordinary Least Squares (OLS) regression. This method was selected because the dependent variable, SDG Index, is continuous, and the aim is to estimate the average relationship between national AI capacities and sustainable development across a global sample of countries. Before estimating the regression models, Pearson correlation coefficients were calculated to examine bivariate relationships among the variables. Multicollinearity was assessed using the variance inflation factors (VIF). All VIF values were below 5, a commonly used conservative threshold for potential multicollinearity concerns [43], suggesting that multicollinearity was not severe according to this criterion. To assess the adequacy of the OLS specifications, additional regression diagnostics were conducted for all models. Heteroscedasticity was examined using the Breusch–Pagan and White tests. Potentially influential observations were assessed using

Cook's distance, leverage, and externally studentized residuals. The Ramsey RESET test was used to examine possible functional-form misspecification, and the Jarque–Bera test was used to assess the normality of the residuals. In addition, all models were re-estimated using HC3 heteroscedasticity-consistent standard errors to assess the robustness of statistical inference to possible heteroscedasticity. Diagnostic results are reported in Supplementary Tables S1–S4. Potentially influential observations were examined diagnostically and were not automatically excluded from the main analysis.

The study estimated three core specifications, with an additional specification including Policy Capacity. In the equations, (i) denotes a country; (SDG_i) is the country's SDG Index score; ($AIINF_i$) represents AI Infrastructure; ($DEVDIFF_i$) represents Development & Diffusion; (HDI_i) denotes the Human Development Index; ($URBAN_i$) is the share of the population living in urban areas; and ($POLICY_i$) represents Policy Capacity. The intercept is denoted by β_0, while $\beta_1 - \beta_4$ denote the coefficients associated with the respective explanatory variables in each specification. The error term is denoted by ε_i. Descriptive statistics, including the means, standard deviations, and observed ranges of the variables.

Model 1 (Basic): Examines the relationship between AI indicators and sustainable development, testing H1 jointly through both AI dimensions.

$$SDG_i = \beta_0 + \beta_1 AIINF_i + \beta_2 DEVDIFFi + \varepsilon_i$$

Model 1a (Auxiliary): Focuses exclusively on the infrastructure aspect to test its primary role in the observed relationship (H2).

$$SDG_i = \beta_0 + \beta_1 AIINF_i + \varepsilon_i$$

Model 2 (Main): Includes HDI and urbanization to determine whether the association between AI Infrastructure and SDG performance remains after accounting for development conditions (H2–H4).

$$SDG_i = \beta_0 + \beta_1 AIINF_i + \beta_2 HDI_i + \beta_3 URBAN_i + \varepsilon_i$$

An additional specification incorporates Policy Capacity to examine whether institutional readiness explains variation in sustainable development beyond technological and socio-economic characteristics.

$$SDGi = \beta_0 + \beta_1 AIINF_i + \beta_2 HDI_i + \beta_3 URBAN_i + \beta_4 POLICY_i + \varepsilon_i$$

To examine whether the relationship between AI and sustainable development differs across countries at different levels of development, countries were divided into four groups according to the UNDP [41] classification: very high ($\geq$0.800), high (0.700–0.799), medium (0.550–0.699), and low ($<$0.550) HDI (H5). For each group, the Pearson's correlation coefficient between AI Infrastructure and the SDG Index was calculated. The subgroup analysis was used to assess whether the strength of the AI–SDG relationship differs across development groups. Differences between correlation coefficients were subsequently tested using Fisher's z transformation. All data processing and statistical analyses were performed using Microsoft Excel 2016 (Microsoft Corporation, Redmond, WA, USA).

3. Results

The descriptive statistics for the variables included in the empirical analysis are presented in Table 2. The final analytical sample comprised 167 countries with complete observations across the variables included in the main models. The SDG Index shows substantial cross-country variation, with scores spanning from 41.55 to 87.02. AI-related indicators also exhibit pronounced differences across countries. AI Infrastructure ranges

from 16.63 to 91.77, while Development & Diffusion shows an even wider range, from 9.19 to 88.16, indicating substantial variation in national AI capabilities and the extent to which AI development is diffused across countries. The HDI ranges from 0.388 to 0.972, reflecting the broad range of socio-economic development represented in the sample. Urbanization also varies considerably, with the share of urban population ranging from 15% to 100%. The descriptive statistics demonstrate substantial heterogeneity in sustainable development performance, AI capacity, human development, and urbanization across the sample.

Table 2. Descriptive statistics of the variables.

Variable	Mean	SD	Min	Max
SDG Index	68.06	10.11	41.55	87.02
AI Infrastructure	45.27	14.96	16.63	91.77
Development & Diffusion	32.85	17.44	9.19	88.16
HDI	0.740	0.157	0.388	0.972
Urban population (%)	61.90	21.15	15.00	100.00
Policy Capacity	47.30	32.79	0.00	100.00

The study estimated three core specifications, with an additional specification including Policy Capacity. The first regression model examined whether the two dimensions of AI capacity, AI Infrastructure and Development & Diffusion, were associated with national sustainable development performance. Model 1 was statistically significant, explaining 63.1% of the variance in the SDG Index ($F(2,164) = 140.26$; Table 3). AI Infrastructure was positively and significantly associated with the SDG Index, whereas Development & Diffusion did not make a statistically significant independent contribution to the model (Table 3). Thus, the positive AI–SDG association is driven primarily by Infrastructure rather than Development & Diffusion. This result is important because it suggests that the relationship between national AI capacity and sustainable development may depend more strongly on the underlying technological and infrastructural capacity required to support AI than on the extent of AI development and diffusion itself.

Table 3. OLS regression results for the SDG Index.

Predictor	Model 1	Model 1a	Model 2	Model 2 (β)	Model 3
Intercept	42.685 ***	43.818 ***	25.436 ***		26.195 ***
AI Infrastructure	0.618 ***	0.535 ***	0.057	0.085	0.016
Standard error	(0.072)	(0.032)	(0.044)		0.051
Development & Diffusion	−0.079	—	—		
Standard error	(0.062)				
HDI	—	—	58.559 ***	0.908	58.396 ***
Standard error			(4.505)		4.486
Urban population (%)	—	—	−0.054 *	−0.112	−0.052 *
Standard error			(0.022)		0.022
R^2	0.631	0.627	0.822		0.824
Adjusted R^2	0.627	0.625	0.818		0.820
F-statistic	140.26 ***	277.87 ***	250.44 ***		190.16 ***
N	167	167	167		167

Note. *** $p < 0.001$, * $p < 0.05$.

Because Development & Diffusion did not make a statistically significant independent contribution in Model 1, an auxiliary regression (Model 1a) was estimated using AI Infrastructure as the sole predictor. This specification was used to assess how much of the explanatory power of the basic two-predictor model was attributable to AI Infrastructure

alone. Model 1a was statistically significant ($F(1,165) = 277.87$) and explained 62.7% of the variance in SDG performance ($R^2 = 0.627$; Table 3). AI Infrastructure remained strongly and positively associated with the SDG Index. The comparison of Models 1 and 1a is particularly informative. Removing Development & Diffusion resulted in only a minimal reduction in explanatory power, with R^2 decreasing from 0.631 to 0.627 ($\Delta R^2 = 0.004$). Accordingly, the results provide initial support for the importance of AI Infrastructure in explaining differences in sustainable development performance between countries, while offering little evidence of an additional independent contribution from Development & Diffusion.

The next step was to determine whether the observed relationship between AI Infrastructure and sustainable development remained after accounting for structural characteristics of countries. Model 2 therefore included AI Infrastructure, HDI, and the share of urban population. The model was highly statistically significant and explained 82.2% of the variance in the SDG Index ($F(3,163) = 250.44$; $R^2 = 0.822$). The inclusion of HDI and urbanization substantially improved the explanatory power of the model compared with the basic AI specification. However, AI Infrastructure was no longer statistically significant after controlling for broader development characteristics ($p = 0.189$; Table 3). In contrast, HDI remained strongly and positively associated with SDG performance, while urbanization showed a statistically significant negative association. Standardized coefficients were examined to compare the relative associations of predictors measured on different scales. HDI had the largest standardized coefficient ($\beta = 0.908$), followed by urbanization ($\beta = -0.112$) and AI Infrastructure ($\beta = 0.085$). Thus, although AI Infrastructure was positively associated with SDG performance in the basic model, its independent association was not statistically distinguishable from zero after accounting for HDI and urbanization.

Because AI Infrastructure and HDI were strongly correlated at the bivariate level ($r = 0.857$), multicollinearity was explicitly assessed for the predictors included in Model 2. Variance Inflation Factors (VIFs) were calculated by regressing each predictor on the remaining predictors. The resulting values were 3.8 for AI Infrastructure, 4.5 for HDI, and 2.0 for urbanization, corresponding to R^2 values of 0.74, 0.78, and 0.49, respectively. Although all VIF values were below the conventional threshold of 5, the strong correlation between AI Infrastructure and HDI indicates substantial overlap in the information captured by these predictors. Accordingly, the loss of statistical significance of AI Infrastructure should be interpreted cautiously. This result does not establish that AI Infrastructure is unrelated to SDG performance, but it indicates that its independent association is not statistically distinguishable from zero in the present specification after accounting for HDI and urbanization. The findings therefore point to a close interrelationship between AI capacity and broader national development conditions, rather than demonstrating that AI Infrastructure has no role in sustainable development. Approximately 74% of the variance in AI Infrastructure and 78% of the variance in HDI are explained by the other predictors in the respective VIF calculations.

To assess whether Policy Capacity made an additional independent contribution to explaining cross-country differences in SDG performance, Model 3 extended Model 2 by including this variable. The model was statistically significant ($F(4,162) = 190.16$, $p < 0.001$) and explained 82.4% of the variance in the SDG Index ($R^2 = 0.824$; adjusted $R^2 = 0.820$). HDI remained positively and strongly associated with SDG performance ($B = 58.396$, $SE = 4.486$, $p < 0.001$), while the share of urban population retained a statistically significant negative association ($B = -0.052$, $SE = 0.022$, $p = 0.019$). Neither AI Infrastructure ($B = 0.016$, $SE = 0.051$, $p = 0.758$) nor Policy Capacity ($B = 0.025$, $SE = 0.016$, $p = 0.117$) made a statistically significant independent contribution in this specification. The inclusion of Policy Capacity therefore did not materially increase the model's explanatory power compared with Model 2.

The diagnostic checks indicated that the main findings of Models 2 and 3 were robust to the use of HC3 heteroscedasticity-consistent standard errors. In Model 2, AI Infrastructure remained statistically insignificant ($p = 0.208$), whereas HDI retained a positive and statistically significant association with the SDG Index ($p < 0.001$), and urban population share retained a negative association ($p = 0.032$). The same pattern was observed in Model 3: AI Infrastructure ($p = 0.769$) and Policy Capacity ($p = 0.129$) were not statistically significant, whereas HDI remained positively associated with the SDG Index ($p < 0.001$) and urban population share remained negatively associated ($p = 0.038$). The Breusch–Pagan and White tests did not indicate statistically significant heteroscedasticity in Models 2 and 3, although the White test indicated potential heteroscedasticity in Models 1 and 1a. The Ramsey RESET test indicated possible functional-form misspecification in Models 1 and 1a, but not in Models 2 and 3. The Jarque–Bera test indicated departures from residual normality in Models 2 and 3. Measures of influence identified observations warranting examination, but these diagnostics were not used as automatic exclusion criteria. Full diagnostic results are provided in Supplementary Tables S1–S4.

Heterogeneity Analysis: AI Infrastructure Across HDI Development Groups

The multivariate results indicate that the relationship between AI Infrastructure and sustainable development is closely associated with the development context. To further examine whether the AI–SDG relationship differed across levels of human development, countries were classified into four groups according to the UNDP HDI classification: very high, high, medium, and low HDI.

Pearson correlations between AI Infrastructure and the SDG Index were positive and statistically significant in all four HDI groups. The correlation was r = 0.379 ($p = 0.0015$) among very-high-HDI countries, r = 0.323 ($p = 0.0418$) among high-HDI countries, r = 0.388 ($p = 0.0213$) among medium-HDI countries, and r = 0.581 ($p = 0.0023$) among low-HDI countries. The corresponding 95% confidence intervals are reported in Table 4.

Table 4. Pearson correlations between AI Infrastructure and the SDG Index across HDI groups.

HDI Group	n	Pearson r	95% CI	*p*-Value
Very high	67	0.379	[0.153, 0.568]	0.002
High	40	0.323	[0.013, 0.577]	0.042
Medium	35	0.388	[0.063, 0.639]	0.021
Low	25	0.581	[0.241, 0.794]	0.002

The corresponding coefficients of determination were $R^2 = 0.144$, 0.105, 0.151, and 0.338, respectively. Thus, the strongest observed within-group association occurred among low-HDI countries, where AI Infrastructure accounted for approximately 33.8% of the variation in SDG performance. The estimated regression coefficients showed the same descriptive pattern, increasing from 0.127 in the high-HDI group to 0.494 in the low-HDI group. To assess whether the observed differences in correlation strength were statistically significant, pairwise comparisons were conducted using Fisher's z transformation. None of the six comparisons between HDI groups was statistically significant (Table 5).

Although the correlation was numerically strongest among low-HDI countries, the differences between HDI groups were not statistically significant. The analysis therefore indicates a positive AI Infrastructure–SDG association within all four groups, but does not provide evidence that the strength of these associations differs significantly across development groups.

Table 5. Comparisons between HDI groups of countries.

Comparison	Z	*p*
Very high vs. High	0.310	0.757
Very high vs. Medium	−0.046	0.963
Very high vs. Low	−1.072	0.284
High vs. Medium	−0.307	0.759
High vs. Low	−1.222	0.222
Medium vs. Low	−0.921	0.357

The results provide partial support for H1 and support for H2 in the basic specification, although the association of AI Infrastructure with SDG performance does not remain statistically significant after controlling for HDI and urbanization. H3 is supported, as HDI shows a strong positive association with SDG performance. H4 is not supported, as urbanization shows a small negative rather than positive association. H5 is also not supported: although the AI Infrastructure–SDG relationship is positive and statistically significant within all four HDI groups, the differences in correlation strength between the groups are not statistically significant.

4. Discussion

AI Infrastructure is strongly associated with SDG performance, but this association does not remain independent once human development and urbanization are taken into account. The positive association between AI Infrastructure and SDG performance indicates that countries with greater technological readiness tend to achieve higher levels of sustainable development. However, once human development and urbanization are factored in, AI Infrastructure no longer provides a statistically significant independent contribution. This finding does not imply that AI is irrelevant to sustainable development, but that national AI capacity is closely intertwined with the economic, human, and institutional characteristics that shape countries' development performance.

Existing research on AI and sustainability has largely examined specific applications, sectors, or individual sustainability objectives. Studies have identified potential contributions of AI to environmental management, energy systems, health, education, and other areas related to the SDGs [12,15,17,18]. A recent review of 792 studies confirms the breadth of this literature, while showing that research on AI and sustainability remains strongly focused on particular applications and disciplinary contexts rather than system-level questions [44]. Nahar [45] similarly found that the effects of AI-based innovation vary across individual SDGs and countries, pointing to the heterogeneous nature of the AI–sustainability relationship. In contrast, the present study examines whether national AI capacity is associated with differences in aggregate SDG performance across countries. The distinction matters because improvements resulting from individual AI applications do not necessarily translate into measurable differences in countries' overall sustainable development performance.

The present findings are also relevant to the recent cross-country evidence on AI and sustainable development. Gallego-Álvarez et al. [46] examined the relationship between AI and the SDGs across 60 countries using the Global AI Index and SDG Index and found a close relationship between structural AI conditions and SDG performance. The present analysis supports this general association but adds an important qualification. Using a larger sample of 167 countries and introducing human development and urbanization into the regression models shows that the positive AI-SDG relationship does not remain statistically significant once these broader development conditions are taken into account. The difference between the two studies is therefore not simply a matter of sample size

or measurement. It concerns the interpretation of the AI–SDG relationship: a country's higher AI capacity is associated with better aggregate SDG performance, but this association may partly reflect the broader development conditions within which AI capacity is built. Very recently, Irikefe et al. [47] used similar indicators in combination with Bayesian Belief Networks and predictive models (LASSO and ANN-MLP), and they identified societal transition and data quality as the most consistent predictors of SDG performance. While their study focuses on modelling SDG performance from multiple AI readiness dimensions, the present study examines whether AI Infrastructure retains an independent association with SDG performance after accounting for human development and urbanization, and whether this association persists across HDI groups.

The distinction between AI Infrastructure and Development & Diffusion provides additional insight. Although both dimensions form part of national AI capacity, only AI Infrastructure was significantly associated with SDG performance, whereas Development & Diffusion did not provide a statistically significant independent contribution. Also, excluding Development & Diffusion changed the explained variance by only 0.4 percentage points. This may indicate that, at the country level, the technological foundations represented by infrastructure are more closely aligned with differences in national capacity than the extent to which AI has already diffused across economic and institutional systems. This finding should not be interpreted as evidence that diffusion is unimportant. AI adoption may be highly relevant for particular sectors and organizations, but its contribution may be more difficult to capture through a single aggregate national indicator. The distinction also highlights an important difference between technological readiness and realized technological use: having the infrastructure required for AI development does not necessarily mean that AI is equally embedded across economic, social, and institutional systems.

Human development is strongly associated with cross-country differences in SDG performance in the present analysis. However, this finding requires cautious interpretation because the HDI and the SDG Index overlap conceptually in several dimensions, particularly health, education, and living standards. Their strong statistical association may therefore partly reflect similarities in the aspects of development captured by the two composite indicators, rather than a wholly independent contribution of human development to SDG performance. The strong correlation between AI Infrastructure and HDI ($r = 0.857$) also indicates substantial overlap between technological readiness and broader development conditions. Although the VIF values remain below the conventional threshold of 5, this overlap warrants caution when interpreting the separate regression coefficients. The large standardized coefficient for HDI ($\beta = 0.908$) should therefore be understood as evidence of a strong conditional association within the present model, not as proof that human development independently causes higher SDG performance or that AI Infrastructure has no substantive relevance. Previous research has emphasized the importance of organizational, technical, processing, and institutional capacities for translating AI into sustainable development outcomes [14,45]. The present findings extend this argument to the country level. More broadly, the findings suggest that national AI readiness and SDG performance are closely associated with the wider development context in which technological capacities emerge and are used.

The negative coefficient for urban population share was contrary to the expected positive association and did not support H4. This result should be interpreted cautiously because the share of the urban population is a broad measure that does not capture the quality, density, spatial organization, or infrastructure of urban settlements. Urban areas may offer advantages through access to employment, education, healthcare, public transport, and shared infrastructure, but they may also face pressures associated with congestion, pollution, housing costs, inequality, and resource consumption. The balance between these oppor-

tunities and pressures can vary across countries depending on planning systems, public services, economic structures, and the capacity to manage urban growth. Wang et al. [10], for example, found that the relationship between AI and sustainable development varies across levels of urbanization and identified threshold effects involving AI Infrastructure and urban development. In the present study, the negative coefficient indicates that a higher urban population share is conditionally associated with a lower SDG Index score after accounting for the other variables in the model. It does not demonstrate that urbanization generally has a negative effect on sustainable development. Rather, it indicates that the urban population share alone may be insufficient to capture the diverse ways in which urban development is related to SDG performance.

The results also point to an important development inequality dimension of AI readiness. Countries with different levels of human development do not enter the process of technological adoption with comparable economic, educational, institutional, and infrastructural capacities. The strong relationship between AI Infrastructure and HDI in the present sample suggests that differences in access to advanced technological capacity are closely associated with wider differences in development conditions. This is consistent with earlier evidence on socio-economic disparities in sustainable development [48] and with the growing emphasis on the context in which AI systems are developed and used [44]. The findings are consistent with the possibility that expanding AI Infrastructure alone may not be sufficient to reduce development gaps. Education, digital skills, institutional capacity, and complementary infrastructure may influence how technological capabilities are adopted and used. However, the present cross-sectional analysis does not directly test these mechanisms or establish whether investments in these areas lead to improved SDG performance. They should therefore be understood as plausible explanations and implications for further research, rather than as causal effects demonstrated by the present results.

The subgroup analysis provides an important qualification to the regression results. The AI Infrastructure–SDG correlation remained positive and statistically significant within all four HDI groups. Although the correlation was numerically strongest among low-HDI countries, Fisher's z tests showed that the differences between the four correlation coefficients were not statistically significant. The results therefore do not support the interpretation that the AI–SDG relationship is confined to countries at a particular level of human development. At the same time, the subgroup analysis and the regression models address different questions. Within each HDI group, countries with higher AI Infrastructure tend to have higher SDG Index scores, whereas across the full sample, differences in human development account for a much larger share of the variation in SDG performance and the independent AI Infrastructure coefficient becomes statistically insignificant. Taken together, these findings suggest that AI Infrastructure is positively related to sustainable development across different development contexts, but that this relationship is embedded in broader differences between countries in human development and related development capacities.

The findings provide a more qualified view of the relationship between AI readiness and sustainable development. The results do not suggest that AI Infrastructure is unrelated to SDG performance: its association is positive in the basic model and remains positive within all four HDI groups. However, its coefficient loses statistical significance when human development and urbanization are taken into account, while HDI remains by far the strongest predictor of SDG performance. The results therefore point to a distinction between technological capacity and the broader development capacity needed to generate sustainable development outcomes. AI Infrastructure may be an important component of this capacity, but the cross-country evidence presented here does not support treating it as an independent explanation of differences in aggregate SDG performance. This distinction is relevant for policies aimed at expanding AI capabilities, as technological investment

may need to be considered alongside the human and institutional conditions that shape countries' ability to use those capabilities.

5. Conclusions

The relationship between artificial intelligence and sustainable development is more complex than a simple comparison of countries with higher and lower AI capacity would indicate. In the basic regression model, AI Infrastructure was positively associated with SDG performance. However, its coefficient was no longer statistically significant after human development and urbanization were included in the model. AI Infrastructure was also positively correlated with the SDG Index within all four HDI groups, although the differences between these group-specific correlations were not statistically significant.

HDI showed the strongest conditional association with SDG performance in the multivariate model. This finding should nevertheless be interpreted cautiously because the HDI and the SDG Index overlap conceptually, particularly in their coverage of health, education, and living standards. The observed association may therefore partly reflect similarities in the dimensions represented by these composite indicators and should not be interpreted as evidence that human development independently causes higher SDG performance. Similarly, the loss of statistical significance of AI Infrastructure does not establish that AI capacity is irrelevant to sustainable development, but it indicates that its independent association was not statistically distinguishable from zero within the present model specification.

The findings suggest that national AI readiness is closely associated with broader differences in development conditions, but this cross-sectional analysis cannot establish how AI capacity and sustainable development influence one another over time. The results support a more contextualized understanding of AI readiness in cross-country comparisons and underline the need for further research using longitudinal data, more disaggregated indicators, and research designs capable of examining causal relationships.

5.1. Policy Implications

The findings suggest that AI policies should be considered in the context of broader national development conditions rather than as a standalone technology agenda. The analysis shows that AI Infrastructure is positively associated with SDG performance in the basic model, but that this association is no longer statistically significant after accounting for HDI and urbanization. The results therefore do not establish the independent effects of particular AI investments or identify which complementary policies would improve SDG performance. In light of the wider literature on AI adoption and development capabilities, the findings point to areas that warrant policy attention and further evaluation. These include digital infrastructure, education and skills development, and institutional capacity to adopt and govern AI. For countries with lower levels of human development, considering these complementary capacities alongside AI investment may be particularly relevant. International cooperation could also support countries facing constraints in technological infrastructure and related capabilities. These recommendations should be understood as policy implications informed by the observed cross-country associations and existing research, rather than as effects directly demonstrated by the present analysis. Their effectiveness should be evaluated in future research using evidence capable of assessing specific interventions and their outcomes.

5.2. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. The cross-sectional design identifies associations between countries but cannot establish temporal ordering or causal relationships. The results therefore cannot determine

whether higher AI capacity contributes to improved sustainable development performance or whether broader development conditions facilitate the development of AI capacity. The analysis combines indicators whose underlying observations refer to different reference years. Although the data were selected from the latest available comparable sources, differences in reference years may reduce temporal comparability and mean that the indicators do not describe country conditions at precisely the same point in time. The findings should therefore be interpreted as cross-country associations based on the available indicator data rather than as a synchronized snapshot of national conditions. The HDI and the SDG Index are composite indicators that overlap conceptually. This overlap may partly explain the strong association between HDI and SDG performance and limits the extent to which HDI can be interpreted as an entirely independent explanation of differences in the SDG Index. The strong correlation between AI Infrastructure and HDI also complicates the separation of their individual associations with SDG performance. Although VIF values were examined, the results indicate that multicollinearity should be considered when interpreting coefficients in some model specifications. The models cannot account for all country-level characteristics that may be related to both AI readiness and sustainable development. Potential omitted factors include differences in governance, economic structure, public-service provision, and other institutional or infrastructural conditions. Moreover, composite indicators may mask differences between specific AI capabilities and individual dimensions of sustainable development. Regression diagnostics indicated possible functional-form misspecification in the simpler models and departures from residual normality in Models 2 and 3. HC3 heteroscedasticity-consistent standard errors were used to assess the robustness of statistical inference, and influence diagnostics identified observations warranting examination. These checks support a more cautious interpretation of the regression estimates but cannot eliminate all concerns about model specification or omitted-variable bias. Future research could address these limitations using longitudinal data with more closely aligned reference years, disaggregated measures of AI capacity and individual SDGs, and research design that better accounts for potential confounding factors. Further work could also investigate whether specific institutional, educational, and digital capabilities are associated with differences in the relationship between AI readiness and sustainable development, and whether targeted policy interventions lead to measurable changes in SDG performance.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/pr14213485/s1, Table S1: OLS regression diagnostic tests; Table S2: Influence diagnostics; Table S3: Variance inflation factors (VIF); Table S4: HC3 robust standard errors.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
HDI	Human Development Index
OLS	Ordinary Least Squares
SDG	Sustainable Development Goal
UNDP	United Nations Development Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
VIF	Variance Inflation Factor

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