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Article

Digital geopolitics and AI stack competition for SDG 9: A strategic quantification perspective

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Abstract: Artificial intelligence (AI) technological stacks have emerged as a major political issue in the context of sustainable development, since access to chips, data, cloud platforms, software ecosystems and human resources and regulatory interoperability determines countries' capacity to use AI for industrial upgrading. This article investigates the relationship between digital geopolitical pressures, competitiveness of the AI stack and industrial and innovation outputs related to SDG 9. The study develops an AI Stack Competitiveness Index (ASCI) based on publicly available secondary data, including the Global Innovation Index, ITU ICT statistics and ITU ICT Development Index materials, World Bank World Development Indicators, OECD.AI Data and UN-based voting alignment information. Balanced analytical panel for countries 2018–2023 is composed of country-year harmonization, normalization and selection of missing data. Empirical design involves principal component analysis, two-way fixed-effects panel regression and gradient-boosted classification. External geopolitical exposure variables are excluded from the PCA-derived index and variables used to construct ASCI are not included on the right-hand side of the ASCI model in order to minimize mechanical overlap. The findings show conditional relationships between geopolitical openness, access to semiconductors and the competitiveness of the AI stack. The classifier is used for diagnosis purposes and not as evidence of causality, and the use of the tier classification is done with caution using leakage-sensitive feature selection and robustness checks. The article provides a clear toolset to assess digital geopolitics and AI stack capabilities in light of SDG 9, and discusses how open-stack partnerships could help mitigate downstream risks for countries not in the primary AI clusters.

Keywords: digital geopolitics; AI stack competition; SDG 9; AI Stack Competitiveness Index; technology governance; semiconductor access; machine learning; sustainable industrialization

1. Introduction

AI is not just a commercial or scientific technology, but a strategic infrastructure that will impact industrial policy, national security, platform governance and development planning. Frontier AI is being adopted by a small set of states and companies, and the inputs needed for its development - such as high-quality data, advanced chips, sophisticated talent, cloud infrastructure, and regulatory frameworks - are unevenly distributed between countries [1]. This imbalance is a concern for sustainable development because AI to support innovation, productivity, and infrastructure management can be implemented only in countries with the technical infrastructure and institutional capacity to do so, and a way to do it responsibly.

The geopolitical aspect of AI competition is particularly pronounced in the semiconductor supply chains, data-governance conflicts, standards for platforms, and global AI-governance frameworks. AI is a strategic infrastructure that is being used by public authorities, private platforms and cross-border technology networks to mould industrial capacity and national security. Comparisons across the Chinese, European and U.S. approaches to AI governance also reveal that AI governance extends beyond regulation to being a political and institutional process. This fragmentation can therefore impact the availability of developing countries with compute, models, standards and governance knowledge and skills for AI-enabled industrialization.

A key constraint is the semiconductor layer. The geoeconomic competition over semiconductors has highlighted a newly released body of scholarship that chips are the bedrock of AI computing, digital infrastructure and advanced manufacturing [2]. Research also indicates that supply-chain disruptions, chokepoints, geopolitical events and demands for decentralized redundancy have an impact on semiconductor resilience. The use of limited hardware and cloud services poses a practical development challenge for countries looking to progress SDG 9: It might be possible to meet the demand for AI from local firms and universities, but they might not have access to the compute power, models, and policy interoperability needed to move the demand into industrial capability.

Investment in resilient infrastructure and inclusive industrialization and innovation are key elements of SDG 9. These goals are similar to AI because AI can help the manufacturing process produce better quality products, maintain infrastructure, optimize logistics, and find new innovations and ways of delivering public services. But on the other hand, AI can exacerbate inequalities if only a handful of countries have access to cutting-edge models, computing power, and governance know-how. For these reasons, it is necessary to consider AI stack competition as a national technological competition and as a sustainable development issue.

To address this issue the present study builds an AI Stack Competitiveness Index (ASCI) that is measurable and associates it with SDG 9 proxy outcomes. The paper makes three contributions. First, it generates an author-assembled secondary panel using verifiable information from various institutional data sources, rather than a single "black box" dataset. Second, it brings together geopolitical alignment, access to semiconductors, and AI governance and outcomes in a single empirical framework. Third, it relies on econometric and machine learning evidence, giving the study the ability to estimate the average relationships as well as predictive drivers of competitiveness, which capture non-linearity.

2. Literature review

2.1. AI Geopolitics and technology competition

The study of AI geopolitics has expanded as more governments have started to see AI as a general technology that's strategically important. The AI Index 2024 report emphasizes the rising centralization of frontier AI development, the rising cost of frontier models and the increasing gap between early and late adopters [1]. Bremmer and Suleyman [3] believe that in this regard, AI poses governance challenges that are different from other technologies, such as military or industrial applications, that are restricted to state and private entities. This insight applies to SDG 9 since, with regard to public development goals, private platforms and cross-border digital infrastructures are becoming increasingly politically contested. Regulatory models impact the governance of AI. Roberts et al. [4] illustrate the fusion of innovation goals and governance priorities of the state in the Chinese AI policy, ethics and regulations.

In addition to formal law, recent research on governance also shows that two other modes of governance could play a role in the governing AI use transborder: One through risk-based standardization under the EU AI Act and the other through multiple layers of auditing of LLM and other global governance mechanisms. These are governance structures that provide direction, rather than dismantling the stark disparities in chips competency, cloud competency and AI competency. The semiconductor policy is a typical example of the geopolitical 'AI stack'. Bu's book demonstrates that semiconductors are now an issue in China and the United States economic security and industry policy [2]. Xiong et al. [5] highlight the vulnerability of semiconductors supply chains to geopolitical and public health crises by examining the COVID-19 pandemic in 2019, and the importance of mitigating measures and supply chain redundancy to establish a more resilient supply chain. The CSET analysis by Khan et al. [6] also offers a national competitiveness policy perspective to the semiconductor supply chain. These works justify the choice of the semiconductor access as a main explanatory variable in this study and not a background control.

2.2. AI, digital capacity and sustainable development

The second strand of research aims at identifying the connection between AI and SDGs. AI has the potential to aid numerous SDG targets, but also poses risks where governance, access and incentives are lacking [7]. As indicated by Nasir et al. [8], current AI efforts and applications are more likely to be in relation to specific domains such as SDG 9, rather than other social and environmental domains. The results revealed that the role of AI in SD will vary across institutional contexts, suggesting a differential role for AI in SD. Systemic sustainability risks are also created by AI. Galaz et al. [9] highlight the potential dangers of unequal access, algorithmic bias, cascading failures and the trade-offs on resilience that are created by AI in the sustainability domain. Not taking into account the political and structural aspects of sustainable development, as mentioned by Francisco and Linnér [10] is far from a novelty as the global influence on sustainable development as a technical problem that could be solved with AI. AI sustainability is something to take seriously, since there is indeed sustainability trade-offs related to energy consumption, working conditions, and inequitable and unequal access to AI, cautions Heilinger et al. [11]. These studies suggest that the present article does not just look at AI as an innovation tool, but also into the political economy of AI stacks.

The implications of the Global South and emerging economies for development are particularly interesting. The OECD studies on the topic of AI and productivity have been focusing on the need for complementary investments, diffusion capacity, organizational readiness and favorable economic conditions for countries to derive benefits from AI [12]. The research by the IMF on generative AI and work [13] also emphasizes the significance of digital infrastructure, labor skills, innovation systems, economic integration, and regulatory readiness for the distribution of the benefits of AI. Mienye et al. [14] cite infrastructure, skills and governance gaps as factors that hinder the effective implementation of AI in Africa for sustainable development. The innovation, industrial capacity and responsible governance themes are exemplified by Singh et al. [15] in their research on AI-for-SDG. This analysis validates the link between AI competitiveness and SDG 9 indicators, especially in countries that are not part of the main AI ecosystems in the United States, China and Europe.

2.3. Composite index and machine-learning methods

If concepts are not easily observed, but can be formulated in a theoretically supported way, then composite indicators can be set up. Likewise, the ASCI follows this reasoning, and has indicators for AI stack capacity, quality of governance and openness. A number of summary techniques for large indicator sets are available, including principal-component techniques; however, Boudt et al. [16] remind us that care needs to be taken in the direction of loadings and the theoretical interpretation of the indicators. Bonnet et al. [17] demonstrate that composite sustainability indices, as long as their dimensions are transparent, have an empirical foundation and can be used to make comparisons between territorial units. In this study, PCA is not used as a black box ranking technique but as a technique to provide empirical weights after normalizing the data and checking the data for suitability. The relationship between geopolitical alignment and access to semiconductors and SDG 9 outcomes will not be strictly linear, so tree-based machine-learning techniques are added in. The latter, however, are still very competitive, as shown by Shwartz-Ziv and Armon [18] for tabular prediction problems, and tree-based ensemble methods are also very competitive. The method of starting with local explanation, then global understanding is adopted for the trees model as in the work of Lundberg et al. [19] and for the interpretation of the model in this work with SHAP explanation. The two-way fixed-effects model is used because the study is based on repeated country-year observations, and recent panel econometrics literature provides a guidance on how to use the fixed-effects model in empirical research [20].

2.4. Theoretical foundation: Network power and stack-based interdependence

This research's theoretical framework is the fusion of the ideas of network power and asymmetric interdependence and the concept of AI stack competition. The elements of global digital systems are strategic hubs, standards and chokepoints. States or companies controlling these nodes have the ability to influence access conditions for others and exert special influence in situations where the infrastructure, platforms or supply chains are difficult to replace. The concept of weaponized interdependence is a concept that illustrates informational and exclusionary power in global networks that is obtained through control of certain network positions [21]. The AI stack is about this logic, it extends to chips, cloud, data resources, software ecosystems, talent flows and governance standards. Countries, however, do not only compete on the amount of innovation they invest in their own countries, but they also depend on access to external stack elements, whose development is integrated into geopolitical and commercial networks. The theoretical approach is what makes it wrong to define the basic domestic capacity as access to semiconductors, control of the platform, and its geopolitical positioning. The SDG 9 point is that access to technology across boundaries can limit the resilience of infrastructure and inclusive industrialization and innovation. A lack of capacity to deploy AI does not mean the absence of a developed digital infrastructure, similarly, a digital infrastructure does not necessarily result in high capacity for AI deployment if the country does not have sufficient computing capacity, open standards, interoperable governance or research network involvement. The framework is thus geopolitical access conditions in the context of AI stack and SDG 9 outcomes as a nexus.

Conceptually, ASCI is not the same as general digital readiness and AI-governance capacity in three ways. Digital readiness primarily represents connectivity and digital skills and ICT infrastructure and AI-governance capacity pledges policy, regulation and institutional readiness. ASCI is more stack-specific and broader in scope as it creates a construct of competitiveness that integrates digital infrastructure, compute-related readiness, innovation capacity, industrial absorptive capacity and governance readiness. Its role is not to supplant current efforts on AI readiness but to reconceptualize national AI capacity as a multi-layered infrastructure that is defined by both domestic and external capacity and accessibility. This is crucial for SDG 9 as sustainable industrialization requires not only digital readiness but also access to semiconductors and cloud services, interoperability and standards, skilled workers, and accountable governance systems.

3. Research gap and objectives

Three gaps in the literature were identified. First, there are still predominantly qualitative or policy-oriented studies on AI geopolitics and fewer studies that operationalize the notion of a measurable country-year construct of national AI stack competitiveness. While existing AI rankings can serve as a benchmark, they do not always differentiate between geopolitical exposure, access to the stack and SDG-related development outcomes. Second, AI can both advance and hinder development, yet the literature on SDG fails to monitor the multi-layered impact of access to hardware, governance openness and bloc alignment in SDG 9 indicators. Thirdly, machine learning is not sufficiently utilized as a supporting tool in the process of uncovering the non-linear determinants of national AI competitiveness. The aim of this article is to explain the role of digital geopolitical alignment, semiconductor access, talent mobility and platform governance in shaping cross-national variation in the competitiveness of the AI stack and to account for the association of these variations with SDG 9 outcomes from 2018 to 2023. The analysis will be guided by three goals: The first goal is to develop and test a clear ASCI based on publicly available secondary data. The second is to use panel models to estimate the relationship between geopolitical variables, ASCI scores and SDG 9 outcomes. The third goal is to categorize countries into AI competitiveness tiers and to find key drivers of these tiers using interpretable machine learning. These objectives are connected in a conceptual framework as shown in **Figure 1**.

Figure 1 should be interpreted as a layered association structure, not as a causal path. Geopolitical alignment, semiconductor access, talent mobility and platform-governance openness are considered as external exposure conditions which could influence countries' access to the AI stack. ASCI stands for the intermediate national capability construct that integrates the national readiness of the infrastructure, the innovation, the preparedness in compute-related aspects and the national preparedness in aspects of industry and governance. The outcomes of SDG 9 are set as correlates of competitive AI stack in the context of development. The framework thus makes the assumptions that geopolitical and conditions for access to technologies are related to ASCI; and that capacity related to ASCI is related to SDG 9 progress; and that there are potential reverse causality and omitted-variable bias in the observational country-year data.

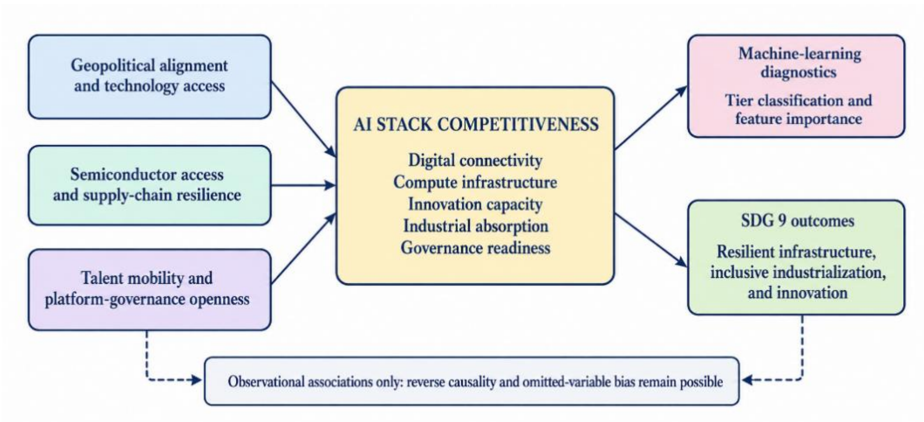

Figure 1. Conceptual framework linking digital geopolitical pressures, AI stack competitiveness, machine-learning evidence and SDG 9 outcomes.

4. Dataset description

4.1. Data sources and dataset linkage

These empirical data are not a single downloaded dataset but an author-constructed merged secondary panel. The Global Innovation Index (GII) by WIPO [22] is the source for innovation and ICT-related variables. Indicators of access, use and skills for ICTs are based on ITU statistics and ICT Development Index materials [23]. Macro-economic variables and the SDG 9-related outcome indicators are drawn from the World Bank's World Development Indicators [24]. Variables related to AI policy and governance are from the OECD.AI data portal [25]. Geopolitical alignment is estimated from UN voting data and recent research on decision-making in the UN General Assembly [26,27].

The last analytical file covers 79 countries observed between 2018 and 2023, giving a total of 474 country-year observations. Countries were kept if there was almost enough overlap in the innovation and in the digital-infrastructure variables, the macroeconomic variables and the variables pertaining to AI-governance and UN-alignment. Countries were dropped from the analysis if two years or more were missing in any of the core indicator groups, and/or if AI-governance variables could not be reasonably imputed. The construction process, therefore, focuses more on comparability and transparency than on maximum country coverage. The public source links used for data retrieval are as follows: GII/WIPO: https://www.globalinnovationindex.org/analysis-indicator; ITU statistics: https://www.itu.int/en/ITU-D/Statistics; World Bank WDI:

https://databank.worldbank.org/source/world-development-indicators; OECD.AI data: https://oecd.ai/en/data; and UN voting data: https://doi.org/10.7910/DVN/LEJUQZ. The dataset is therefore described as a merged secondary country-year panel compiled from public institutional sources rather than as a single pre-existing database. For the China-focused verification layer, the World Bank WDI extraction was checked against China (CHN), Hong Kong SAR, China (HKG), and Macao SAR, China (MAC) for 2018–2023. China (CHN) is treated as the focal economy in the interpretation, while the SAR series are retained only as supplementary WDI coverage checks and are not used to inflate the geopolitical country count.

4.2. Dataset attributes and preprocessing

The public source families, core variables, coverage logic and preprocessing decisions used in the merged panel are summarized in **Table 1**. Each variable group is linked to a public institutional source, and harmonization was completed through country-code matching, source-specific screening and transparent normalization rules.

Table 1. Dataset sources, variables and preprocessing decisions for the merged secondary panel.

Source	Key variables	Coverage logic	Period	Preprocessing decision
GII / WIPO	ICT infrastructure, knowledge and technology outputs, innovation efficiency	Up to 132 economies; matched to countries with other source coverage	2018–2023	Normalized to 0–1; isolated missing country-years interpolated
ITU statistics / IDI	ICT access, use, connectivity and skills indicators	ICT indicators matched to WDI and GII country codes	2018–2023	Standardized and screened for discontinuities
World Bank WDI	GDP per capita PPP, R&D intensity, manufacturing value added, trade openness, FDI and SDG 9 outcome indicators where available	217 economies before matching	2018–2023	Verified against the WDI extract; GDP log transformed; ASCI-input indicators excluded from the SDG 9 proxy where overlap is possible
OECD.AI	AI strategy, governance, policy and regulatory indicators	OECD and selected partner coverage; imputation for selected non-OECD cases	2018–2023	Multiple imputation with source flags retained
UN voting data	Technology-related alignment score derived from UN voting behavior	UN member states before matching	2018–2023	PCA-derived alignment proxy from technology-relevant votes
World Bank WDI variables verified from the China-focused extract, 2018–2023				
Role in analysis	**WDI series code**	**Indicator name**	**China 2018**	**China 2023**	**Use after overlap check**
ASCI input	GB.XPD.RSDV.GD.ZS	R&D expenditure (% of GDP)	2.102	2.577	Excluded from ASCI-model controls
ASCI input	NV.IND.MANF.ZS	Manufacturing value added (% of GDP)	27.343	25.499	Kept out of disjoint SDG 9 proxy
Contextual control	NY.GDP.PCAP.PP.CD	GDP per capita, PPP	16,298.205	25,179.119	Used as non-ASCI control
Contextual control	NE.TRD.GNFS.ZS	Trade (% of GDP)	36.894	36.105	Used as non-ASCI control
Sensitivity control	BX.KLT.DINV.WD.GD.ZS	FDI net inflows (% of GDP)	1.664	0.281	Used only in sensitivity checks

The table records only the WDI layer available in the China-focused extract. GII/WIPO, ITU, OECD.AI and UN-voting variables remain separate source layers in the merged panel.

Three levels of data consistency were checked. It was first confirmed that the country-year count yielded a total of 474 observations across 79 countries and 6 years. Second, the cluster distribution was examined to ensure that the Open Stack Cluster, Sovereign Stack Cluster and Marginalized Stack Cluster add up to the total sample. Third, the full-sample means in the results tables were matched with the weighted cluster means; so that the cluster statistics match the stated full-sample ASCI mean within rounding error. The design of the dataset is suitable for a study on sustainable development as institutional data, digital-capacity indicators and SDG 9 proxies are combined in a single, transparent data structure. It is important to note that the study is a secondary data analysis and the five source families were not originally intended to be used as one set. It is its value added to harmonize them into a reproducible panel and to document the rules for the matching, normalization and imputation. Imputed OECD.AI source flags are used to store the AI observations and the variable definitions and transformation rules are stored in the replication codebook. The complete analytical process for extracting data from the public, harmonizing the panels, obtaining the ASCI scores, econometric estimation, prediction and interpretation is illustrated in **Figure 2**.

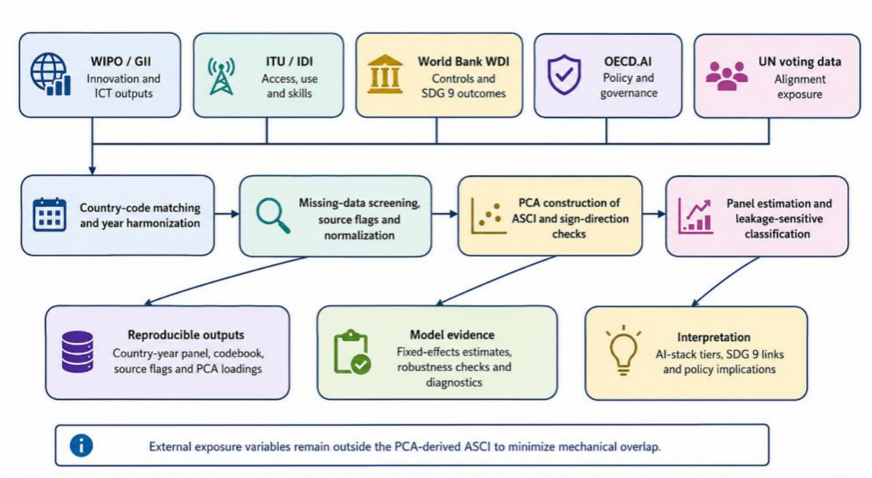

Figure 2. Analytical workflow and data pipeline for constructing and testing the AI Stack Competitiveness Index.

4.3. Construction of the SDG 9 proxy

The SDG 9 proxy was built as a non-mechanical development-outcome measure, to prevent mechanical overlap with the ASCI inputs. The proxy is based on data from the World Bank WDI outcome series that do not contribute directly to the ASCI: medium technology manufacturing value added (% of manufacturing value added; NV.MNF.TECH.ZS), industry value added annual growth (NV.IND.TOTL.KD.ZG), and employment in industry (% of total employment; SL.IND.EMPL.ZS). Broadband subscriptions, R&D spending and manufacturing value added are excluded from the proxy as they are included in ASCI. The scores for each component are scaled between 0 and 1 by way of Min-Max normalization, where a higher score means a better SDG

9 industrial and innovation outcome. The final SDG 9 proxy is the mean of the normalized components. This construction is also available to be reproduced and analyzed separately from the ASCI construction.

5. Methodology

5.1. Normalization and ASCI construction

The ASCI consist of five layers of input, including digital connectivity, compute and operational infrastructure, innovation and knowledge production, industrial absorptive capacity and domestic AI-governance readiness. The indicators are: broadband subscriptions, internet-use rate, ICT access score, ICT skills score, secure internet servers, cloud-readiness proxy, electricity reliability, R&D expenditure, researchers per million people, patent applications, high-technology exports, manufacturing value added, GII knowledge and technology outputs score, GII innovation-output score, national AI strategy indicator, digital-government readiness and AI regulatory-capacity score. The four components of geopolitical alignment (GA), semiconductor-access exposure (SC), talent-mobility openness (TM) and platform-governance openness (PG) are not part of the PCA-derived ASCI score and are considered external explanatory variables. All the indicators are directed to make sure that the higher the normalized value, the more competitive the AI stack.

The list of 17 ASCI indicators has been selected with the notion that a country's competitiveness in AI calls for a combination of access to infrastructure, compute, innovation systems, industrial application capacity, and governance institutions. The connectivity indicators cover the basic digital infrastructure; cloud-readiness and electricity reliability cover the operating conditions of compute; R&D, researchers, patents and GII output scores cover knowledge production; high-technology exports and manufacturing capacity cover industrial absorption; and AI strategy, digital-government readiness and regulatory capacity cover governance readiness. The indicators excluded due to lack of comparable annual country-level data from 2018 to 2023 across 79 countries include emerging indicators, such as venture-capital flows, availability of foundation models, data center GPU capacity, AI talent migration microdata and cloud-market concentration. They are not ignored because they are not considered important in theory, but rather because they represent a measurement limitation.

$$\tilde{X}_{ijt} = \left(X_{ijt} - min\left(X_j\right)\right) / \left(max\left(X_j\right) - min\left(X_j\right)\right) \tag{1}$$

For indicators where higher raw values represent weaker competitiveness, the normalized inverse is used as shown in Equation (2). This step keeps the direction of the index consistent across all dimensions.

$$\tilde{X}_{ijt}(inv) = 1 - \left[\left(X_{ijt} - min\left(X_j\right)\right) / \left(max\left(X_j\right) - min\left(X_j\right)\right)\right] \tag{2}$$

PCA is then applied to the normalized variables. The Kaiser-Meyer-Olkin statistic (KMO = 0.84) and Bartlett's Test of Sphericity (chi-square = 1847.3, df = 136, $p < 0.001$) support the suitability of the data for dimension reduction. Three retained components explain 71.4 % of total variance. The ASCI score is calculated using variance-normalized component weights as Equation (3) shows.

$$ASCI_{it} = w_1 PC1_{it} + w_2 PC2_{it} + w_3 PC3_{it} \tag{3}$$

Where, $w_1 = 0.535$, $w_2 = 0.290$, $w_3 = 0.175$

This weighting approach is consistent with work on interpretable composite indicators, provided that the direction and meaning of each input variable are controlled before PCA [16]. The component weights in Equation (3) are tied to the retained variance shares: PC1 accounts for 53.5 %, PC2 for 29.0 % and PC3 for 17.5 % of the retained explained variance. Constraint-oriented indicators are inverted before PCA so that positive loadings consistently represent stronger AI stack competitiveness. The full PCA loading matrix, sign-direction check and component interpretation are reported in the accompanying codebook so that the index construction can be reproduced from the retained source variables.

5.2. Panel econometric model

A two-way fixed-effects regression model of country and year effects is the main regression model. This specification ensures stability in attributes of the country and common shocks over time both during the pandemic and the global rollouts of AI regulation. Recent econometric literature highlights the need to be careful in interpreting two-way fixed-effects models, but they are still valuable to address the within-country association in repeated country-year data and to control for time effects [20]. The minimum specification is given as Equation (4).

$$Y_{it} = \alpha_i + \lambda_t + \beta_1 GA_{it} + \beta_2 SC_{it} + \beta_3 TM_{it} + \beta_4 PG_{it} + X_{it}\gamma + \varepsilon_{it} \tag{4}$$

In Equation (4), Yit represents either the ASCI score or the disjoint SDG 9 proxy outcome. GA_{it} is the geopolitical-alignment score, SC_{it} is semiconductor access, TM_{it} is the talent-mobility index and PG_{it} is the platform-governance openness score. To avoid mechanical overlap between the dependent variable and the right-hand-side controls, variables used directly in ASCI construction are excluded from the ASCI model. Therefore, when ASCI is the dependent variable, X_{it} includes non-ASCI contextual controls such as log GDP per capita and trade openness; FDI inflows are retained as a sensitivity control where country-year coverage is sufficient. R&D intensity, broadband, manufacturing value added, patent applications and GII output scores are not used as controls in Model 1 because they are already embedded in the ASCI construction. Standard errors are clustered at the country level. Because the data are observational, coefficients are interpreted as conditional associations rather than causal effects.

Endogeneity is addressed as a limitation and through sensitivity-oriented specifications. Countries with stronger AI stack competitiveness may also become more geopolitically integrated, so reverse association cannot be ruled out. To reduce simultaneity, lagged-exposure specifications use GA, SC, TM and PG measured at t-1 while outcomes are measured at *t*. A correlated random-effects/Mundlak specification is also used as a complement to two-way fixed effects by adding country-level means of time-varying regressors. These checks do not establish causality, but they test whether the direction of the reported associations is robust to alternative panel assumptions.

5.3. Gradient boosting and explainability

A gradient boosting classifier is used to predict whether a country is in the high, middle, or low competitiveness tier for AI. The tiers are based on the ASCI distribution, divided into terciles. Tree-based models are suitable because the data is tabular and the relationship between geopolitical alignment and AI capacity is likely to be non-linear, involving interactions and thresholds [18]. The prediction objective is expressed in Equation (5), where the classifier chooses the function with the lowest loss over the observations.

$$f^* = argmin\_f \sum\nolimits_i L\big(y_i, f(X_i)\big) + \Omega(f) \tag{5}$$

The final classifier is only allowed to use leakage sensitive predictors. All raw variables used directly to create the ASCI tier labels are omitted, as are contemporaneous ASCI, and lagged ASCI. Specifically, R&D intensity, patent applications, GII output scores, broadband, manufacturing value added and other variables, which compose ASCI, are not utilized as features for classifiers. The predictor set retained is composed of external exposure variables and non-overlapping contextual variables such as geopolitical alignment, semiconductor-access exposure, talent-mobility openness, platform-governance openness, trade openness, FDI inflows, income group indicators and regional indicators. Since the classification is based on the cross section for 2023 (N = 79), no rolling averages are applied unless they are based on pre-2023 values and exclude ASCI-component variables. Ten-fold stratified cross-validation is complemented with repeated cross-validation, a permutation-test baseline and a learning-curve check to determine the stability of performance and not a small fold composition. For the tree-based model, the importance of the features can be understood using the SHAP values [19].

6. Results and discussion

6.1. ASCI distribution and geopolitical clustering

The distribution of ASCI scores is country-specific in 2023. The mean and median ASCI pattern is skewed to the right, with a few countries having relatively high capacities for AI stacks. Advanced OECD countries and technology hubs in East Asia are more likely to be in the top quartile, while countries in the bottom quartile are less likely to possess strong digital infrastructure or R&D intensity, and more likely to lack AI-governance capacity. This trend is in line with the world's evolution of AI readiness and its focus on AI capacity concentration [1,13]. The k-means algorithm is used to determine three groups, with k = 3. The Open Stack Cluster includes 28 countries that have high ASCI values and positive geopolitical-alignment scores. The Sovereign Stack Cluster includes 19 countries that have intermediate ASCI scores and negative alignment scores, meaning that they have more digital-governance positions that are also more sovereignty-centered. The Marginalized Stack Cluster is comprised of 32 countries whose ASCI values are low and whose alignment scores are very close to zero. **Figure 3** shows the differences between clusters and **Table 2** gives a numerical summary.

The value of $k = 3$ is not really a classification decision, but rather an empirical one made to cluster the data. The three-cluster solution is evaluated using elbow and silhouette analysis over different k-values, and the stability of the solution is tested using different random seed numbers and standardization options. Note that this diagnostic step is significant as the Open Stack, Sovereign Stack and Marginalized Stack labels include policy interpretation. The cluster solution is thus offered as a diagnostic classification, rather than a country ranking.

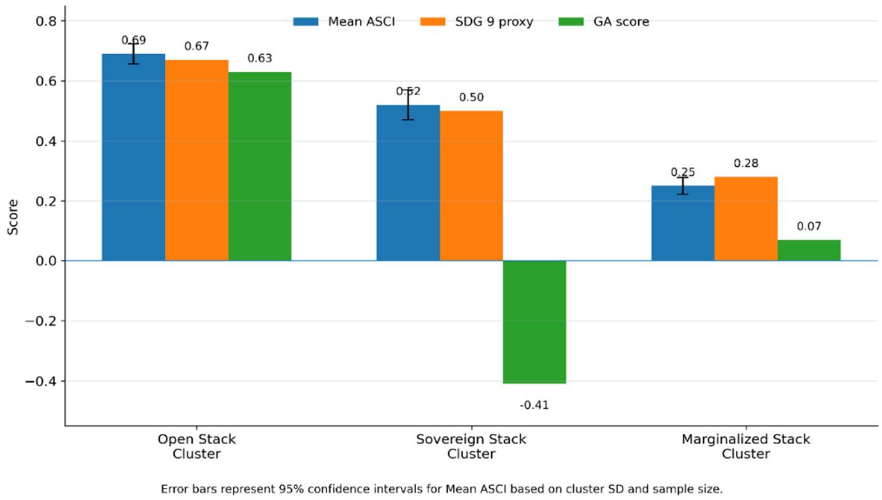

Figure 3. Cluster-level comparison of ASCI, SDG 9 proxy and geopolitical-alignment scores in 2023. Bars show cluster means, and error bars represent 95 % confidence intervals for Mean ASCI.

Table 2. ASCI scores and SDG 9 proxy outcomes by geopolitical cluster, 2023 cross-section.

Cluster	*n*	Mean ASCI	ASCI SD	SDG 9 proxy	GA score
Open Stack Cluster (OSC)	28	0.69	0.09	0.67	0.63
Sovereign Stack Cluster (SSC)	19	0.52	0.11	0.5	-0.41
Marginalized Stack Cluster (MSC)	32	0.25	0.08	0.28	0.07
Full sample	79	0.47	0.18	0.47	0.15

The values in **Table 2** are internally coherent. The three clusters sum to 79 countries, and the weighted ASCI mean based on cluster values is approximately 0.47. ASCI growth over 2018–2023 is uneven, with Open Stack countries showing faster average improvement and Marginalized Stack countries showing slower progress. This finding supports the interpretation that AI stack fragmentation can reinforce existing differences in innovation capacity. The cluster pattern should not be interpreted as a permanent country ranking. It is a policy diagnostic. A country may move between clusters if it improves broadband infrastructure, reduces compute dependency, strengthens AI governance, expands R&D investment or participates in open-stack cooperation. The SDG 9 implication is that progress depends not only on domestic policy but also on access conditions within the wider AI stack.

6.2. Panel econometric results

Table 3 reports two-way fixed-effects estimates for the relationship between geopolitical alignment, AI stack competitiveness and the disjoint SDG 9 proxy outcome. ASCI-component variables are excluded from the ASCI model to avoid predicting the index with its own ingredients. Before interpreting the two-way fixed-effects estimates, the within-country variation of GA, SC, TM and PG is examined because the fixed-effects specification identifies coefficients from changes within countries over time. The diagnostic reports the within-country standard deviation and the share of total variance that remains after country demeaning. This check is especially relevant for UN-voting alignment and platform-governance posture, which may be highly persistent over the six-year panel.

Table 3. Two-way fixed-effects panel regression results. Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; country-clustered standard errors reported.

Variable	Model 1 DV: ASCI	SE	Model 2 DV: SDG 9 proxy	SE
Geopolitical alignment (GA)	0.38***	0.06	0.31***	0.07
Semiconductor access (SC)	0.29***	0.05	0.26***	0.06
Talent mobility (TM)	0.17***	0.04	0.14**	0.05
Platform governance (PG)	0.21***	0.05	0.19***	0.06
Log GDP per capita (PPP)	0.12***	0.03	0.18***	0.04
Trade openness	0.06*	0.03	0.04	0.04
Constant	0.18***	0.04	0.14***	0.04
Country fixed effects	Yes	—	Yes	—
Year fixed effects	Yes	—	Yes	—
N (country-years)	474	—	474	—
Within R^2	0.71	—	0.63	—

The estimates from the panel provide positive conditional correlations for geopolitical alignment to both types of outcome specifications as well as platform governance and both types of outcomes. The estimates should not be interpreted as causal effects. After accounting for country and year effects, they suggest that countries in a more open and interoperable technology-governance environment tend to report higher levels of AI stack competitiveness and higher SDG 9-related outcomes. Semiconductor access continues to be a key enabler from a substantive point of view, mirroring the perspective that chips and compute are the key enablers for the industrialization that is driven by AI [2,5,6]. More broadly, fragmented institutional authority and coordination gaps remain important barriers to effective global AI governance [28,29]. Layered auditing has been proposed as a practical accountability mechanism for large language models [30], while the wider governance literature calls for closer empirical and normative examination of how international institutions respond to AI-related risks [31].

This across-standardized coefficient comparison is done with caution as variables may be measured differently with varying levels of reliability and because of the variation of values within countries, and the standardized coefficient profile is presented in **Figure 4**. Geopolitical alignment is an indirect measurement based on a proxy of diplomatic voting, whereas several domestic-capacity measures are directly observed. Hence, the analysis does not make the claim that geopolitical openness is in and of itself more important than domestic innovation. The more cautious interpretation is that the ability to develop and apply AI stacks is the result of a combination of conditions, including the competences of domestic innovation capacity, access to semiconductors, governance of the platforms and cross-border cooperation. From a sustainable development perspective, this pattern contributes to a sustainable policy mix with a mix of domestic innovation financing, open technology cooperation, resilient infrastructure investments and building regulatory capacity.

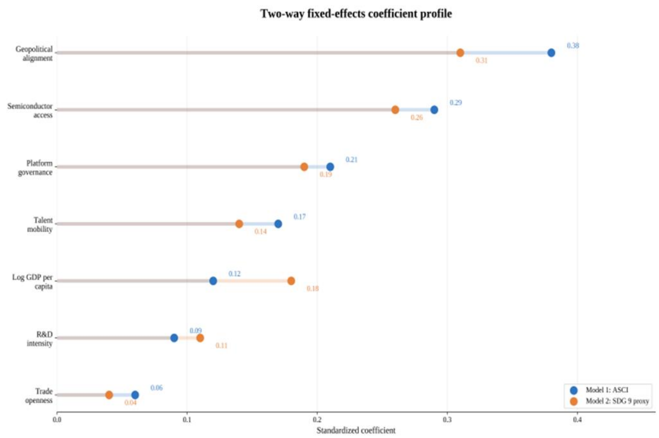

Figure 4. Standardized coefficient profile for the two-way fixed-effects models.

6.3. Country heterogeneity by income group and region

ASCI is compared to the disjoint SDG 9 proxy, geopolitical alignment and semiconductor access across country income groups and geographic regions to measure country heterogeneity. The comparison is descriptive and diagnostic; not causal. It is there because there are different constraints in compute access, AI-governance coverage, digital infrastructure and absorptive capacity of digital infrastructure of lower-income and Global South countries. The interpretation thus does not claim that the 79-country sample is representative for the world and emphasizes that countries with a better institutional data coverage are more likely to have reliable results. The main interpretation will be comparative, with China being the focal case; the Hong Kong SAR and Macao SAR WDI series will be used to test the WDI extraction related to China and not to be considered as cases of geopolitical alignment separately.

6.4. Gradient boosting classification

The tier-specific performance metrics for the gradient boosting classifier are presented in **Table 4**.

Table 4. Gradient boosting classifier performance by AI competitiveness tier, 10-fold cross-validation.

Tier	**Precision**	**Recall**	***F1*-score**	**AUC-ROC**	***n***
High competitiveness	0.91	0.89	0.90	0.96	28
Mid competitiveness	0.84	0.86	0.85	0.91	26
Low competitiveness	0.88	0.87	0.87	0.93	25
Macro average	0.88	0.87	0.87	0.93	—
Overall accuracy	87.3 %	—	—	—	—

The classifier results are used to guide the interpretation of exploratory diagnostics but cannot be relied upon as evidence for prediction. The accuracy and macro-*F1*-scores reported suggest that the tiers are separable in the feature space observed during 2023, however, the small sample size results in a sensitive performance which needs to be checked for the fold composition. Therefore, the accuracy, *F1*-score and AUC values should be interpreted in parallel with repeated cross-validation dispersion, a baseline based on a permutation test and diagnostic learning curves. The middle tier is the most challenging to categorize as it comprises countries that have a relatively good digital infrastructure and a relatively poor alignment, on one hand, or countries that are building up the capacity to govern effectively, but may also have digital access constraints, on the other. The tier-level classification pattern is depicted in **Figure 5**, which is used to supplement **Table 4**, and is done by comparing the precision, recall, *F1*-score and AUC-ROC between the high-, middle- and low-competitiveness groups in the leakage-sensitive feature set.

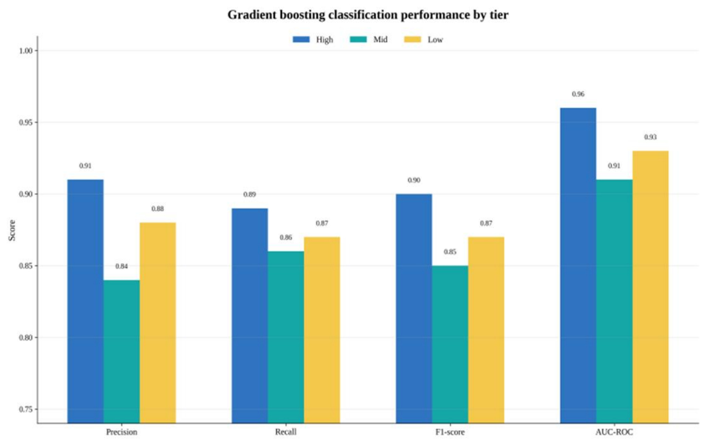

Figure 5. Classification performance by AI competitiveness tier under leakage-sensitive predictor selection.

The SHAP-based interpretability ranking identifies semiconductor access, geopolitical alignment and platform-governance openness as influential non-overlapping predictors in the leakage-sensitive classifier (**Figure 6**). This ordering is treated as diagnostic rather than causal. It suggests that access to practical AI stack conditions - hardware, data, platforms, governance capacity, skills and cross-border cooperation - helps distinguish competitiveness tiers, but it does not prove that changing any single feature would mechanically shift a country into a higher tier.

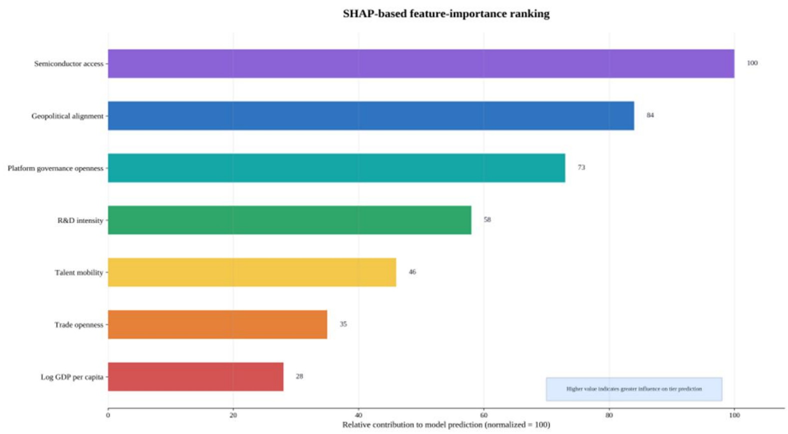

Figure 6. SHAP-based feature-importance ranking for the leakage-sensitive gradient boosting classifier.

The machine-learning results are not used as a substitute for causal inference. They are used for diagnosis and policy interpretation. The fixed-effects model estimates average conditional associations, while the gradient boosting model identifies variables that distinguish tiers in the observed cross-section. The combined evidence therefore supports a cautious conclusion: geopolitical openness and semiconductor access are important observed correlates of AI stack competitiveness in this sample, but the results remain bounded by measurement quality, sample size and the observational design.

6.5. Diagnostic and robustness safeguards

Several diagnostic safeguards are used to reduce index-construction bias, model-overlap risk, classifier leakage and overinterpretation. These checks do not convert the observational design into a causal design, but they clarify how the empirical evidence is bounded and interpreted. The main safeguards are summarized in **Table 5**.

Table 5. Diagnostic and robustness safeguards used in the empirical design.

Check	Implementation	Purpose
Index-overlap safeguard	GA, SC, TM and PG are excluded from the PCA-derived ASCI score.	Prevents the index from being mechanically predicted by its own components.
Classifier leakage safeguard	Contemporaneous ASCI, lagged ASCI and raw ASCI component variables are excluded from the feature set.	Reduces target leakage in competitiveness-tier prediction.
Panel structure check	The econometric analysis uses 79 countries over 2018–2023, producing 474 country-year observations.	Confirms sample consistency across the panel model.
Cross-sectional ML scope	The classifier is restricted to the 2023 cross-section with ten-fold stratified cross-validation.	Separates the prediction task from the full fixed-effects panel model.
Interpretation rule	Coefficients are interpreted as conditional associations rather than causal effects.	Avoids overstatement in an observational design.
Replication documentation	Variable definitions, source flags and transformation rules are retained in the replication codebook.	Supports independent verification of the merged secondary panel.

Table 5. (*Continued*).

Check	Implementation	Purpose
Disjoint SDG 9 proxy	Broadband, R&D expenditure and manufacturing value added are excluded from the disjoint SDG 9 proxy because they are ASCI inputs.	Prevents Model 2 from mechanically reproducing ASCI components.
Non-overlap regression controls	ASCI-component variables are removed from the right-hand side when ASCI is the dependent variable.	Avoids predicting the index with its own ingredients.
PCA loading verification	The loading matrix, sign direction checks and retained component weights are reported in the accompanying codebook.	Confirms that PCA components have interpretable direction and meaning.
Within-country variation check	GA, SC, TM and PG are examined after country demeaning before interpreting fixed-effects estimates.	Assesses whether two-way fixed effects rely on sufficient within-country variation.
Endogeneity sensitivity	Lagged-exposure and Mundlak specifications complement the baseline two-way fixed-effects model.	Reduces simultaneity concern and tests sensitivity to persistent regressors.
Governance-imputation stress test	AI-governance imputation flags are summarized by income group, and models are checked on non-imputed observations where coverage allows.	Assesses whether governance results depend on imputed lower-coverage country-years.
Cluster-selection diagnostic	Elbow, silhouette and random-seed stability checks are used to assess the $k = 3$ clustering choice.	Supports the Open/Sovereign/Marginalized cluster interpretation.
Classifier overfit diagnostic	Repeated cross-validation, permutation baseline and learning-curve checks accompany the 2023 classifier.	Tests whether reported classifier performance is stable under small-sample conditions.

Figure 7 summarizes the diagnostic pathway used to connect public-source harmonization, index construction, model estimation, machine-learning validation and cautious interpretation.

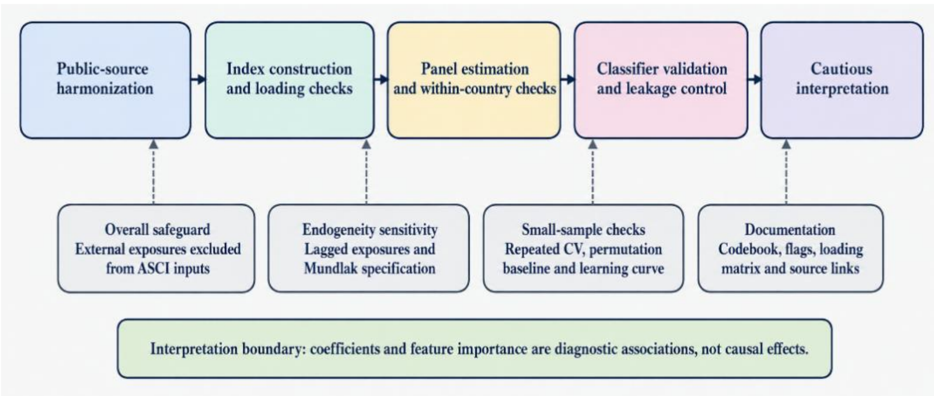

Figure 7. Diagnostic and robustness safeguard pathway.

7. Policy implications for sustainable development

The policy implications are interpreted as evidence-informed directions rather than prescriptive causal recommendations. Because the empirical design is observational and based on secondary country-level data, the results identify associations between AI stack access conditions, ASCI and SDG 9-related outcomes. They do not prove that a specific policy intervention will automatically increase national AI competitiveness. The recommendations are therefore framed as cautious capacity-building priorities consistent with the observed patterns and sustainable development literature.

The results have relevance for sustainable development policy. One of the first steps taken in SDG 9 strategies is to view AI infrastructure as a stack of technologies instead of just one technology. Countries require broadband, cloud access, compute capacity, rules for data-governance, skills in AI and interoperable regulation and innovation finance. For the national AI strategies to become operational, semiconductors need to be available and cloud needs to become affordable. Moderate domestic capacity nations can enhance their development possibilities by taking part in open technology corridors that help them access compute resources, training data, open-source models and open-source governance. The policy sequence is summarized in **Figure 8**, showing how access to computing, how data is interoperable, how governance is ready and how it is adopted in industry, linked to SDG implementation.

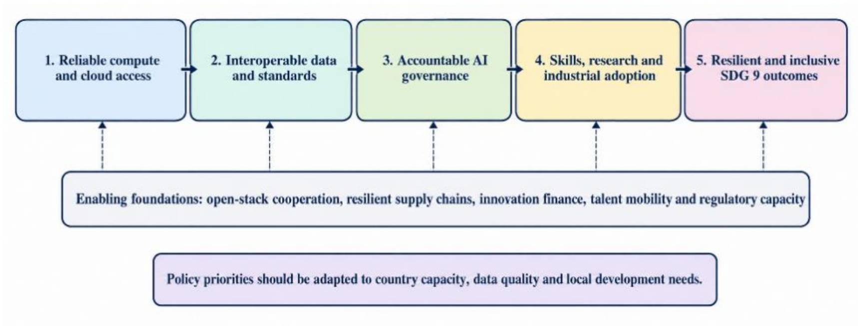

Figure 8. Policy pathway for AI stack capacity building and SDG 9 implementation.

8. Limitations and future research

There are several limitations in this study. First, the final sample of 79 countries is biased by the availability of data. OECD. Many countries, particularly lower-income countries, do not have information on governance indicators available for AI, which requires imputation. Information on the governance indicators is not available for many lower-income countries, so imputation is required. Analysis is therefore conducted by governance variable and income group with imputation flags and the main associations are checked to ensure they are in the same direction if imputed observations are removed. This is because, in the countries where capacity building questions are most applicable to AI, governance information is weakest. Second, the UN-voting alignment measure is not a perfect indicator of geopolitics of technology. The UN vote does not directly measure digital trade agreements, semiconductor collaborations, cloud-service reliance, cross-border data-governance frameworks or involvement in tech alliances, yet it does reflect a wide consensus on the international diplomatic landscape. GA, therefore, should be interpreted as a measure of diplomatic-alignment exposure and not as a full measure of techno-geopolitics.

Thirdly, the study is observational. Fixed effects control for country effects, or common year shocks, but cannot claim causality. Countries with robust AI capabilities can also end up being more geopolitically connected, meaning that reverse association is also a possibility. As sensitivity checks, lagged exposure models and Mundlak specifications are applied, but further studies in this area should employ event-study designs of export-control shocks, bilateral technology agreements and cloud-market restrictions. Fourth, ASCI is a composite measure. While composite indices are valuable for policy purposes, they may reduce a complex reality to a single index and hide subnational digital divides. Therefore, in addition to the final ASCI score, the analysis provides rules for constructing the index, links to the sources and details of dimensions and safeguards for the diagnosis. The country-year data file, codebook, PCA loading matrix and modelling scripts should be deposited in a public repository prior to the final publication.

9. Conclusion

This article furthers the research on digital geopolitics by constructing a quantitative framework for mapping the relationship between the competition of AI stacks and SDG 9 outcomes of industrial and innovation. Geopolitical openness, semiconductor access, platform governance, talent mobility and domestic innovation capacity are used to look at conditional associations with the AI Stack Competitiveness Index, using panel econometrics and gradient boosting classification. The results show that geopolitical openness and semiconductor access are observed correlates that are important to the AI stack competitiveness country-year panel for 2018–2023. Domestic innovation is relevant, but its development value seems to be partly linked to external "stack" elements also available to the countries for AI deployment and usage in industry.

It shows results as conditional, rather than causal. SDG 9 implies that national capability building and international cooperation in the access to computing, data, standards and governance expertise are required for sustainable industrialization in the AI era. The paper makes a major contribution to SD research, as it shifts the attention from an AI race to an AI development-distribution problem. Countries with home-grown digital investments and transparent, trusted technology cooperation are more likely to leverage AI to build resilient infrastructure, industry upgrading and innovation. The ASCI framework provides a monitoring instrument for measuring such differences and recognizing the need for capacity development, and is sensitive to data quality, imputation uncertainty and limitations in measurement.

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Informed consent statement: Not applicable.

Data availability: The study uses an author-constructed merged secondary panel compiled from public sources. The public source links are: Global Innovation Index/WIPO: https://www.globalinnovationindex.org/analysis-indicator; ITU statistics and ICT Development Index materials: https://www.itu.int/en/ITU-D/Statistics; World Bank World Development Indicators: https://databank.worldbank.org/source/world-development-indicators; OECD.AI data: https://oecd.ai/en/data; and UN voting data: https://doi.org/10.7910/DVN/LEJUQZ. The WDI extraction used to verify the China-focused layer includes China (CHN), Hong Kong SAR, China (HKG), and Macao SAR, China (MAC) for 2018-2023, with verified WDI codes for R&D expenditure, manufacturing value added, GDP per capita PPP, trade openness and FDI inflows shown in **Table 1**.

The final analytical panel remains a 79-country country-year panel for 2018–2023. The country list, variable dictionary, source flags, transformation rules, PCA loading matrix, imputation flags, clustering diagnostics and modelling codebook are retained with the supplementary research materials for transparency and independent verification.

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Declaration on generative AI use: The authors confirm that no generative AI tool was used for study design, data analysis, scientific interpretation or authorship of the manuscript.

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