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Beyond the AI divide: A straightforward approach to identifying global and local overperformers in AI preparedness

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ABSTRACT

This study introduces a straightforward data-driven framework to identify countries that outperform in artificial intelligence (AI) preparedness relative to their economic complexity, utilizing the IMF's Artificial Intelligence Preparedness Index and a multidimensional Economic Complexity Index derived from trade and research data. Employing weighted least squares, the study estimates expected AIPI scores and classifies countries as global or local overperformers if their observed scores exceed predictions and surpass income-group medians. The analysis identifies 10 high-income global overperformers and 14 local overperformers across middle- and low-income groups, revealing regulation and ethics as universal drivers of overperformance, with digital infrastructure and human capital varying by economic context. Case studies elucidate diverse coordination models—state-led, market-responsive, and distributed innovation—while highlighting transferability constraints due to institutional and historical factors, among others. The replicable methodology provides policymakers and other key actors a robust tool to benchmark AI readiness and design context-specific strategies, addressing the global AI divide. The study opens avenues for future research into refined AI preparedness metrics, alternative identification techniques, and comparative analyses of national innovation systems.

1. Introduction

The transformative potential of artificial intelligence (AI) is reshaping economies, societies, and global competitiveness (Brynjolfsson & Unger, 2023), making its adoption a critical priority for nations worldwide.² The most prominent accounting and consulting firms claim that AI is projected to contribute significantly to the global economy, with estimates ranging from US\$2.6 trillion to US\$4.4 trillion annually (Chui et al., 2023), to US\$15.7 trillion by 2030, driven by productivity and

consumption gains (PwC, 2017). Cockburn et al. (2018) found that AI related to deep learning techniques advances the technology frontier, while Bostrom (2014) anticipates the emergence of an artificial “super-intelligence”, or an artificial general intelligence (AGI) for the foreseeable future. Seminal peer-review articles (Babina et al., 2024; Brynjolfsson et al., 2025; Brynjolfsson & Mitchell, 2017; Liu et al., 2023; Noy & Zhang, 2023) and some other recent NBER publications³ (Acemoglu, 2024; Aghion et al., 2019; Trammell & Korinek, 2023) highlight that AI has the potential to significantly boost productivity and

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² The UN Secretary-General's High-level Advisory Body on Artificial Intelligence (HLAB-AI) has published the final report “*Governing AI for Humanity*,” advocating for the establishment of a globally inclusive and distributed AI institutional framework rooted in international cooperation. The report emphasizes the need for collaboration among governments and stakeholders to ensure AI promotes development while safeguarding human rights (UN HLAB-AI, 2024).

³ National Bureau of Economic Research (NBER) publications, including working papers, are highly regarded as they are produced by leading economists, often serve as precursors to top peer-reviewed journal articles, and are widely cited in academic and policy discussions.

economic growth by automating tasks⁴ and driving innovation. However, the realization of these gains depends on complementary policies, institutions, and societal adaptation to ensure equitable and sustainable outcomes (Korinek, 2024; Korinek & Vipra, 2024). To summarize, AI, and particularly generative AI, has the potential to boost economic growth and productivity but poses risks of labor market disruptions, including premature de-professionalization—where skilled jobs are replaced or diminished before workers can fully capitalize on their expertise—and challenges for emerging markets and developing economies (EMDEs), such as reduced opportunities for high-skill job creation, increased inequality, and difficulties in integrating AI technologies into less-developed industrial and educational systems (Liu, 2024).

Such substantial socio-economic impacts underscore the critical importance for countries to adopt and integrate AI technologies to remain competitive and keep a sovereign public policy.⁵ However, the benefits of AI are not uniformly distributed. The 2023 Government AI Preparedness Index (AIPI) from the International Monetary Fund (IMF) reveals significant disparities in AI preparedness and readiness among nations, highlighting a growing divide between those equipped to leverage AI and those at risk of falling behind (Cazzaniga et al., 2024).⁶ Related to this, Liu and Wang (2024) highlight that middle-income countries exhibit unexpectedly high engagement with generative AI tools relative to their economic scale, while low-income economies are notably underrepresented. In this context, it becomes imperative to identify effective strategies for enhancing a country's AI readiness. This paper aims to explore such strategies, providing a framework for nations to efficiently bolster their AI capabilities and ensure inclusive growth in the evolving digital landscape.

The methodology outlined in this paper is straightforward: it evaluates AI preparedness at the country level using the AIPI and compares it to each country's assessed level of economic complexity. This approach identifies countries that outperform in AI preparedness and readiness relative to their economic complexity for a given income level, aiming to uncover the factors driving their overperformance. Economic complexity refers to the knowledge intensity of an economy, captured by the diversity and sophistication of the goods and services it produces. The Economic Complexity Index (ECI), initially developed by Hidalgo and Hausmann (2009), measures this complexity by analyzing a country's export mix, reflecting its capabilities to produce and export diverse, high-value products. More recently, the ECI expanded to technology, based on patents data, and research, based on research papers (Stojkoski et al., 2023), since official trade data overlook key information about innovative activities, particularly those related to digital technologies (Stojkoski et al., 2024).

Using this methodology, we categorize distinct groups of AI overperformers based on their ECI and their preparedness and readiness levels. Notably, overperformers are not simply the countries with the highest AIPI scores but those that (i) meet a minimum AIPI threshold based on their income levels and (ii) outperform their predicted scores given their economic complexity. Among high-income economies, global overperformers include Australia, Japan, the Netherlands, New Zealand, three of the four Asian Tigers (Hong Kong SAR, China; the

Republic of Korea; Singapore), and Northern European countries such as Denmark, Finland, and Norway—aligning with findings on the long-term determinants of AIPI detailed later. Upper-middle-income local overperformers comprise Albania, China, Costa Rica, Indonesia, Kazakhstan, Malaysia, and Ukraine. Finally, lower-middle- and low-income local overperformers include Ghana, India, Morocco, Rwanda, Sri Lanka, Tunisia, and Viet Nam.

From this list of AI overperformers, we observe that AI regulation and ethics consistently emerge as top drivers of AI preparedness across income groups, emphasizing the universal importance of institutions in managing AI integration. In low- and lower-middle-income countries (LICs/LMICs), regulation and workforce development dominate, reflecting foundational priorities amid resource constraints, while digital infrastructure and innovation receive less emphasis. For upper-middle-income countries (UMICs), regulation and human capital remain critical, but digital infrastructure becomes increasingly significant as technological capacities expand. High-income countries (HICs) prioritize regulation alongside well-established digital infrastructure and innovation systems, supported by advanced workforce readiness strategies.

This progression illustrates how AI preparedness strategies align with the unique capacities and priorities of each income group, offering tailored policy pathways for countries aiming to enhance their AI readiness. By understanding these patterns, policymakers, scholars, international institutions and relevant stakeholders can adopt fitted strategies to develop their countries' AI ecosystems based on their specific economic and institutional contexts and might effectively bridge the gap in the global AI divide.

Then a preliminary qualitative comparative analysis, derived from Nelson's (1993) national innovation systems framework, identifies diverse coordination mechanisms—state-led, market-responsive, and distributed innovation models—that shape effective AI strategies. The analysis also highlights transferability challenges, underscoring how institutional and historical contexts, among others, influence the adaptability of successful AI preparedness approaches.

This study also discusses the limitations of existing AI preparedness indices, including the AIPI, which relies on broad proxies like internet penetration and formal metrics. These measures often fail to capture connectivity quality, informal digital/learning ecosystems, and adaptive regulatory frameworks, particularly in lower-income contexts, necessitating more nuanced and inclusive metrics to accurately assess AI readiness. Some additional extensions (e.g., accounting more directly for collective cognitive abilities) are also proposed.

To summarize the contributions are threefold. First, the paper proposes to advance the understanding of AI preparedness overperformance by proposing a data-driven methodology that integrates the AIPI with a multidimensional ECI, establishing a replicable benchmark for future research. Second, it identifies diverse coordination mechanisms—state-led, market-responsive, and distributed innovation models—that drive effective AI strategies across income groups, through a preliminary qualitative comparative analysis, while highlighting transferability challenges due to specific contexts. Finally, the study critically evaluates the limitations of existing AI preparedness indices, advocating for refined metrics, thereby offering policymakers, as well as other key actors, actionable insights for tailoring AI readiness strategies to diverse economic contexts.

The remainder of the paper is structured as follows. Section II reviews the literature, grounding AI literacy in digital infrastructure, human capital, and regulatory frameworks, and theorizes overperformance through institutional complementarities, path dependency, state capacity, and technology diffusion. Section III describes the data and methodology. Section IV presents the main empirical findings. Section V examines specific drivers of AI preparedness based on case studies, and a preliminary qualitative analysis, as well as transferability challenges. Section VI discusses the limitations of existing AI preparedness indices. Finally, Section VII concludes and suggests avenues

⁴ In a recent meta-analysis, Vaccaro et al. (2024) found that human-AI systems (i.e., complementary rather than full automatized systems) often perform worse than humans alone or AI alone. But the analysis also suggests promising directions for the future development of more effective human-AI systems (e.g., the development of generative AI for creation tasks).

⁵ “The late 2022 launch of GPT-3.5, OpenAI's generative Artificial Intelligence (AI) chatbot, sparked a media frenzy about the onrushing evolution of AI and what it portends for the human race and the planet at large. During the recently concluded Global Digital Summit, World Bank President Ajay Banga observed that ‘even people who are relatively naive about AI are rushing toward AI, because of the fear of being left behind.’” [<https://accountability.worldbank.org/en/news/2024/Developing-AI-for-development>].

⁶ See <https://www.imf.org/external/datamapper/datasets/AIPI>.

for future research on AI preparedness.

2. Literature review

2.1. Foundations of AI literacy

AI preparedness or AI literacy – the ability to understand, use, and critically assess AI systems – builds directly on broader ICT and digital literacies, preparedness, and readiness. In recent work, [Lintner \(2024\)](#) defines AI literacy as “the ability to understand, interact with, and critically evaluate AI systems and AI outputs,” and [Yang et al. \(2025\)](#) emphasize its “interdisciplinary nature,” linking algorithmic reasoning to foundational digital skills. Complementing these perspectives, some empirical studies demonstrate how data and technology competencies vary across firms and organizations. For instance, [Elsaify and Hasan \(2021\)](#) found that a bit less than 17.0 % of the 1285 largest US firms encompassed⁷ participate in inter-firm data exchanges, with participation heavily skewed toward those possessing advanced data capabilities. Likewise, [Ongena \(2023\)](#) operationalizes data literacy as a multidimensional skill set in 120 Dutch governmental agencies and shows that agencies scoring high on data-literacy measures outperform peers in (internal) performance metrics, and enhancing data literacy also affects the fairness of the organization supporting equitable treatment for employees. These findings strongly suggest that building ICT/digital literacy both at the national and organizational levels must address both basic technical skills and the ability to manage and interpret data.

According to the 2025 AI Index Report from Stanford University ([HAI, 2025](#)), a robust digital infrastructure is foundational for AI preparedness. By extension, insufficient internet connectivity (broadband) likewise constrains AI learning and information access in underserved areas, even in high-income countries ([Hunt et al., 2024](#)). In the US, for instance, CS graduates are rising (up 22.0 % over the past decade) reflecting growing interest, but teachers feel unprepared, since nearly 81.0 % of US K–12 CS teachers agree AI should be taught, yet under half feel equipped to teach ([HAI, 2025](#)). Moreover, access to energy remains limited in some EMDEs, especially in sub-Saharan African (SSA) countries, due to basic infrastructure gaps like electricity, due to a lack of physical access, prohibitive energy prices, repeated power outages, or a combination of these factors ([HAI, 2025](#); [World Bank, 2019](#)). This disparity underscores that without reliable power and broadband infrastructure, educational gains cannot fully translate into AI readiness.

Governments are investing heavily in AI infrastructure and capacity ([HAI, 2025](#)).⁸ Even so, infrastructure must keep pace with rapidly rising demand, since AI training compute requirements are doubling roughly every five months (with power use doubling annually). In practice this means building more high-speed data centers and backbone networks. Equitable AI deployment thus depends on “last-mile” connectivity – high-speed broadband and local compute facilities – so that schools and workers everywhere can access AI tools.

Beyond broadband access and data-center capacity, firms also require reliable platforms for AI workloads. For instance, [Sze et al. \(2024\)](#) note in their study of blockchain-metaverse models, based on a content analysis of thirty-two expert reports, that firms need “scalable digital platforms” alongside human competencies to innovate sustainably. This aligns with broader findings that connectivity improvements

⁷ [Elsaify and Hasan \(2021\)](#) encompassed the 1000 largest public US firms and 285 largest private US firms in their study.

⁸ The AI Index Report highlights significant national initiatives since 2024. Notably, Canada announced US\$2.4 billion AI infrastructure package, China launched a US\$47.5 billion semiconductor fund, France committed US\$117 billion to AI infrastructure, India pledged US\$1.25 billion, and Saudi Arabia’s Project Transcendence includes a US\$100.0 billion initiative. Meanwhile, total private AI investment in the US reached US\$109.1 billion in 2024 ([HAI, 2025](#), p. 4, 17, 20).

disproportionately benefit users and firms with existing digital skills, reinforcing the complementarity between infrastructure and ICT/digital literacy.

A dedicated digital education also remains a key enabler of AI preparedness ([HAI, 2025](#)). For example, two-thirds of countries now include equivalent of K–12 computer science (CS) – up from one-third in 2019 – with especially rapid gains in Africa and Latin America. Macroeconomic evidence underscores the role of human capital in technology adoption. [Hjort and Poulsen \(2019\)](#) exploit submarine-cable rollouts in 12 African countries to show that improved connectivity raises firm productivity and incomes, particularly in skill-intensive sectors. At the organizational level, research highlights complementary capabilities: [Mulyana et al. \(2024\)](#) identify several digital transformation dimensions, including “knowledge and capability” and “innovation culture” as ambidextrous mechanisms driving successful digital transformation in Bank Rakyat Indonesia, the oldest commercial bank of Indonesia, showing a performance uplift when these dimensions align. [Heubeck et al. \(2024\)](#) further demonstrate that social capital – trust and shared norms – is necessary to translate ICT awareness into global teamwork effectiveness based on a sample of 271 “technologically sensitive and aware” firms located in Austria, Germany and Switzerland. Together, these studies suggest that a workforce’s ICT/digital literacy requires not only formal education and training but also organizational cultures and networks that enable skill deployment.

Regulatory activity on AI surged in recent years ([HAI, 2025](#)). US agencies introduced 59 new AI-related rules in 2024 (more than double 2023) and mentions of AI in legislation jumped 21.3 % across 75 countries (ninefold since 2016). Concurrently, multilateral bodies like the African Union, European Union (EU), Organization for Economic Cooperation and Development (OECD), and United Nations (UN) released new AI institutional frameworks emphasizing transparency and trust, and several countries pledged international AI “safety institutes” at global summits in 2023–24. These national strategies and global partnerships are designed to build AI capacity and establish guardrails for responsible use. However, due to uneven resources and fragmented regulations, AI preparedness and equitable deployment are likely to evolve at different paces across various regions and countries.

Regulatory clarity and institutional frameworks likely shape AI adoption, and more generally digital transformation. [Sze et al. \(2024\)](#) embed ethical considerations—such as transparency and stakeholder accountability—within sustainable innovation strategies, underscoring how key principles filter into firm behavior and education programs.⁹

Based on the literature, a rigorous national AI preparedness strategy must build upon well-rounded ICT/digital literacy as the foundation for AI literacy. Empirical and theoretical studies converge on three pillars:

1. Digital infrastructure: powerful data centers and cloud services, reliable, high-speed connectivity and platforms for AI deployment.
2. Human capital: robust education systems and organizational practices that cultivate data and AI skills.
3. Institutions & regulations: adaptive legal frameworks and ethical guidelines that guide AI adoption.

Composite indicators such as the IMF’s AIPI aims to synthesize these pillars into actionable insights. By targeting investments where AIPI reveals weaknesses—whether in education, infrastructure, or regulatory adaptability—governments can foster a population equipped to adopt, manage, and benefit from AI. Innovation, such as research and development (R&D) in deep learning, along with economic integration through substantial investments and global collaboration, constitutes a distinct pillar in the AIPI. However, according to the literature, these

⁹ Furthermore, [Ongena’s](#) work suggests that Dutch government agencies with high data-literacy practices often exhibit better policy implementation, hinting at a feedback loop between IT literacy and institutional quality ([Ongena, 2023](#)).

aspects seem to be more crucial for AI development and leadership in technology than for AI preparedness per se (Cockburn et al., 2018; HAI, 2025).¹⁰

2.2. The concept and potential drivers of overperformance

The concept of overperformance used in this paper is likely closely link to the established concept of economic complexity. Initially developed by Hidalgo and Hausmann (2009), their article provides a quantitative framework for assessing a country's productive capabilities through the lens of its export basket. The original ECI is then constructed using international trade data, linking countries to the products they export competitively.¹¹ Accordingly, high ECI score—characteristic of nations like Japan or Switzerland—indicates a diverse portfolio of sophisticated, non-ubiquitous products, signaling advanced technological and institutional capabilities. As aforementioned, the ECI expanded recently to technology, based on patents data, and research, based on research papers (Stojkoski et al., 2023), since trade data can miss key information about innovative activities.¹² This is particularly relevant for digital-related activities, which are often overlooked in official statistics (Stojkoski et al., 2024). In essence, the multidimensional ECI aims to capture a country's ability to compete, including the digital frontier.

Thus, the multidimensional ECI is a powerful measure of national “know-how” (Hidalgo, 2015), encapsulating the collective skills, infrastructure, and organizational capacity required to produce complex goods and services.¹³ It reflects the tacit knowledge and institutional quality embedded in a country's economy, offering a holistic proxy for its capacity to innovate and adapt across domains, including digital activities, especially its augmented version (Stojkoski et al., 2023).

As a result, a positive correlation between economic complexity and AI preparedness is anticipated. Indeed, countries with elevated ECI scores are well-positioned to leverage their existing knowledge networks for AI development and deployment, as these networks support both the creation and application of cutting-edge technologies. This correlative approach has also been adopted in the most recent Human Development Report dedicated to “People and Possibilities in the Age of AI” (UNDP, 2025).¹⁴

In this context, overperformance in AI preparedness is empirically captured when a country's AIPI (or equivalent index) score surpasses what its ECI would predict, often assessed via regression analysis. This gap suggests that some nations achieve AI readiness levels that exceed their baseline economic complexity through targeted policies or

¹⁰ For instance, a 142-fold reduction in model size achieving high performance, exemplified by Microsoft's Phi-3-mini, which, with only 3.8 billion parameters, matches the performance of Google's PaLM (540 billion parameters) on the Massive Multitask Language Understanding (MMLU) benchmark between 2022 and 24 (HAI, 2025, p. 15). This efficiency gain reflects the power of R&D in creating more scalable AI technologies. Additionally, new reasoning paradigms, such as OpenAI's o1 model, which scored 74.4 % on the International Mathematical Olympiad (IMO) compared to GPT-4o's 9.3 %, illustrate how innovation drives performance improvements (HAI, 2025, p. 15). However, this enhanced reasoning capability comes at a cost: the o1 model is nearly six times more expensive and 30 times slower than GPT-4o (HAI, 2025, p. 14). This aligns with the rapidly growing digital infrastructure needs mentioned earlier.

¹¹ The index captures two key dimensions, namely the diversity of a country's exports and the ubiquity of those products, where ubiquity reflects how many other countries export the same goods.

¹² Moreover, trade-based metrics of complexity can systematically underestimate the complexity of economies that are distant from global markets (Stojkoski et al., 2023).

¹³ For example, manufacturing a precision instrument demands not only technical expertise but also robust supply chains, a skilled labor force, and regulatory stability.

¹⁴ More specifically UNDP (2025, p. 185).

investments.

That said, the concept of overperformance in AI preparedness requires theoretical grounding that explains why certain countries systematically exceed expectations based on their underlying economic complexity. This phenomenon can be possibly understood through the lens of institutional complementarities and strategic policy coordination, drawing insights from comparative political economy and innovation systems literature.

Economic complexity measurement, as developed by Hidalgo and Hausmann (2009) and extended by Stojkoski et al. (2023) provides a baseline measure of national productive capabilities as described above. However, while comparing AI preparedness to a multidimensional ECI is useful for identifying potential overperformers as discussed in the rest of the paper, it does not, in itself, explain why certain countries might overperform. This calls for further elaboration on the potential theoretical foundations underlying such overperformance.

The theoretical explanation for overperformance likely lies in what may be termed “strategic capability building”—deliberate policy interventions that create complementarities between existing knowledge stocks and emerging technological opportunities. This concept builds upon the national innovation systems framework (Lundvall, 1992; Nelson, 1993), which highlights how the state and other key actors—such as citizens and national organizations—including private operators, state-owned enterprises (SOEs), universities and governmental agencies—interact within specific institutional arrangements, firm strategies, and knowledge infrastructures to generate technological capabilities that exceed the sum of their individual parts (Fagerberg et al., 2010).

Path dependency mechanisms might provide additional theoretical insight into overperformance patterns (David, 1985). Countries may achieve AI preparedness levels beyond their economic complexity through historical investments in complementary technologies or institutional arrangements that prove unexpectedly valuable for AI deployment. For instance, nations with early investments in digital government services or telecommunications infrastructure (e.g., Kazakhstan, Singapore) may find these legacy systems provide platforms for AI integration that newer, more complex economies lack.

State capacity theory offers another lens for understanding overperformance, particularly the role of policy coordination and implementation effectiveness. Countries with strong administrative capabilities may achieve disproportionate returns on AI investments through superior policy design, inter-agency coordination, and adaptive implementation mechanisms. This perspective draws from Acemoglu and Robinson's (2012) work on institutional quality,¹⁵ suggesting that better administrative and institutional effectiveness can either enhance existing economic sophistication (e.g., Denmark, Singapore) or partially offset its limitations (e.g., Rwanda).

Technology diffusion theory (Rogers, 2003) suggests that overperformance may also result from optimal positioning within global knowledge networks. Countries that serve as bridges between advanced AI developers and emerging markets may acquire capabilities through knowledge spillovers and collaborative arrangements that exceed their domestic innovation capacity (e.g., Malaysia, Singapore). This

¹⁵ More precisely, Acemoglu and Robinson (2012) emphasize the central role of both inclusive political and economic institutions in fostering development. Inclusive political institutions distribute power broadly across society and place constraints on executive authority through mechanisms such as regular elections, checks and balances, and the rule of law. Inclusive economic institutions, in turn, protect property rights, enforce contracts, promote fair competition, and support open markets and innovation. That said, it seems that political institutions that fundamentally promote accountability and ensure that elites have skin in the game, alongside economic institutions that fundamentally encourage sound management and the efficient allocation of productive resources, might be actually key drivers of development.

mechanism might explain how smaller economies with limited research infrastructure (e.g., Rwanda) can achieve high AI preparedness through strategic international partnerships and selective technology adoption.

The interaction between these theoretical mechanisms suggests that overperformance in AI preparedness likely emerges from deliberate policy strategies that create synergies between the state and other key actors. Countries achieving such overperformance would typically exhibit coordination across these actors, generating multiplicative effects on technological capabilities that exceed what would be predicted from a multidimensional ECI.

2.3. Data and methodology

2.3.1. Data

The AIPI serves as our main output of interest and is designed by the IMF to assess the readiness of 174 countries to adopt and integrate AI technologies as of 2023 (Cazzaniga et al., 2024). It is built around four core pillars that are deemed essential for smooth AI adoption: (i) digital infrastructure, (ii) human capital and labor market policies, (iii) innovation and economic integration, and (iv) regulation and ethics. Each dimension is calculated by averaging a set of normalized sub-indicators that capture specific aspects relevant to AI readiness, such as internet penetration (pillar i), science, technology, engineering, and mathematics (STEM) education (pillar ii), R&D investment (pillar iii), and adaptable legal frameworks (pillar iv).¹⁶ The global AIPI index, scaled from 0 to 1, combines these four pillars, each contributing up to 0.25. Higher scores indicate greater AI preparedness, providing stakeholders with a benchmark for identifying areas needing improvement to enhance AI integration across economies. The AIPI focuses on AI adoption preparedness rather than invention and technology leadership—dominated by China and the United States, as highlighted in both the AI Index Report (HAI, 2025),¹⁷ and the “Draghi Report” (European Commission, 2024)¹⁸—thereby enabling a comparative assessment of preparedness levels across all economies.

The AIPI distribution (Fig. 1) reveals substantial disparities in AI preparedness and readiness across nations. Research underscores that AI readiness is influenced by a country’s economic structure, infrastructure, and policy environment. For example, Liu and Wang (2024) find strong correlations between income level, digital infrastructure, and human capital with AI uptake, with higher-income nations demonstrating more advanced AI ecosystems.¹⁹ These findings align with growing evidence of a widening divide between countries equipped to leverage AI and those at risk of being left behind (Cazzaniga et al., 2024).

A methodological decision in this study is the choice of the recent AIPI from the IMF over the AI Readiness Index developed by the private UK-based consulting firm Oxford Insights, or the Network Readiness Index developed by the private DC-based Portulans Institute.²⁰ This decision is primarily driven by the IMF’s reputation as a globally recognized multilateral institution and supposed to be accountable,

¹⁶ More details here: <https://www.imf.org/external/datamapper/AIPINote.pdf>.

¹⁷ In 2024, US-based institutions produced 40 notable AI models, significantly outpacing China’s 15 and Europe’s three. While the US maintains its lead in quantity, Chinese models have rapidly closed the quality gap: performance differences on major benchmarks such as MMLU and HumanEval shrank from double digits in 2023 to near parity in 2024. Meanwhile, China continues to lead in AI publications and patents (HAI, 2025, p. 3).

¹⁸ European Commission (2024, Fig. 2 p. 36).

¹⁹ Additionally, Liu and Wang (2024) show that countries with high English proficiency and a specialization in digitally tradable services have shown higher adoption rates, underscoring the importance of digital connectivity and linguistic compatibility with generative AI tools.

²⁰ See <https://staging2.oxfordinsights.com/ai-readiness/>, and <https://networkreadinessindex.org/>.

which ensures greater scrutiny and transparency in the development of its products. In contrast, the outputs of private entities like Oxford Insights or Portulans Institute, though valuable, do not operate within the same level of oversight or accountability. Furthermore, the AI Readiness Index is explicitly designed to assess the extent to which governments are prepared to deploy AI in public service delivery.²¹ In contrast, the AIPI aims to focus on a more comprehensive evaluation of how countries can harness AI capabilities effectively.²² That said, the choice of index does not significantly impact a broader contribution of this study, which is a proposed methodology aimed at being adaptable and replicable.

To measure the economic complexity of each country, we consider ECIs for trade, technology, and research available on the Observatory of Economic Complexity (OEC) website.²³ However, since the ECI for technology, derived from patent data, is available for fewer countries (90 compared to 133 for ECI trade and 130 for ECI research), we perform a Principal Component Analysis (PCA) using only ECI trade and ECI research for 2021–22. PCA is used here to extract the main underlying patterns across both standardized ECI,²⁴ helping to identify similarities among countries in terms of AI preparedness. PCA reduces the complexity of the data by summarizing it into a few key dimensions that explain most of the variation. The first principal component, which explains over 50 % of the variance, is used here to represent the multidimensional economic complexity of each country. The component is then normalized and scaled between 0 and 1 across the sample of countries. Such ex-post procedure does not affect the underlying structure but ensures the resulting index is on a common, intuitive scale, comparable to the AIPI.

As highlighted by Hidalgo (2023), ECI offers valuable insights into a country’s productive capabilities by analyzing the diversity and sophistication of its exports, and by extension, its academic research. The paper demonstrates how metrics derived from ECI, such as relatedness and complexity, can guide industrial policies and diversification strategies, positioning ECI as a critical tool for identifying opportunities for structural transformation and economic upgrading. As aforementioned in the previous section, ECI’s relevance logically extends to capturing ability to adopt cutting-edge technology, such as AI preparedness and readiness, as it reflects a country’s knowledge intensity, innovation capacity, and productive capabilities, or, simply speaking, a national “know-how” (Hidalgo, 2015). Higher ECI scores suggest that economies are better equipped to adopt advanced technologies like AI due to their diversified industrial base, robust infrastructure and a skilled workforce.

Finally, the income levels of countries are classified using the World Bank’s Atlas Method, incorporating updated income classifications for FY25 based on 2023 GNI per capita data.²⁵ This classification is crucial for distinguishing between global AI overperformers, likely concentrated among HICs, and local overperformers within LICs, LMICs, and UMICs.

2.3.2. Methodology

To identify AI global and local overperformers, we adopt a two-step

²¹ Ibid.

²² The Network Readiness Index also has a broader scope, similar to the AIPI, but it doesn’t focus on AI preparedness per se. Instead, it aims to emphasize the adoption of general ICT solutions (<https://networkreadinessindex.org/>).

²³ See <https://oec.world/en/rankings/eci/hs6/hs96?tab=ranking>.

²⁴ Standardizing the inputs before applying PCA is crucial, as it ensures that each ECI contributes equally to the analysis. This prevents variables with larger scales from disproportionately influencing the results and distorting the underlying patterns.

²⁵ See <https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025>.

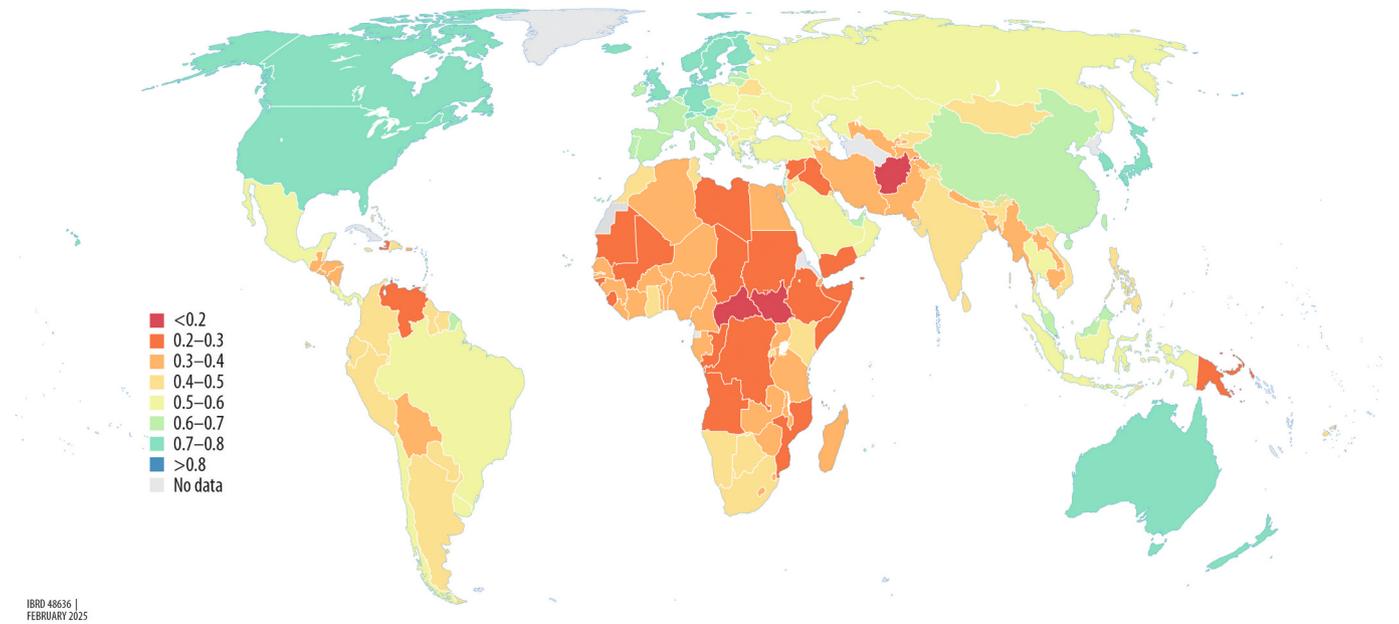


Fig. 1. Global distribution of AIPI (2023). Source: IMF, AIPI data mapper [https://www.imf.org/external/datamapper/AI_PI@AIPI/ADVEC/EME/LIC]. Notes: The map is checked and validated by the World Bank Cartography Unit as of February 02, 2025.

approach: (i) identifying countries with AIPI scores above the weighted median and average scores of their respective income groups,²⁶ and (ii) determining those with AIPI scores exceeding their predicted values based on their economic complexity. Formally, a weighted least square (WLS) approach is considered:

$$AIPI_i = \alpha + \beta ECI_i + \varepsilon_i, \tag{1}$$

where : $\min_{\alpha, \beta} P_i (AIPI_i - (\alpha + \beta ECI_i))^2$ (2)

$$\widehat{AIPI}_i = \widehat{\alpha} + \widehat{\beta} ECI_i \tag{3}$$

The \widehat{AIPI} index for country i is then predicted by an intercept $\widehat{\alpha}$, and the first component of the ECI on trade and research $\widehat{\beta}$, weighted by the population size of each country.²⁷ Such weighting is crucial to ensure the real-world representativeness of AI preparedness and economic complexity index scores.²⁸ The ex-ante idiosyncratic error term (ε_i) or ex-post residual term ($\widehat{\varepsilon}_i$) captures respectively the theoretical and actual gap between observed $AIPI$ and predicted \widehat{AIPI} scores. Accordingly, a country is classified as an overperformer if:

$$\begin{cases} AIPI_i > \widehat{AIPI}_i, \text{ or } \widehat{\varepsilon}_i > 0 \\ AIPI_i > AIPI_{i,threshold} \end{cases} \tag{4}$$

where $AIPI_{i,threshold}$ indicates the relevant average and median AIPI score for country i for relevant income categories.

²⁶ Average and median scores for income groups are calculated using population size for 2023 (“SP.POP.TOTL”), sourced from the World Bank’s open data via the “wbopendata” module in Stata (Azevedo, 2020). Population data for Taiwan, China, is retrieved from the Statista website [https://www.statista.com/statistics/319793/taiwan-population/].

²⁷ This parsimonious linear specification, based on a multidimensional ECI and estimated via WLS, offers a transparent and tractable benchmark for identifying overperformance. It avoids overfitting while preserving interpretability, enabling meaningful cross-country comparisons. Moreover, it serves as a baseline from which future studies can build or diverge to explore more complex modeling choices.

²⁸ Unweighted ordinary least squares (OLS) estimates do not alter the classification of overperforming countries at global level as highlighted hereafter.

3. Empirical findings

3.1. Global overperformers

The analysis of the two charts below, one unweighted and the other weighted by population size, reveals important insights about the relationship between the AIPI and the ECI trade, research composite obtained from 125 matching countries at a global level (Fig. 2).²⁹ The unweighted approach is used solely in Fig. 2a to provide a benchmark and ensure consistency with the regular population-weighted approach used throughout the rest of the paper. A strong relationship emerges between AIPI and ECI, with R^2 values of 0.79 (unweighted) and 0.70 (weighted), indicating that approximately three-quarters of the variance in AIPI is explained by the variance in ECI, and vice versa. The partial correlations (r) of 0.89 (unweighted) and 0.84 (weighted) further indicate a very high positive linear correlation, and it is statically significant at 0.1 %. These results highlight the strong (and expected) link between economic complexity and AI preparedness, demonstrating that greater economic sophistication—reflected in the diversity and complexity of exports and research output—significantly enhances a country’s capacity to adopt and integrate AI technologies effectively, irrespective of population weighting.

Both charts highlight the top performers in AI preparedness, concentrated in the northeast quadrants. Consistent with Bayesian model averaging (BMA) findings in the Appendix and the critical role of initial conditions in AI readiness, these top performers are exclusively HICs.³⁰ To identify global overperformers within this group, we focus on countries with an observed AIPI score exceeding 0.7—corresponding to the population-weighted average and median AIPI scores for HICs (rounded to one decimal)—and surpassing their predicted AIPI score (i. e., above the linear fit line) given their level of trade and research economic complexity. These 10 overperformers, marked in yellow, include Australia, Japan, the Netherlands, New Zealand, three of the four Asian

²⁹ All scatter plots benefit from the “white_cividis” scheme from Naqvi (2022).

³⁰ The Appendix discuss and leverages the BMA to explore a wide range of possible long-term factors that could be linked to AI preparedness. The goal is not to recommend specific policies, but to highlight general patterns and relationships that emerge from the data.xxx

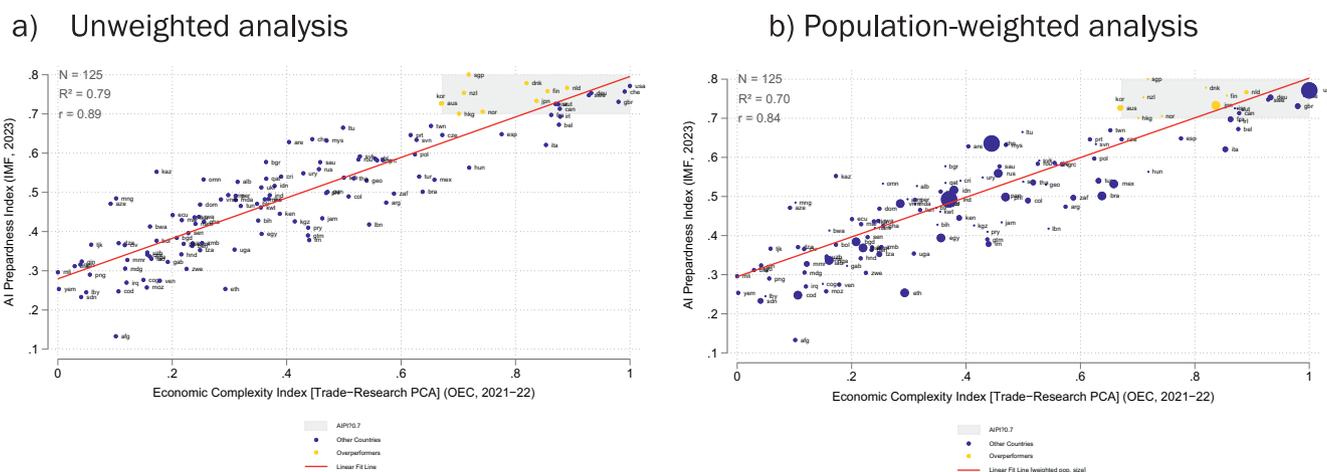


Fig. 2. Global relationship between AIPI and ECI. **Source:** The AIPI score for 2023 is obtained from the IMF website [https://www.imf.org/external/datamapper/datasets/AIPI] and the ECI on trade and research for 2021–22 are obtained from the OEC website [https://oec.world/en/rankings/eci/hs6/hs96?tab=ranking]. **Notes:** The first principal component (PCA) of ECI trade and ECI research, with an eigenvalue exceeding 50 %, is used to capture the multidimensional aspects of national economic complexity. Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020), with data for Taiwan Province of China obtained from the Statista website. All countries with an observed AIPI score exceeding 0.7 (the weighted average and median score for HICs) are highlighted in the grey quadrant. Among these, only countries with AIPI scores surpassing their predicted values (above the linear fit line) are marked in yellow and identified as global overperformers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Tigers (Hong Kong SAR, China; the Republic of Korea; Singapore), as well as Northern European countries such as Denmark, Finland, and Norway.³¹ Their observed AIPI scores are statistically significantly above their predicted scores (at 0.1 % threshold). The relative prominence of East Asian economies, particularly the three recently developed Asian Tigers and particularly Singapore—ranked #1 in observed AIPI score for 2023, much above its predicted score—aligns with BMA findings in the Appendix, which underscore the significant influence of “Confucian cultural values” on AI preparedness. By contrast, other HICs with strong AIPI scores, such as the United States and Switzerland, do not qualify as overperformers. This is because their observed AIPI scores align with the predictions based on their high levels of economic complexity rather than exceeding them. Additionally, the largest economies, like the United States, may face challenges in scaling top-level AI implementation uniformly across regions (Hunt et al., 2024).

3.2. Local overperformers

Fig. 3, weighted by population size, demonstrates a positive but more moderate (yet still economically significant) correlation between AIPI and multidimensional economic complexity for the subgroup of 69 LMICs and UMICs, with an R^2 value of 0.45 and r of 0.67 (statistically significant at 0.1 %). This suggests that while economic complexity likely plays a role in shaping AI preparedness for these countries, policy decisions appear to have a more substantial independent impact on AIPI

performance. A likely explanation, explored further in the next section, is that some of these countries, especially among UMICs, have greater macro-fiscal capacity than LICs (Choudhary et al., 2024), enabling them to implement ambitious digital and AI-specific policy agendas. However, these countries often lack a fully developed infrastructure, and specifically digital infrastructure (pillar i of AIPI) and a sufficiently skilled workforce (pillar ii of AIPI), which are still in the process of being built, especially in comparison to HICs (World Bank, 2021, 2024c).

Local overperformers are the seven countries with an observed AIPI score exceeding 0.5—equivalent to the population-weighted average and median AIPI scores for the subgroup (rounded to one decimal)—and surpassing their predicted AIPI scores based on their trade and research economic complexity. These overperformers include Albania, China, Costa Rica, Indonesia, Kazakhstan, Malaysia, and Ukraine. Their observed AIPI scores are statistically significantly above their predicted scores (at the 1.0 % threshold). Among them, China and Malaysia stand out with the highest observed AIPI scores, reaffirming the strong AI readiness of East Asian countries in addition to industrialized nations. Kazakhstan also exhibits a notably high observed AIPI score relative to its economic complexity—its export basket being heavily reliant on hydrocarbons and mineral products, which limits its ECI trade score (ranked #76 out of 133 countries) and its research economic complexity is low (ranked #121 out of 130 countries) for the 2021–22 period. While the drivers of this overperformance will be examined further in the next section, it is important to emphasize China’s critical role in the global AI landscape. As a co-leader in AI innovation and technology alongside the United States (European Commission, 2024; HAI, 2025), China has made significant investments in chip/semiconductor supply chains,³² and in digital infrastructure in general (de Seta, 2023)³³, in January

³¹ With an impressive AIPI score of 0.76 in 2023 and an ambitious digital agenda, Estonia has the potential to be considered among the AI preparedness overperformers. However, a lack of data on its multidimensional economic complexity limits such classification. Estonia’s third national AI Strategy (2024–26) prioritizes advancing AI skills and competencies through education and training reforms, including the introduction of new Master’s and PhD programs, elective AI courses, and vocational education. The strategy also emphasizes society-wide upskilling initiatives, such as a digital academy and public sector training programs that aim to train 10.0 % of employees annually. Additionally, the Ministry of Education and Research offers specialized AI training for teachers, students, and public sector managers, while the Ministry of Economic Affairs and Communications targets 80.0 % AI literacy across society and widespread AI adoption—100 % in the public sector and 75.0 % in the private sector—by 2030 (Digital FOSS, 2024).

³² China launched a US\$47.5 billion semiconductor fund in 2024 (HAI, 2025, p. 4). For further information, see https://www.economist.com/business/2024/01/01/welcome-to-the-era-of-ai-nationalism, as well as https://www.reuters.com/technology/china-sets-up-475-bln-state-fund-boost-semiconductor-industry-2024-05-27/.

³³ For a deep dive on the infrastructure and superstructure of the “social credit” system (社会信用体系 shehui xinyong tixi), see Durand (2024, chap. 2).

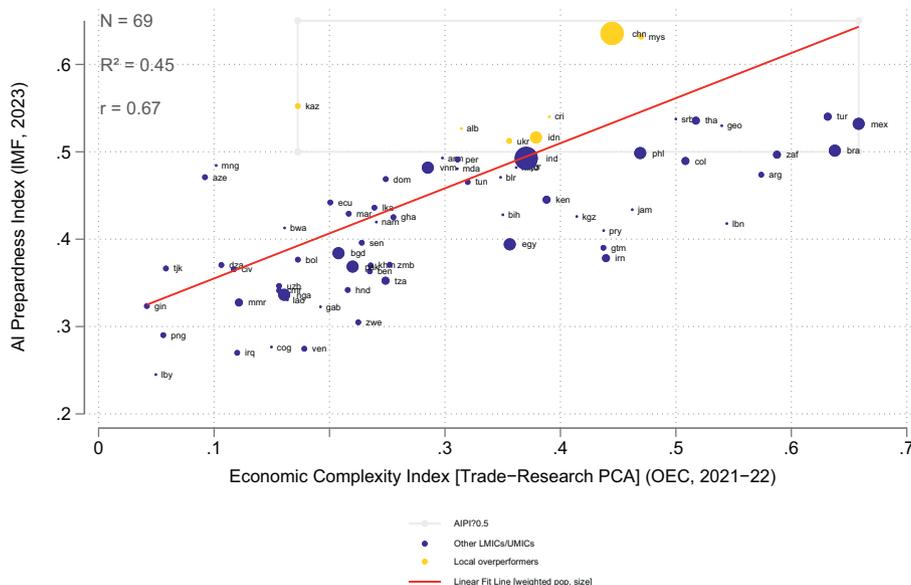


Fig. 3. AI preparedness and economic complexity in LMICs and UMICs: Identifying local overperformers. **Source:** The AIPI score for 2023 is obtained from the IMF website [https://www.imf.org/external/datamapper/datasets/AIPI] and the ECI on trade and research for 2021–22 are obtained from the OEC website [https://oec.world/en/rankings/eci/hs6/hs96?tab=ranking]. **Notes:** The first principal component (PCA) of ECI trade and ECI research, with an eigenvalue exceeding 50 %, is used to capture the multidimensional aspects of national economic complexity. Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020). All countries with an observed AIPI score exceeding 0.5 (the weighted average and median score for the subgroup) are highlighted in the grey quadrant. Among these, only countries with AIPI scores surpassing their predicted values (above the linear fit line) are marked in yellow and identified as local overperformers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2024, introduced draft guidelines aimed at standardizing the AI sector (PRC MIIT, 2024).³⁴ Furthermore, in December 2024, China’s Ministry of Industry and Information Technology (MIIT) established an artificial intelligence standardization technical committee. This committee is tasked with developing industry standards in areas such as large language models (LLMs) and AI risk assessment. Lastly, DeepSeek-R1, an open-source reasoning model developed by the Chinese AI startup DeepSeek (or 深度求索) was publicly released on January 20, 2025. A notable aspect of this LLM is its cost-effectiveness. The model was developed with an investment of under US\$6.0 million, a fraction of the expenditure—estimated to be multiple billions—reportedly associated with training models like OpenAI’s o1. It also relies on inferior chips.³⁵ By contrast, certain UMICs with relatively high observed AIPI scores, such as Brazil, Mexico and Türkiye, appear to underperform relative to their multidimensional ECI.

Last but not least, Fig. 4, also weighted by population size, highlights the relationship between AIPI and multidimensional economic complexity for the subgroup of 43 LICs and LMICs, with an R^2 value of 0.70 and r of 0.83 (statically significant at 0.1 %). This stronger correlation aligns with the earlier explanation regarding fiscal buffers. Unlike certain UMICs, these countries, particularly LICs, face severe fiscal constraints, including notably low levels of tax mobilization, which

³⁴ These guidelines propose the development of over 50 national and industry-wide AI standards by 2026 and contributions to more than 20 international AI standards, focusing on key technologies and practical applications. This comprehensive approach underscores China’s strategic commitment to AI dominance.

³⁵ “In terms of performance, DeepSeek-R1 has demonstrated capabilities comparable to leading models like OpenAI’s o1. For instance, on the MATH-500 benchmark, which assesses high-school-level mathematical problem-solving, DeepSeek-R1 achieved a 97.3 % accuracy rate, slightly outperforming OpenAI o1’s 96.4 %. In coding tasks, it scored 49.2 % on the SWE-bench Verified benchmark, edging out OpenAI o1’s 48.9 %.” [https://venturebeat.com/ai/ca-lm-down-deepseek-r1-is-great-but-chatgpts-product-advantage-is-far-from-over].

significantly limit their policy options (Choudhary et al., 2024). As a result, they are compelled to prioritize cost-effective digital and AI-specific strategies whenever feasible. This also highlights that, similar to HICs at the opposite end of the spectrum, their AI preparedness is on average very closely linked to their trade and research complexity. However, this relationship functions at a much lower equilibrium, constrained by their critical multidimensional development challenges (UNSD, 2024).

Nonetheless, seven countries have been identified as overperformers in AI preparedness, with an observed AIPI score exceeding 0.4—equivalent to the population-weighted average and median AIPI scores for the subgroup (rounded to one decimal): Ghana, India, Morocco, Tunisia, Rwanda, Sri Lanka, and Viet Nam. Their observed AIPI scores are statistically significantly above their predicted scores (at the 0.1 % threshold). While the inclusion of countries like India, Tunisia, and Viet Nam is consistent with their well-established digital agendas, which emphasize leveraging technology for economic growth, institutional improvements, and social development, Rwanda’s presence is particularly striking as the only LIC among the overperformers. Rwanda’s strong performance can be partly attributed to its high domestic revenue mobilization, supported by effective donor engagement, and a vertically integrated decisional structure that facilitates bold reforms (IMF, 2023; Todd, 2019).³⁶ This fiscal capacity, coupled with a high Country Policy and Institutional Assessment (CPIA) score (World Bank, 2024b), so a substantial International Development Association (IDA) envelope allocation, and a business-friendly environment (World Bank, 2024a), enables the country to advance an ambitious digital agenda. A notable example of this commitment is Rwanda’s Ministry of Information Communication Technology and Innovation (MINICT) co-developing the AI Playbook for Small States in collaboration with

³⁶ Todd (2019) includes a few dedicated sections on Rwanda but further explores its traditional family system, specifically the stem family model and its implications. The relatively small size of the country (approximately 26,000 km²) also likely contributes to more efficient revenue collection.

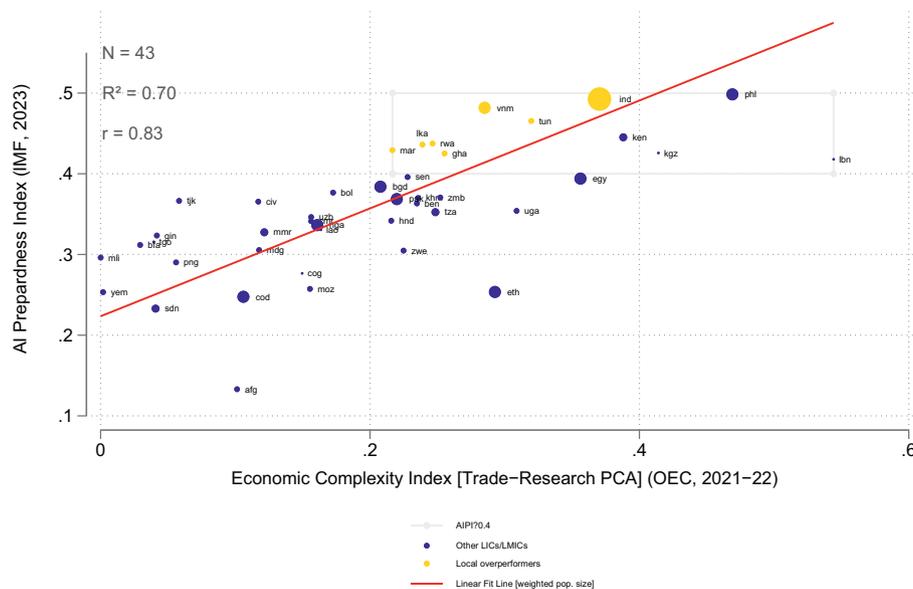


Fig. 4. AI preparedness and economic complexity in LICs and LMICs: Identifying local overperformers. **Source:** The AIPI score for 2023 is obtained from the IMF website [<https://www.imf.org/external/datamapper/datasets/AIPI>] and the ECI on trade and research for 2021–22 are obtained from the OEC website [<https://oec.world/en/rankings/eci/hs6/hs96?tab=ranking>]. **Notes:** The first principal component (PCA) of ECI trade and ECI research, with an eigenvalue exceeding 50 %, is used to capture the multidimensional aspects of national economic complexity. Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020). All countries with an observed AIPI score exceeding 0.4 (the weighted average and median score for the subgroup) are highlighted in the grey quadrant. Among these, only countries with AIPI scores surpassing their predicted values (above the linear fit line) are marked in yellow and identified as local overperformers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Singapore’s Ministry of Digital Development and Information under the Digital Forum of Small States initiative (Digital, 2024). In contrast, a few LMICs with relatively high observed AIPI scores, such as Kenya, Kyrgyzstan, Lebanon, and the Philippines, fall short of the performance levels suggested by their multidimensional ECI.

4. Decoding overperformance: insights into AI preparedness success

4.1. Unpacking the pillars of overperformance across income groups

Fig. 5 provides a comparative visual representation of the pillars driving AI preparedness across the three groups of overperformers. Each income group exhibits distinct patterns in the emphasis placed on the four pillars of AI preparedness described in the “Data” Section: digital infrastructure (pillar i), human capital and labor markets (pillar ii), innovation and integration (pillar iii), and regulation and ethics (pillar iv).

In low-income and lower-middle-income overperformers, regulation and ethics emerge as the most significant driver of AI preparedness, accounting for 30.1 % of the emphasis (Indian and SSA models as detailed hereafter). This highlights the critical role of institutions in building trust and establishing frameworks for AI deployment, even amid considerable structural challenges. Following closely is the focus on human capital and labor markets (25.3 %, Indian model), reflecting the pressing need to develop skills and prepare the workforce for a technology-driven future. However, digital infrastructure (22.0 %) and innovation and integration (22.6 %) are less emphasized, likely constrained by limited fiscal resources and technological investment capacity.

For upper-middle-income overperformers, the emphasis shifts, with digital infrastructure taking the lead (28.8 %, Chinese and Kazakh models), reflecting the growing technological capabilities and infrastructure investments of these nations. Regulation and ethics remain essential at 24.5 % (Malaysian model), underscoring the importance of robust institutional framework in fostering AI readiness. Human capital and labor markets (24.0 %, Malaysian and Kazakh models) also maintain a strong focus as these nations work to enhance workforce preparedness. Innovation and integration, however, remain the least prioritized pillar at 22.7 %, possibly due to structural constraints, though this requires careful interpretation. For instance, China’s status may be underestimated in this metric due to the “economic integration” component, which accounts for tariff and non-tariff barriers, as well as restrictions on capital and labor movement. This underscores that robust domestic innovation can thrive even with lower scores in economic integration measures.

High-income overperformers present a more balanced profile, with regulation and ethics taking the lead at 27.9 % (Singapore and North Europe model), emphasizing the importance of institutional frameworks in managing advanced AI integration. Digital infrastructure follows at 24.7 % (Singapore model), reflecting the continuous effort to maintain a technological edge. Innovation and integration (24.3 %) gain slightly more prominence compared to lower-income groups, while human capital and labor markets (23.1 %) play a supporting role, as these countries already benefit from well-established systems for education and workforce development.

Across all income levels, regulation and ethics consistently top the list, but the relative emphasis on digital infrastructure, workforce development, and innovation adapts to the specific needs and capacities of each economic group.

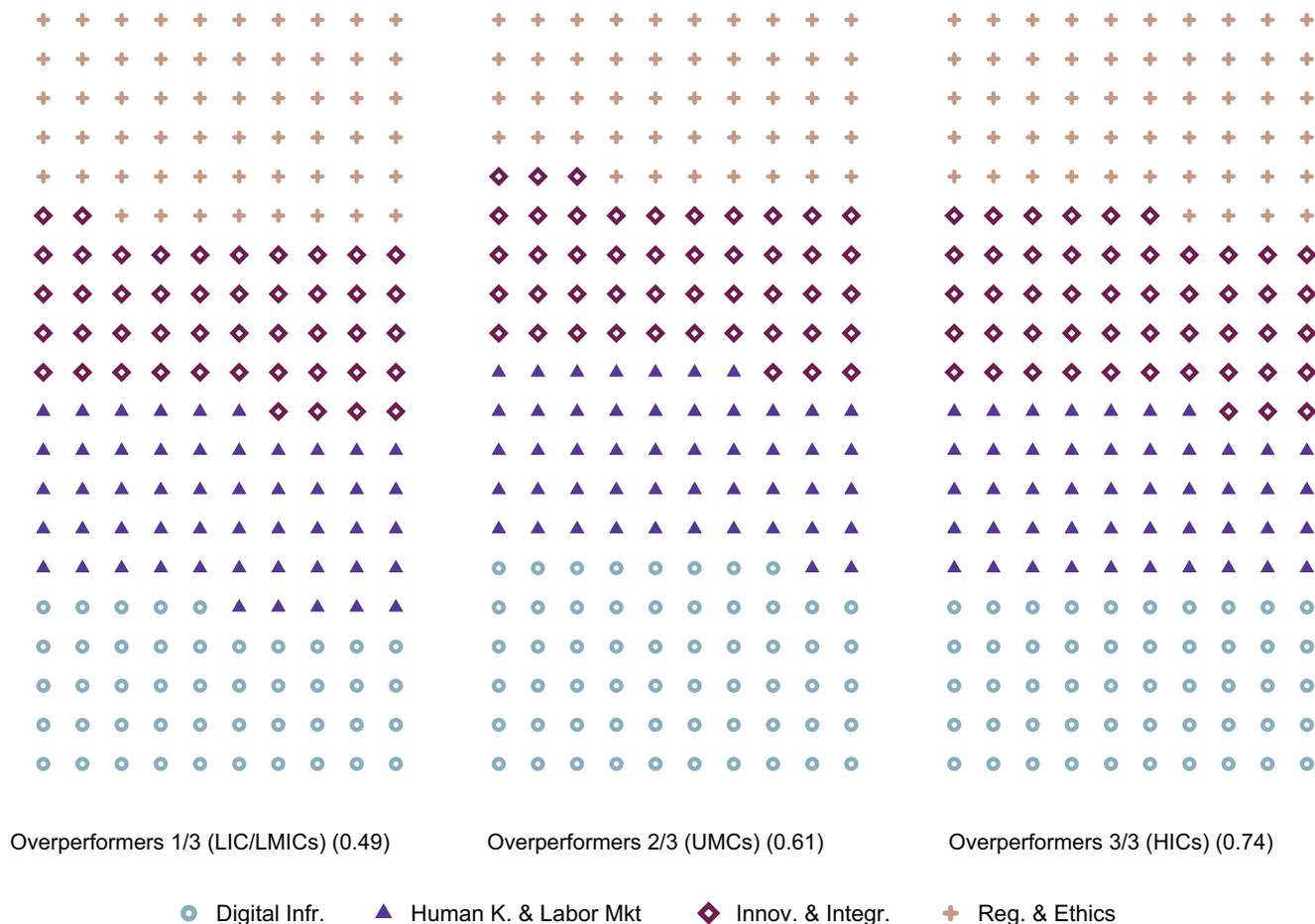


Fig. 5. Key pillars driving overperformance across income groups of overperformers. **Source:** The AIPI score and pillars for 2023 are obtained from the IMF website [<https://www.imf.org/external/datamapper/datasets/AIPI>]. **Notes:** Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020). Weighted average AIPI scores per group in parenthesis. Each symbol represents 0.5 % of the total AIPI score per group. Digital Infrastructure (pillar i, ○): Investments and capabilities in foundational technologies to support AI readiness. Human Capital & Labor Markets (pillar ii, ▲): Workforce skills and readiness for AI-driven economies. Innovation & Integration (pillar iii, ◆): The ability to innovate and integrate AI into industries and economic activities. Regulation & Ethics (pillar iv, +): Institutional frameworks and ethical guidelines to support responsible AI deployment. The “waffle” package is taken from Naqvi (2024a, 2024b).

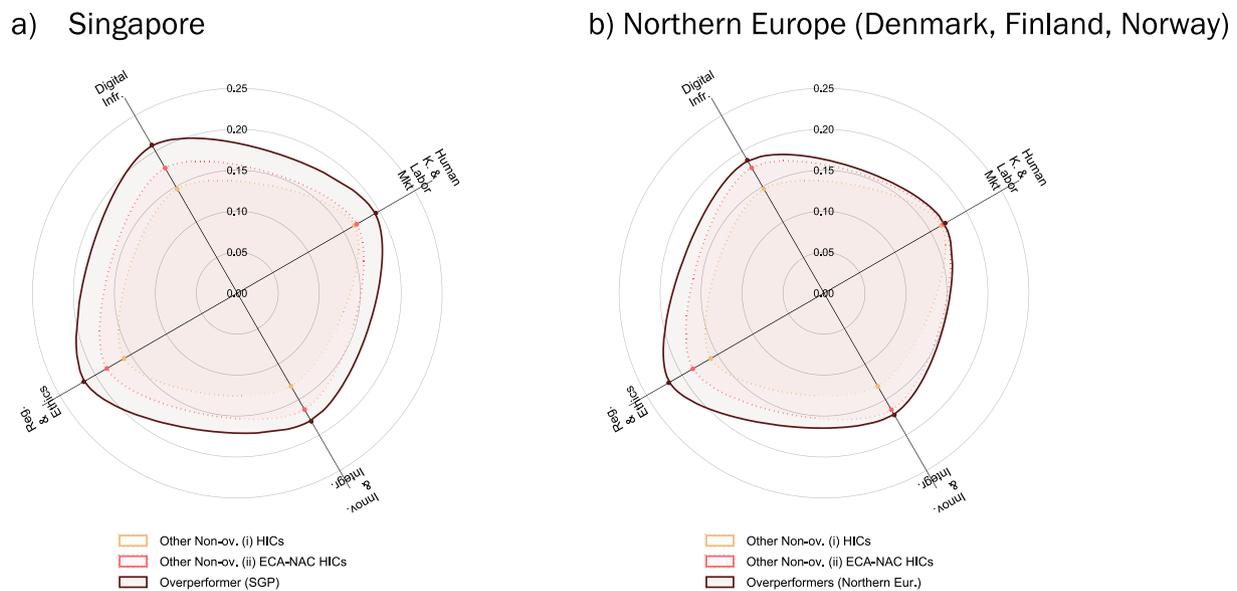


Fig. 6. Selected HICs (global) overperformers. **Source:** The AIPI score and pillars for 2023 are obtained from the IMF website [https://www.imf.org/external/da/tamapper/datasets/AIPI]. **Notes:** Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020). Weighted average AIPI scores per group in parenthesis. Dotted yellow shows the weighted average pillar scores for non-overperformer HICs in Europe, Central Asia, or North America, while dotted red shows the scores for all other non-overperformer HICs. The “spider” package is taken from Naqvi (2024a, 2024b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Key pillars and strategic approaches of selected overperformers

Overperforming countries across different income levels demonstrate distinct but complementary approaches to AI preparedness, with each emphasizing specific pillars that align with their developmental stage and comparative advantages. HICs overperformers like Singapore and Northern European nations (Denmark, Finland, Norway) prioritize comprehensive regulatory frameworks and ethical guidelines, leveraging their institutional capacity to establish trust-based AI ecosystems. Singapore’s Model AI Governance Framework and AI Verify testing toolkit exemplify this approach,³⁷ while Denmark’s mandatory data ethics disclosure requirements for large operators represent a pioneering regulatory innovation.³⁸ Fig. 6 below illustrates that the regulatory pillar systematically outperforms the control groups average in both Singapore and Northern Europe.³⁹

UMICs overperformers pursue more targeted strategies that capitalize on existing strengths. China’s exceptional digital infrastructure development (Fig. 7a), including massive 5G and fiber-optic investments (de Seta, 2023) supports its AI ambitions, while Malaysia combines robust regulatory frameworks with substantial human capital investments (Fig. 7b), allocating approximately US\$2.4 billion annually to skills development.⁴⁰ Kazakhstan’s digital transformation focuses on AI-focused education, reskilling programs, and widespread AI literacy campaigns, as well as infrastructure modernization, achieving 92.9 % internet penetration⁴¹ and developing Central Asia’s most powerful

³⁷ See <https://www.pdpc.gov.sg/help-and-resources/2020/01/model-ai-governance-framework>.

³⁸ See <https://2021.ai/news/denmark-introduces-mandatory-legislation-for-ai-and-data-ethics>.

³⁹ As the global leader in AIPI ranking, Singapore also excels in other key pillars.

⁴⁰ See <https://www.weforum.org/stories/2025/06/malaysia-steven-sim-workforce-future-ai/>.

⁴¹ See <https://globalcio.com/articles/main/digital-transformation-of-kazakhstan-economy/>.

supercomputer facility (Fig. 7c).⁴²

Overperformers among LICs and LMICs exhibit notable progress in key areas despite limited resources. India stands out for its comprehensive strategy that combines human capital development—exemplified by the FutureSkills Program⁴³—with ethical governance through its “Responsible AI for All” initiative⁴⁴ (Fig. 8a). In SSA, Ghana and Rwanda have established dedicated offices for responsible AI⁴⁵ and enacted privacy protection laws aligned with international standards,⁴⁶ positioning themselves as regional leaders in ethical AI development (Fig. 8b).

These diverse approaches reflect each country’s recognition that AI preparedness requires strategic focus rather than uniform implementation across all pillars. Singapore combines regulatory excellence with global infrastructure leadership and human capital development, while other countries achieve overperformance by excelling in areas that complement their existing capabilities and institutional frameworks.

Actors’ interactions and innovation system dynamics.

As suggested in the “Literature review” section overperformance of these countries can be understood through the lens of national innovation systems, where the interaction between state actors, citizens, and organizations creates enabling environments for AI adoption. Drawing on Nelson’s (1993) framework of national innovation systems, three distinct but interconnected patterns of actor coordination seems to emerge from a preliminary qualitative comparative analysis.

State-led coordination model characterizes countries like Singapore, China, Denmark, Ghana, and Rwanda, where government agencies assume primary responsibility for establishing AI preparedness

⁴² See <https://timesca.com/kazakhstan-unveils-central-asias-most-powerful-supercomputer/>.

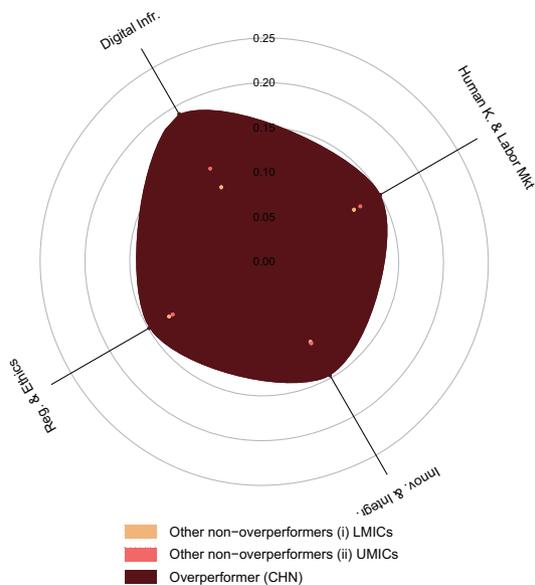
⁴³ See <https://indiaai.gov.in/hub/indiaai-futureskills>.

⁴⁴ See https://www.niti.gov.in/sites/default/files/2022-11/Ai_for_All_2022_02112022_0.pdf.

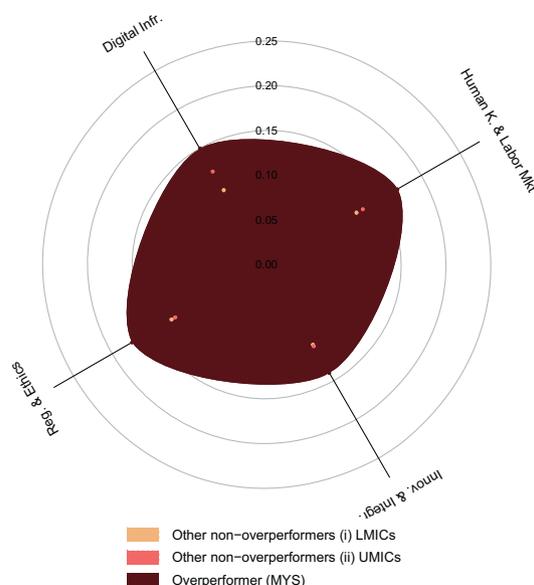
⁴⁵ See <https://theconversation.com/ai-policies-in-africa-lessons-from-ghana-and-rwanda-253642>.

⁴⁶ See <https://allafrica.com/stories/202401230345.html>.

a) China



b) Malaysia



c) Kazakhstan

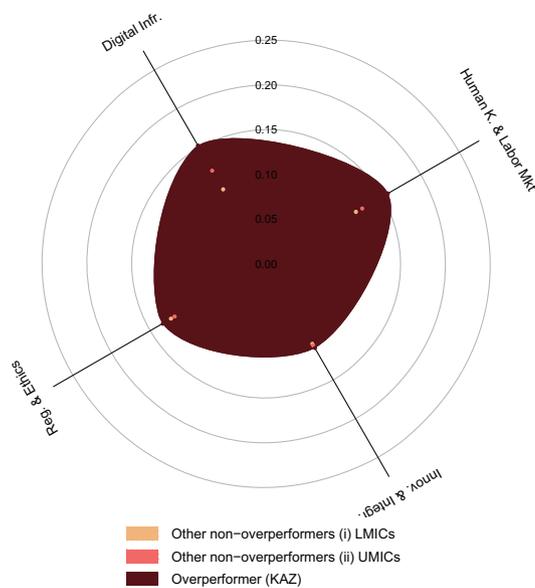


Fig. 7. Selected UMICs overperformers. **Source:** The AIPI score and pillars for 2023 are obtained from the IMF website [<https://www.imf.org/external/datamapper/datasets/AIPI>]. **Notes:** Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020). Weighted average AIPI scores per group in parenthesis. Dotted yellow shows the weighted average pillar scores for non-overperforming LMICs and dotted red shows them for non-overperforming UMICs. The “spider” package is taken from Naqvi (2024a, 2024b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

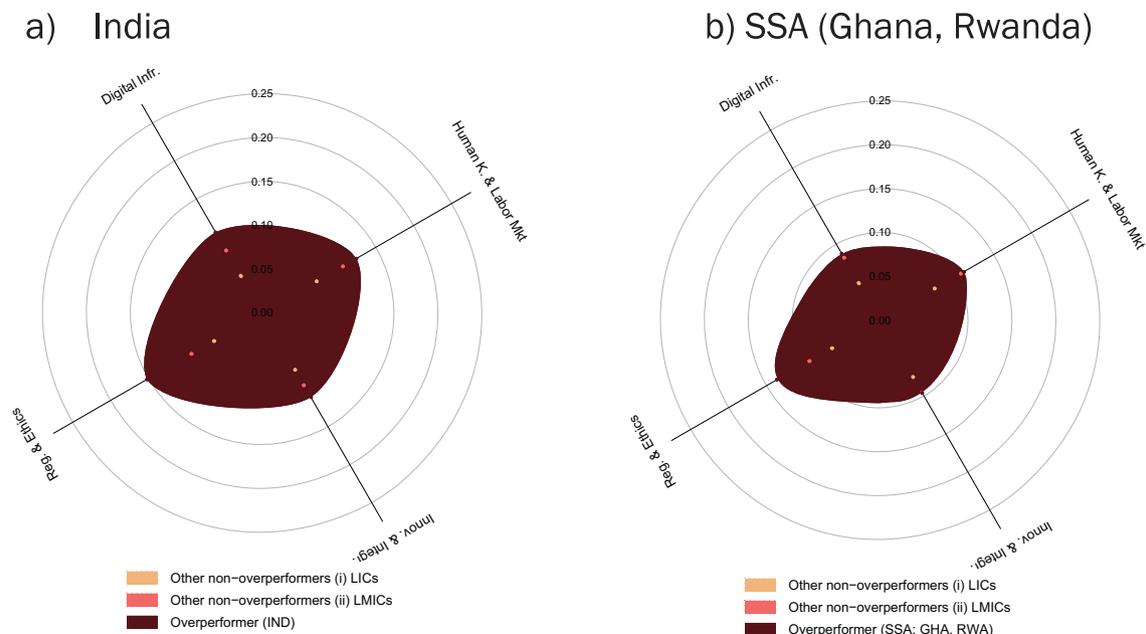


Fig. 8. Selected LICs/LMICs overperformers. **Source:** The AIPI score and pillars for 2023 are obtained from the IMF website [<https://www.imf.org/external/database/datasets/AIPI>]. **Notes:** Population size for 2023, used for the weighted analysis, is sourced from the “wbopendata” module in Stata (Azevedo, 2020). Weighted average AIPI scores per group in parenthesis. Dotted yellow shows the weighted average pillar scores for non-overperforming LMICs. The “spider” package is taken from Naqvi (2024a, 2024b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

frameworks. In Singapore, the Infocomm Media Development Authority (IMDA) coordinates with multiple ministries to implement the National AI Strategy, while the Personal Data Protection Commission (PDPC) ensures ethical compliance.⁴⁷ Denmark’s government collaborates with industry consortiums to create cybersecurity and data ethics certification schemes,⁴⁸ demonstrating how state leadership can facilitate private sector adoption through standardization. China exemplifies state-led coordination at scale through its New Generation Artificial Intelligence Development Plan, where central government directives coordinate massive infrastructure investments with provincial implementation, enabling the construction of the world’s largest 5G network and extensive fiber-optic systems.⁴⁹ Ghana’s establishment of a Responsible AI Office along with the Open Data Initiative (GODI) demonstrates how democratic EMDEs can adopt state-led approaches by creating specialized institutions that coordinate stakeholder engagement and monitor policy implementation. Rwanda’s Responsible AI Office (RAIO) and Centre for the Fourth Industrial Revolution (C4IR) illustrate how resource-constrained states can effectively coordinate AI development through institutional innovation and strategic international partnerships.⁵⁰

Market-responsive facilitation emerges in countries like Malaysia and Kazakhstan, where state actors create enabling conditions while

⁴⁷ See <https://www.pdpc.gov.sg/help-and-resources/2020/01/model-ai-governance-framework>.

⁴⁸ See <https://2021.ai/news/denmark-introduces-mandatory-legislation-for-ai-and-data-ethics>.

⁴⁹ An unofficial translation of the AIDP is available on Stanford’s DigiChina website: <https://digichina.stanford.edu/work/full-translation-chinas-new-generation-artificial-intelligence-development-plan-2017/>.

⁵⁰ This includes partnerships with the German operator BioNTech and with the US Carnegie Mellon private university [<https://www.newtimes.co.rw/article/13974/news/technology/7-initiatives-placing-rwanda-as-major-player-in-ai-field>].

allowing private sector and civil society organizations to drive implementation. Malaysia’s statutory levy system requires private operators to fund workforce training while providing flexible platforms like MyMAHIR for skills development.⁵¹ The government’s role focuses on anticipatory regulation through the AI Governance Guidelines while enabling organizational adaptation.⁵² Kazakhstan’s approach emphasizes infrastructure provision through SOEs like Kazakhtelecom⁵³ while supporting private sector innovation through initiatives like Astana Hub, which incubates technology startups and facilitates research partnerships.⁵⁴

Distributed innovation networks characterize countries like India, where multiple actors operate semi-autonomously within broad national frameworks. The IndiaAI Expert Group coordinates with various ministries,⁵⁵ while private sector partnerships and academic institutions contribute to talent development through programs like the FutureSkills initiative. This distributed approach allows for experimentation and adaptation across different sectors and regions, though it requires sophisticated coordination mechanisms to maintain coherence.

The interaction patterns reveal that successful AI preparedness depends on alignment between actor capabilities and institutional design. Countries with strong state capacity can effectively implement comprehensive frameworks, while those with dynamic private sectors benefit from facilitative approaches that leverage market mechanisms.

⁵¹ See <https://www.weforum.org/stories/2025/06/malaysia-steven-sim-workforce-future-ai/>.

⁵² Ibid.

⁵³ See <https://www.budde.com.au/Research/Kazakhstan-Telecoms-Mobile-and-Broadband-Statistics-and-Analyses>.

⁵⁴ This includes partnership with the Finnish operator Nokia [<https://www.csis.org/analysis/building-digital-public-infrastructure-lessons-learned-kazakhstan>].

⁵⁵ See <https://indiaai.gov.in/news/indiaai-2023-expert-group-report-first-edition>.

The critical factor appears to be the establishment of clear roles and communication channels that enable each actor type to contribute effectively while maintaining overall system coherence.

4.2.1. *Transferability challenges and adaptive implementation*

The apparent success of these overperforming countries raises important questions about the transferability of their approaches to other contexts. The innovation systems literature suggests that institutional architectures reflect path-dependent historical developments and embedded social structures that resist direct replication. Each country’s AI preparedness strategy builds upon existing capabilities, regulatory traditions, and stakeholder relationships that may not exist elsewhere (Fagerberg et al., 2010; Nelson, 1993).

Singapore’s comprehensive regulatory approach requires sophisticated bureaucratic capacity and strong government-industry trust relationships that took decades to develop. The city-state’s small size and political system enable rapid decision-making and implementation that would be difficult to replicate in larger, more decentralized countries. Similarly, Denmark’s mandatory ethics disclosure builds upon existing corporate governance traditions and stakeholder capitalism norms that may not exist in countries with different business cultures.

Malaysia’s skills development model depends on established levy systems and tripartite labor relations that emerged from specific historical circumstances. The willingness of private operators to fund workforce training reflects negotiated social contracts that cannot be simply imposed elsewhere. Kazakhstan’s infrastructure-focused approach leverages its strategic geographic position and natural resource wealth to attract international partnerships, advantages that are inherently non-transferable (Table 1).

The analysis suggests that successful adaptation requires identifying the underlying coordination mechanisms rather than copying specific policies or institutions. Countries seeking to improve AI preparedness should focus on strengthening actor relationships and communication channels appropriate to their existing institutional context. This might involve building state capacity where government coordination is necessary, strengthening market mechanisms where private sector leadership is viable, or developing new institutional forms that bridge public and private capabilities.

The transferability challenges become particularly evident when examining countries with fundamentally different institutional architectures. China’s state-led approach achieves exceptional digital infrastructure development through centralized planning and massive resource mobilization that requires authoritarian governance structures and state-owned enterprise coordination mechanisms unavailable in democratic contexts. The ability to implement unified national strategies across provincial governments while directing private sector investment toward strategic priorities reflects political and economic systems that cannot be replicated in countries with different governance

structures.

Ghana’s approach demonstrates how democratic EMDEs can adapt state-led coordination through institutional innovation within existing governance frameworks. The Responsible AI Office and Ghana Open Data Initiative represent efforts to create specialized capabilities for AI governance while working within democratic accountability structures and civil society engagement requirements. However, this approach faces resource constraints and capacity limitations that make comprehensive implementation challenging compared to countries with greater state resources or more established institutional capabilities.

India’s distributed innovation network approach presents unique transferability challenges related to scale and coordination complexity. The country’s federal structure requires coordination across multiple ministries, state governments, and diverse private sector actors, creating implementation challenges that smaller or more centralized countries may not face. However, India’s experience also demonstrates how large, diverse countries can achieve AI preparedness through experimentation and adaptation rather than uniform implementation. The FutureSkills Program and Centers of Research Excellence model show how distributed approaches can leverage existing educational and industrial capabilities while allowing for regional variation. This suggests that other large federal countries might benefit from India’s approach to managing coordination complexity through institutional multiplicity rather than centralized control.

5. **Potential limitations of preparedness indicators**

The methodological decision to employ the AIPI developed by the IMF in this study, rather than alternative indices such as the AI Readiness Index by Oxford Insights, or the Network Readiness Index developed by the private DC-based Portulans Institute is grounded in the IMF’s status as a globally recognized multilateral institution, as aforementioned in the “Data” section. The IMF’s rigorous standards of accountability, scrutiny, and transparency in the development of its analytical tools lend credibility to the AIPI. In contrast, while private entities like Oxford Insights or Portulans Institute provide valuable contributions, they operate without the same level of oversight. As also aforementioned in the “Data” section, the AI Readiness Index focuses more specifically on government preparedness for AI deployment in public services, whereas the AIPI offers a broader assessment of a country’s capacity to harness AI capabilities across multiple dimensions. That said, the choice of index does not materially alter a broader contribution of this study, which is the proposed methodology designed to be adaptable and replicable across different datasets and indices. By prioritizing a replicable and transparent data-driven framework, this study enables policymakers and other key actors to assess their country’s AI preparedness relative to its economic complexity, ensuring the robustness of its findings regardless of the specific index employed.

Table 1
Actor interaction patterns and transferability constraints.

Country	Primary coordination mechanism	Key actors	Transferability constraints
Singapore	State-led comprehensive planning	IMDA, PDPC, universities, multinational corporations	Small size, strong state capacity, established trust
Denmark	Regulatory standardization	Government, industry consortiums, civil society	Corporate governance culture, regulatory tradition
China	Centralized infrastructure coordination	State Council, SOEs, provincial governments	Authoritarian capacity, scale resources, political system
Malaysia	Market-facilitated development	KESUMA, ¹ private operators, training institutes	Established levy systems, tripartite relations
Kazakhstan	Infrastructure-enabled growth	SOEs, private operators, Astana Hub	Geographic advantages, resource wealth
Ghana	Institutional framework building	RAI Office, GODI, civil society organizations	Democratic governance requirements, resource constraints
Rwanda	Institutional innovation	RAIO, C4IR, international partners	Political stability, external support, development stage
India	Distributed experimentation	Multiple ministries, private sector, academia	Scale requirements, coordination complexity

Source: Author’s construction. Notes: ¹: KESUMA is Malaysia’s Ministry of Human Resources, which oversees workforce development and skills training programs.

Nevertheless, the AIPI, like any related composite index, is subject to limitations that may affect the accuracy of its assessments, particularly in certain country contexts. One notable limitation is its reliance on internet penetration as the main component for digital infrastructure.⁵⁶ While internet access is a critical enabler of AI development, and although the digital infrastructure pillar accounts for secure internet servers per capita,⁵⁷ penetration rates do not capture the quality, reliability, or speed of connectivity—factors that are equally essential for the effective deployment of AI (Brynjolfsson & McAfee, 2014). For instance, a country may exhibit high internet penetration but suffer from poor connectivity, which could impede the real-time data processing required for AI applications. Also, the digital pillar of AIPI does not account directly for the presence of data centers or supercomputers.⁵⁸

Another limitation arises from the use of various education components (e.g., public education spending, STEM enrollment) as a measure of AI-related human capital.⁵⁹ While these components are undoubtedly important for building AI capabilities, they do not account directly for the quality of education, the relevance of curricula to cutting-edge AI technologies, or the availability of informal learning opportunities such as online courses or on-the-job training (Autor, 2015).

The AIPI also relies on regulation proxies to assess the enabling environment for AI preparedness.⁶⁰ However, these proxies may not fully capture the complexity of regulatory frameworks, which can vary widely in their effectiveness and adaptability to rapidly evolving technologies like AI (Acemoglu & Restrepo, 2018). Simple regulatory indicators may overlook the nuanced ways in which legal and institutional environments facilitate or hinder AI innovation, particularly in countries with weak monitoring structures or limited regulatory capacity.

The AIPI (and related indicators aforementioned) also likely exhibit systematic measurement biases that systematically favor countries with formalized institutional structures while underrepresenting informal digital ecosystems that characterize AI capability development in many lower-income contexts (Cariolle & Aker, 2023; Heeks, 2018). This bias manifests across the index's constituent pillars in ways that systematically undervalue alternative pathways to AI readiness. For instance, the digital infrastructure pillar's emphasis on internet penetration rates and secure server density overlooks innovative connectivity arrangements such as community-based mesh networks in urban informal settlements, shared device programs, and mobile money systems that create extensive digital transaction networks and data flows relevant for AI applications. Similarly, the human capital assessment through formal educational credentials fails to capture the extensive informal learning ecosystems that characterize digital skill development, including diaspora knowledge transfer mechanisms (Valette, 2018), but also peer-to-peer coding networks⁶¹ and community-based technical training that might generate AI-relevant capabilities.

Additionally, our analysis on general trends revealed a noteworthy pattern: several East Asian countries, particularly those influenced by Confucian traditions, consistently overperform in AI preparedness relative to their income levels. This trend, observed in countries ranging from Viet nam to Singapore and China, warrants further investigation. It is possible that cultural norms emphasizing social harmony and collective design, as highlighted by Kung and Ma (2014), create an environment conducive to AI preparedness. Alternatively, higher average cognitive abilities in these countries may contribute to their strong

performance (Jones, 2011; Lynn & Meisenberg, 2010). Given that collective cognitive abilities have been shown to positively impact economic performance (Madsen, 2016) future iterations of the AIPI could benefit from incorporating more direct measures of cognitive skills if they prove relevant for readiness in cutting-edge technologies like AI.

To address these limitations and enhance the accuracy of AI preparedness assessments, several avenues for refining the AIPI or similar indices can be explored. First, the index could incorporate more nuanced measures of digital infrastructure, such as internet speed, reliability, and the availability of cloud computing resources, rather than over relying on penetration rates. For human capital, the AIPI could be improved by including indicators of the quality of education, such as international test scores, various cognitive indicators, or the prevalence of AI-specific training programs, as well as measures of informal learning and workforce skills development. It could also account for the prevalence of specific collective values found to be correlated with AI adoption.⁶² Across both pillars, the development of qualitative and/or quantitative assessments of informal digital and learning ecosystems would be especially pertinent to capture critical aspects of AI preparedness in EMDEs. In terms of regulation, more detailed assessments of the regulatory environment could be obtained through expert surveys or case studies that evaluate the adaptability and effectiveness of legal frameworks for AI innovation.

Moreover, to better account for the unique challenges faced by LICs and fragile settings, the AIPI could adopt alternative data sources or estimation techniques to fill gaps in traditional datasets. For example, dedicated satellite imagery or mobile phone data could be used as alternative estimates digital infrastructure in regions where official statistics are lacking (Mortier et al., 2025).

In conclusion, while the AIPI undoubtedly provides a valuable framework for assessing AI preparedness, its limitations—particularly in data-scarce contexts and its reliance on broad proxies—suggest room for refinement. By incorporating more granular measures of digital infrastructure, human capital, and regulatory environments, and by exploring the role of cultural and cognitive factors, future iterations of the AIPI could offer a more accurate and comprehensive evaluation of countries' readiness to harness AI, and possibly other cutting-edge technologies.

6. Discussion

This study presents a straightforward data-driven framework to identify countries that outperform in AI preparedness relative to their economic complexity, utilizing the IMF's AIPI and a multidimensional ECI derived from trade and research data. Employing weighted least squares, the analysis identifies 10 high-income global overperformers (e.g., Northern Europe, Singapore) and 14 local overperformers across middle- and low-income groups (e.g., China, Ghana, India, Kazakhstan, Malaysia, Rwanda). Regulation and ethics emerge as consistent drivers of overperformance across all income levels, with digital infrastructure and human capital contributing in context-specific ways depending on economic development. Case studies illustrate diverse coordination models—state-led, market-responsive, and distributed innovation—highlighting their implementation strategies and transferability challenges due to specific contexts. The methodology's replicability offers policymakers, scholars, international institutions and relevant stakeholders a practical tool to benchmark AI readiness, identify best

⁵⁶ See <https://www.imf.org/external/datamapper/AIPINote.pdf>.

⁵⁷ Ibid.

⁵⁸ Ibid. It does account indirectly for drivers of infrastructure development, such as data centers, through e-commerce metrics and government digital infrastructure.

⁵⁹ Ibid.

⁶⁰ Ibid.

⁶¹ This is likely reinforced by online platforms such as GitHub, conditional on a stable internet access (Liao, Qi, and Zhou, 2020).

⁶² Such information could be obtained from World Values Surveys: <http://www.worldvaluessurvey.org/wvs.jsp>.

practices, and design tailored interventions to address the global AI divide.

The study's contributions are threefold. First, it advances the understanding of AI preparedness by integrating AIPI with ECI, providing a replicable benchmark to quantify overperformance relative to economic complexity. Second, it delineates distinct coordination mechanisms driving AI readiness through qualitative case studies, emphasizing state, market, and distributed innovation systems while acknowledging transferability constraints. Third, it critically assesses the limitations of existing AI preparedness indices, advocating for refined metrics, particularly in lower-income contexts. These contributions aim to equip policymakers and other key actors with actionable insights to enhance AI readiness within diverse economic and institutional frameworks.

Future research can extend this framework through three key avenues: (i) refining measures of AI preparedness, (ii) advancing techniques for identifying overperformers, and (iii) deepening comparative analyses grounded in national innovation systems and possibly other theoretical background. First, refining AI preparedness measures involves moving beyond broad proxies such as internet penetration and formal digital and education metrics, which often fail to capture the quality and adaptability of digital infrastructure and human capital. Incorporating metrics like internet speed, cloud computing availability, or AI-specific training programs could enhance the accuracy of indices like the AIPI. Additionally, integrating qualitative assessments of informal digital and learning ecosystems—such as community-based mesh networks or peer-to-peer coding initiatives—would better reflect alternative pathways to AI readiness in resource-constrained settings. Incorporating alternative data sources (e.g., remote sensing data, mobile phone data) to address gaps in conventional statistics, alongside socio-cultural factors such as collective values or cognitive abilities associated with technology adoption, as identified in prior studies, could also enhance the precision of these indices, capturing nuanced drivers of AI preparedness.

Second, the proposed model can be considered as a baseline that can

Appendix A. Appendix

A.1. AI preparedness and structural correlates: A Bayesian exploration

Employing Bayesian Model Averaging (BMA), we analyze a comprehensive set of 67 historical, political, and economic indicators from growth determinants literature to identify robust predictors of national AIPI. The BMA framework,⁶³ as implemented in this study, enables the isolation of the most robust determinants of AI preparedness from a wide range of potential predictors, as defined and built by as defined and built by [Sala-i-Martin et al. \(2004\)](#).⁶⁴ This study uses BMA to explore a wide range of possible long-term factors that could be linked to AI preparedness. The goal is not to recommend specific policies, but to highlight general patterns and relationships that emerge from the data. Given the high level of uncertainty about which factors matter most, BMA accounts for that uncertainty by identifying variables that consistently appear as important across many possible models. This approach helps reveal broad trends and stylized facts, but it should not be used to guide concrete policy decisions.

[Fig. A.1](#) illustrates the inclusion probabilities of various covariates in the top 5000 models. The results highlight that initial conditions—such as life expectancy, higher education levels, and economic size in 1960—along with cultural and geographic influences, including Confucian heritage and an East Asian regional dummy, are positively correlated with AIPI. Conversely, the indicator political instability, captured by the frequency of revolutions and military coups, shows a negative association with AIPI.⁶⁵

⁶³ BMA addresses the challenge of model uncertainty by allowing for the evaluation of multiple competing models rather than relying on a single model specification. In the context of this study, BMA provides a systematic way to assess the relative importance of various predictors of AI preparedness and readiness, through the AIPI, by calculating each variable's posterior inclusion probability (PIP).

⁶⁴ Their database is available on the website of the American Economic Association (AEA): <https://www.aeaweb.org/articles?id=10.1257/0002828042002570>.

⁶⁵ Furthermore, historical trade openness emerges as a significant driver of AI adoption. However, this correlation should be interpreted cautiously, as one of the AIPI pillars (pillar iii: innovation and economic integration) directly captures aspects of trade openness and liberalization. The exact definitions of variables and their sources are available in ([Sala-i-Martin et al., 2004](#), p. 820–821).

be replicated, modified, or expanded. The current approach, based on WLS, provides a robust starting point. By serving as a replicable baseline, the proposed methodology allows researchers to adapt and refine the model, incorporating additional variables or alternative statistical approaches to capture a broader range of factors influencing overperformance.

Third, deepening comparative analyses through the lens of national innovation systems, as proposed by [Nelson \(1993\)](#), would provide richer insights into the specific drivers of AI preparedness. The study's preliminary qualitative comparative analysis identifies distinct coordination models, but further research could systematically compare these across a wider range of contexts. For instance, exploring how centralized versus decentralized governance structures shape AI readiness could reveal optimal strategies for different institutional settings. Furthermore, analyzing path dependency, state capacity, and technology diffusion ([Acemoglu & Robinson, 2012](#); [David, 1985](#); [Rogers, 2003](#)) could elucidate how historical investments in digital infrastructure and education, coupled with the pivotal role of targeted institutions, public policies, and coordination mechanisms, enable countries to achieve exceptional AI readiness as early adopters. These comparative analyses would enhance understanding of how institutional complementarities and global knowledge diffusion drive AI preparedness, guiding policymakers and other key actors toward context-specific strategies.

By pursuing these research avenues, future studies can improve the precision of AI preparedness assessments, refine the identification of overperformers, and provide deeper insights into the institutional dynamics shaping AI readiness, ultimately supporting more effective AI policy development across diverse economic contexts.

Declaration of competing interest

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

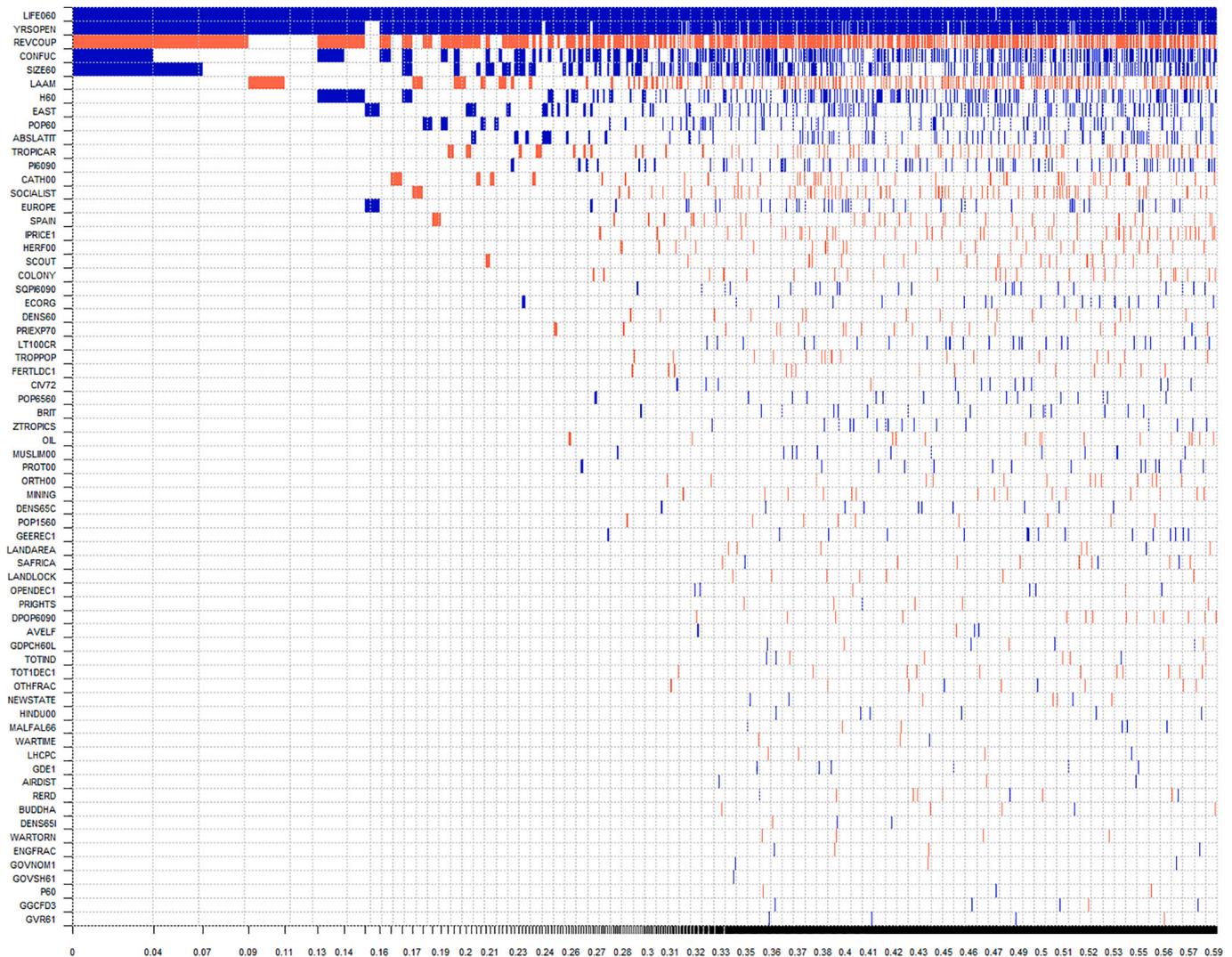


Fig. A.1. Model Inclusion in BMA on AIPI [Unit information prior (UIP); random model prior].
 Source: Author’s construction, based on the AIPI and the database from Sala-i-Martin et al. (2004). The database is available here: <https://www.openicpsr.org/openicpsr/project/116024/version/V1/view>. Notes: The BMA considers a chain of 30 million recorded draws with 10 million burn-ins, by applying the birth-death sampler, using the BMS package from Zeugner and Feldkircher (2015). The figure depicts the results of BMA. The explanatory variables are ranked according to their Posterior Inclusion Probabilities (PIPs) from the highest on the top to the lowest at the bottom. The horizontal axis shows the values of cumulative posterior probability. Blue (darker in greyscale) and red (lighter in greyscale) colors denote the positive and negative sign of the estimated parameter of explanatory variable, respectively. No colour means the corresponding explanatory variable is not included in the model.

The results from the BMA align with existing literature on the risks of a growing AI divide, emphasizing that established industrialized nations and East Asian economies, particularly those with Confucian cultural influences (i.e., China; Hong Kong SAR, China; the Republic of Korea; Singapore; Taiwan, China), consistently lead in AI preparedness and readiness. Conversely, politically unstable countries face significant challenges in this domain. This finding motivates the approach in the current paper to move beyond these general trends and stylized facts by identifying both global and local AI overperformers relative to the complexity of their economic structures. The goal is to uncover how countries can learn from these champions to effectively enhance their AI policy agendas.

Table A.1
Macro covariates and AI preparedness [BMA].

	Post Mean	Post SD	PIP	Cond.Pos.Sign
(Intercept)	-0.009	NA	1.000	NA
LIFE060	0.007	0.002	0.998	1.000
YRSOPEN	0.145	0.049	0.946	1.000
REVCROUP	-0.091	0.068	0.690	0.000
CONFUC	0.119	0.157	0.403	1.000
SIZE60	0.006	0.009	0.360	1.000
LAAM	-0.013	0.027	0.200	0.000
H60	0.117	0.263	0.188	1.000
EAST	0.012	0.035	0.122	1.000
POP60	0.000	0.000	0.076	1.000
ABSLATIT	0.000	0.000	0.071	1.000
TROPICAR	-0.004	0.015	0.071	0.000
PI6090	0.000	0.000	0.062	1.000
CATH00	-0.003	0.014	0.058	0.000
SOCIALIST	-0.004	0.019	0.054	0.000
EUROPE	0.005	0.024	0.047	0.989
SPAIN	-0.002	0.010	0.033	0.006
IPRICE1	0.000	0.000	0.026	0.000
HERF00	-0.001	0.011	0.019	0.000
SCOUT	0.000	0.004	0.017	0.000
COLONY	-0.001	0.006	0.017	0.000
SQPI6090	0.000	0.000	0.017	0.981
ECORG	0.000	0.001	0.016	1.000
DENS60	0.000	0.000	0.015	0.000
PRIEXP70	-0.001	0.010	0.015	0.028
LT100CR	0.001	0.006	0.014	1.000
TROPPPOP	-0.001	0.006	0.013	0.009
FERTLDC1	-0.001	0.009	0.013	0.000
CIV72	0.001	0.007	0.012	0.963
POP6560	0.008	0.095	0.012	0.980
BRIT	0.000	0.003	0.011	1.000
ZTROPICS	0.001	0.007	0.011	1.000
OIL	0.000	0.006	0.011	0.000
MUSLIM00	0.000	0.005	0.010	0.996
PROTO0	0.000	0.005	0.010	0.988
ORTH00	-0.001	0.013	0.009	0.000
MINING	-0.001	0.015	0.009	0.000
DENS65C	0.000	0.000	0.008	0.981
POP1560	-0.001	0.022	0.008	0.028
GEEREC1	0.008	0.121	0.008	0.989
LANDAREA	0.000	0.000	0.008	0.275
SAFRICA	0.000	0.004	0.008	0.281
LANDLOCK	0.000	0.003	0.007	0.000
OPENDEC1	0.000	0.004	0.007	0.681
PRIGHTS	0.000	0.001	0.006	0.069
DPOP6090	-0.007	0.139	0.006	0.017
AVELF	0.000	0.003	0.005	0.895
GDPCH60L	0.000	0.002	0.005	0.833
TOTIND	0.000	0.005	0.005	0.590
TOT1DEC1	-0.001	0.020	0.005	0.010
OTHFRAC	0.000	0.002	0.005	0.143
NEWSTATE	0.000	0.001	0.005	0.651
HINDU00	0.000	0.006	0.005	0.912
MALFAL66	0.000	0.002	0.005	0.595
WARTIME	0.000	0.005	0.005	0.080
LHCPC	0.000	0.000	0.004	0.330
GDE1	0.001	0.027	0.004	0.932
AIRDIST	0.000	0.000	0.004	0.698
RERD	0.000	0.000	0.004	0.417
BUDDHA	0.000	0.004	0.004	0.172
DENS651	0.000	0.000	0.004	0.574
WARTORN	0.000	0.001	0.004	0.185
ENGFRAC	0.000	0.002	0.004	0.418
GOVNOM1	0.000	0.009	0.004	0.563
GOVSH61	0.000	0.008	0.004	0.940
P60	0.000	0.004	0.004	0.436
GGCFD3	0.000	0.012	0.003	0.809
GVR61	0.000	0.007	0.003	0.617

Source: Author's construction, based on the AIPI and the database from Sala-i-Martin et al. (2004). The database is available here: <https://www.openicpsr.org/openicpsr/project/116024/version/V1/view>. Notes: The BMA considers a chain of 30 million recorded draws with 10 million burn-ins, by applying the birth-death sampler, using the BMS package from Zeugner and Feldkircher (2015). SD, and PIP stand for standard deviation, and posterior inclusion probability, respectively. Acronyms of covariates are available in Sala-i-Martin et al. (2004).

A.2. Observed vs. expected AI preparedness: Stylized patterns in the sample

Table A.2
Descriptive statistics.

	Economy	Region	Income level	ECI (multi., scaled)	AIPI (observed)	AIPI (predicted)	Overperformer
1	Afghanistan	South Asia	LIC	0.101	0.133	0.291	No
2	Albania	Europe and Central Asia	UMC	0.314	0.527	0.466	Yes (Local)
3	Algeria	Middle East and North Africa	UMC	0.106	0.370	0.358	No
4	Argentina	Latin America and Caribbean	UMC	0.574	0.474	0.600	No
5	Armenia	Europe and Central Asia	UMC	0.298	0.493	0.457	No
6	Australia	East Asia and Pacific	HIC	0.671	0.727	0.636	Yes (Global)
7	Austria	Europe and Central Asia	HIC	0.875	0.725	0.739	No
8	Azerbaijan	Europe and Central Asia	UMC	0.092	0.471	0.351	No
9	Bangladesh	South Asia	LMC	0.208	0.384	0.362	No
10	Belarus	Europe and Central Asia	UMC	0.348	0.471	0.483	No
11	Belgium	Europe and Central Asia	HIC	0.876	0.672	0.740	No
12	Benin	Sub-Saharan Africa	LMC	0.235	0.363	0.380	No
13	Bolivia	Latin America and Caribbean	LMC	0.173	0.377	0.339	No
14	Bosnia and Herzegovina	Europe and Central Asia	UMC	0.350	0.428	0.484	No
15	Botswana	Sub-Saharan Africa	UMC	0.161	0.413	0.387	No
16	Brazil	Latin America and Caribbean	UMC	0.638	0.501	0.633	No
17	Bulgaria	Europe and Central Asia	HIC	0.364	0.577	0.480	No
18	Burkina Faso	Sub-Saharan Africa	LIC	0.029	0.312	0.243	No
19	Cambodia	East Asia and Pacific	LMC	0.236	0.370	0.381	No
20	Cameroon	Sub-Saharan Africa	LMC	0.156	0.341	0.328	No
21	Canada	North America	HIC	0.877	0.713	0.740	No
22	Chile	Latin America and Caribbean	HIC	0.555	0.586	0.577	No
23	China	East Asia and Pacific	UMC	0.445	0.635	0.533	Yes (Local)
24	Colombia	Latin America and Caribbean	UMC	0.508	0.489	0.566	No
25	Congo, Dem. Rep.	Sub-Saharan Africa	LIC	0.106	0.247	0.294	No
26	Congo, Rep.	Sub-Saharan Africa	LMC	0.150	0.277	0.323	No
27	Costa Rica	Latin America and Caribbean	UMC	0.390	0.540	0.505	Yes (Local)
28	Croatia	Europe and Central Asia	HIC	0.558	0.582	0.578	No
29	Czechia	Europe and Central Asia	HIC	0.672	0.646	0.636	No
30	Denmark	Europe and Central Asia	HIC	0.819	0.779	0.711	Yes (Global)
31	Dominican Republic	Latin America and Caribbean	UMC	0.249	0.469	0.432	No
32	Ecuador	Latin America and Caribbean	UMC	0.201	0.442	0.407	No
33	Egypt, Arab Rep.	Middle East and North Africa	LMC	0.356	0.394	0.461	No
34	Ethiopia	Sub-Saharan Africa	LIC	0.293	0.254	0.419	No
35	Finland	Europe and Central Asia	HIC	0.856	0.758	0.730	Yes (Global)
36	France	Europe and Central Asia	HIC	0.862	0.698	0.733	No
37	Gabon	Sub-Saharan Africa	UMC	0.192	0.323	0.403	No
38	Georgia	Europe and Central Asia	UMC	0.540	0.530	0.582	No
39	Germany	Europe and Central Asia	HIC	0.932	0.753	0.768	No
40	Ghana	Sub-Saharan Africa	LMC	0.255	0.425	0.394	Yes (Local)
41	Greece	Europe and Central Asia	HIC	0.568	0.582	0.583	No
42	Guatemala	Latin America and Caribbean	UMC	0.437	0.390	0.529	No
43	Guinea	Sub-Saharan Africa	LMC	0.042	0.324	0.251	No
44	Honduras	Latin America and Caribbean	LMC	0.216	0.342	0.368	No
45	Hong Kong SAR, China	East Asia and Pacific	HIC	0.701	0.701	0.651	Yes (Global)
46	Hungary	Europe and Central Asia	HIC	0.719	0.563	0.660	No
47	India	South Asia	LMC	0.370	0.493	0.471	Yes (Local)
48	Indonesia	East Asia and Pacific	UMC	0.379	0.516	0.499	Yes (Local)
49	Iran, Islamic Rep.	Middle East and North Africa	UMC	0.439	0.378	0.530	No
50	Iraq	Middle East and North Africa	UMC	0.120	0.270	0.365	No
	Country	Region	Income level	ECI (multi., scaled)	AIPI (observed)	AIPI (predicted)	Overperformer
51	Ireland	Europe and Central Asia	HIC	0.878	0.693	0.741	No
52	Israel	Middle East and North Africa	HIC	0.870	0.725	0.737	No
53	Italy	Europe and Central Asia	HIC	0.853	0.621	0.728	No
54	Côte d'Ivoire	Sub-Saharan Africa	LMC	0.117	0.366	0.302	No
55	Jamaica	Latin America and Caribbean	UMC	0.462	0.434	0.542	No
56	Japan	East Asia and Pacific	HIC	0.837	0.733	0.720	Yes (Global)
57	Jordan	Middle East and North Africa	UMC	0.368	0.483	0.493	No
58	Kazakhstan	Europe and Central Asia	UMC	0.173	0.552	0.392	Yes (Local)
59	Kenya	Sub-Saharan Africa	LMC	0.388	0.445	0.483	No
60	Kuwait	Middle East and North Africa	HIC	0.355	0.461	0.475	No
61	Kyrgyz Republic	Europe and Central Asia	LMC	0.414	0.426	0.500	No
62	Lao PDR	East Asia and Pacific	LMC	0.164	0.330	0.333	No
63	Lebanon	Middle East and North Africa	LMC	0.544	0.418	0.587	No
64	Libya	Middle East and North Africa	UMC	0.050	0.245	0.329	No
65	Lithuania	Europe and Central Asia	HIC	0.499	0.665	0.548	No
66	Madagascar	Sub-Saharan Africa	LIC	0.118	0.305	0.302	No
67	Malaysia	East Asia and Pacific	UMC	0.470	0.632	0.546	Yes (Local)

(continued on next page)

Table A.2 (continued)

	Country	Region	Income level	ECI (multi., scaled)	APII (observed)	APII (predicted)	Overperformer
68	Mali	Sub-Saharan Africa	LIC	0.000	0.296	0.223	No
69	Mexico	Latin America and Caribbean	UMC	0.658	0.532	0.643	No
70	Moldova	Europe and Central Asia	UMC	0.311	0.481	0.464	No
71	Mongolia	East Asia and Pacific	UMC	0.102	0.484	0.356	No
72	Morocco	Middle East and North Africa	LMC	0.217	0.429	0.368	Yes (Local)
73	Mozambique	Sub-Saharan Africa	LIC	0.155	0.257	0.327	No
74	Myanmar	East Asia and Pacific	LMC	0.122	0.327	0.305	No
75	Namibia	Sub-Saharan Africa	UMC	0.241	0.420	0.428	No
76	Netherlands	Europe and Central Asia	HIC	0.890	0.766	0.747	Yes (Global)
77	New Zealand	East Asia and Pacific	HIC	0.710	0.754	0.655	Yes (Global)
78	Nigeria	Sub-Saharan Africa	LMC	0.161	0.336	0.331	No
79	North Macedonia	Europe and Central Asia	UMC	0.362	0.482	0.490	No
80	Norway	Europe and Central Asia	HIC	0.742	0.706	0.672	Yes (Global)
81	Oman	Middle East and North Africa	HIC	0.255	0.533	0.424	No
82	Pakistan	South Asia	LMC	0.220	0.369	0.370	No
83	Panama	Latin America and Caribbean	HIC	0.471	0.501	0.534	No
84	Papua New Guinea	East Asia and Pacific	LMC	0.056	0.290	0.261	No
85	Paraguay	Latin America and Caribbean	UMC	0.437	0.410	0.529	No
86	Peru	Latin America and Caribbean	UMC	0.311	0.491	0.464	No
87	Philippines	East Asia and Pacific	LMC	0.469	0.498	0.537	No
88	Poland	Europe and Central Asia	HIC	0.624	0.597	0.612	No
89	Portugal	Europe and Central Asia	HIC	0.617	0.646	0.608	No
90	Qatar	Middle East and North Africa	HIC	0.364	0.535	0.480	No
91	Romania	Europe and Central Asia	HIC	0.525	0.584	0.562	No
92	Russian Federation	Europe and Central Asia	HIC	0.456	0.559	0.527	No
93	Rwanda	Sub-Saharan Africa	LIC	0.246	0.437	0.388	Yes (Local)
94	Saudi Arabia	Middle East and North Africa	HIC	0.459	0.577	0.528	No
95	Senegal	Sub-Saharan Africa	LMC	0.228	0.396	0.376	No
96	Serbia	Europe and Central Asia	UMC	0.500	0.537	0.561	No
97	Singapore	East Asia and Pacific	HIC	0.718	0.801	0.660	Yes (Global)
98	Slovak Republic	Europe and Central Asia	HIC	0.528	0.592	0.563	No
99	Slovenia	Europe and Central Asia	HIC	0.627	0.634	0.613	No
100	South Africa	Sub-Saharan Africa	UMC	0.588	0.497	0.607	No

	Country	Region	Income level	ECI (multi., scaled)	APII (observed)	APII (predicted)	Overperformer
101	Korea, Rep.	East Asia and Pacific	HIC	0.670	0.727	0.635	Yes (Global)
102	Spain	Europe and Central Asia	HIC	0.776	0.648	0.689	No
103	Sri Lanka	South Asia	LMC	0.239	0.436	0.383	Yes (Local)
104	Sudan	Sub-Saharan Africa	LIC	0.041	0.233	0.251	No
105	Sweden	Europe and Central Asia	HIC	0.928	0.748	0.766	No
106	Switzerland	Europe and Central Asia	HIC	0.991	0.757	0.798	No
107	Taiwan, China	East Asia and Pacific	HIC	0.652	0.669	0.626	No
108	Tajikistan	Europe and Central Asia	LMC	0.058	0.366	0.262	No
109	Tanzania	Sub-Saharan Africa	LMC	0.249	0.352	0.390	No
110	Thailand	East Asia and Pacific	UMC	0.517	0.536	0.570	No
111	Togo	Sub-Saharan Africa	LIC	0.039	0.316	0.250	No
112	Tunisia	Middle East and North Africa	LMC	0.320	0.465	0.437	Yes (Local)
113	Türkiye	Europe and Central Asia	UMC	0.632	0.540	0.629	No
114	Uganda	Sub-Saharan Africa	LIC	0.309	0.354	0.430	No
115	Ukraine	Europe and Central Asia	UMC	0.356	0.512	0.487	Yes (Local)
116	United Arab Emirates	Middle East and North Africa	HIC	0.404	0.628	0.500	No
117	United Kingdom	Europe and Central Asia	HIC	0.980	0.731	0.792	No
118	United States	North America	HIC	1.000	0.771	0.803	No
119	Uruguay	Latin America and Caribbean	HIC	0.429	0.549	0.513	No
120	Uzbekistan	Europe and Central Asia	LMC	0.156	0.346	0.328	No
121	Venezuela, RB	Latin America and Caribbean	UMC	0.178	0.275	0.395	No
122	Viet Nam	East Asia and Pacific	LMC	0.285	0.482	0.414	Yes (Local)
123	Yemen, Rep.	Middle East and North Africa	LIC	0.002	0.253	0.225	No
124	Zambia	Sub-Saharan Africa	LMC	0.252	0.371	0.392	No
125	Zimbabwe	Sub-Saharan Africa	LMC	0.225	0.305	0.374	No

Source: The APII score for 2023 is obtained from the IMF website [<https://www.imf.org/external/datamapper/datasets/APII>] and the ECI on trade and research for 2021–22 are obtained from the OEC website [<https://oec.world/en/rankings/eci/hs6/hs96?tab=ranking>]. Notes: The first PCA of ECI trade and ECI research, with an eigenvalue exceeding 50 % (normalized and scaled between 0 and 1 across the sample of countries) is reported here. Global and local overperformers are identified through a two-step approach: (i) comparing APII scores to the weighted median and average of income groups, and (ii) identifying scores exceeding predicted values based on economic complexity. Population size for 2023, used for the weighted analysis to obtain the APII predicted score, is sourced from the “wbopendata” module in Stata (Azevedo, 2020), with data for Taiwan Province of China obtained from the Statista website. For more details, see the “Data and Methodology” and “Empirical Findings” sections.

Data availability

Data will be made available on request.

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