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RESEARCH ARTICLE

Superpower Competitiveness in the 4IR: AI, FinTech

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ABSTRACT

This study compares the competitiveness of the USA, EU, China and India over 2017–2025, using verified international indices (GII, GTCI, NRI) and descriptive indicators of AI, FinTech, human capital and innovation. Three exploratory propositions, motivated by endogenous growth in 4th Industrial Revolution, dynamic comparative advantage, and institutional theory, are examined. Innovation scores converge modestly relative to incomes per head. Talent competitiveness (GTCI) and Global innovation (GII) move together in levels, but initial talent does not predict later gains. Risk-based regulation is not associated with higher FinTech adoption: the EU records the lowest adoption, China the highest, the USA leads in capitalization. A Network Readiness Index (NRI) integrating talent, infrastructure, capital, regulatory complexity is partly computable. Three qualitative 2030 scenarios, with multipolar specialization most plausible, are exploratory, not forecasts. Policy implications (prioritizing human-capital investment, adaptive governance, infrastructure complementarity, open knowledge flows against costly technological decoupling) are hypotheses for testing on larger samples.

Keywords: Fourth Industrial Revolution; artificial intelligence; FinTech; competitiveness; convergence; human capital; multicriteria analysis

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1. Introduction: The Fourth Industrial Revolution and Global Economic Reconfiguration

1.1. Objectives and Analytical Framework

The Fourth Industrial Revolution (4IR) denotes a structural transformation characterized by the fusion of technologies across the physical, digital, and biological domains[1]. Its two most economically consequential vectors — artificial intelligence (AI) and financial technology (FinTech) — are reshaping competitiveness, trade patterns, and the global distribution of economic power in ways that traditional factor-endowment trade theories capture only partially: competitive position increasingly reflects accumulated knowledge, institutional quality, and network scale rather than static resource endowments. The study addresses three research

questions:

- RQ1: How have innovation-capacity indicators evolved across the four entities over 2017–2025, and is there evidence of convergence?
- RQ2: To what extent is human capital quality, proxied by the Global Talent Competitiveness Index (GTCI), associated with innovation outcomes?
- RQ3: How do divergent regulatory frameworks for AI and FinTech relate to comparative advantages and disadvantages at the superpower level?

The framework draws on three theoretical traditions, each motivating one proposition. Endogenous growth theory[2] explains how human capital investment and knowledge accumulation generate self-sustaining innovation capacity and, because ideas are non-rival and increasingly codified, suggests that measured innovation capabilities can diffuse across borders faster than income levels. Dynamic comparative advantage theory[3] extends trade theory to knowledge-intensive industries in which learning-by-doing and scale externalities make competitive position path-dependent and policy-sensitive. Institutional economics[4] emphasizes that regulatory frameworks, property rights, and governance quality condition whether technological opportunity is converted into broad-based economic gain. Following the multicriteria tradition of Buracas[5] and Buracas et al.[6], these theories motivate three exploratory propositions:

- **P1:** Innovation index scores converge across the entities faster than per capita incomes (sigma-convergence: declining cross-sectional dispersion[7]).
- **P2:** Lagged GTCI scores are positively associated with subsequent GII improvement, conditional on R&D intensity and institutional quality.
- **P3:** Entities with adaptive, risk-based AI governance frameworks exhibit higher FinTech adoption and innovation output than those with laissez-faire or prohibitive approaches.

The study distinguishes three evidential levels: (i) *statistical association* in the observed data; (ii) *theoretical interpretation*, i.e. mechanisms that would rationalize an association; and (iii) *causal inference*, which the design does not permit. Statements about 2030 are *projections*, separated from *observed data*.

Figure 1 situates the analysis in the distribution of world output on a single, consistently defined series (PPP). **Table 1** shows that China's share of world GDP at PPP was 18.3% in 2017 and 18.8% in 2024, against 15.3% and 14.8% for the USA, so China's PPP economy exceeded the USA's by roughly 27% in 2024 (18.8/14.8). India's share rose from 7.5% to 8.2%. Aggregate scale is an imperfect predictor of innovation leadership: in 2025 the USA, with a PPP share below China's, leads China on all three core indices (**Table 2**).

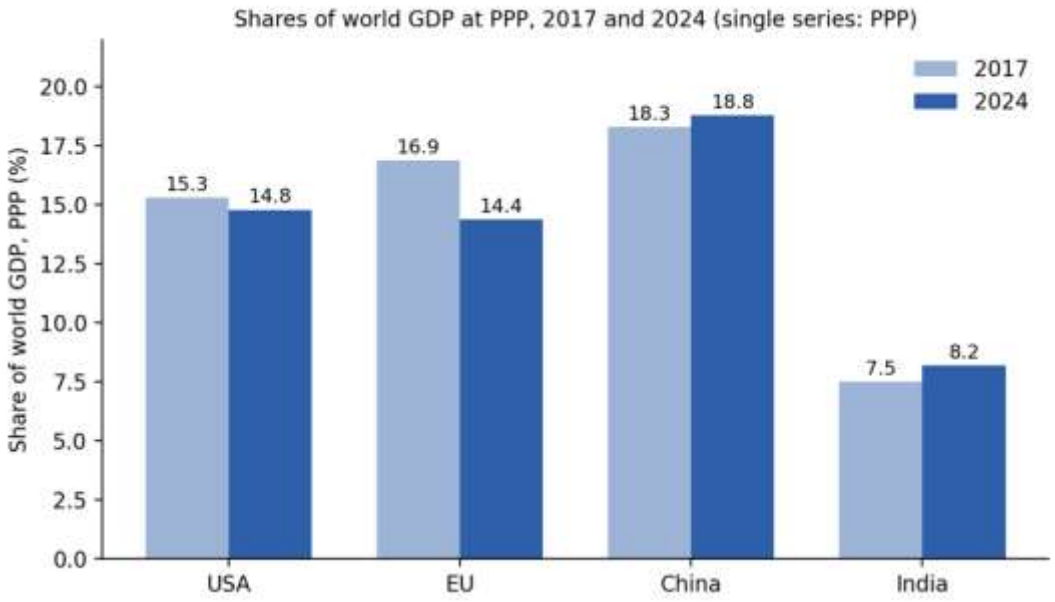


Figure 1. Shares of world GDP at PPP, 2017 and 2024.

Source: IMF World Economic Outlook[8], as in Table 1.

1.2. Superpower Selection Criteria

Selection of the four focal entities employs six operationalized criteria. *Economic scale* (at least 5% of world GDP, PPP): together the four entities account for 56.2% of world GDP at PPP in 2024 (**Table 1**)[8]. *Population scale* (at least 300 million): the entities together represent a large part of the world population, providing the scale required for technological experimentation, market formation, and workforce development. *Technological infrastructure*: divergent capabilities — from the USA's AI research leadership to China's deployment scale (98% 5G coverage; **Table 6**) — enable comparative pathway analysis. *Trade significance*: the entities account for a large share of global merchandise trade. *Institutional diversity*: four distinct governance models — market-driven (USA), social market (EU), state-directed (China), and democratic developmental (India) — offer contrasting, though non-experimental, settings. *Strategic projection*: IMF and World Bank forecasts[8] indicate that these entities will remain prominent in the 2030–2050 global economy. The EU is treated as a single aggregate; values reported as "EU (mean)" are simple averages of member-state scores, which preserves scale comparability but understates intra-EU heterogeneity. The sample is a purposive selection, and no statistical generalization beyond it is claimed.

1.3. Macroeconomic Foundations: Key Indicators 2017–2024

Table 1 presents the macroeconomic context. At constant 2015 prices, the USA's share of world GDP is stable (23.6% in 2017, 23.3% in 2024), China's rises from 16.0% to 19.1%, the EU's falls from 17.7% to 16.2%, and India's rises from 3.0% to 3.5%. China's R&D expenditure rose from 2.1% to 2.6% of GDP (2017–2023), against India's stagnation at 0.7% — a gap of roughly 3.7 times in 2023. China's trade surplus doubled to $823 billion while the US deficit widened to $773 billion, reflecting divergent industrial-policy trajectories[9]. India (7.0%) and China (5.0%) outpaced the USA (2.8%) and the EU (1.1%) in 2024. At 2024 growth rates, India's real output would double in roughly a decade and the EU's in over sixty years; this simple

compounding, which assumes constant growth, underlies the illustrative projections of Section 7.

Table 1. Comparative macroeconomic indicators of the four superpowers, 2017–2024.

Indicator	Year	USA	EU	China	India
Share of world GDP (PPP, %)	2017	15.3	16.9	18.3	7.5
	2024	14.8	14.4	18.8	8.2
Share of world GDP (constant 2015 prices, %)	2017	23.6	17.7	16.0	3.0
	2024	23.3	16.2	19.1	3.5
GDP per capita (PPP, US$)	2017	55,837	42,450	14,239	6,089
	2024	85,373	62,400	25,015	11,100
Annual GDP growth rate (%)	2017	1.7	1.8	6.5	7.4
	2024	2.8	1.1	5.0	7.0
Consumer price inflation (%)	2017	1.4	1.5	2.0	5.1
	2024	2.9	2.4	0.2	4.9
Unemployment rate (%)	2017	4.9	7.6	4.1	4.9
	2024	4.1	5.9	5.1	4.2
R&D expenditure (% of GDP)	2017	2.8	2.1	2.1	0.7
	2023*	3.5	2.2	2.6	0.7
Trade balance (billion US$)	2017	−566	+435	+420	−157
	2023	−773	+41	+823	−78

** Latest available. Constant-price shares: World Bank, GDP at constant 2015 US$ (world total 80,642 billion in 2017 and 96,830 billion in 2024; EU = EU27 aggregate). Other series: IMF[8]; World Bank[10]; OECD[11]; Eurostat[12]; National Bureau of Statistics of China[13]. Sources and editions are listed in Appendix Table A1.*

1.4. Competitiveness Indices: Verified Values and Convergence Analysis

Table 2 reports the core indices (GII, GTCI, NRI) for their published editions, with scores and ranks. The EU is represented by the simple mean of member-state scores where it could be computed. The GTCI was not published every year (the editions used are 2017, 2023 and 2025), and the 2025 edition was produced with the Portulans Institute, so GTCI ranks across editions are not strictly comparable.

Table 2. Core international indices: score, ranks of superpowers.

Index (edition; economies covered)	USA	EU (mean of 27 members)	China	India
GII 2017 (127)	61.4 (4th)	not computed	52.5 (22nd)	35.5 (60th)
GII 2024 (133)	62.4 (3rd)	not computed	56.3 (11th)	38.3 (39th)
GII 2025 (139)	61.7 (3rd)	45.8 (2nd–49th)	56.6 (10th)	38.2 (38th)
GTCI 2017 (118), rank	4th	not computed	54th	92nd
GTCI 2023, rank	3rd	not computed	40th	103rd
GTCI 2025 (135)	69.41 (9th)	60.71 (3rd–55th)	48.65 (53rd)	34.03 (100th)
NRI 2024	not retrieved	not computed	rank 17th	53.63 (49th)
NRI 2025 (127)	79.13 (1st)	not computed	65.74 (24th)	54.43 (45th)

EU = simple mean of member-state scores, with the rank range of members in parentheses. Sources: WIPO[14–16]; INSEAD[17–19]; Portulans Institute[20,21]; links in Appendix Table A1.

To assess Proposition P1, the coefficient of variation (CV = population standard deviation / mean) of GII scores was computed for the three entities with verified values (USA, China, India); the EU is excluded because no EU aggregate is available for 2017 and 2024. The CV declined from 0.216 (2017) to 0.195 (2024) and 0.193 (2025), a fall of 9.7% and 10.6%. The CV of GDP per capita (PPP, **Table 1**) declined from 0.858 to 0.796 (−7.2%). Dispersion in GII scores therefore fell only slightly more than dispersion in incomes, and no significance test is meaningful. The 2017–2024 GII gains were 1.0 (USA), 3.8 (China) and 2.8 points (India); regressing gain on initial level gives a slope of −0.05 points per point ($r = -0.49$, $n = 3$), a weak catch-up pattern of descriptive value only. Two mechanisms may contribute to convergence: the inputs that composite indices reward are amenable to rapid policy-directed accumulation, and bounded scales mechanically compress gaps as followers improve. P1 is therefore at most weakly consistent with the data. Rank movements are more pronounced: China rose from 22nd (2017) to 11th (2024) and 10th (2025), India from 60th to 39th and 38th, and the USA held 3rd–4th; India's rise has coincided with the Digital India and Make in India programmes[22]. In 2025 China (56.6) scores well above the EU member-state mean (45.8).

2. Research Methodology

2.1. Index Selection and Treatment

The study draws on three core international indices, selected for cross-country comparability, publication regularity, and documented methodology: the Global Innovation Index (GII; innovation output), the Global Talent Competitiveness Index (GTCI; human capital), and the Network Readiness Index (NRI; digital infrastructure and connectivity). They are examined individually rather than combined into a weighted composite, and are complemented by descriptive indicators of AI, FinTech, education, and innovation drawn from international statistical sources (Sections 3–6). **Table 3** lists the publisher, scale and coverage of each index. Regulatory quality is taken from the NRI indicator of that name (0–100). Composite indices with insufficient time-series coverage, such as the WEF–Huawei Global Digitalization Index, were not used.

Table 3. Core international indices: selection and measurement properties.

Index	Publisher	Scale	Coverage	Dimension
Global Innovation Index (GII)	WIPO	0–100	127 economies (2017); 133 (2024); 139 (2025)	Innovation output
Global Talent Competitiveness Index (GTCI)	INSEAD	0–100	118 countries (2017); 135 (2025)	Human capital
Network Readiness Index (NRI)	Portulans Institute	0–100	127 economies (2025)	Digital infrastructure

Coverage differs by edition and affects comparability across years.

2.2. Convergence Analysis Protocol

Sigma-convergence — a decline in cross-sectional dispersion — is assessed through the coefficient of variation (CV, population standard deviation divided by the mean) of index scores across the entities with

verified data. Beta-convergence — initially lagging entities improving faster than leaders[7] — is reported as a descriptive slope of score gains on initial levels. With three or four units the slope has one or two degrees of freedom and a bootstrap would resample too few units to be informative; neither measure is treated as a formal test of P1.

2.3. Human Capital–Competitiveness Relationship

Proposition P2 is examined descriptively. An annual panel regression of GII rank change on lagged GTCI, R&D/GDP and WGI is not feasible: the GTCI is not published every year (there is no 2024 edition), and with three to four entities, rank changes that are mechanically interdependent, and several parameters, such a model would have too few degrees of freedom for inference. **Table 4** therefore juxtaposes the verified GTCI and GII values of each entity. A regression design becomes feasible only with a panel of many economies.

Table 4. Initial talent competitiveness and subsequent innovation gains.

Entity	GTCI rank, 2017 (of 118)	GTCI rank, 2025 (of 135)	GII rank 2017 → 2025	GII score gain 2017–2024
USA	4th	9th	4th → 3rd	+1.0
China	54th	53rd	22nd → 10th	+3.8
India	92nd	100th	60th → 38th	+2.8

Computed from Table 2. With three units no coefficient is reported; the table is descriptive, verified data (n = 3; EU excluded for lack of verified aggregates).

2.4. Readiness Index: Formal Specification

The 4IR Readiness Index (RI) is defined for entity *i* as $RI_i = [(T_i \times INF_i) + K_i] / RC_i$, where T is the GTCI score divided by 100, INF the NRI Technology pillar score divided by 100, K venture-capital investment as a share of GDP relative to the highest value among the entities, and RC regulatory complexity, defined as 100 divided by the NRI indicator "Regulatory quality" (0–100). The multiplicative T×INF term reflects complementarity (talent without infrastructure, and infrastructure without talent, yield suboptimal returns[23]); regulatory complexity enters the denominator on the assumption that compliance burdens scale down the return on the combination. The formula is a stylized heuristic, not an estimated model, and its functional form and normalization are modelling choices. The index is unbounded above and undefined if the regulatory-quality input is zero. **Table 5** reports the inputs and the scores for the entities with complete inputs (China and India); a regulatory-quality input was not available for the USA and the EU in the sources consulted, and no sensitivity analysis is reported.

Table 5. Readiness Index inputs and recomputation.

Component	USA	EU	China	India
T: GTCI 2025 score / 100	0.694	0.607 (mean)	0.487	0.340
INF: NRI 2025 Technology pillar / 100	0.825	not computed	0.644	0.531
NRI regulatory quality (0–100)	not computed	not computed (members: Denmark 88.3, Netherlands 87.1, Finland 86.4, Germany 78.7, France 71.1, Poland 61.8, Portugal 61.1)	33.3	38.8
RC = 100 / regulatory quality	not computed	not computed	3.00	2.58
K: VC % GDP relative to maximum	1.000	0.349	0.222	0.175
RI recomputed	not computed	not computed	0.178	0.138

Sources: INSEAD[19]; Portulans Institute NRI 2025 country profiles[21] (USA, China, India, and the member states shown).

2.5. Data Sources and Observation Period

The 2017–2025 window covers the diffusion wave of AI and FinTech following the commercialization of deep learning (2016–2017). Data are drawn from the primary institutional source of each index, supplemented by the IMF World Economic Outlook[8], World Bank Development Indicators[10], OECD MSTI[11], Eurostat[12], the Stanford HAI AI Index[24], and national statistical agencies. Appendix Table A1 lists the sources with portals and editions. Values for 2025 are provisional and are marked as such. India's tertiary enrolment follows the UNESCO UIS 2024 release (31.4%), consistent with the AISHE 2022–23 survey[25]. All adoption rates are expressed as percentages of the digitally active population.

3. Artificial Intelligence: Core Technology Reshaping Global Competition

3.1. AI Development Trajectories 2017–2025

Table 6 documents the transformation of AI ecosystems. US private AI investment rose from $18.2 billion (2017) to $109.1 billion (2025), driven by the generative-AI wave. China's reported AI funding is $12.9 billion in 2025, with a shift toward state-backed semiconductor and industrial-AI projects following regulatory tightening on consumer-technology platforms. India's 5G coverage rose from zero (2018) to 92% of the population (2025), a deployment speed exceeding that of many EU member states, in a leapfrogging pattern that parallels its FinTech adoption[26].

Table 6. AI and digital infrastructure indicators, 2017–2025.

Indicator	Year	USA	EU	China	India
AI startups (active entities)	2017	1,393	769	383	95
	2025	18,240	8,110	4,205	3,650
AI investment (billion US$)	2017	18.2	4.8	7.4	0.7
	2025	109.1	19.4	12.9	2.8
Cloud market share (% global revenue)	2017	56.0	18.0	9.0	2.5
	2025	52.3	16.5	14.2	4.8
Supercomputer systems (Top 500)	2017	169	107	202	9
	2025	171	126	40*	6
Data center capacity (MW)	2017	11,288	4,523	6,940	527
	2025	53,700	20,800	19,600	1,800
5G network coverage (% pop.)	2018	38.0	27.0	86.0	0.0
	2025	95.0	81.0	98.0	92.0
Internet penetration (% pop.)	2017	88.5	85.2	54.3	34.5
	2025	94.2	93.8	77.5	54.0
Fixed broadband (per 100 pop.)	2017	33.5	31.8	26.3	1.4
	2025	41.2	44.2	48.5	3.1
AI research papers (annual)	2017	10,243	8,215	8,045	1,567
	2025	34,800	29,100	52,400†	9,200
AI patents filed (cumulative)	2017	8,290	3,452	30,391	289
	2025	332,788	85,400	723,149	12,274

** 2025 values provisional. China ceased Top 500 international submissions for strategic-security reasons, although its domestic supercomputing capacity is estimated to be large; the figure is not comparable. † China leads in volume; citation-weighted impact remains lower than the USA's. Data sources: Stanford HAI[24]; WIPO[27]; ITU[28]; TOP500.org[29]; IDC[30]; CB Insights[31].*

China's annual AI research output (52,400 publications, 2025) exceeds that of the USA (34,800) and the EU (29,100) in volume, yet citation-weighted metrics indicate that the USA retains the intellectual frontier. The divergence between volume-driven and frontier-driven systems may be institutionally rooted, as frontier research may depend on openness and academic autonomy that China's weak Enable pillar (Section 5.2) constrains; this interpretation is consistent with, but does not test, the institutional-quality hypothesis (P3). US data-center capacity rose from 11,288 MW to 53,700 MW (a factor of 4.8) to support large-model training. Electricity costs also matter for compute-intensive workloads; a comparison between the EU and China would require industrial tariff series in a single currency and tariff class (for example from Eurostat and the IEA), and none is used here.

3.2. National AI Strategies: Comparative Analysis

The United States maintains fundamental-research strength through world-class universities and technology corporations, amplified by DARPA-style entrepreneurial-state seed funding[32]. Immigration restrictions and expanding global talent pools may erode its attraction advantage, and the permissive regulatory stance that accelerates deployment also raises documented algorithmic-bias and privacy concerns[33].

The European Union's "trustworthy AI" framework, formalized in the 2024 AI Act[34], introduces a risk-based architecture categorizing AI systems by their safety and fundamental-rights impact. This carries a deployment cost for European firms, yet also exports EU standards through market-access requirements — Bradford's[35] "Brussels Effect".

China's New Generation AI Development Plan[36] targeted world leadership by 2030. Its advantages — the world's largest internet and mobile-user base supplying training data[37], rapid deployment in facial recognition and smart-city applications, and tight government–industry coordination[38] — coexist with concerns about surveillance and authoritarian use arising from the fusion of commercial AI with state security objectives.

India's National AI Strategy (NITI Aayog) emphasizes AI for social good — healthcare, agriculture, education, and financial inclusion. A large English-speaking engineering workforce, a mature IT-services base, and an expanding startup ecosystem (Bengaluru, Hyderabad, Pune) are set against binding constraints: limited AI research investment relative to leading economies, rural digital-infrastructure gaps, and shortages of advanced AI talent.

3.3. AI-Driven Social Change: Labor Markets and Structural Transformation

The nexus between AI adoption and social structure is inadequately captured by competitiveness metrics alone. Applying the task-substitution framework of Acemoglu and Restrepo[39], which distinguishes automation that displaces labor from technologies that create new tasks, each entity exhibits a distinctive risk profile. In the USA, white-collar substitution risk concentrates in legal, financial-analysis, and creative services. In China, displacement risk for a very large workforce in routine assembly and processing is likely to be a dominant social challenge of the 2025–2035 decade; published estimates of its scale vary and none is relied on here. India's demographic dividend depends on technology-enabled job creation outpacing automation in the BPO and IT-services sectors, which Baldwin's[40] "globotics" identifies as simultaneously enabled and threatened by remote intelligence. The EU's labor-market institutions may moderate displacement speed but may also slow AI diffusion. These dynamics suggest that social outcomes of 4IR adoption are shaped by the interaction of technological capacity with institutional architecture, in line with the varieties-of-capitalism literature[41] and relevant to P3.

4. Financial Technology: Reshaping Global Finance Architecture

4.1. FinTech Ecosystem Evolution 2018–2025

Table 7 documents the FinTech transformation. India's cashless transaction share rose from 23% to 68% — the largest absolute gain among the four entities (45 percentage points) — supported by the Unified Payments Interface (UPI), which processed over 12 billion transactions monthly by 2025. China leads in digital transaction value ($12.4 trillion) and mobile-payment users (980 million), although aggregate FinTech investment declined after regulatory tightening on Ant Group and allied platforms; it also holds the largest number of annual blockchain patent filings (12,500, 2025), focused on industrial applications and the digital

yuan (e-CNY).

Table 7. FinTech development and adoption indicators, 2018–2025.

Indicator	Year	USA	EU	China	India
FinTech adoption rate (% digitally active pop.)	2018	46.0	42.0	87.0	52.0
	2025	82.5	76.0	91.5	84.0
Mobile payment users (millions)	2018	73	156	583	278
	2025	115	312	980	640
Digital transaction value (billion US$)	2018	1,235	876	5,497	238
	2025	3,150	2,840	12,400	2,100
Cashless transaction share (% of total vol.)	2018	66.0	58.0	71.0	23.0
	2025	81.0	74.0	88.0	68.0
FinTech unicorns (no. of companies)	2018	21	7	9	3
	2025	182	64	48	26
FinTech investment (billion US$)	2018	25.5	8.3	25.6	2.0
	2025	58.4	14.2	11.6	5.1
Blockchain patents (annual submissions)	2018	456	234	790	67
	2025	3,840	1,210	12,500	450
Regulatory sandboxes (active programs)	2018	12	28	6	3
	2025	18	34	14	11
Crypto regulation (legal framework)	2025	SEC / GENIUS Act	MiCA (active)	Prohibited	VDA taxed
Cross-border remittance cost (avg. % fee)	2018	5.4	5.8	6.2	6.8
	2025	4.1	3.8	4.9	5.2

*2025 values provisional. *Data sources: BIS[42]; World Bank[10]; EY FinTech Adoption Index[43]; WIPO[27]; KPMG Pulse of FinTech[44]; McKinsey Global Payments Report[45]; CB Insights Global Unicorn Club[31]; European Commission MiCA implementing acts (2025).*

Adoption and capitalization emerge as distinct competitive margins. China leads in usage and transaction value; the USA leads in equity value creation, hosting 182 FinTech unicorns — about 1.6 times the EU and China combined (64 + 48 = 112) — consistent with its mature venture-capital ecosystem. The EU has positioned itself as a regulatory standard-setter through the Markets in Crypto-Assets (MiCA) and Digital Operational Resilience Act (DORA) frameworks, both operative in 2025, and offers arguably the most predictable environment for digital-asset firms. The evidence bearing on P3 is assessed in Section 4.4.

4.2. Digital Payment Infrastructure and Financial Inclusion

China's mobile-payment infrastructure largely bypassed card-based intermediaries: Alipay and WeChat Pay dominate a market in which urban cash use has become marginal. Government standardization of QR-code protocols and the e-CNY pilots address interoperability while extending central bank monitoring capacity — a dual objective with implications for financial inclusion and civil-liberty debates. India's trajectory, built on the India Stack open digital public infrastructure, is identified by UNCTAD[26] as a potentially replicable leapfrogging model: UPI's open, standardized architecture enabled private-sector

innovation at scale while maintaining public oversight, although digital-identity limitations, rural connectivity gaps, and an immature data-protection framework constrain inclusive expansion. The USA operates a sophisticated but legacy-constrained payment infrastructure: path dependencies around Visa/Mastercard network dominance slow the adoption of more efficient alternatives, and the absence of a national digital-identity system complicates KYC compliance. The EU's Single Euro Payments Area and instant-payment regulation provide the architecture for harmonized cross-border payments, with Nordic members demonstrating good practice in privacy-preserving digital identity.

4.3. Central Bank Digital Currencies (CBDC): Strategic Competition

China's e-CNY is the most advanced major-economy CBDC, piloted across 26 cities and integrated into existing payment infrastructure. Its strategic objectives — reducing dependence on dollar-denominated international payments, extending monetary-policy transmission, and enhancing transaction monitoring — are reinforced by Belt and Road pathways, although international adoption remains limited by geopolitical concerns and the network externalities of the dollar system. The EU's digital-euro project faces coordination challenges across heterogeneous national financial systems. The US Federal Reserve maintains a deliberately cautious stance, weighing financial stability, disintermediation, and privacy. India's Reserve Bank conducts retail and wholesale pilots balancing inclusion against systemic risk.

4.4. Evidence on Proposition P3 (Regulatory Design and FinTech Outcomes)

P3 asserts that adaptive, risk-based governance is associated with higher FinTech adoption and innovation output than laissez-faire or prohibitive approaches. A clearly specified test would require a coded regime variable, an outcome measure, and variation in both across enough units; with four entities and one regime observation each, no such test is feasible. **Table 8** therefore juxtaposes, descriptively, the author's regime coding (a judgement that would need an explicit rubric) and 2025 outcomes from **Table 7**.

Table 8. Regulatory approach and FinTech outcomes*, 2025.

Entity	Regulatory approach (AI/FinTech)	Adoption (% digitally active pop.)	FinTech unicorns	FinTech investment (US$ bn)	Regulatory sandboxes
USA	Permissive, sectoral and fragmented	82.5	182	58.4	18
EU	Risk-based, comprehensive (AI Act, MiCA, DORA)	76.0	64	14.2	34
China	State-directed; crypto prohibited; platform tightening	91.5	48	11.6	14
India	Enabling public infrastructure; VDA taxed	84.0	26	5.1	11

**Descriptive; regime coding is judgemental. The pattern does not support P3.*

The EU, the clearest risk-based case, records the lowest adoption rate and fewer unicorns and less investment than the USA, while the highest adoption occurs in China, a state-directed regime. The table is consistent with a weaker, interpretive claim: regulatory design appears to be related to *which* margin an

economy captures — mass adoption (China, India), equity formation (USA), or standard-setting (EU). This is a theoretical interpretation of descriptive differences, not an empirical finding or a causal inference, since adoption and capitalization are also shaped by market size, payments-system legacy, and venture-capital depth. P3 is reported as not supported on adoption and untested on innovation output.

5. Human Capital Development: Foundation of 4IR Competitiveness

5.1. Education Systems and Skills Development 2017–2025

4IR success depends not only on producing elite researchers but on broad digital literacy, workforce adaptability, and effective human–AI collaboration at scale. **Table 9** documents the transformation of education systems. China's tertiary enrolment rose from 25% to 60.2%, among the fastest higher-education expansions at this scale, creating a talent reserve for AI and advanced manufacturing and underpinning its bid to escape the middle-income trap[46]. India's STEM graduate density rose from 2.6 to 4.1 per 1,000 population and its annual output (about 2.5 million STEM graduates) is reportedly the world's largest, with the National Education Policy 2020[47] targeting quality upgrading; yet secondary completion (56.5%) and enduring educational inequality[48] remain first-order constraints.

Table 9. Education and skills development indicators, 2017–2025.

Indicator	Year	USA	EU (Avg)	China	India
Tertiary education enrolment (gross %)	2017	80.0	67.5	25.0	19.0
	2025	82.2	74.5	60.2	31.4*
Secondary education completion (%)	2017	66.0	72.0	19.0	42.0
	2025	92.0	88.5	48.0	56.5
Adult literacy rate (%)	2017	99.0	99.5	95.1	74.4
	2025	99.0	99.8	97.4	81.0
STEM graduates (per 1,000 pop., annual)	2017	5.3	4.8	4.7	2.6
	2025	4.5	4.6	8.2	4.1
Quality of math & science education (1–7)	2017	4.6	4.9	4.4	3.7
	2025	4.8	5.1	5.8	4.2
Pupil–teacher ratio (primary)	2017	14.1	13.5	16.8	23.4
	2025	14.5	12.2	15.2	19.8
Education expenditure (% GDP)	2017	5.0	4.8	4.0	3.1
	2025	6.1	5.1	4.2	4.1
Availability of scientists/engineers (1–7)	2017	5.2	5.0	4.6	4.3
	2025	5.6	5.3	5.8	4.8
Lifelong learning participation (%)	2017	43.0	45.8	18.5	7.2
	2025	48.5	43.1	35.0	12.5
Digital literacy rate (%)	2017	87.0	82.0	54.3	34.5
	2025	92.5	88.0	74.0	48.5

*2025 values provisional. *UNESCO UIS 2024 release, consistent with AISHE 2022–23. Data: WEF[49]; World Bank EdStats[50]; UNESCO Institute for Statistics[51]; Government of India AISHE[25].*

5.2. Global Talent Competition and GTCI Pillar Analysis

Table 10 presents 2025 GTCI pillar rankings. Regarding Proposition P2, GTCI and GII order the three entities with verified data identically in every edition (USA first, China second, India third), so the two indices co-move in levels (**Table 4**). The GII gains, however, do not line up with the initial GTCI position: China, in the middle, gained most in score (+3.8), India gained most in rank, and the USA, with the highest GTCI, gained least. With three units this is descriptive only and does not identify a direction of effect. P2 is therefore not supported as a predictive claim. The co-movement of levels is consistent with endogenous growth theory[2] and with evidence on global talent flows[52]. A plausible, untested interpretation is that R&D spending is an input whose productivity is conditioned by the talent system deploying it.

Table 10. Global Talent Competitiveness pillar rankings, GTCI.

GTCI pillar	USA	EU (Avg)	China	India	Strategic priority
Enable (regulatory/market)	7th	1st–5th	60th+	100th+	US: AI regulatory clarity; EU: talent mobility
Attract (openness/appeal)	28th	10th–20th	80th+	120th+	China: improve international appeal
Grow (education/upskilling)	2nd	1st–15th	40th	90th	India: vocational and IT pipeline expansion
Retain (sustainability/QoL)	14th	1st–10th	70th	110th	EU: social sustainability and green QoL
Vocational/technical skills	2nd	1st–10th	45th	105th	USA: maintaining AI specialist pipeline
Global knowledge skills	13th	5th–15th	30th	85th	All: AI-adaptive soft-skills integration
Overall rank (2025)	9th	3rd–55th (member range)	53rd	100th	—

Overall ranks: INSEAD[19]. Pillar ranks are indicative. Table 2 gives the 2017 and 2023 ranks (USA 4th and 3rd, China 54th and 40th, India 92nd and 103rd); the 2023 and 2025 editions are not strictly comparable.

The pillar decomposition identifies each entity's apparent binding constraint. For the USA, the Retain pillar (14th) and global knowledge skills (13th) lie below its Grow and Vocational ranks (both 2nd), which may reflect internationally mobile talent's concerns over social cohesion, healthcare accessibility, and institutional stability; this reading is interpretive. The EU leads in Retain, anchored by Denmark, Sweden, and Finland. China's 53rd overall rank is associated with a weak Enable pillar (60th+), reflecting regulatory unpredictability and information-access restrictions that may cap its attraction of international talent beyond the returning diaspora and, as suggested in Section 3.1, constrain its transition from volume-driven to frontier-driven innovation. India's uniformly low pillar ranks indicate that its talent story remains one of scale rather than ecosystem quality.

6. Innovation Systems and Technological Capabilities

6.1. Research and Development: Investment and Productivity

National innovation systems — the institutional networks supporting innovation generation and diffusion

— vary substantially across the four entities. The World Bank's Knowledge Assessment Methodology identifies four enabling pillars: the economic-incentive and institutional regime; education and human capital; innovation infrastructure; and ICT physical capital. Business investment in knowledge-based capital has contributed up to 34% of average labor-productivity growth in the EU and USA[11].

Table 11 documents innovation output. China leads in scientific and technical publication volume (785,000 annually in 2025) and approaches the USA in patenting intensity (1,285 versus 1,473 applications per million population in 2025), while also leading global industrial-robot installations[53]. As with publications, volume-based counts overstate the quality-adjusted position. India consolidated its role as the world's digital back office, with ICT services approaching 50% of total service exports — the highest specialization ratio among the four entities — built on capabilities accumulated since the 1990s software boom[54]. That specialization concentrates exposure to the generative-AI substitution risks of Section 3.3 and may turn a near-term advantage into a medium-term restructuring challenge.

Table 11. Innovation and technology output indicators, 2017 and 2025*.

Indicator	Year	USA	EU (Avg)	China	India
Patent applications (per million pop.)	2017	859	468	823	46
	2025	1,473	448	1,285	62
Scientific & technical publications (thousands)	2017	409	523	426	136
	2025	462	612	785	194
High-tech exports (% manufactured exports)	2017	19.0	16.8	27.2	8.9
	2025	20.8	19.4	31.5	11.2
ICT service exports (% service exports)	2017	8.1	7.3	9.6	37.6
	2025	9.4	11.8	10.5	49.8
R&D researchers (per million pop.)	2017	4,232	3,545	1,177	216
	2025	4,620	4,310	1,780	295
Venture capital investment (% GDP)	2017	0.39	0.15	0.04	0.02
	2025	0.63	0.22	0.14	0.11
Knowledge-intensive employment (% total)	2017	41.3	38.7	22.5	15.8
	2025	44.2	42.5	27.8	18.5
Technology absorption level (1–7 scale)	2017	6.2	5.9	5.4	5.1
	2025	6.4	6.1	5.9	5.5

*2025 values provisional. *Data: WIPO[15,27]; Eurostat[12]; OECD MSTI[11]; WEF[49]; World Bank[10]; IMF[8]; KPMG[44].*

6.2. Triple Helix Configuration: University–Industry–Government Relations

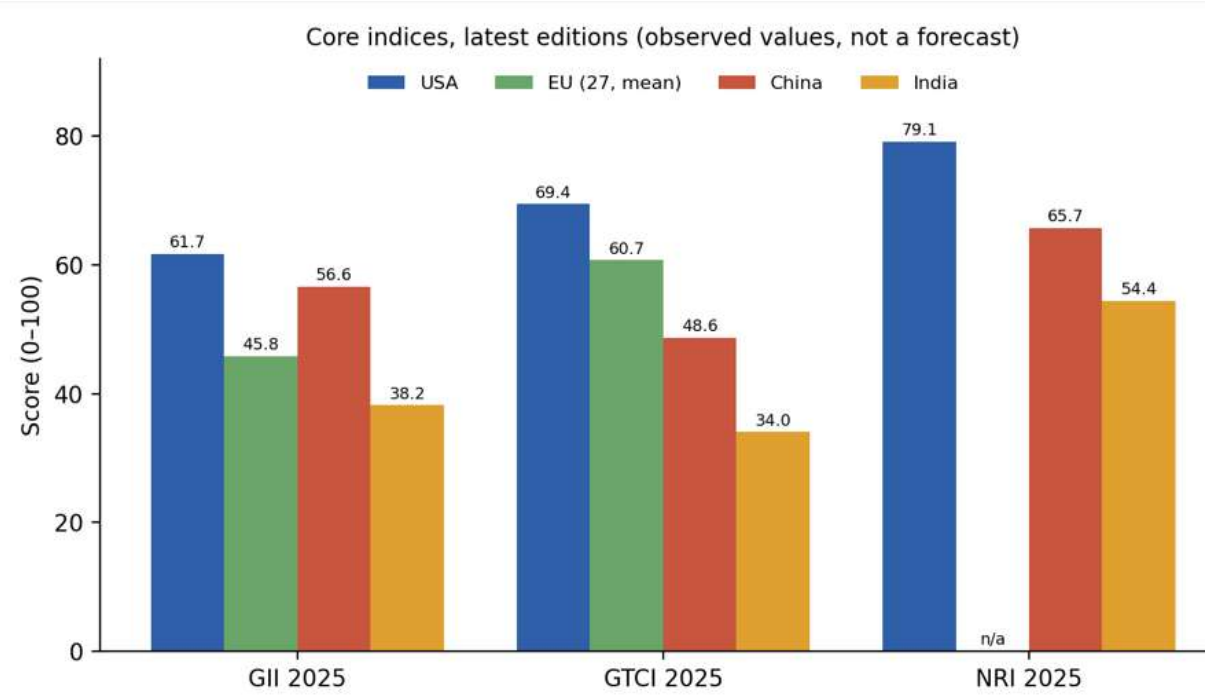
Applying the Triple Helix framework[55], each entity exhibits a distinctive configuration. The USA operates a highly commercialized helix in which technology-transfer offices, venture capital, and mission-oriented public seed funding generate dense innovation networks. The EU's configuration is more institutional: Horizon Europe structures cross-border university–industry linkages, but commercialization is slower. China's state-led model maximizes government–industry coordination while constraining the academic autonomy on which fundamental breakthroughs depend. India's helix remains nascent: the Indian

institutes of technology and science (IITs and IISc) are world-class nodes, but weak linkages to industry and government limit technology-transfer efficiency. The discussion is qualitative; with four entities, no statistical association between Triple Helix integration and social outcomes can be assessed.

7. Comparative Assessment: Strategic Implications and 2030 Scenarios

7.1. Integrated Competitiveness Analysis: Core Indices and the Readiness Index

Figure 2 shows the 2025 values of the three core indices for the four entities. The USA leads on all three; China is second on the GII and the NRI but, with a score of 48.65 (53rd), trails the EU mean (60.71) on the GTCI; India is last on all three. The EU mean on the GII (45.8) lies below China's (56.6), a result of averaging 27 member states with very different scores.



Note: observed values, not a forecast. EU = simple mean of 27 member states; EU NRI not computed. Sources: WIPO[16]; INSEAD[19]; Portulans Institute[21].

Figure 2. Core indices, latest editions (GII 2025, GTCI 2025, NRI 2025).

The Readiness Index of Section 2.4 can be computed for China (0.178) and India (0.138); a regulatory-quality input was not available for the USA and the EU (**Table 5**). A qualitative reading of the inputs is nonetheless possible: the USA combines the highest talent and technology scores; China has a strong technology pillar (64.37) but a low regulatory-quality score (33.3), which in the formula implies high regulatory complexity; India's lower technology pillar (53.07) and talent score (0.340) combine with a regulatory-quality score (38.8) only slightly above China's. These observations describe relative positions under a stylized formula and are not estimates of a causal quantity.

Adjacent composites offer only a partial cross-check (**Table 12**). Oxford Insights ranks the USA first and India 27th; a rank for China and the IMD Future Readiness Indicator were not available, and Federal Reserve

staff note that China's Oxford Insights rank is considerably lower than its GII rank[56].

Table 12. Adjacent readiness composites, 2025*.

Composite	USA	EU	China	India
Oxford Insights Government AI Readiness Index 2025 (195 governments), rank (score)	1st (87.20)	no aggregate (Estonia 19th, 68.96)	not retrieved	27th (66.55)
IMD Future Readiness Indicator 2025, rank	not retrieved	no aggregate	not retrieved	not retrieved

**2025 partial. Sources: Oxford Insights[57], via secondary reports (ComplexDiscovery; Astana Times, January 2026); Federal Reserve Board[56]. Values should be checked against the primary report.*

7.2. Critical Success Factors for 2030 Competitiveness

Five factors emerge from the analysis as plausible determinants of competitiveness; they are hypotheses consistent with the evidence, not established causes. First, *human capital development at scale*: talent competitiveness co-moves with innovation performance in levels (**Table 4**), although the four-entity data do not show that it predicts later gains. Reducing educational inequality is important: China and India narrowed HDI education-inequality gaps by 7–8 percentage points (2017–2024), though India's 31.1% remains a major constraint. Second, *institutional quality and adaptive governance*: frameworks balancing innovation promotion with protection against algorithmic bias, privacy erosion, and societal harm bear on competitiveness and legitimacy; the EU's AI Act and GDPR show that regulatory leadership can attract compliance-focused investment while protecting citizens, although Section 4.4 finds no association between risk-based regulation and higher FinTech adoption. Third, *enabling infrastructure*: the growth of US data-center capacity and China's 98% 5G coverage, against India's rural connectivity deficit, illustrate infrastructure's centrality; the T×INF term is a stylized formalization of non-linear returns, echoing evidence on public-capital productivity[58]. Fourth, *innovation-ecosystem integration*: dense university–industry–government linkages may translate research excellence into deployment, the Silicon Valley model and Horizon Europe representing contrasting speed–stability trade-offs. Fifth, *managed international engagement*: talent flows, research collaboration, and standard-setting remain important amplification channels, and technological decoupling would reduce them.

7.3. Exploratory Scenarios for 2030 Global Economic Architecture

The scenarios below are exploratory and qualitative; they are not forecasts and no probabilities are attached. The assumptions are: (a) recent trends continue without structural breaks; (b) provisional 2025 values are representative; and (c) index scores are valid proxies for capabilities. A linear extrapolation of China's GII rank trend (22nd in 2017 to 10th in 2025, about 1.5 places per year) would bring it into the top five only around 2029–2030; this is a mechanical result that ignores diminishing returns near the frontier. The USA is assumed to retain frontier-technology leadership (quantum computing, fusion energy, bio-AI), with its applied-technology lead (batteries, EVs) under pressure from Asian manufacturers.

Scenario 1 — Multipolar specialization. The USA holds the intelligence lead (IP, frontier research, frontier AI architectures); China the execution lead (manufacturing, scaling, FinTech deployment); the EU serves as regulatory anchor (standards, compliance frameworks, ESG); India represents the highest-growth market (talent pipeline, consumer scale). The global economy functions through specialized interdependence rather than singular dominance — demanding multilateral coordination mechanisms but enabling diverse innovation pathways.

Scenario 2 — Bipolar technology decoupling (conditional on US–China escalation and export-control intensification of the kind rivalry theorists anticipate[59]). Competition hardens into rival technology ecosystems, with third countries aligning to American or Chinese standards and platforms. Reduced knowledge flows and duplicated R&D would impose efficiency losses; their size is not quantified here and would require empirical estimation. EU regulatory autonomy and India's non-alignment posture could provide partial buffers.

Scenario 3 — Chinese technological ascendancy (requires China simultaneously to overcome institutional constraints on frontier innovation, achieve durable semiconductor independence following export controls, and attract international talent beyond the returning diaspora). Chinese platforms and standards would then achieve global norm status. Current conditions — the 2024 semiconductor export controls and China's weak Enable pillar (60th+) — suggest substantial barriers to all three conditions holding jointly.

8. Policy Implications (2025–2030)

The following implications are hypotheses derived from descriptive findings and qualitative scenarios; they are not causal conclusions and require testing on larger samples. They are organized by cross-cutting theme rather than by entity.

8.1. Human Capital Investment

The four-entity data do not show that initial GTCI predicts later innovation gains (Section 5.2, **Table 4**): talent competitiveness and innovation performance co-move in levels, and the largest score gain occurred in the middle-ranked entity. Investment in education quality, lifelong-learning infrastructure, and talent-mobility frameworks is therefore advocated on theoretical grounds and on the level association, not on a demonstrated predictive effect. Reducing educational inequality is most urgent for India (31.1% HDI education inequality, 2024) and China (17.2%), where gains could translate most directly into expanded effective talent supply.

8.2. Adaptive Governance: Balancing Innovation and Risk

The descriptive evidence on P3 is mixed (Section 4.4). Risk-based frameworks, exemplified by the EU's AI Act architecture, are associated with standard-setting influence and a predictable environment for compliance-oriented firms, but not with higher FinTech adoption or capital formation than in the more permissive USA or the state-directed China. The shared challenge is regulatory capacity that keeps pace with technological change: technical expertise within agencies, multi-stakeholder processes, and international standard-setting cooperation.

8.3. Infrastructure Complementarity: Digital and Physical

The stylized multiplicative T×INF term expresses the view, supported by the public-capital literature, that talent and infrastructure are complements. India's case is illustrative: a world-class IIT-educated engineering elite coexists with rural connectivity deficits that exclude the broader talent pool; its NRI Technology pillar (53.07) is the lowest of the three entities with retrieved values (USA 82.47, China 64.37). Investment extending connectivity, reliable power, and logistics to underserved populations is therefore plausibly both an equity goal and a competitiveness investment.

8.4. International Cooperation: Managing the Decoupling Risk

Under Scenario 2, decoupling would reduce knowledge flows and duplicate R&D expenditure; the size of the loss is not quantified in this study. International cooperation on AI-governance norms, data-governance frameworks, and technology standards can be considered a global public good. Despite bilateral tensions, multilateral mechanisms — the OECD AI Policy Observatory, ISO/IEC technical committees, and UN AI-governance frameworks — represent candidate policy investments for all four entities.

9. Conclusions, Research Contributions, and Limitations

9.1. Principal Findings

This study examined 4IR competitive dynamics across the USA, EU, China, and India over 2017–2025 through three core international indices (GII, GTCI, NRI) and descriptive indicators. Given four entities and index-based data, all findings are descriptive or associational. *P1 (sigma-convergence):* on GII values for the USA, China and India, the CV fell by about 10% (0.216 to 0.195 in 2024; 0.193 in 2025), against about 7% for GDP per capita; the difference is small, bounded scales compress gaps mechanically, and no significance test is possible, so P1 is at most weakly consistent with the data. *P2 (human capital):* GTCI and GII order the entities identically in every edition, but the data do not show that initial GTCI predicts later gains; P2 is not supported as a predictive claim. *P3 (institutional quality):* the EU, with the most comprehensive risk-based regime, has the lowest FinTech adoption of the four, so the proposition is not supported on adoption; regulatory design appears instead to be related to which competitive margin an economy captures, an interpretation that remains untested.

Further observations: (i) China's publication-volume leadership diverges from the USA's citation-weighted frontier leadership; (ii) FinTech adoption follows leapfrogging patterns in populous developing economies, with open-standard digital public infrastructure (India's UPI) as a key enabling factor; (iii) China's Top 500 withdrawal signals strategic opacity that degrades comparative assessment; (iv) India's STEM graduate volume reportedly exceeds that of the other entities in absolute terms, a foundation conditional on quality improvement; (v) index editions change in scale, coverage and method, so ranks across editions must be compared with care, as the GTCI 2023–2025 change shows.

9.2. Theoretical Contributions

The study documents, with verified index values, that innovation and talent indices co-move across the

four entities, in the spirit of endogenous growth theory[2], and that dispersion in innovation scores has fallen only slightly faster than dispersion in incomes, which does not by itself corroborate dynamic comparative advantage theory[3]. It also provides a transparent audit of how composite-index comparisons can mislead when editions, scales and coverage differ.

9.3. Limitations and Future Research

Six limitations bound interpretation. *Statistically*, three to four entities constitute a minimal sample: no inference is possible and rank changes are interdependent. *Methodologically*, index-based analysis cannot identify causal effects, and the Readiness Index is a stylized formula whose inputs are only partly available [60-61]. *Measurement*: indices change scale, coverage and methodology across editions, and EU values are averages that conceal heterogeneity. *Data*: some 2025 observations are provisional[62,63], several series rely on commercial sources, and could not be independently verified. *Projection*: the 2030 scenarios are qualitative and rest on extrapolation and assumptions. *Geographically*, the scope omits informative cases (Singapore, Israel, South Korea, Brazil, Nigeria). Future research should (i) extend the analysis to the full GII, GTCI and NRI country panels, which would allow inference; (ii) exploit worldwide regulatory discontinuities[64], such as the EU AI Act implementation thresholds, India's UPI rollout as natural experiments a/o; (iii) complement macro evidence with firm- and worker-level data; and (iv) track the social-cohesion and governance consequences of divergent AI regulatory regimes.

9.4. Concluding Statement

The comparative evidence for 2017–2025 is consistent with the view that competitive success in AI- and FinTech-intensive industries depends less on economic scale than on human-capital quality, innovation-ecosystem integration, and institutional adaptability esp. innovative AI; although the evidence base is too small to establish this. Qualitatively, the most plausible 2030 configuration is multipolar specialization — the USA retaining the intelligence frontier, China the deployment and execution lead, the EU anchoring regulatory standards, and India emerging as a dynamic talent and consumer market — provided international cooperation is preserved. The costs of technological decoupling are not quantified here and remain to be established empirically.

Conflict of interest

The author declare that he has no conflict of interest.

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Appendix. Table A1. Data sources: portals and editions

Source	Used in	Portal	Edition(s)
IMF World Economic Outlook	Table 1; Fig. 1	https://www.imf.org/en/Publications/WEO	April 2024
World Bank (WDI, EdStats, WGI)	Tables 1, 9, 11	https://databank.worldbank.org	2023–2025
OECD (MSTI; Education at a Glance)	Tables 1, 9, 11	https://www.oecd.org	2024–2025
Eurostat	Tables 1, 9, 11	https://ec.europa.eu/eurostat	2024–2025
WIPO (GII; IP Indicators)	Tables 2, 6, 7, 11	https://www.wipo.int	GII 2017, 2024, 2025
INSEAD (GTCI)	Tables 2, 4, 10	https://www.insead.edu/global-talent-competitiveness-index	2017, 2023, 2025
Portulans Institute (NRI)	Tables 2, 5	https://networkreadinessindex.org	2024, 2025
Oxford Insights; IMD	Table 12	https://oxfordinsights.com; https://www.imd.org	2025
ITU; Stanford HAI; TOP500; IDC; CB Insights	Table 6	portals as in the Bibliography	2025
BIS; EY; KPMG; McKinsey	Table 7	portals as in the Bibliography	2025
UNESCO UIS; AISHE	Table 9	https://uis.unesco.org; https://aishe.gov.in	2024–2025