

Talent-Rich, Compute-Poor: A Layer Decomposition of India's Position in the Global AI Race

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Short Report

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Abstract

Is India losing the artificial intelligence (AI) race? Headline rankings give an ambiguous answer: the Stanford Global AI Vibrancy Tool places India third of 36 countries in 2024, while the Oxford Insights Government AI Readiness Index 2025 places it 27th of 195. This short report reconciles the two by decomposing India's distance to the United States and China into additive layer contributions, using each index's own official weights. Both weighting schemes are first validated: the Stanford default pillar weights reproduce the published United States score (78.58 versus 78.6) and India's third place (Spearman $\rho = 0.93$ with the published top 13), and the Oxford dimension weights, recovered by least squares, reproduce all 195 published totals to within 0.006 points. Against the United States, capital and firm depth plus compute and infrastructure account for 63.3% of India's gap in the Stanford index and 56.8% in the Oxford index, whereas talent accounts for 0.1% and 5.4%, respectively. India's compute capacity is 1/220 of the United States' and its private AI investment 1/94. Between 2017 and 2024 the composition of the gap migrated from research towards capital and compute. The ranking is, however, a scale artefact: on a per-capita basis India falls to last of 36. India is best described as talent-rich and compute-poor, a configuration that public compute programmes of the current size cannot by themselves close.

JEL codes: O33; O38; O53; O57; F63

1. Introduction

Public debate frequently frames AI as a race in which the United States and China lead and everyone else trails. India occupies an awkward place in that narrative. It is the most populous country, one of the largest exporters of software services and a deep source of engineering talent, yet no Indian organisation appears among the developers of the frontier models that dominate public attention. Whether India has “fallen behind” therefore depends on what is being measured, and composite indices that aggregate many dimensions into one score can hide precisely the information needed to answer the question.

Two widely used indices illustrate the problem. The Stanford Global AI Vibrancy Tool (GVT) ranks India third in 2024, behind only the United States and China (Fattorini et al., 2024; Stanford HAI, 2025). The Oxford Insights Government AI Readiness Index (GARI) 2025 ranks India 27th of 195 countries, behind Brazil (Oxford Insights, 2025). The two rankings measure different constructs – ecosystem activity in the first case, state capacity to harness AI in the second – but neither tells us *where* India's distance to the frontier is located.

The academic literature offers little help. A Scopus search conducted on 6 October 2026 for documents combining AI terms, India, and compute, semiconductors, industrial policy, catch-up, competitiveness or innovation systems (articles and reviews, 2018 onwards) returned 79 records, most of them technical machine-learning applications. Only six address India's national position in the AI value chain. They examine India's architectural role in global AI infrastructure (Ustyuzhantseva, 2025), technonationalism and the national innovation system (Rugmini Devi et al., 2025), Indo-US technological cooperation (Rahim & Shanshul, 2025), comparative future-industry policy (Gao et al., 2026), semiconductor entry by a domestic conglomerate (Ghosal & Kulkarni, 2025), and a Porter-diamond comparison of five AI industries that includes India (Dong & Meng, 2022). None decomposes India's gap by layer using the official weights of the indices that drive public perception.

This report fills that gap with a deliberately simple and fully replicable tool: an additive decomposition of the index gap between India and a reference country into layer contributions. The theoretical motivation comes from the catch-up literature, which holds that latecomers close distance unevenly across the layers of a sectoral system and that windows of opportunity open in some layers while entry barriers persist in others (Perez & Soete, 1988; Lee, 2013; Lee & Malerba, 2017). India’s software trajectory is a well-documented case of catch-up concentrated in human capital and services capability rather than in capital-intensive assets (Arora & Gambardella, 2005; Athreye, 2005). The working hypothesis is that the same pattern reproduces itself in AI: **H1** – India’s AI gap with the frontier is concentrated in capital and compute rather than in talent. The report tests H1 with two independently constructed indices; convergence across them is the core evidence.

2. Data and method

2.1 Sources

The GVT dataset (release of 24 September 2025) covers 66 countries for 2017–2024, of which 36 are ranked. Its 23 ranking indicators are min–max normalised to 0–100 within the ranked set each year and grouped into seven pillars: R&D, Responsible AI, Economy, Talent, Policy and Governance, Public Opinion and Infrastructure (Stanford HAI, 2025). One Infrastructure indicator (exports of semiconductor device parts) is empty for every country in 2024 and is excluded. The analysis uses absolute (non-per-capita) indicators, which is the tool’s default view; per-capita indicators are used as a robustness check. The GARI 2025 data cover 195 countries, six pillars and 14 dimensions on a 0–100 scale (Oxford Insights, 2025). Both datasets were retrieved programmatically from the publishers’ websites; file hashes and retrieval times are recorded in the replication package.

2.2 Layer framework

To compare indices built on different taxonomies, pillars and dimensions are mapped onto five analytical layers of the AI value chain (Table 1). The mapping is made *ex ante*, on the conceptual content of each component, and each component is assigned to exactly one layer. GARI has no direct research-output component, so the Research and models layer is defined only for the GVT.

Table 1
Analytical layers and their operationalisation in the two indices

Layer	Stanford GVT pillars (default weight)	Oxford GARI 2025 dimensions (weight, %)
Capital and firm depth	Economy (8)	AI sector maturity (10.0)
Compute and infrastructure	Infrastructure (6)	Compute capacity (8.3); enabling technical infrastructure (8.3); data quality (8.3)
Research and models	R&D (10); Responsible AI (2)	—
Talent	Talent (6)	Human capital (7.5)
Governance and diffusion	Policy and Governance (2); Public Opinion (2)	Policy vision (4.0); policy commitment (6.0); governance principles, regulatory compliance, government digital policy, e-government delivery, AI technology diffusion (7.5 each); societal transition, safety and security (5.0 each)
Note: GVT weights are the tool's default slider values (scale 0–10). GARI weights are recovered from the published scores (Section 2.4) and sum to 100.		

2.3 Decomposition

Let $S_{c,k}$ denote the score of country c on component k (a GVT pillar or a GARI dimension) and w_k its official weight. The composite index is the weighted mean

$$I_c = \sum_k w_k S_{c,k} / \sum_k w_k \quad (1)$$

Because the index is linear in its components, the gap between a reference country r and India decomposes exactly into additive contributions:

$$G_r = I_r - I_{IND} = \sum_k g_{r,k}, \text{ with } g_{r,k} = w_k (S_{r,k} - S_{IND,k}) / \sum_j w_j \quad (2)$$

and the share of component k in the gap is

$$s_{r,k} = 100 \times g_{r,k} / G_r \quad (3)$$

A negative $g_{r,k}$ means India outperforms the reference country on that component, so shares can exceed 100% on some components and be negative on others. Layer shares are sums of component shares within each layer. For the GVT, pillar scores are unweighted means of their normalised indicators, because within-pillar indicator weights are not published. When a pillar is unavailable in early years (Responsible AI before 2019 and Public Opinion before 2021), weights are renormalised over the available pillars. Being an accounting identity, Eq. (2) attributes the gap but does not identify causal effects.

2.4 Validation of the weighting schemes

The GVT default pillar weights were read from the tool's weight controls: R&D 10, Economy 8, Talent 6, Infrastructure 6, Responsible AI 2, Policy and Governance 2, Public Opinion 2. Applying them reproduces the published United States score (78.58 against 78.6) and places India third, as in the published ranking, with a

score of 20.52 against the published 21.59. The residual reflects the unpublished within-pillar weights. The Spearman correlation between the reproduced and published ranks of the top 13 countries is 0.934 ($p < 0.001$).

GARI does not publish its weights alongside the country data. Regressing the 195 published totals on the 14 dimension scores without an intercept recovers a clean set of weights (Table 1) that reproduces every published total with a maximum absolute error of 0.006 points, which is rounding error. At the pillar level these weights imply Infrastructure 25%, Development and diffusion 25%, Governance 15%, Public sector adoption 15%, Policy capacity 10% and Resilience 10%. The recovery is an algebraic reconstruction, not a statistical estimate, and the near-zero residual is reported as a fit diagnostic rather than as a finding.

3. Results

3.1 The scale of the frontier gap

Raw indicators show the order of magnitude behind the normalised scores (Table 2). In 2024 India’s measured compute capacity was 29.4 petaflops (Rmax), about 1/220 of the United States’. Its private AI investment of US\$1.16 billion was about 1/94, and India produced no notable AI model, against 47 for the United States and 26 for China. On talent the picture inverts: India’s relative AI skill penetration (1.98) and AI hiring growth ratio (0.33) both exceed the United States’ values.

Table 2
Selected raw indicators, 2024

Indicator	United States	China	India	US / India
Compute capacity, Rmax (PFLOPS)	6,477.9	319.1	29.4	220×
TOP500-class supercomputers (count)	173	63	6	29×
Private AI investment (US\$ billion)	109.08	9.29	1.16	94×
Newly funded AI companies (count)	1073	98	74	14.5×
Notable AI models (count)	47	26	0	n.d. (India = 0)
Relative AI skill penetration	1.90	n.a.	1.98	0.96× (India higher)
AI hiring rate, YoY ratio	0.25	n.a.	0.33	0.74× (India higher)

Source: Stanford HAI (2025), Global AI Vibrancy Tool dataset. Compute capacity is the aggregate Rmax of systems listed in public supercomputer rankings and understates China, which has reduced its submissions; it does not capture commercial cloud GPU capacity. n.a. = not available; n.d. = not defined.

3.2 Stanford GVT: pillar scores and decomposition

Table 3 reports 2024 pillar scores for selected countries. India’s third place rests on two pillars: Talent (53.5, practically level with the United States at 54.0) and R&D (23.7, a scale effect of publication and open-source volume). On Infrastructure (4.3) India scores below every other country in Table 3, including Brazil (14.0); on Economy (4.0) it trails the United States (100.0), China (8.8) and the United Kingdom (7.5).

Table 3
Stanford GVT 2024: pillar scores, index and ranks (36 countries)

Country	R&D	Resp. AI	Econ.	Talent	Policy	Opin.	Infra.	Index	Rank (off.)	Rank (eq.)	Rank (p.c.)
United States	66.9	100.0	100.0	54.0	68.0	59.1	96.9	78.6	1	1	3
China	67.3	40.1	8.8	31.9	3.7	52.6	41.3	38.2	2	2	30
India	23.7	6.3	4.0	53.5	2.7	52.5	4.3	20.5	3	5	36
Singapore	4.6	5.8	2.2	62.1	13.5	26.1	17.0	17.5	4	7	2
United Kingdom	8.2	10.0	7.5	33.4	44.0	20.1	17.4	16.5	6	6	17
South Korea	6.0	2.2	3.0	28.7	26.6	55.8	28.0	16.5	7	4	15
Brazil	2.7	2.2	1.1	38.0	2.9	42.5	14.0	12.3	16	16	35

Note: Index uses the official default weights. Rank (off.), Rank (eq.) and Rank (p.c.) are ranks under official weights, equal pillar weights and per-capita indicators with official weights, respectively.

Table 4 decomposes India's gap. Against the United States (58.06 points under official weights), Economy contributes 36.8%, Infrastructure 26.6% and R&D 20.6%, while Talent contributes 0.1%. Against China (17.69 points), the gap is dominated by R&D (68.4%) and Infrastructure (34.9%). Talent contributes – 20.3%, which means India's talent advantage offsets a fifth of the distance. Under equal pillar weights, Responsible AI and Policy and Governance gain share at the expense of R&D, but capital and compute together still account for 47.4% of the gap with the United States and Talent for 0.1%.

Table 4
Decomposition of India's Stanford GVT gap, 2024: index points (share of gap)

Pillar	vs US, official	vs US, equal	vs China, official	vs China, equal
Economy	21.34 (36.8%)	13.72 (24.1%)	1.08 (6.1%)	0.69 (4.9%)
Infrastructure	15.45 (26.6%)	13.24 (23.3%)	6.18 (34.9%)	5.29 (37.5%)
R&D	11.99 (20.6%)	6.17 (10.8%)	12.10 (68.4%)	6.22 (44.1%)
Responsible AI	5.21 (9.0%)	13.39 (23.6%)	1.88 (10.6%)	4.83 (34.2%)
Policy and Governance	3.63 (6.2%)	9.33 (16.4%)	0.06 (0.3%)	0.15 (1.0%)
Public Opinion	0.37 (0.6%)	0.95 (1.7%)	0.01 (0.0%)	0.02 (0.1%)
Talent	0.09 (0.1%)	0.07 (0.1%)	-3.60 (-20.3%)	-3.08 (-21.8%)
Total gap (index points)	58.06	56.86	17.69	14.11

3.3 Oxford GARI: dimension decomposition

The GARI decomposition (Table 5) reconstructs the published India–United States difference of 21.81 points exactly. AI sector maturity is the largest single contributor (24.2%), followed by compute capacity (16.2%) and

enabling technical infrastructure (9.3%). Human capital contributes 5.4%. Policy commitment is the only dimension on which India leads the United States. Against China the pattern is more mixed. Compute capacity (27.6%) and AI sector maturity (20.8%) remain large, but India leads China on government digital policy and e-government delivery, a reflection of its digital public infrastructure. Unlike in the GVT, however, human capital also accounts for 17.4% of the gap with China.

Table 5
Decomposition of India’s GARI 2025 gap by dimension: index points (share of gap)

Dimension	Weight (%)	vs United States	vs China
AI sector maturity	10.0	5.29 (24.2%)	2.02 (20.8%)
Compute capacity	8.33	3.54 (16.2%)	2.68 (27.6%)
Enabling technical infrastructure	8.33	2.03 (9.3%)	0.33 (3.4%)
AI technology diffusion	7.5	1.86 (8.5%)	1.24 (12.8%)
Regulatory compliance	7.5	1.83 (8.4%)	1.25 (12.9%)
Data quality	8.33	1.55 (7.1%)	0.75 (7.8%)
Government digital policy	7.5	1.25 (5.8%)	-2.22 (-22.8%)
Human capital	7.5	1.18 (5.4%)	1.70 (17.4%)
Societal transition	5.0	1.05 (4.8%)	0.96 (9.8%)
Governance principles	7.5	0.94 (4.3%)	2.81 (29.0%)
Safety and security	5.0	0.83 (3.8%)	0.83 (8.6%)
E-government delivery	7.5	0.82 (3.7%)	-2.29 (-23.6%)
Policy vision	4.0	0.40 (1.8%)	0.40 (4.1%)
Policy commitment	6.0	-0.75 (-3.4%)	-0.75 (-7.7%)
Total (reconstructed vs published)	100.0	21.81 (published 21.81)	9.71 (published 9.72)

3.4 Convergence across indices

Aggregating components into the layers of Table 1 yields the central result (Table 6 and Fig. 1). Against the United States, capital and compute together account for 63.3% of India’s gap in the GVT and 56.8% in GARI. Talent accounts for 0.1% and 5.4%. Two indices built by different teams, for different purposes and with different indicators locate the gap in the same place, which supports H1. The one divergence concerns talent relative to China. The GVT measures labour-market talent (skill penetration and hiring on a professional network), where India leads. GARI measures the educational base (human capital), where China leads. The tension is informative rather than contradictory: India’s advantage lies in deployable market talent, not in the depth of its educational pipeline.

Table 6
Layer shares of India's gap (%), official weights

Layer	GVT vs US	GARI vs US	GVT vs China	GARI vs China
Capital and firm depth	36.7	24.2	6.1	20.7
Compute and infrastructure	26.6	32.6	34.9	38.7
Research and models	29.6	—	79.0	—
Talent	0.1	5.4	-20.3	17.5
Governance and diffusion	6.9	37.7	0.4	23.1
Note: Shares sum to 100 within each column (up to rounding). GARI has no research-output component. Negative values indicate an Indian advantage.				

3.5 Trajectory, 2017–2024

India's GVT score under official weights rose from 12.34 in 2017 (11th) to 20.52 in 2024 (3rd), with a temporary fall to 13th in 2022 (Fig. 2). Its gap with the United States narrowed from 70.74 to 58.06 points. The composition of that gap shifted. The R&D share fell from 36.7% to 20.6%, while the combined capital and compute share rose from 54.4% to 63.3%. India has been closing the knowledge gap faster than the asset gap, so the frontier distance is becoming *more* concentrated in capital and compute over time. China's apparent decline (55.82 to 38.21) should be read with caution: min–max normalisation against a fast-moving United States and China's reduced reporting to public supercomputer lists both compress its measured score.

3.6 Robustness

Four checks qualify the results. First, under equal pillar weights India falls from third to fifth, and its gap composition is essentially unchanged (Table 4). Second, a leave-one-pillar-out exercise shows that India's third place depends on R&D: without it India falls to ninth, whereas removing any other pillar leaves it third or fourth. Third, and most importantly, the ranking is a scale artefact. On per-capita indicators India ranks last of the 36 ranked countries, and China ranks 30th. Fourth, in GARI India trails Brazil (22nd) overall but leads every emerging comparator on compute capacity and AI sector maturity (Table 7). India is therefore not behind its peers; it is behind the frontier, and specifically in the asset-heavy layers.

Table 7
India and emerging comparators in GARI 2025 (selected pillars and dimensions)

Country	Rank	Total	Infra-structure	Dev. & diffusion	Compute capacity	Sector maturity	Human capital	Policy capacity
United States	1	88.4	91.8	88.2	90.9	100.0	74.6	92.5
China	8	76.3	78.4	74.7	80.7	67.3	81.4	92.5
India	27	66.5	63.3	54.9	48.5	47.1	58.8	96.0
Brazil	22	69.5	65.5	46.6	38.6	37.1	46.5	88.0
Türkiye	53	58.9	52.8	45.7	13.3	12.7	74.5	77.0
Malaysia	38	62.3	60.5	55.4	19.8	32.1	77.4	80.5
Viet Nam	45	60.0	57.4	47.0	10.7	22.1	66.5	53.5
Indonesia	46	59.9	60.3	44.1	21.1	27.5	45.5	77.0
South Africa	65	53.9	60.0	37.3	29.6	21.3	41.1	43.0
Mexico	77	48.3	52.1	34.1	12.5	19.6	34.4	35.0

Source: Oxford Insights (2025). Infrastructure, Development and diffusion, and Policy capacity are pillars; the remaining columns are dimensions.

4. Discussion and policy implications

The answer to the motivating question is therefore qualified. India has not fallen behind in the AI race as a whole. It is the third most vibrant AI ecosystem by absolute scale and the strongest of the large emerging economies on the asset-heavy dimensions. It is, however, far from the frontier, and that distance is concentrated in capital and compute. The convergence of two independent indices on this conclusion, and the drift of the gap towards these layers since 2017, describe a stable configuration that can be summarised as *talent-rich, compute-poor*.

The configuration is consistent with the catch-up literature. Windows of opportunity in a new techno-economic paradigm open unevenly. Latecomers can leapfrog in layers with low entry barriers, such as skills, open-source contribution and applications. Capital-intensive layers with strong scale economies remain controlled by incumbents (Perez & Soete, 1988; Lee & Malerba, 2017). In AI, training compute for leading systems has grown far faster than in earlier eras of machine learning (Sevilla et al., 2022), which raises the entry barrier precisely in the layer where India is weakest. Access to advanced semiconductors is moreover shaped by a geopolitical contest over a small number of chokepoints (Miller, 2022). India's services-led specialisation, which built world-class capability in deployable talent with modest capital requirements (Arora & Gambardella, 2005; Athreye, 2005), positions it well for diffusion and application. It does not, by itself, generate frontier assets.

Three implications follow. First, the scale of public effort matters. In March 2024 India approved the IndiaAI Mission, with an outlay of ₹10,371.92 crore over five years and a target of at least 10,000 GPUs of public

compute built through public–private partnership (Prime Minister’s Office, 2024). At approximately US\$1.25 billion over five years, the entire programme is roughly equal to one year of India’s private AI investment in 2024 and around 1% of United States private AI investment in that single year (Table 2). Programmes of this size can widen access to compute; they cannot close a 220-fold capacity gap. Second, India’s comparative advantage in market talent and digital public infrastructure (visible in its lead over China on government digital policy and e-government delivery) points to a diffusion-led strategy. Under such a strategy India competes on adoption, applied models and services built on the frontier rather than on frontier training itself. Third, debates about India’s AI position should abandon single-rank comparisons. A third place that turns into a 36th place per capita, and into 27th place on a state-capacity index, is not a stable fact about the country. It reflects which layers an index weights.

5. Limitations

The analysis has five limitations. (i) The decomposition is an accounting identity; it locates the gap but does not establish what causes it. (ii) Within-pillar GVT weights are unpublished, which explains the 1.07-point difference between the reproduced and published Indian score; the layer conclusions are unchanged under equal weights. (iii) The GVT compute indicator relies on public supercomputer lists. It omits commercial cloud and private GPU clusters and understates China. (iv) GARI 2025 adopted a new methodology that is not comparable with earlier editions, so it supports only a cross-section. Its 2025 reference year also differs from the GVT’s 2024. (v) The layer mapping in Table 1 involves judgement; the alternative of reporting component-level shares (Tables 4 and 5) is provided so that readers can regroup components. Composite indicators are sensitive to normalisation and weighting choices (Saisana et al., 2005; Nardo et al., 2008), which is why both official and equal weights are reported.

6. Conclusion

Using the official weights of two independent composite indices, validated against their published scores, this report shows that between 57% and 63% of India’s AI gap with the United States lies in capital and compute, while talent accounts for at most 5%. Over 2017–2024 the gap has migrated towards these asset-heavy layers even as India climbed the absolute ranking. India is not losing the AI race across the board. It is running a different race, strong in talent and diffusion and structurally constrained in frontier assets. The replication package allows the decomposition to be updated as each index releases new data.

Declarations

Competing interests.

The author declares no competing interests.

Ethics approval.

Not applicable. The study uses publicly available, country-level aggregate data and involves no human participants.

Use of generative AI.

The author used Claude (Anthropic) to assist with writing data-retrieval and analysis code and with language editing. All data were retrieved from the primary sources, every reported figure was recomputed from the replication script, and all references were verified by the author, who takes full responsibility for the content.

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Author contribution.

The author is solely responsible for the conception, data curation, analysis, writing and revision of this work.

Data and code availability.

The raw data files (Stanford HAI Global AI Vibrancy Tool dataset, release of 24 September 2025; Oxford Insights GARI 2025 country data), a download manifest with SHA-256 hashes and retrieval times, and the Python replication script that produces every table and figure are deposited on Zenodo under the same title as this report (<https://doi.org/10.5281/zenodo.23212820>).

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Figures

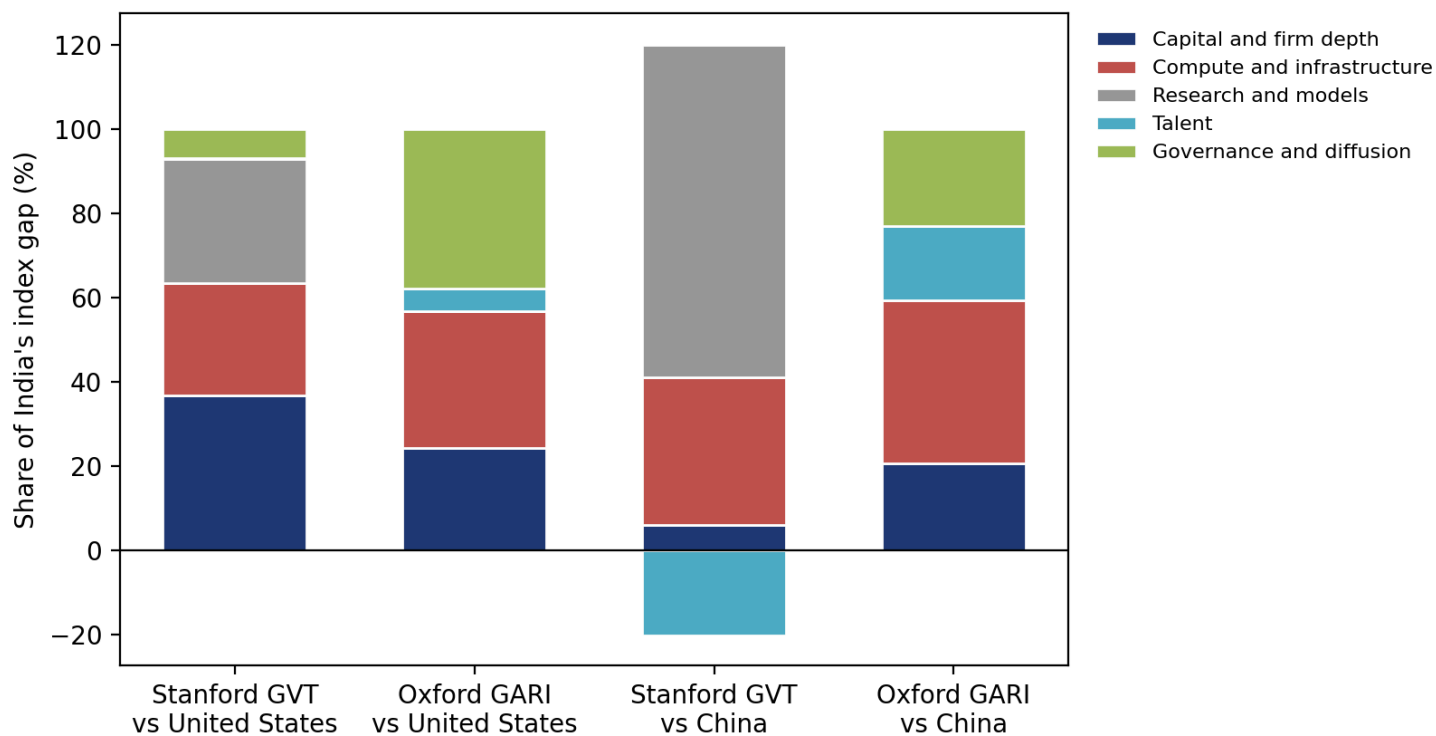


Figure 1

Figure 1. Layer shares of India's index gap under official weights. Source: author's calculations from Stanford HAI (2025) and Oxford Insights (2025).

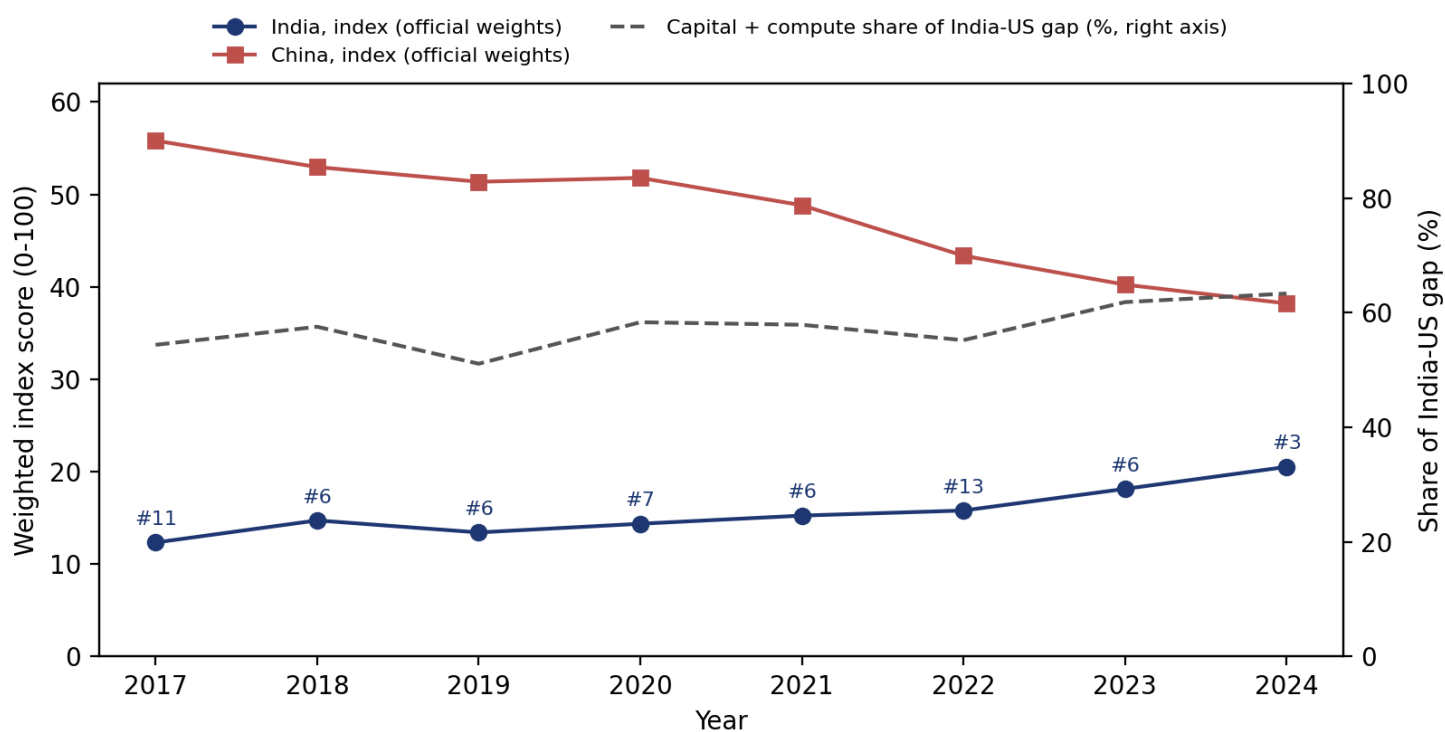


Figure 2

Figure 2. India and China in the GVT under official weights, 2017–2024, with India's rank (labels) and the combined Economy and Infrastructure share of the India–United States gap (dashed, right axis).