



*Research Article*

## AI Asymmetry in the Global Economy: Indices, Scenarios, and Policy Tools

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**Abstract:** This study introduces the AI Regional Asymmetry (AIRA) methodology—a comprehensive framework for assessing and mitigating disparities in artificial intelligence (AI) development across countries and regions. Building on economic theories of inequality and resource complementarity, AIRA comprises four interlinked stages: (1) construction of a synthetic AI asymmetry index based on 23 indicators consolidated into four key dimensions — computational chasm, talent gravity, data monopolization, and capital cycle; (2) quantification of asymmetry using economic inequality metrics such as quantile gaps, Gini, and Theil indices; (3) identification of complementary country profiles to form strategic alliances — vertical, horizontal, or multilateral — aimed at resource exchange and imbalance reduction; and (4) scenario modeling to simulate the dynamic impacts of such alliances on global AI market structures. Applied to Belarus as a case study, the methodology reveals potential partnership configurations within the CIS region, with leading economies such as the United States and China, and with developing countries, thereby illustrating opportunities for regional strengthening and global asymmetry reduction. The framework offers policymakers quantitative tools for fostering equitable AI ecosystems, underscoring international cooperation as a strategic pathway to narrow digital divides and promote sustainable, inclusive growth in AI-driven markets.

**Keywords:** AI asymmetry; AI governance; AI regional asymmetry; Digital divide; Economic sustainability

### 1. Introduction

From an economic perspective, most technologies serve as productivity tools that affect specific sectors or processes. AI—particularly machine learning and large language models—is fundamentally different. Rather than a mere tool, it constitutes a metatechnology—a framework for creating and optimising other technologies and processes. This position AI within the rare category of general-purpose technologies (GPTs) (Wan and Wu, 2025; Guo et al., 2025; Savastano et al., 2024; Tredinnick and Laybats, 2023; Allen and Choudhury, 2022; Carter et al., 2020). A GPT exhibits three defining characteristics: pervasiveness (diffusion and adoption across most economic sectors), continuous improvement (sustained performance and efficiency gains), and innovation-enabling potential (capacity to generate new products, processes, and business models) (Gu and Liu, 2024; Kalai et al., 2024; Jacobides et al., 2021; Crafts, 2021). Historical examples include steam engines, electricity, internal combustion engines, and the In-

ternet. AI satisfies all three criteria, positioning it as a transformative force for industries and economies at both the macro and global levels.

AI applications now permeate nearly all domains: in agriculture — precision farming, yield forecasting, and harvest optimisation; in healthcare — drug discovery, medical imaging analysis, and personalised treatment design; in finance — fraud detection, algorithmic trading, and risk assessment; in manufacturing — predictive maintenance, supply chain optimisation, and robotic process automation; and in services — personalised recommendations, customer support, and content generation (Babkin et al., 2025; Ranade and Eyman, 2024; Hung, 2024; Chun et al., 2024; Festa et al., 2023; Babkin et al., 2022b; Babkin et al., 2022a; Babkin et al., 2021; Beliatskaya and Knyazkova, 2017). AI's self-reinforcing capacity for improvement is driven by expanding data volumes, advances in computing power, and algorithmic innovation. It underpins a cascade of derivative innovations — new products (autonomous vehicles, AI-powered diagnostics, and generative design), new processes (hyper-efficient logistics, dynamic pricing, and automated research), and new business models (AI-as-a-service, data marketplaces, and outcome-based economies) (Qenaat et al., 2025).

Beyond its role in value-added growth, AI has profound implications for labor automation and the reconfiguration of production factors (Bran et al., 2024; Wagner, 2020). As a production factor—AI capital—AI encompasses algorithms, trained models, and robotic systems. Far from being merely another component of capital, it orchestrates the integration of other factors while complementing them (Mykhailova et al., 2024; Xu and Liang, 2024). The world may now be experiencing a “Productivity Paradox 2.0,” wherein the benefits of AI are tangible yet not yet visible in macroeconomic statistics due to measurement constraints, implementation costs, and temporal lags. The expected productivity surge will materialise only when business processes are fundamentally redesigned around AI rather than superficially enhanced by it (Hajikhani et al., 2025; Capello et al., 2022). The Cobb–Douglas production function warrants reevaluation in this context. The parameter A (total factor productivity) is now heavily influenced by AI, while K (capital) should be disaggregated into non-intelligent capital and AI capital, the latter demonstrating a distinct — and likely exponentially higher — marginal product (Filippucci et al., 2024). As a driver of growth, labor is undergoing structural transformation. The value of routine mental and manual labor continues to decline, whereas that of distinctly human skills — creativity, strategic reasoning, empathy, and AI oversight — is dramatically rising, exacerbating skill-based wage inequality. Concurrently, AI has redefined the economic role of data, elevating it to the primary raw material of the digital economy and the cornerstone of digital capital formation. Governments and corporations that control vast, high-quality, proprietary datasets enjoy advantages analogous to those of oil-rich nations in the twentieth century, generating new forms of economic rent and barriers to entry. The pervasive integration of artificial intelligence (AI) has renewed interest in endogenous growth models, where technological progress becomes an intrinsic component of economic dynamics. Investment in AI R&D, data accumulation, and human capital formation yields increasing returns to scale and powerful network effects—potentially leading to market winners.

Conceptualising AI as both a general-purpose technology and a production factor is not a mere theoretical exercise. This study provides a crucial analytical framework for understanding the structural transformations reshaping the global economy. This lens clarifies the intensifying geopolitical contest for AI dominance, the strategic reallocation of capital by firms and investors, and the urgent need for adaptive policies in education, social welfare, antitrust regulation, and AI ethics. Analyzing the global AI market without this foundation is to conflate a new industrial revolution with a single emerging sector.

Despite the growing body of research on AI and digital inequality, existing studies remain methodologically fragmented, relying on either descriptive comparisons, isolated readiness indicators, or qualitative geopolitical narratives. An integrated analytical framework that operationalizes AI development through a multi-factor index, quantifies cross-country asymmetry using inequality metrics, and embeds these measurements into a scenario-based modeling pipeline

is still lacking. This study proposes a formalized methodology for assessing global AI asymmetry and evaluating alternative cooperation scenarios aimed at mitigating structural disparities to address this gap.

The current configuration of the global AI market is not merely uneven; it is characterised by self-perpetuating structural asymmetry that risks crystallising a rigid international hierarchy. This disparity extends beyond a simple technological gap—it reflects deep-seated differences in economic capacity rooted in AI's dual role as a GPT and a production factor. The result is a bimodal global structure: a small cohort of “AI powers” juxtaposed against a long tail of “AI consumers,” with a fragile intermediate tier of “AI aspirants.” Four reinforcing forces drive this dynamic: Computing Power, Talent Gravity, Data Monopolisation, and the capital supercycle.” These interactions generate virtuous cycles for frontrunners and vicious cycles for laggards. In this study, these forces are operationalised as analytical dimensions of a composite index and serve as the basis for subsequent inequality measurement and scenario analysis.

The computational divide manifests in the concentration of high-performance computing resources—critical for training foundation models such as GPT-4 and Gemini—within a handful of advanced economies. Hyperscale data centers and artificial intelligence (AI) accelerators (e.g., NVIDIA graphics processing units, Google TPUs) have become strategic assets (Zhang et al., 2024; Tian et al., 2024). Export restrictions on advanced semiconductors, such as U.S. controls targeting China, intentionally deepen this asymmetry. The gravitational pull of talent produces dense clusters of AI expertise in a few global hubs — Silicon Valley, Shenzhen, London, and Zurich— draining human capital from peripheral regions and widening innovation divides (Williams, 2025). The data factor underscores the correlation between AI performance and access to vast, diverse, and high-quality datasets. Major platforms — Google, Meta, Amazon, Alibaba, and Tencent— act as global data extraction systems, converting global user data into proprietary economic advantage (Jiang et al., 2025; Chang et al., 2023). Nations lacking such platforms are relegated to data peripheries, exporting raw digital material without value capture. Finally, the capital supercycle reflects the concentration of venture funding and R&D investment in established AI ecosystems, generating self-reinforcing innovation loops and discouraging capital inflows to emerging markets (Zhang, 2024; Kitsara, 2022).

The cumulative result is a pattern of global technological inequality (Dinker, 2024; Kitsara, 2022)—a self-reinforcing hierarchy where frontrunners accumulate compounding advantages while others face systemic exclusion. Economically, this leads to the outflow of digital and human capital from “AI consumer” states toward “AI powers,” exacerbating global inequality and redefining competitiveness (Vyshnevskiy, 2024; Rahaman et al., 2024; Costas, 2022; Dahlin, 2021). Absent coordinated policy action—through national initiatives and multilateral frameworks—these asymmetries will intensify, institutionalizing a durable global divide. Modelling this emergent paradigm and formulating mechanisms to counteract the consolidation of AI hegemony is a challenge for economics and policy research (Svoboda, 2024). The results of this study should be interpreted as structurally indicative, particularly in contexts where cross-country data availability and comparability remain limited.

## 2. Methods

The proposed AIRA methodology provides an integrated framework for assessing and modelling disparities in AI development across countries and regions. This study focuses on identifying the structural drivers of these asymmetries, quantifying their magnitude, and designing strategies to mitigate them through the establishment of international alliances and cooperative programs that strengthen local AI ecosystems. The AIRA methodology consists of four inter-related yet methodologically distinct stages, each yielding specific analytical insights into the configuration of AI market asymmetries:

1. Constructing a composite AI asymmetry index
2. Assessing cross-national disparities with respect to the key factors identified earlier,

quantifying the degree of asymmetry

3. evaluating economic complementarities among countries to support the formation of strategic alliances aimed at reducing inequality; and
4. These alliances can be used to simulate alternative integration pathways for national AI markets within the evolving global AI landscape.

The empirical implementation of the AIRA framework relies on internationally comparable secondary data drawn from open and authoritative sources, including World Bank Open Data, OECD statistical databases and the OECD AI Policy Observatory, the Stanford AI Index, UNESCO Institute for Statistics, ITU databases, IMF and BIS statistics, WIPO patent databases, and selected industry and policy reports on computing infrastructure, semiconductor markets, and AI regulation. All indicators are harmonised at the country level for the most recent comparable reference period (2024) or, where necessary, the closest available year.

The empirical analysis covers a cross-country sample of 30 countries, including 8 CIS member states (Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Russia, Tajikistan, and Uzbekistan), selected 9 OECD economies (Chile, Italy, France, Germany, Japan, Mexico, Poland, South Korea, and the United Kingdom), and major global AI leaders (China, the OECD benchmark, and the United States), enabling comparison across regional, advanced, and intermediate AI ecosystems (Supplementary Material, Table S1). Belarus is selected as a representative intermediate AI economy because of its structural position between advanced and developing AI ecosystems and its active participation in regional digital cooperation frameworks.

Listwise exclusion or nearest-year substitution is used to address missing values, depending on indicator stability and data availability. No winsorization or logarithmic transformations were applied; all indicators were normalized using min–max scaling to ensure cross-country comparability. Equal weighting is adopted as the baseline aggregation rule to avoid in advance normative bias across dimensions, while alternative weighting approaches are conceptually considered for robustness. The indicator-level effective coverage after harmonization is reported in Supplementary Material (Table S2).

## 2.1 Asymmetry Index

The AIRA methodology is anchored in a composite index that consolidates key AI development metrics into four overarching factors: the compute divide, talent gravity, data monopolization (encompassing critical dataset availability, openness, and controllability), and capital cycle. An initial pool of 60 candidate variables was rigorously examined to construct the final set of indicators grouped under these four dimensions. The construction of the AIRA index is supported by a structured reduction logic and robustness considerations to mitigate concerns regarding the potential arbitrariness of indicator selection. The initial indicator pool was reduced based on redundancy elimination, outcome-based measures exclusion, and international data availability constraints, ensuring conceptual coherence within each factor block. In addition, the index structure's robustness was assessed qualitatively by examining the stability of relative country positions under alternative aggregation assumptions, including variations in factor weighting, partial exclusion of indicators, and alternative normalization approaches. Applying a structured reduction procedure, the selection process yielded 23 indicators that capture mechanisms that either amplify or mitigate asymmetries in the global AI market. Table 1 presents the AIRA framework's expanded indicator dictionary, including definitions, units of measurement, expected direction of influence, and principal source base.

**Table 1** Expanded indicator dictionary of the AI ecosystem assessment index.

No.	Factor	Indicator	Definition	Unit	Expected direction	Main source base	Reference period
1	Computational chasm	AI chip density	Availability of AI chips relative to the population size	units per 100,000 people	Positive	SIA, industry reports, semiconductor market data	2023–2024
2	Computational chasm	AI chip availability on the market	Average waiting time for access or procurement of AI chips	days	Negative before normalization; reverse-coded in aggregation	Industry reports and semiconductor market data	2023–2024
3	Computational chasm	Power consumption of AI data center	Use of electricity in AI-related data center infrastructure	kWh	Positive	IEA: infrastructure statistics	2023–2024
4	Computational chasm	Average cost of computing power rental	Average cost of renting AI computing power	US\$ per hour	Negative before normalization; reverse-coded in aggregation	Industry reports and cloud market data	2023–2024
5	Computational chasm	Share of renewable energy in artificial intelligence computing	Share of renewable energy used in artificial intelligence computing	%	Positive	IEA: energy statistics	2023–2024
6	Computational chasm	Investment in the production of AI chips	Investment in AI chip production and semiconductor capacity	US\$ billion	Positive	OECD: Industry and policy reports	2023–2024
7	Computational chasm	Export restrictions on artificial intelligence chips	Number of restrictions on AI chip export control	count	Negative before normalization; reverse-coded in aggregation	Official Export Control Databases	2023–2024
8	The gravity of talent	Net migration of AI specialists	Net migration balance of AI specialists	Net migration balance	Positive	UNESCO; OECD; statistics of labor mobility	2023–2024
9	The gravity of talent	Share of STEM graduates	Share of STEM graduates	%	Positive	UNESCO Institute for Statistics	2023–2024
10	The gravity of talent	Average salary of AI specialists	Average annual salary of AI specialists	US\$ per year	Positive	OECD; Labor Market Statistics; Industry Reports	2023–2024
11	The gravity of talent	Number of publications in the AI field	Annual AI publication output	count	Positive	Stanford AI Index and bibliometric databases	2023–2024
12	The gravity of talent	Retention rate of AI specialists	Retention rate of AI specialists	%	Positive	OECD; UNESCO; proxies for labor mobility	2023–2024
13	The gravity of talent	Funding for AI specialists' training programs	Funding for AI training and upskilling programs	US\$ million	Positive	OECD; education statistics; public policy documents	2023–2024
14	Data monopolization	Local dataset size	Number of nationally available or controlled AI-relevant datasets	petabytes	Positive	Open-data and digital infrastructure sources, ITU	2023–2024
15	Data monopolization	Share of Open Datasets	Share of Open Datasets	%	Positive	Open data portals; ITU; OECD	2023–2024
16	Data monopolization	Open data maturity index (ODM)	Maturity of the National Open-Data Ecosystem	index, 0–100	Positive	ITU, OECD, open-data assessments	2023–2024
17	Data monopolization	Data export restrictions	Number of restrictions on cross-border data transfer	count	Negative before normalization; reverse-coded in aggregation	Official regulatory and policy databases	2023–2024
18	Data monopolization	Average data access cost	Average data access cost	US\$ per GB	Negative before normalization; reverse-coded in aggregation	Industry reports and market sources	2023–2024
19	Data monopolization	Number of fundamental artificial intelligence models developed under national control	Number of domestically controlled foundational artificial intelligence models	count	Positive	Stanford AI Index; Industry and Research Reports	2023–2024

**Table 1** Expanded indicator dictionary of the AI ecosystem assessment index (cont.)

No.	Factor	Indicator	Definition	Unit	Expected direction	Main source base	Reference period
20	Capital cycle	Volume of AI venture capital	AI venture financing relative to GDP	% of GDP	Positive	OECD; International Monetary Fund; venture investment databases	2023–2024
21	Capital cycle	Public investment in artificial intelligence	Public investment in artificial intelligence	US\$ billion	Positive	OECD AI Policy Observatory; Public policy documents	2023–2024
22	Capital cycle	Adoption of AI in key sectors	Adoption of AI in key sectors	%	Positive	World Bank; Organization for Economic Cooperation and Development; sectoral digitalization indicators	2023–2024
23	Capital cycle	Number of IPOs of AI companies	Number of IPOs of AI companies	count per year	Positive	Financial market statistics; OECD; Bureau of Economic Statistics	2023–2024
24	Capital cycle	Share of AI products in technology exports	Share of AI products in technology exports	%	Positive	World Bank; trade statistics; Organization of Economic Cooperation and Development	2023–2024

The indicator reduction was guided by three principles. First, duplicate elimination: in cases of highly correlated variables, one was retained to avoid redundancy (for instance, “investments in chip production” and “number of AI chip patents” both represent industry intensity, yet the former offers a more direct measure). Second, exclusion of outcome-based indicators, such as the “number of AI unicorns,” which reflect the downstream effects of talent, capital, and infrastructure interactions rather than structural inputs, are excluded. Third, the removal or substitution of indicators lacking reliable, standardised international data sources, for example, the “data diversity index,” is required. The resulting AI asymmetry index is computed as an aggregate of subindices—either through arithmetic or weighted averaging—after normalisation to ensure cross-country comparability. This structure allows for transparent factor decomposition and facilitates empirical analysis of how specific domains contribute to disparities in AI development. The index structure is subsequently tested for internal coherence and sensitivity to alternative weighting and normalization assumptions to ensure robustness. A compact sensitivity analysis confirms the robustness of the cross-country ranking: Spearman rank correlations with the baseline specification remain at 0.997–0.999 across all alternative specifications, whereas the top and bottom segments of the ranking remain largely unchanged (Supplementary Material, Table S3).

The mathematical formulation of the AIRA model corresponds to the methodology’s index calculation stage. Let a set of countries  $C=c_1, c_2, c_3, \dots, c_n$ . For each country  $k \in C$ , we observe indicators  $x(i, j, k)$ , where  $i \in 1, 2, 3, 4$  denotes the factor (Compute Divide, Talent Gravity, Data Monopolization, Capital Cycle);  $j \in 1, \dots, m_i$  represents the indicator within factor  $i$ ; and  $k$  identifies the country. Hereafter,  $x(i, j, k)$  denotes raw indicator values, while  $z(i, j, k)$  refers to the normalised values computed using min–max scaling across the cross-country sample.

#### Step 1. Indicator normalization

To ensure cross-country comparability, all indicators are rescaled to the interval  $[0,1]$ . For direct relationships (where higher values indicate greater AI capacity):

$$z_{i,j,k} = \frac{x_{i,j,k} - \min_k(x_{i,j,k})}{\max_k(x_{i,j,k}) - \min_k(x_{i,j,k})} \quad (1)$$

For inverse relationships (where higher values indicate lower AI capacity):

$$z_{i,j,k} = \frac{\max_k(x_{i,j,k}) - x_{i,j,k}}{\max_k(x_{i,j,k}) - \min_k(x_{i,j,k})} \quad (2)$$

Alternatively, a unified expression can be employed using a direction parameter  $d_j \in \{+1, -1\}$ , where  $d_j = +1$  for direct and  $d_j = -1$  for inverse indicators:

$$z_{i,j,k} = \frac{d_j \left( x_{i,j,k} - \min_k(x_{i,j,k}) \right)}{d_j \left( \max_k(x_{i,j,k}) - \min_k(x_{i,j,k}) \right)} \quad (3)$$

Step 2. Construction of factor sub-index

Each factor sub-index  $F_{i,k}$  is calculated as the arithmetic mean of the normalized indicators:

$$F_{i,k} = \frac{1}{m_i} \sum_{j=1}^{m_i} z_{i,j,k} \quad (4)$$

A weighted mean may also be employed:

$$F_{i,k} = \sum_j w_j z_{i,j,k}, \quad \text{where } \sum_j w_j = 1 \quad (5)$$

Equal weighting is applied as a baseline assumption to avoid imposing in advance normative priorities across factors, while alternative weighting schemes are explored for sensitivity. Accordingly, the reported results should be interpreted as structurally indicative rather than statistically exhaustive.

Step 3. The composite asymmetry index

The overall AIRA index for country  $k$  is obtained by aggregating the following four factor sub-indices:

$$AIRA_k = \frac{1}{4} \sum_{i=1}^4 F_{i,k} \quad (6)$$

This composite measure enables cross-country comparison of AI ecosystem maturity and asymmetry, supporting the AIRA methodology's subsequent quantification, clustering, and scenario modeling stages.

## 2.2 Assessing Asymmetry

Assessing asymmetry entails quantifying the configuration of the global AI market to identify structural imbalances that foster dependencies among participants over time. Within the AIRA methodology, the magnitude of cross-country disparities in AI development is evaluated using established economic inequality metrics: quantile spreads (P90/P10 and P90–P10), which capture differentiation between leaders and laggards; the Gini coefficient, which gauges the overall concentration of AI resources and opportunities; and the Theil index, which decomposes inequality into between-country and within-group components. Collectively, these three measures enable AIRA to translate qualitative discussions of the “digital divide” into rigorous, quantitative assessments of AI asymmetry.

### 2.2.1 Quantile Spreads

$$Q_{10/90} = \frac{P_{90}(AIRA)}{P_{10}(AIRA)} \quad (7)$$

$$Q_{10-90} = P_{90}(AIRA) - P_{10}(AIRA) \quad (8)$$

where:

$P_{90}(AIRA)$ - the 90th percentile of the distribution of  $AIRA_k$  (score of the “leaders”);

$P_{10}(AIRA)$ - the 10th percentile of the distribution of  $AIRA_k$  (score of the “laggards”);

$Q_{10/90}$ -the relative spread (leader-to-laggard ratio);

$Q_{10-90}$ - the absolute spread (difference between leaders and laggards).

Higher values of  $Q$  indicate stronger divergence between technologically advanced and lagging countries.

### 2.2.2 Gini Coefficient

$$G = \frac{\sum_{k=1}^N \sum_{l=1}^N |AIRA_k - AIRA_l|}{2N^2 \overline{AIRA}} \quad (9)$$

where:

$AIRA_k$ -denotes the asymmetry index score of country  $k$ ;

$N$ -denotes the total number of countries;

$\overline{AIRA}$ -denotes the mean asymmetry index across all countries;

$|AIRA_k - AIRA_l|$ -denotes the absolute difference between countries  $k$  and  $l$ .

The Gini coefficient ranges from 0 to 1.  $G = 0$  denotes perfect equality (identical scores across all countries), whereas  $G = 1$  signifies extreme inequality (one country monopolises all AI resources). The intermediate values reflect varying levels of asymmetry (Table 2).

**Table 2** Gini coefficient interpretation scale.

The Gini coefficient range	Interpretation of the distribution asymmetry
0	Absence of asymmetry (perfect equality, symmetrical distribution)
$0 < G < 0.2$	Weak asymmetry (low inequality, near symmetry)
$0.2 \leq G < 0.4$	Moderate asymmetry (average inequality, typical for many countries)
$0.4 \leq G < 0.6$	Marked asymmetry (high inequality and strong skewness)
$0.6 \leq G \leq 1$	Extreme asymmetry (maximum inequality and pronounced positive skewness)

### 2.2.3 Theil Index

Under perfect equality, the Theil index equals zero, whereas higher values indicate an increasing concentration of AI resources among a limited number of countries. Importantly, the Theil index is decomposable, allowing inequality to be partitioned into between-group (e.g., CIS, EU, and US blocs) and within-group (intra-bloc variations) components. By combining these three metrics—quantile spreads, Gini, and Theil—the AIRA framework transforms the AI divide into a structured, quantitative representation of asymmetry.

$$T = \frac{1}{N} \sum_{k=1}^N \frac{AIRA_k}{\overline{AIRA}} \ln \left( \frac{AIRA_k}{\overline{AIRA}} \right) \quad (10)$$

## 2.3 Identifying the Potential of Strategic Alliances

The subsequent stage of the AIRA methodology focuses on identifying countries or regions that exhibit complementary profiles across the four key factors. In the context of AI asymmetry, an alliance denotes a collaboration among nations or regions aimed at mitigating disparities in AI development drivers — computing power, talent, data, and capital — through resource sharing, joint investments, educational initiatives, and regulatory harmonization. Alliances may take three distinct configurations: vertical (donor–recipient), horizontal (peer-to-peer), or multilateral (bloc-based) partnerships. Their shared goal is to reduce structural imbalances and enhance

the resilience of local AI ecosystems. A disparity matrix is constructed to operationalize this stage. Each country pair is assigned a score based on the aggregate gaps in their factor-specific subindices, which produces a strategic alliances' priority map. Factor-specific gaps underlying the aggregate disparity score allow alliances to be interpreted in terms of dominant complementarities across compute, talent, data, or capital dimensions.

### 2.3.1 Disparity matrix

For a given country pair  $(c_i, c_j)$ , the factorial disparity is defined as follows:

$$D_{i,j} = \sum_{f=1}^F w_f * |I_{i,f} - I_{j,f}| \quad (11)$$

where  $i, j$  are country indices (e.g.,  $i = \text{Belarus}$ ,  $j = \text{Germany}$ );

$f \in \{1, \dots, F\}$  is the asymmetry factor index, with  $F = 4$  (Compute Divide, Talent Gravity, Data Monopolization, Capital Cycle);

$I_{i,f}$  is the normalized value of factor  $f$  for country  $i$ ;

$w_f$  is the weight of factor  $f$  (e.g.,  $w_f = 0.25$  for equal weighting);

$D_{i,j}$  is the disparity score between countries  $i$  and  $j$ .

The disparity matrix is designed as a first-order structural screening tool that captures economic complementarities across AI development factors under ceteris paribus conditions. It abstracts from geopolitical, regulatory, and institutional constraints, which are addressed at the interpretation stage rather than being formalized in the metric itself. Importantly, the aggregate disparity score is decomposable into factor-specific gaps, allowing the identification of dominant drivers of potential alliances rather than assuming full substitutability across dimensions. On this basis, alliance configurations may be interpreted in terms of complementarity types: vertical alliances correspond to asymmetric profiles (e.g., countries with strong compute and capital capacities partnering with talent- or data-rich economies), whereas horizontal alliances reflect structurally similar profiles aimed at joint scaling and coordination. The practical feasibility of the identified alliance configurations is conditional on institutional compatibility, regulatory alignment, and external constraints (e.g., sanctions or policy distance), which are not formalised in the metric but act as an exogenous feasibility filter at the implementation stage. Lower values of  $D(i, j)$  indicate greater structural proximity and, consequently, stronger potential for partnership, whereas higher values reflect increasing divergence.

## 2.4 Modeling Scenarios for Asymmetry Reduction

The final stage of the AIRA methodology involves scenario modeling, based on the idea that alliances can reduce inter-country disparities in AI development through shared data centers, talent exchanges, open data repositories, and collaborative investment programs. Following simulation, the AIRA Index is recalculated for participating countries, producing updated estimates of Gini, Theil, and quantile spreads to quantify changes in inequality. This enables AIRA to characterise both the static structure and dynamic evolution of global asymmetries, illustrating how alliance configurations reshape the global AI landscape. The following mathematical model formalizes the extent to which alliances can reduce global asymmetry:

$$I_{i,f}^{new} = I_{i,f} + a_{i,j,f}(I_{j,f} - I_{i,f}) \quad (12)$$

where  $I_{i,f}^{new}$  is the updated value of factor  $f$  for country  $i$  after alliance with country  $j$ ;

$I_{i,f}, I_{j,f}$  are the initial values of factor  $f$  for countries  $i$  and  $j$ ;

$a_{i,j,f}$  is the alliance transfer coefficient,  $0 \leq a_{i,j,f} \leq 1$ , representing the share of the gap that cooperation can close ( $a = 0$  means no transfer;  $a = 1$  means full equalisation).

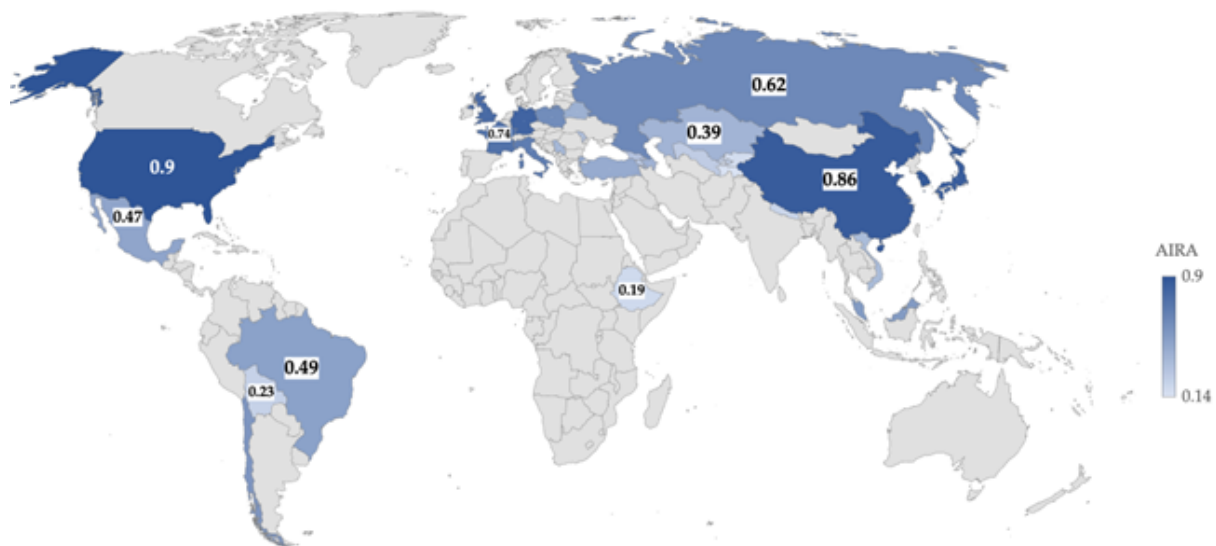
The transfer coefficient  $a(i, j, f)$  is interpreted as a scenario parameter reflecting low, medium, or high cooperation intensity. It is bounded to exclude instantaneous full equalisation. For il-

lustrative purposes,  $a_{(ij, f)}$  is assumed to take values in the range of approximately 0.2–0.6, corresponding to partial gap reduction under alternative cooperation scenarios rather than full convergence. By construction, the model assumes diminishing returns to cooperation because the transfer coefficient is bounded ( $a < 1$ ) and applied to factor-specific gaps, preventing instantaneous or full equalisation of AI capacities within a single scenario. The formulation is intentionally stylised and serves as a comparative scenario device rather than a dynamic forecasting model. After recomputing  $I(i, f)^{new}$ , the updated AIRA Index and inequality metrics are recalculated to model alternative alliance scenarios and evaluate their potential to reduce global AI asymmetry and enhance systemic balance.

### 3. Results and Discussion

The empirical testing of the AIRA methodology was conducted using Belarus as a focal case, given its growing involvement in regional digital cooperation and its intermediary position between technologically advanced and developing economies. The analysis sought to quantify the country's AI development level across four structural dimensions — Compute Divide, Talent Gravity, Data Monopolization, and Capital Cycle — and identify alliance-based pathways for mitigating asymmetry. Empirical calculations were performed on a cross-country dataset covering 8 CIS members, selected 9 OECD economies, and major 3 global AI leaders using internationally comparable data for the 2024 reference year, with Belarus as a representative intermediate case for detailed scenario illustration.

The baseline AIRA index for Belarus was calculated at 0.41, placing it significantly below both the CIS regional average (0.56) and the OECD benchmark (0.80). Figure 1 presents the cross-country distribution of AIRA scores in the analytical sample, which visualizes the spatial concentration of AI ecosystem capacity across countries. The full country-level ranking is reported in Supplementary Material (Table S1).

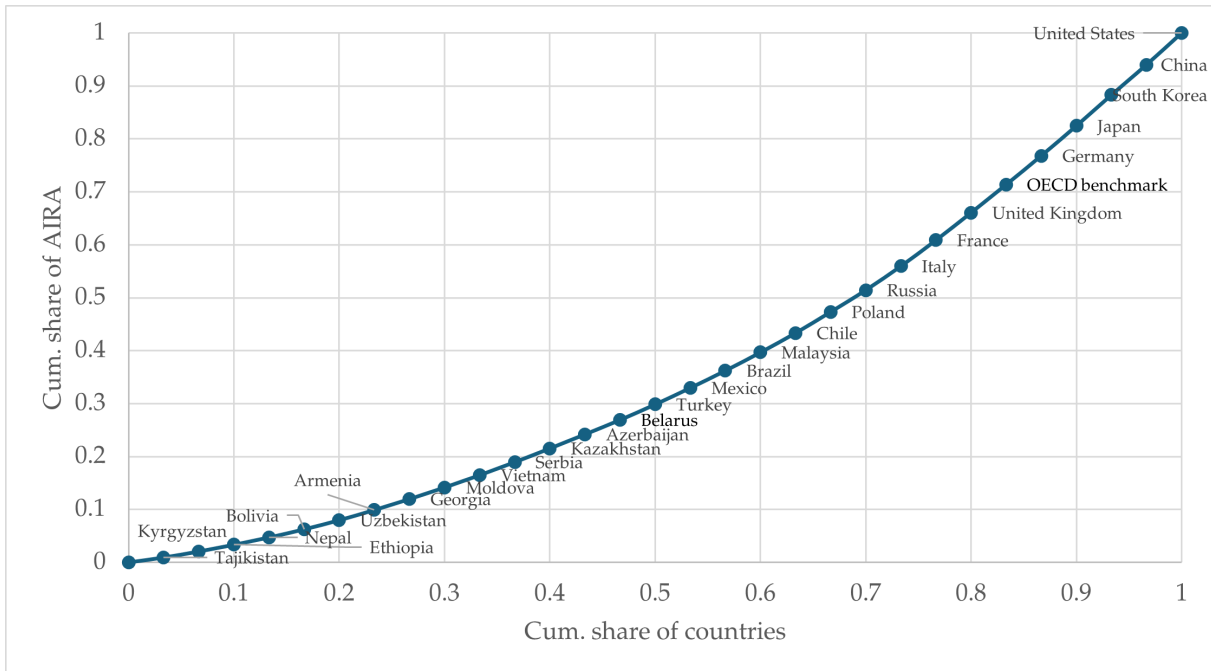


**Figure 1** Cross-country distribution of the AIRA scores

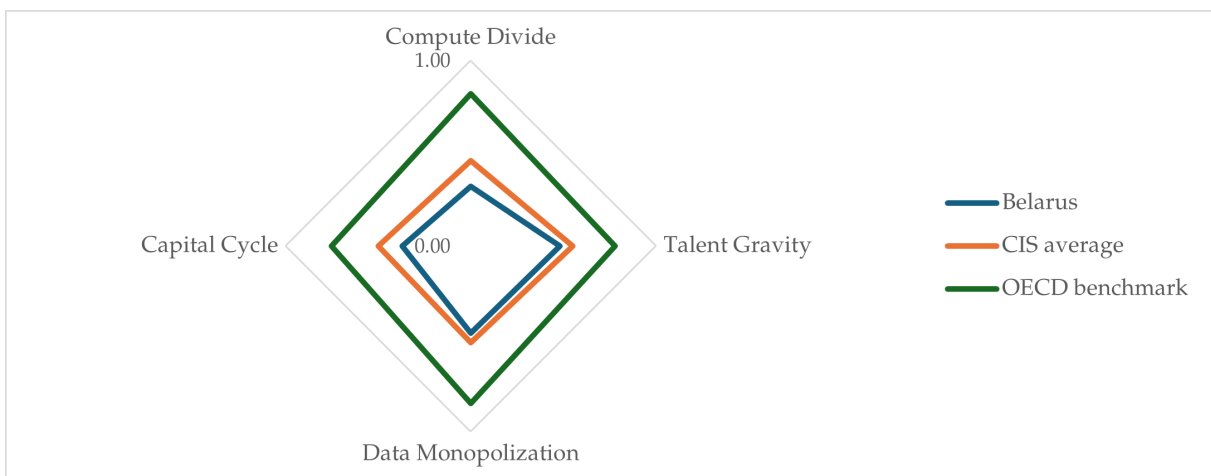
Figure 2 further illustrates this distribution in cumulative form through the Lorenz curve, highlighting the pronounced concentration of AI development capacity in the sample's upper tail. The corresponding values are reported in Table S1 of the Supplementary Material.

For the global baseline distribution, the AIRA-based Gini coefficient equals 0.58, indicating a high concentration of AI development capacity, while the corresponding Theil index equals 0.42, confirming pronounced between-country inequality. Under the vertical alliance scenario, the global Gini declines to 0.51 and the Theil index to 0.34, reflecting a measurable reduction in structural asymmetry. The decomposition of this value by factors revealed pronounced dispari-

ties in computing power (subindex 0.32) and capital availability (0.37), whereas the dimensions of talent (0.48) and data (0.47) were relatively more balanced. Figure 3 further illustrates this factor imbalance, which compares the four AIRA subindices for Belarus with the CIS average and the OECD benchmark.



**Figure 2** Lorenz curve of the AIRA distribution across countries



**Figure 3** Factor Structure of the AIRA Index: Belarus, CIS Average, and OECD Benchmark

These findings indicate that Belarus’s AI ecosystem is primarily constrained by infrastructure and investment gaps rather than human or informational capacity. This configuration is consistent with the structural profile of intermediate AI economies, where human capital formation outperforms infrastructure and investment capacity. Based on the disparity matrix, Belarus’s potential alliances cluster into three analytically distinct configurations: regional partnerships within the CIS, vertical integration with global AI leaders, and expansionary South–South cooperation with developing economies, each driven by different factor-wise complementarities and convergence mechanisms.

### 3.1 Regional alliances within the Central Asian nation

Inter-country comparisons within the Commonwealth of Independent States identified three distinct groups of potential partnerships based on complementarity profiles. The Belarus–Russia pair exhibited the largest structural disparity, with an aggregate difference of 0.21, mainly driven by a 42% gap in computing resources and a 38% gap in capital mobilization. Under a moderate cooperation intensity ( $a^{BY,RU} = 0.4$ ), the simulation demonstrated an 8% improvement in the overall AIRA score of Belarus, reaching 0.44. The corresponding inequality measures for the CIS cluster improved measurably: the Gini coefficient decreased from 0.31 to 0.27, whereas the Theil index fell from 0.19 to 0.15, indicating a tangible but limited convergence effect within the region. The Belarus–Kazakhstan disparity score was only 0.12, indicating structural proximity and high potential for horizontal cooperation. Under a stronger transfer coefficient ( $a^{BY,KZ} = 0.5$ ), the TGF increased by 11%, reflecting the gains from personnel mobility and shared academic programs. The overall intra-CIS variance decreased by 6%, confirming that horizontal partnerships can foster resilience and incremental convergence among mid-level economies. Alliances with Uzbekistan ( $D^{BY,UZ} = 0.17$ ) and Armenia ( $D^{BY,AM} = 0.14$ ) revealed complementary patterns: Belarus demonstrated relative strengths in computing and capital, while its partners contributed human capital and expanded digital markets. In simulated cooperation scenarios, these alliances produced an average improvement of 5%–7% in the AIRA composite index of the participating countries, coupled with reduced dependence on foreign AI technologies and services. Overall, the CIS-level modeling suggests [Trinka1.1] that regional cooperation primarily serves as a stabilizing mechanism, reinforcing internal capacity and diminishing the risk of technological isolation, even though its global equalizing impact remains modest. In these cases, convergence effects are primarily driven by factor-specific complementarities rather than full-spectrum equalisation across all AI dimensions.

### 3.2 Vertical alliances with global leaders

Beyond the regional context, the analysis explored Belarus's potential integration with global AI leaders — notably the United States, China, and the European Union — where the asymmetry is much deeper but the potential convergence effect is more pronounced. The Belarus–US pair displayed the most substantial overall disparity ( $D^{BY,US} = 0.49$ ), with Belarus lagging in all four dimensions. Even with a conservative alliance transfer coefficient ( $a^{BY,US} = 0.3$ ), the model projected a significant rise in Belarus's AIRA index—from 0.41 to 0.55. At the global level, this partnership scenario resulted in a decline in the Gini coefficient from 0.58 to 0.51, reflecting a 12% reduction in global AI asymmetry. The largest improvements occurred in the Compute Divide (+0.16) and Talent Gravity (+0.09) subindices, which were attributed to technology transfer, cloud infrastructure access, and joint professional training initiatives. A Belarus–China alliance ( $D^{BY,CN} = 0.43$ ) produced similar results, although with a distinct emphasis on data and industrial AI deployment. The data monopolization index for Belarus improved from 0.47 to 0.61, while China benefited from more cost-effective implementation in local markets. These outcomes underline the bidirectional nature of such partnerships—combining synergies between technological assistance and market access. Engagement with EU member states ( $D^{BY,EU} = 0.39$ ) showed potential for sectoral integration. Under a moderate cooperation assumption ( $a^{BY,EU} = 0.25$ ), Belarus's Capital Cycle subindex rose by 12%, reflecting increased investment flows, while European partners benefited from lower operational costs and an expanded talent pipeline. The cumulative modeling results for vertical alliances demonstrate that these partnerships can substantially narrow global disparities while simultaneously reinforcing Belarus's domestic AI capacity. This outcome validates the hypothesis that global asymmetry can be mitigated through targeted integration between developed and intermediate economies rather than through isolated capacity-building efforts. These effects should be interpreted as medium-term convergence potentials under sustained cooperation rather than as short-term or automatic outcomes.

### 3.3 Expansionary South–South Alliances

In the third type of alliance, South–South cooperation, Belarus functions as a donor of expertise and technological resources to developing economies in Central Asia, Africa, and Latin America. In these cases, the disparity index was averaged ( $D^{BY,AFR} = 0.29$ ), with a transfer coefficient ( $a^{BY,AFR} = 0.35$ ). Simulation results showed that resource transfer—primarily in the form of training programs, computing access, and advisory services—generated an average increase of 0.06 in the AIRA index of recipient countries. Although these alliances had a negligible impact on Belarus’s position (an improvement of roughly 4%–5%), they enhanced its strategic standing as a regional technology intermediary and contributor to digital capacity-building across the Global South. This configuration emphasizes the systemic interdependence of AI development: by expanding the number of active innovation participants, improvements in peripheral economies reduce the global asymmetry indirectly. Hence, while the immediate gains for Belarus are moderate, the broader benefits include expanded economic influence and enhanced participation in multilateral frameworks. From a systemic perspective, such alliances indirectly reduce asymmetry by expanding the global base of AI-capable economies. Table 3 summarizes the top-ranked alliance candidates for Belarus identified by the AIRA disparity matrix, reporting their disparity scores, dominant factor-wise gaps, assumed cooperation intensity, and the resulting changes in the AIRA index under alternative alliance configurations.

**Table 3** Top candidate alliances for Belarus based on the AIRA disparity matrix.

Alliance type	Partner country/group	country	D score	Dominant factor gaps	Assumed $a$	Predicted AIRA change
CIS (regional, vertical)	Russia		0.21	Compute, Capital	0.40	+8% (0.41 → 0.44)
CIS (regional, horizontal)	Kazakhstan		0.12	Talent	0.50	+6%
Vertical (global)	United States		0.49	Compute, Talent	0.30	+34% (0.41 → 0.55)
Vertical (global)	China		0.43	Data, Compute	0.30	+10%
South–South (expansionary)	Developing economies (Central Asia, Africa, and Latin America)		0.29 (avg.)	Talent and cost-efficient deployment	0.35	+4–5% (Belarus); +0.06 for partners

### 3.4 A Comparative Scenario Analysis

To summarize the quantitative findings, three primary alliance types were evaluated—CIS regional, global vertical, and South–South expansionary. Their comparative metrics are presented in Table 4.

**Table 4** Comparative effects of alliance scenarios on AI asymmetry reduction (Belarus case study).

Scenario Type	Average Disparity (D)	Transfer coefficient ( $a$ )	Gini (Before)	Gini (After)	Avg. Belarus AIRA	Change (%)
CIS Regional	0.16	0.45	0.31	0.27	0.44	+7.3%
Global Vertical	0.44	0.30	0.58	0.51	0.55	+34.1%
South–South	0.29	0.35	0.52	0.48	0.43	+4.9%

The reported indicators summarize shifts in the overall distribution of AI capacity across countries rather than changes in bilateral positions. These results provide several key insights. First, vertical alliances yield the strongest reduction in asymmetry, achieving an average Gini

decline of 0.07 and an increase of over 30% in the Belarus AIRA index. Second, horizontal partnerships within the CIS exhibit limited but stable convergence potential, thereby reducing intra-bloc inequality and enhancing regional resilience. Finally, although South–South cooperation is less transformative in quantitative terms, it contributes to long-term structural balance and international recognition through technology diffusion and human capital transfer.

### 3.5 Interpretation and implications

Scenario modeling confirms the AIRA framework’s analytical robustness and policy relevance. By combining multi-factor index construction, inequality measurement, and scenario-based simulation, the methodology transcends descriptive diagnostics and enables a quantitative evaluation of alliance efficiency. The results indicate the relative effectiveness of a hybrid integration strategy combining regional, vertical, and expansionary alliances from an analytical standpoint:

1. Engage in regional horizontal cooperation within the CIS to stabilize its technological base;
2. Pursuing selective vertical alliances with global leaders to accelerate convergence and attract investment.
3. Expanding targeted South–South partnerships to export AI-related knowledge and services.

Thus, the findings reaffirm that addressing AI asymmetry requires multi-level integration—simultaneously national, regional, and global. The AIRA framework’s practical contribution lies in its capacity to quantify these interactions and forecast the structural effects of cooperative strategies on the evolving geography of the global AI economy.

## 4. Conclusions

In conclusion, the AIRA methodology provides a comprehensive and empirically grounded analytical framework for diagnosing, quantifying, and mitigating asymmetries in the development of global AI. By integrating a multidimensional index of AI ecosystem factors with established measures of economic inequality and scenario-based alliance modeling, it converts abstract notions of the “digital divide” into a rigorous analytical and policy instrument. The Belarus case study demonstrates the model’s applicability and explanatory depth, revealing that differentiated alliance strategies — vertical with global technology leaders, horizontal within regional blocs, and expansionary toward developing economies — can jointly foster technological convergence and systemic resilience. Simultaneously, the case should be interpreted as illustrative of an intermediate AI economy rather than as a universally representative benchmark. AIRA functions as a decision-support mechanism, offering governments and international organizations a structured analytical basis for evaluating cooperative strategies, comparing investment priorities, and assessing potential macroeconomic effects of AI-driven globalization. From a broader perspective, it emphasizes that narrowing AI asymmetry is not only a technological challenge but also an economic and geopolitical priority that determines future growth’s inclusiveness and sustainability. Subsequent research may expand the framework through dynamic data integration, including multi-period modelling over medium-term horizons (e.g., 5–10 years), cross-sectoral calibration, and empirical testing in varied regional contexts, thereby enhancing its predictive capacity, scenario realism, and policy utility.

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### Author Contributions

Conceptualization, methodology and writing, Vladimir Glukhov, Aleksandr Babkin, Elena Shkarupeta and Tatyana Belyatskaya; formal analysis, Tatyana Belyatskaya and Michael Kozukov; data curation, Elena Shkarupeta and Kaxramon Mambetjanov; review and editing, Elena Shkarupeta; supervision, Aleksandr Babkin. All authors have read and agreed to the published version of the manuscript.

### Conflict of Interest

The authors declare no conflicts of interest.

### Declaration of AI

AI tools (ChatGPT, GPT-5.4) were used solely to improve the English language quality of the manuscript and to ensure consistency in reference formatting and citation style. These tools did not contribute to the generation of original scientific content, data analysis, interpretation of results, or conceptual development. The authors take full responsibility for the accuracy, originality, and integrity of all scholarly content presented in the paper.

### Supplementary Materials

Supplementary file where the upload is on the website.

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