Centre for
Society and Policy

State of Foundational Infrastructure for Artificial Intelligence in India

July 2026

Background

This policy brief is part of a broader series that undertakes a detailed landscaping exercise of India’s AI ecosystem. The series maps key stakeholders, ecosystem developments and technological capabilities. It aims to generate nuanced insights into AI governance by examining regulatory frameworks alongside technological advancements, thereby contributing to a more holistic understanding of policy approaches, institutional capacities, and strategic priorities shaping India’s AI trajectory. The brief is developed under the independent academic policy research project “Understanding India’s Perspective on AI Policy and Governance", conducted at the Centre for Society and Policy (CSP) from November 2024 to December 2025. The project focuses on building a comprehensive understanding of India’s AI ecosystem and its positioning within the global AI value chain. Its core objective is to analyse both the opportunities and challenges arising from India’s distinct position in the AI ecosystem.

The project has produced four policy briefs that collectively offer an evidence-based assessment of India’s evolving AI landscape. These briefs examine institutional, economic, geographic, and infrastructural dimensions of AI development, with the aim of informing emerging trends, national capacities, and key policy priorities. The methodology for these briefs combines secondary research, indicator-based assessment, and comparative analysis. It draws on official government documents, Union Budget materials, central and state ministry reports, and industry studies. In addition, data platforms such as Clarivate (Web of Science), Tracxn, and other public databases were used to analyse startup activity, investment patterns, research output, innovation trends, and infrastructure capacity. These findings are synthesised through a thematic analytical framework to identify key patterns, gaps, and emerging priorities.

Within this context, the present brief focuses on assessing India’s AI foundational infrastructure across four key pillars: compute, data, model development, and data centres. It maps ongoing initiatives that are strengthening the country’s preparedness for the next generation of AI systems while identifying critical gaps and emerging opportunities. By analysing these pillars in an integrated manner, the brief seeks to provide a comprehensive view of India’s evolving capabilities to advance sovereign, inclusive, and globally competitive AI leadership.

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1. Introduction

India's emergence as a major global player in AI depends on its ability to build a strong foundation across four interconnected pillars: compute infrastructure, high-quality data ecosystems, domestic model-development capacity, and AI-ready data-centre infrastructure. These components shape the country's ability to train, deploy and govern AI systems that reflect India's linguistic diversity, socio-economic realities and national priorities. Global discussions on AI, including the AI Safety Summits, G20 declarations, the Hiroshima AI Process, and the BRICS 2025 Declaration, increasingly recognise the importance of access to AI infrastructure alongside safety, governance, talent, and innovation. Countries that secure timely access to advanced compute, large-scale data infrastructure, and robust model ecosystems are better positioned to drive innovation, support strategic sectors, and safeguard their digital autonomy.

The country generates one of the largest volumes of digital data in the world, enabled by Aadhaar, UPI, DigiLocker, ABDM, DIKSHA, and other digital public infrastructures. Building sovereign resilient AI infrastructure is increasingly important for India's ability to develop and deploy AI systems that reflect its linguistic, cultural, and socio-economic diversity. This requires reliable access to compute, data, models, and data-centre infrastructure at sufficient scale. However, India's ability to expand these capabilities is shaped by structural constraints, including dependence on global supply chains for advanced GPUs and uneven data preparedness across sectors. Sovereign capability refers to ensuring resilient, affordable, and reliable access to critical AI infrastructure while progressively strengthening domestic compute and data-centre capacity to reduce strategic dependencies. One follows the other: broader and more resilient access enables India's AI ecosystem to grow, while stronger domestic capacity improves the long-term security, resilience, and autonomy of that access.

This policy brief provides an ecosystem assessment of India's current AI foundational infrastructure across four pillars, such as compute, data, model development, and data centres. It identifies ongoing initiatives that are strengthening India's readiness for the next generation of AI systems, identifies key gaps, and highlights emerging opportunities. By examining these four pillars together, the brief aims to offer an integrated view of the capabilities India is developing to achieve sovereign, inclusive, and globally competitive AI leadership.

2. Methodology and Data Collection Approach

Each pillar, including compute, data, AI model capacity, and data centres, was analysed through a relevant set of sub-indicators, including infrastructure readiness, governance and regulatory frameworks, accessibility and affordability, linguistic and regional inclusion, the hardware and tool ecosystem, and geographic distribution.

Indicator-Based Assessment

The study identified a set of indicators for each pillar to establish a baseline understanding:

- Compute: number and class of GPUs under the IndiaAI Mission compute pillar; petaflops and system counts under the National Supercomputing Mission (NSM); India's position in the TOP500 rankings; and indicative GPU-hour prices available in India. The AI firms working in compute.
- Data: number and sectoral spread of datasets on NDAP, AI Kosh; coverage of key sectoral platforms; availability of language resources under Bhashini.
- AI Model Capacity: count and type of model-layer startups and companies (LLMs, SLMs, domain models, tools/MLOps) from Tracxn; public information on IndiaAI-funded foundation models and academic consortia.
- Data Centres: number of operational facilities and IT load (MW/GW); national and regional capacity growth; and pipeline estimates.

Secondary Research and Baseline Landscaping

The indicator-based assessment was complemented by secondary research to develop a baseline understanding of India's foundational infrastructure for AI. This involved a review of:

- Government platforms and official documentation, including the IndiaAI Mission (compute pillar and model programs), National Supercomputing Mission (NSM) materials, AIRAWAT-PSAI documentation, the National Data & Analytics Platform (NDAP), AI Kosh, data.gov.in, ABDM, Digital India Bhashini, Digital India program reports, and relevant MeitY and NITI Aayog releases.
- Policy and standards documents, such as notifications and rules under the Digital Personal Data Protection framework, the National Data Governance Framework Policy (NDGFP), DEPA and Account Aggregator guidelines, and Bureau of Indian Standards (BIS) publications, including IS/ISO/IEC 8183 and the IS/ISO/IEC 5259 series on data quality.

- Analytical and sectoral studies by industry bodies and multilateral organisations (for example, NASSCOM, FICCI, and others) to provide additional details on AI infrastructure, data readiness, and emerging sovereign AI strategies.

Market Data Review

To understand private-sector activity and market structure, the study draws on Tracxn datasets (September 2025). The dataset utilises Tracxn's prompt classification of "Native AI". Firms were further categorised into Compute, Data, and Model segments. Tracxn data on Indian AI firms[1] working on compute (GPU clouds, HPC orchestration, hardware, and interconnect innovators), AI models and tooling (LLMs, SLMs, generative AI, developer tools & MLOps), and data-layer companies (annotation, synthetic data, and data platforms) was analysed to understand the following:

- Functional categories of work,
- Funding stages and maturity,
- Geographic concentration and emerging clusters, and
- The balance between core model development and applied tooling or services.

Global infrastructure and pricing information was obtained from:

- TOP500 rankings for HPC and supercomputing systems,
- Data-centre mapping sources (such as DataCenterMap and equivalent datasets) for facility counts and city-wise capacity, and
- Publicly available cloud-provider documentation (AWS, Azure, Google Cloud, Yotta, E2E Networks, and others) for indicative GPU configurations and price ranges.

Limitations of the Study

- Real-time GPU availability, hyperscaler capacity, and model-training runs are not always publicly disclosed, especially by private cloud providers.
- Certain datasets (e.g., startup revenues, GPU procurement details, or deal-level model funding) are either proprietary or incomplete in public databases.
- Estimates for India's data-centre pipeline vary by source; figures were harmonised through cross-validation, but some variability persists.

[1] Here, the term "AI firms" is used to collectively refer to both startups and companies. This classification is adopted due to the limitations of the Tracxn platform, which does not distinguish between startups and established companies in its dataset.

- Model-development ecosystems evolve rapidly; some startups may pivot or cease operations after data collection.

3. Pillars of foundational Infrastructure for AI

3.1 Compute

This section presents a comprehensive landscape assessment of India's AI compute capacity, the IndiaAI Mission's compute pillar, domestic AI firms, and foreign hyperscaler platforms.

High-performance compute has become the strategic backbone of global AI leadership. Nations that possess reliable access to large GPU and accelerator clusters can advance multilingual foundation models, conduct frontier research, scale industry applications, and build resilient digital public infrastructure. Compute is, therefore, not merely a technical utility but a national-level capability with economic and geopolitical implications.

India's demand for compute has accelerated sharply across academia, startups, industry, and government. However, global semiconductor constraints, export controls on advanced accelerators, and reliance on proprietary software stacks shape access. To address this, India's compute landscape has evolved into a layered system that includes an expanding national compute pillar under the IndiaAI Mission, domestic private providers, a growing ecosystem of compute-focused startups, and hyperscalers. Harnessing this diverse landscape requires improving affordability and accessibility while reducing structural dependencies and ensuring that smaller institutions and MSMEs can meaningfully participate in AI development.

3.1.1 Compute Landscape

3.1.1.1 Providing Access to Compute: IndiaAI Mission

The IndiaAI Mission has established a dedicated national compute pillar that federates GPU capacity across multiple sources. This pillar is intended to ensure broad-based access for researchers, academia, startups, MSMEs, early-stage innovators, and government entities. The scale of this initiative marks a substantial shift in India's AI readiness. As of May 2025, India had provisioned more than 34,000 GPUs under the AI Mission's compute pillar, significantly ahead of the original target of 10,000 GPUs. Based on the IndiaAI compute portal as of November 2025, 22,754 of these GPUs had been allocated to users, supported by a total subsidy commitment of ₹4,39,63,04,866 [1].

User onboarding data from India AI illustrates the diversity of beneficiaries: 62 researchers and academic institutions, 33 startups and MSMEs, 4 IndiaAI Fellows, 22 students, 22 early-stage startups, 9 early-stage researchers, and 42 government entities had been onboarded by November 2025. These numbers demonstrate that access to compute infrastructure is reaching established institutions, innovators, startups and researchers[2].

A distinctive feature of the IndiaAI Mission compute pillar is its ability to substantially reduce compute costs. Sovereign facilities such as AIRAWAT-PSAI indicate that non-subsidised A100-class GPU capacity can cost approximately **₹160 per GPU-hour** [2] under research agreements, which is markedly more affordable than typical global on-demand pricing. On the contrary, publicly available benchmark data for international cloud providers show the hourly rent for a single NVIDIA A100 GPU in the range of **US $3.67 to US $4.10 per hour** [3] (nearly ₹325–₹363 at an exchange rate of ₹87/USD).

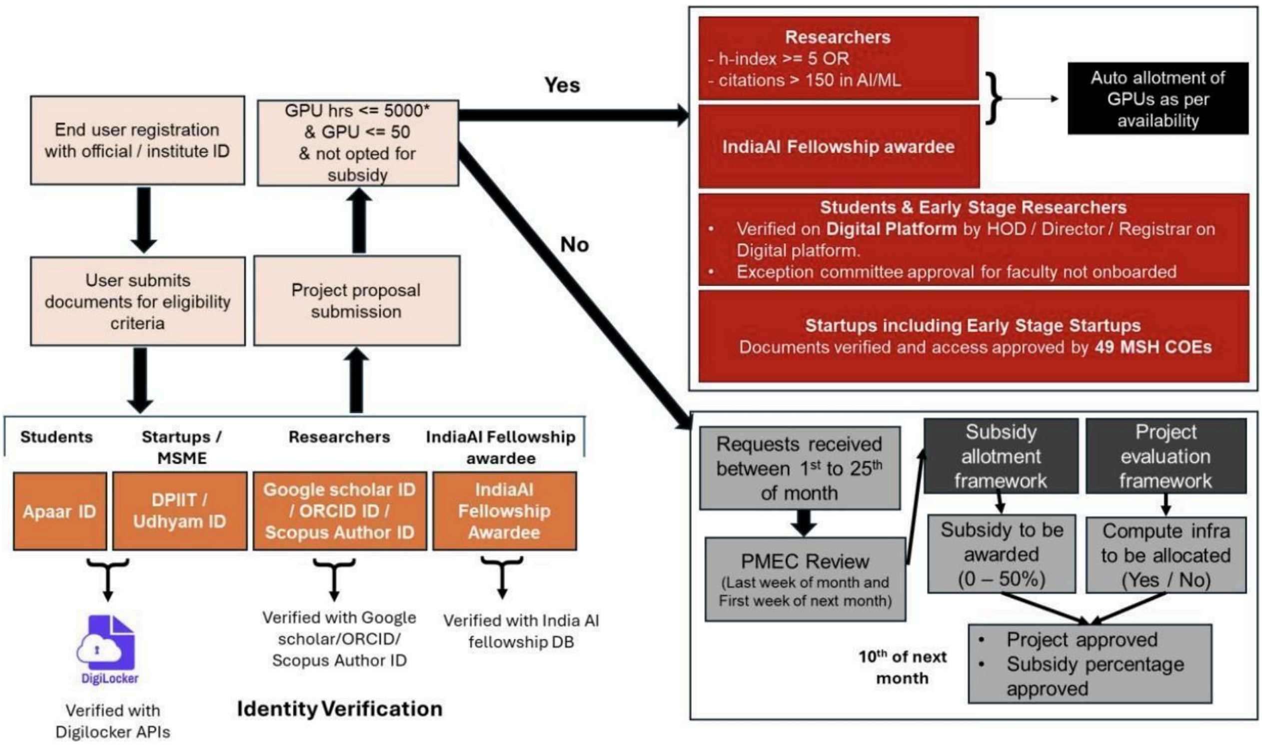

Fig. 1: ***Compute Workflow and Allocation Workflow under IndiaAI Compute Pillar,***
Source: End-user policy for the IndiaAI Compute Portal

Under the IndiaAI Mission compute pillar, end users first register on the IndiaAI compute portal with their official or institutional ID, verify their email and mobile number, and upload

[2] https://compute.indiaai.gov.in/endusers (India AI Compute portal).

basic eligibility documents. After submitting a short project proposal and a bill of materials, the system electronically verifies their identity and eligibility through DigiLocker and other authorised databases. For non-subsidised requests up to 5,000 GPU-hours and 50 GPUs, senior researchers (h-index ≥ 5 or ≥ 150 citations) and IndiaAI Fellows receive automatic allocation subject to availability, while students, early-stage researchers, and faculty are endorsed by authorised institutional verifiers, and startups and early-stage startups are cleared by MeitY Startup Hub Centres of Excellence. Larger requests or any request seeking subsidy are batched and reviewed by the Programme Monitoring and Evaluation Committee (PMEC) [4], which applies a standard evaluation framework (project clarity, national importance, social-good alignment, and team experience) to decide both capacity allocation and the subsidy level. The PMEC may approve a subsidy of up to 40 per cent of the approved compute cost, with sanctioned projects and subsidy percentages published monthly. Empanelled GPU capacity is priced at about ₹150 per GPU-hour for high-end accelerators and ₹115.85 per hour for lower-tier GPUs. With subsidies of up to 40%, eligible users can access AI-ready GPUs at effective rates as low as roughly ₹70 per GPU-hour. This positions the IndiaAI Compute pillar as a national price anchor for academic, startup, and public-sector AI projects.

Domestic GPU-cloud providers such as E2E Networks, JarvisLabsAI, and NxtGen Datacenter and Cloud Technologies Private Limited are offering cost-effective GPU access. E2E Networks, for example, lists a 1× A100-40 GB instance at about ₹180 per GPU-hour via the IndiaAI portal. Meanwhile, global benchmarks show that on-demand A100-class GPUs cost around US$4.10 per hour (₹370 per GPU-hour). These features enable domestic providers to offer rates that are approximately 30-60% lower and, in some cases, substantially lower than those charged by major international hyperscalers. India’s compute ecosystem operates along a three-tiered pricing structure: subsidised IndiaAI compute (lowest cost and highest accessibility), domestic commercial GPU clouds (mid-range, locally governed pricing), and foreign hyperscaler platforms (highest cost but broadest tooling and automation capabilities).

3.1.1.2 India HPC Infrastructure (AIRAWAT and NSM)

High-performance computing (HPC) has become a strategic pillar for countries advancing in artificial intelligence, scientific research, industrial innovation, and national security. In the June 2025 TOP500 [5] rankings, the United States hosts 175 of the world’s 500 fastest supercomputers, followed by China with 47 systems, reflecting deep and sustained investment in large-scale computational infrastructure. India has made steady progress but remains in an early scaling phase relative to global leaders. As of March 2025, India has 34 supercomputers with a combined compute capacity of 35 petaflops[3] across universities, research institutions, and national laboratories under the National Supercomputing Mission. However, India's presence in global rankings remains limited, with only a small single-digit number of systems appearing in recent TOP500 lists.

Complementing the IndiaAI compute pillar, India's HPC infrastructure forms the strategic core of national compute capability. AIRAWAT-PSAI, implemented by C-DAC Pune, is India's flagship AI supercomputing platform. When integrated with PARAM Siddhi-AI, AIRAWAT provides a peak capacity of approximately 410 AI petaflops in mixed precision, with sustained double-precision performance of about 8.5 petaflops [6]. AIRAWAT was ranked #75 in the TOP500 list in 2023 and serves as a shared facility for large-scale AI model training, multilingual and Indian-context AI research, and experimental foundation-model development. Access to AIRAWAT is administered through C-DAC's National PARAM Supercomputing Facility, which includes subsidised rates and initial credits for eligible academic and startup users.

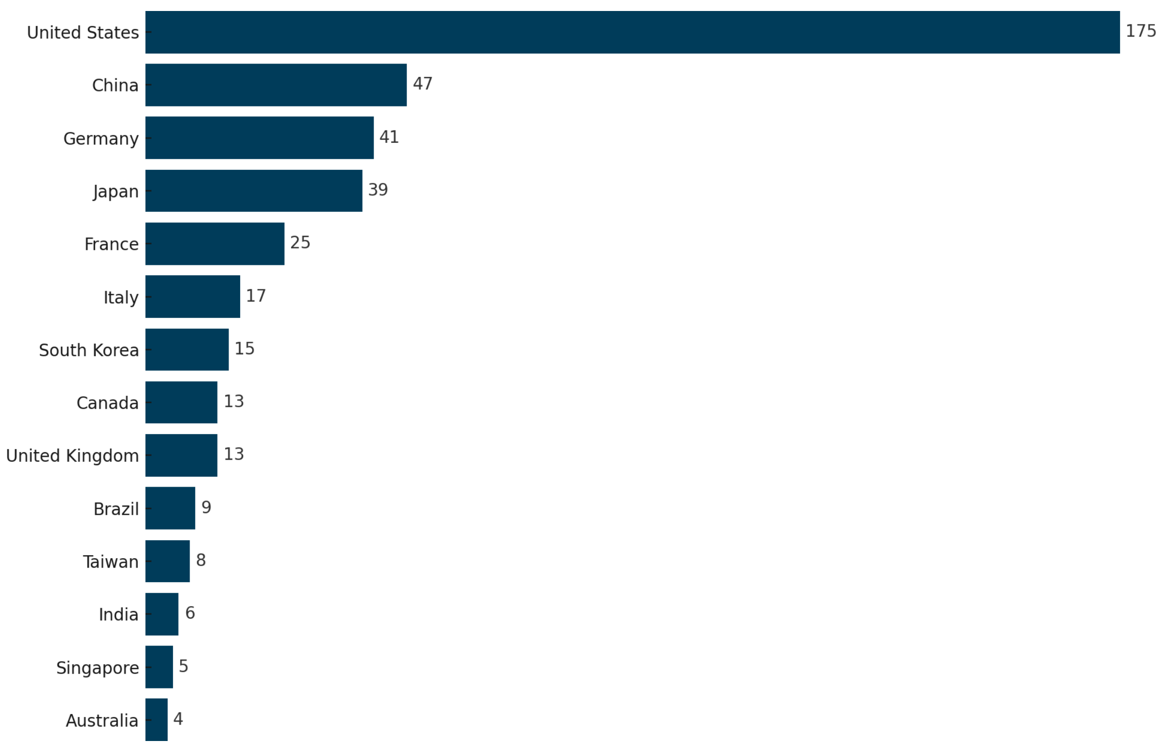

Fig 2: Number of HPC on the TOP500 supercomputer list, country-wise (June 2025)
Source: https://www.top500.org/lists/top500/2025/06/highs/

In parallel, NSM has progressively deployed supercomputers across premier institutions, reaching a combined capacity of about 35 petaflops across 34 systems as of March 2025.

3 https://www.pib.gov.in/PressReleasePage.aspx?PRID=2124920&utm

The NSM has catalysed indigenous hardware and software development through initiatives such as the Rudra server board, Trinetra interconnects, and a domestically developed HPC software stack. More than 5,930 expert users from over 100 institutes access NSM systems, collectively executing more than 7.3 million high-performance computational jobs [7]. While NSM systems are essential for public research and operate entirely under Indian jurisdiction, their GPU scale remains insufficient for frontier-class foundation-model training, which can require 10,000–20,000 GPUs for a single run. The IndiaAI compute pillar, therefore, complements sovereign HPC by offering pooled, AI-optimised accelerator resources.

Fig. 3. NSM systems available in different Academic institutions in India

3.1.2 AI Firms in the Indian Compute Ecosystem

Domestic private cloud providers, such as Yotta Data Services, E2E Networks, Sify, and others, operate AI-capable cloud environments and data centres within India. Yotta, for example, has announced large-scale deployments of NVIDIA accelerators, including H100-class GPUs, and has integrated parts of NVIDIA's software stack, including NIM, NeMo, and DGX Cloud Lepton, through its Shakti Cloud platform[4]. These providers offer flexible, pay-per-use or on-demand access to AI compute for enterprises, developers, startups, and research users.

As per the Traxcn data, our analysis shows that there are more than 18 firms that are directly or indirectly working on compute. These firms represent a diverse layer of domestic AI infrastructure capabilities, collectively offering GPU cloud services, high-performance computing platforms, decentralised compute networks, edge AI hardware, and specialised interconnects, as well as chip-level innovation.

Geographically, the ecosystem is concentrated in a few emerging technology hubs. Bengaluru dominates the landscape with 7 firms, reflecting its established position as India's deep-tech and AI capital. Delhi hosts smaller clusters, while individual firms spread across cities like Hyderabad, Coimbatore, Pune, Mumbai, Prayagraj, Indore, Thiruvananthapuram, Kangra, and Noida. This distribution highlights that while compute innovation remains Bengaluru-centric, meaningful activity is emerging across Tier-2 and Tier-3 cities as well.

The majority of firms are in the unfunded (9) or seed stage (3), with only a handful having progressed to Series A (3) or Series B (1). Two companies are publicly listed (Brain Chip and E2E Networks). However, most of the ecosystem remains in its formative phase.

4 https://yotta.com/press-releases/yotta-and-nvidia-launch-shakti-cloud-on-dgx-cloud-lepton-to-power-indias-sovereign-ai-ambitions/

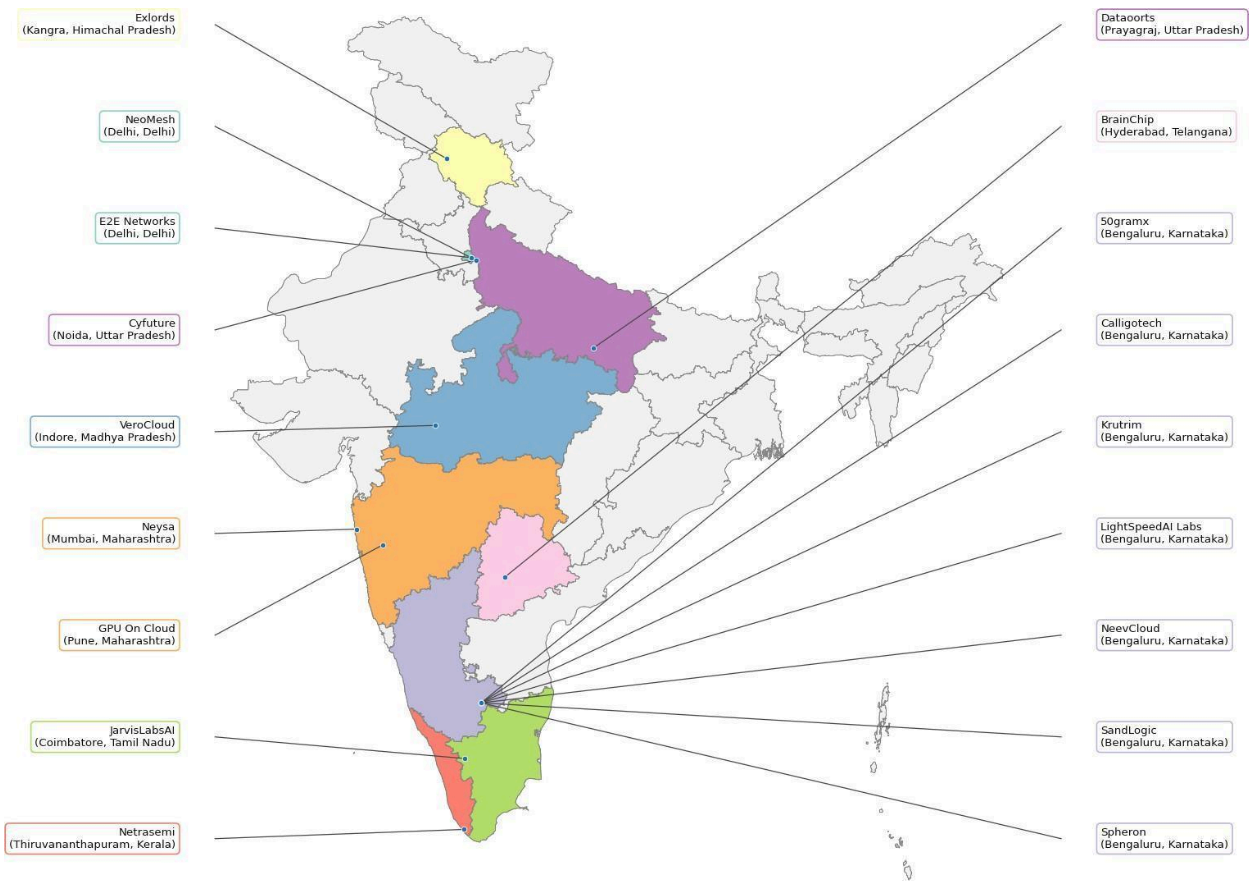

Fig. 4: AI Firms working on Compute in India
Source: Traxcn (September 2025)

A thematic analysis of the companies'/startups' service offerings reveals five distinct clusters:

Cluster	Description	Companies
1. GPU rental & cloud compute services	Provide on-demand GPU and cloud compute capacity for developers, researchers, and startups, offering a lower-cost alternative to international hyperscaler instances.	50gramx, JarvisLabsAI, Dataoorts, GPU On Cloud, NeevCloud, E2E Networks
2. HPC orchestration & middleware providers	Offer enterprise-grade orchestration layers for deploying and managing high-performance computing (HPC)	Calligotech, Cyfuture, NeoMesh,

	workloads, including workload optimisation and HPC-as-a-service.	VeroCloud
3. Specialised hardware & chip-level innovators	Develop optoelectronic processors, system-on-chip (SoC) designs, edge-integrated AI boards, and related toolchains that strengthen India's indigenous hardware capability.	LightSpeedAI Labs, Netrasemi, Exlords
4. Integrated cloud and AI infra builders	Combine cloud compute provisioning with model hosting, orchestration platforms, and proprietary AI stacks to offer end-to-end AI infrastructure services.	Krutrim, Neysa
5.Decentralised compute networks	Build distributed GPU/CPU networks, often using blockchain-based orchestration, to aggregate underutilised compute and make it available as a shared resource.	Spheron

Table 1: Clusters of Companies in India's Compute Ecosystem.
Source: Traxcn, September 2025.

These companies are demonstrating that India's AI ecosystem is steadily building capability across the compute value chain, from hardware innovation and cloud GPU provisioning to HPC orchestration and decentralised infrastructure. However, the funding remains nascent, undercapitalised, and fragmented compared to global computing markets. Strengthening this ecosystem will require coordinated procurement incentives, scale-up financing, and integration with the IndiaAI Compute pillar, so that domestic startups can evolve from peripheral participants to critical pillars of India's national AI infrastructure.

Foreign hyperscalers, Amazon Web Services (AWS), Microsoft Azure, and Google Cloud, dominate the overall volume and diversity of GPU instances available in India. AWS offers instance families such as P4d and G5; Azure supports the NC and ND series; and Google Cloud provides A100, L4, and access to TPU-based systems in nearby regions. Hyperscalers bring mature MLOps tooling, global-scale automation, and substantial capital investment to India, with multi-billion-dollar commitments. Despite these advantages, they are entirely foreign-owned, and access to advanced accelerators is susceptible to export controls or geopolitical constraints[5].

3.1.3 Key Gaps in India's Compute Ecosystem

1. Frontier-scale GPU capacity remains limited and fragmented

Although the IndiaAI Compute pillar has provisioned over 34,000 GPUs and NSM systems together offer about 35 petaflops across several institutions, this capacity is still modest relative to the needs of frontier-class foundation models. Institutions thinly spread capacity rather than concentrating it in a few exascale, AI-optimised clusters.

Potential Measures

- Develop AI-specific industrial and R&D zones that are explicitly designed to host exaflop-class GPU clusters, with long-term incentives for enterprises and cloud providers to deploy high-density, AI-optimised infrastructure.

- Create sustained support schemes for AI compute, such as multi-year GPU subsidies, low-cost financing, and viability-gap funding for AI data centres, so that institutions can commit to long-horizon compute investments.

2. Public-led, subsidy-driven investment with shallow private risk capital

The current architecture is largely state-anchored: sovereign HPC under NSM and the IndiaAI Compute pillar act as the main price-setters, with subsidised GPU hours often below ₹100 per hour. Domestic cloud/compute providers and firms are still at a formative stage; most compute-focused firms are unfunded or at seed/Series A, and lack the scale and financing depth to independently build large GPUs or take on long-term capacity risk. This creates questions about the sustainability of relying heavily on public subsidies as the primary economic anchor.

Potential Measures

- Move from one-off subsidies to longer-horizon co-investment models (anchor tenancy, blended finance, and credit guarantees) that crowd in private capital for GPU clusters, while using IndiaAI as a demand aggregator rather than a perpetual price-subsidy mechanism.

[5] Bureau of Industry and Security, Department of Commerce, (Jan 15, 2025)"Framework for Artificial Intelligence Diffusion ," Federal Register.

3. Dependence on imported hardware and proprietary software stacks

India’s current GPU and accelerator bases are almost entirely imported, and domestic chip-level innovators (e.g., specialised hardware and interconnect startups) remain small in number and scale. Sovereign systems such as AIRAWAT and NSM mostly run on proprietary hardware and driver ecosystems, which are exposed to export controls and vendor-specific roadmaps. This limits long-term hardware sovereignty and bargaining power. Strengthening compute capability does not require complete domestic production across the entire technology stack. In the near- to medium-term, the priority could be to ensure secure, diversified, and resilient access to critical compute technologies while progressively building domestic capabilities in strategically important segments over the longer term.

Potential Measures

- Integrate indigenous hardware initiatives into future NSM and IndiaAI procurements; create a roadmap and procurement preference for domestically designed boards, interconnects, and cooling solutions once they reach minimum performance thresholds.
- Pursue government-to-government (G2G) agreements and strategic partnerships to mitigate the impact of restrictive export policies and secure predictable access to advanced accelerators while India builds its own design capabilities over the longer term.
- International approaches also demonstrate that control need not require complete technological self-sufficiency. Emerging approaches in the European Union combine domestic capacity-building with requirements related to data location, supply-chain assurance, and strategic dependencies, while Singapore places greater emphasis on risk-based cloud security, certification, and resilience[6] [7]. These approaches offer useful pathways for India to balance access to global technologies with greater control and resilience over critical AI infrastructure.

3.2 Data

India generates an enormous variety of data across its public and private sectors, but much of it is not yet easily usable for AI development. Data exists in silos, in different formats, and with varying degrees of accessibility. A major effort is underway to transition from simply having data to making it AI-ready, meaning it is well organised, annotated, and available under the right conditions for use in model training and analytics.

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[6] https://digital-strategy.ec.europa.eu/en/policies/cloud-and-ai-development-act
[7] https://www.imda.gov.sg/regulations-and-licensing-listing/ict-standards-and-quality-ofservice/it-standards-and-frameworks/cloud-computing-and-services

India's approach to digital public goods, often termed the India Stack, has thus organically expanded the pool of data available for innovation. For example, at the Kumbh Mela 2025 gathering, India demonstrated AI integration with its digital infrastructure, AI tools processed real-time data from railways and police databases to manage crowds[8], and a Bhashini-powered chatbot provided multilingual voice services to attendees. This exemplifies how AI-ready data streams from public platforms are being put to use in governance[9].

3.2.1 Data Landscape

(a) Population-scale Digital Public Infrastructure

India's Digital India initiative has accelerated the creation and use of digital data at an unprecedented scale. Flagship digital public infrastructure such as Aadhaar (a biometric digital ID covering over 1.31 billion people (about 95 per cent of Indians), the Unified Payments Interface (UPI) for digital payments, and DigiLocker for paperless document storage have transformed service delivery and generated massive datasets on identity, finance, and citizen services. These systems operate at a population scale and high velocity, creating rich data streams that can support AI models if they are harnessed responsibly, with appropriate safeguards.

(b) National Data Platforms for AI

In recent years, the Government of India has launched targeted initiatives to make public data more usable for AI and analytics. A notable step was the creation of the National Data & Analytics Platform (NDAP) by NITI Aayog in 2022. NDAP is a user-friendly, interoperable data portal that, as of November 2025, hosts 6,088 foundational datasets from 53 ministries, harmonised to a common schema to enable cross-sectoral analysis. The platform is explicitly designed to make government data accessible, interoperable, and interactive through a unified interface [8].

The national open data portal data.gov.in also hosts thousands of datasets from central and state ministries. However, many of these datasets are still available in basic formats (such as PDFs or unstructured CSV files) and often lack consistent documentation or metadata. This limits their direct usability for machine learning and highlights the need for systematic efforts to make data AI-ready. [9]

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[8] https://www.thehindu.com/news/national/uttar-pradesh/maha-kumbh-2025-authorities-employ-ai-to-handle-rush-predict crowd-surges/article69120210.ece
[9] https://www.pib.gov.in/PressReleasePage.aspx?PRID=2108810#:~:text=For%20Mahakumbh%202025%2C%20AI.

To address this gap, the IndiaAI Mission has created AI Kosh as a central repository for high-quality datasets. As of 14 November 2025, AI Kosh, owned and operated by the Government of India under the IndiaAI Mission, hosts over 3,528 curated non-personal datasets across 20 sectors, including census data, Indian language resources, and satellite imagery. AI Kosh aims to:

- catalogue datasets with clear metadata (source, format, language, licence),
- indicate their readiness for AI use, and
- provide tiered access (fully open, registration-based, or permissioned, depending on sensitivity) [10].

(c) Sectoral Data Platforms

Beyond general repositories, India has rich data streams in key sectors:

Sector	Key data platforms	Details
Healthcare	Ayushman Bharat Digital Mission (ABDM), including ABHA IDs, facility & professional registries.	Over 79.9 crore ABHA accounts created; 4.18 lakh facilities & 6.79 lakh professionals registered.
Agriculture	Soil Health Card scheme, soil test results database, and datasets on soil health.	A large-scale dataset of soil-health cards (state/UT-wise, multi-year) is available via the data portal.
Education	Platforms such as DIKSHA & administrative datasets (UDISE+, NAS)	Usage and infrastructure data are published in CSV/open formats; further annotation may be needed.
Urban & Mobility	City data portals (e.g., in Pune and Surat) offering traffic, utilities, air-quality APIs; national transport datasets (e.g., Vahan)	Mixed levels of openness; many datasets are accessible, but some are restricted to partner entities.

Geospatial	ISRO portal Bhuvan (satellite imagery and mapping layers) & volunteer platforms like OpenStreetMap India	Free access to base layers; higher-resolution / specialised data often requires registration or agreements.

Table 2: Key Data Platforms (Sector-wise)

(d) Language Data and the Bhashini Ecosystem

A major pillar of India's AI data ecosystem is domain-specific language data. Under the IndiaAI mission, the MeitY launched Digital India Bhashini, aimed at collecting and curating language datasets and building AI language tools for all 22 scheduled Indian languages. Since its inception in 2022, Mission Bhashini has enabled the creation of extensive speech and text corpora in multiple Indian languages.

As of November 2025, over 350 AI models supporting 22 scheduled languages and tribal languages have been built under Bhashini. It has also supported the translation of more than 200 online courses into 8 Indian languages, expanding multilingual access to education [11]. Several government departments now use Bhashini's translation APIs to deliver services in local languages, including platforms such as Pehchaan and SabhaSaar.

At the same time, Bhashini illustrates the challenges of data generation at scale. The "Bhasha Daan" crowdsourcing campaign for collecting voice samples has so far gathered fewer than 80,000 usable language samples, underscoring the need for sustained incentives, community engagement, and outreach to build large, representative corpora for India's linguistic diversity. This highlights the need for more structured and strategic language-data initiatives alongside large-scale collection drives to generate sufficient AI-compatible datasets across India's diverse languages.

3.2.2 Policy and Standards for Data:

3.2.2.1 Policies

(a) Personal Data Protection Framework

India's data-governance ecosystem is anchored in a layered legal and regulatory framework that addresses personal data protection, data sharing, and sectoral safeguards. At its core is the Digital Personal Data Protection Rule, 2025 (DPDP Rule), notified on 14 November 2025. The DPDP framework provides a comprehensive statutory regime for the "processing of digital personal data in a manner that recognises both the right of individuals to protect their personal data and the need to process such personal data for lawful purposes" [12]. Under this regime, data fiduciaries[10] are required to obtain “free, specific, informed, unconditional and unambiguous” consent, process data only for specified purposes, and implement “reasonable security safeguards”, among other obligations. This establishes the baseline for lawful and accountable use of personal data in AI systems.

(b) Governance of Non-Personal and Public-Use Data

In parallel with personal data protection, India is building an architecture for responsible data sharing and reuse of non-personal and anonymised datasets. The National Data Governance Framework Policy (NDGFP), which remains in draft form, proposes mechanisms for creating anonymised public-use datasets from both government and private sources to support AI, research, and innovation. Its core objective is to ensure that large pools of anonymised non-personal data can be safely accessed by India’s research and innovation ecosystem without compromising privacy or security [13].

To implement this vision, NDGFP calls for the establishment of an India Data Management Office (IDMO) under the Digital India Corporation. IDMO is tasked with formulating rules, standards, and guidelines for data sharing, and for implementing an India Datasets program that curates high-value, anonymised datasets for broader use[11]. Together, NDGFP and IDMO provide the institutional scaffolding for unlocking public-value data while managing risks

(c) User-Centric Data Sharing: DEPA and Consent Managers

A third pillar of India’s data-governance architecture is the Data Empowerment and Protection Architecture (DEPA)[12]. DEPA is a framework that enables individuals to share their own data (for example, financial or healthcare data) with third-party services through licensed consent managers. In the financial sector, DEPA has been implemented via the RBI’s Account Aggregator system, which allows personal data to be securely aggregated and shared in real time with explicit user consent [14].

While DEPA is not an open-data initiative in the traditional sense, it is an important component of India’s AI data ecosystem because it creates a secure, consent-based

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[10] Data Fiduciary means any person who, alone or in conjunction with other persons, determines the purpose and means of processing personal data.

[11] https://www.pib.gov.in/PressReleasePage.aspx?PRID=1845318#:~:text=The%20Draft%20National%20Data%20Governance.system

[12] ttps://www.niti.gov.in/sites/default/files/2023-03/Data-Empowerment-and-Protection-Architecture-A-Secure-Consent-Based.pdf

pipeline of authorised user data for AI applications. By giving individuals greater control over how their data is accessed and used, DEPA seeks to balance privacy with innovation and offers a replicable template for other sectors such as health, education, and mobility.

3.2.2.2 Standards:

In addition to rules, policies, and frameworks, India is also prioritising the development of technical standards for data and AI. India's data ecosystem for AI is increasingly anchored in formal standards adopted through the Bureau of Indian Standards (BIS), particularly under AI Sectional Committee (LITD 30), which mirrors the work of ISO/IEC JTC 1/SC 42 on AI. These standards provide a common vocabulary and set of technical expectations for how data is collected, processed, documented, and evaluated for AI and analytics.

(a) Available Standards on AI Data Life Cycle Framework

A central reference is IS/ISO/IEC 8183:2023, Information technology – Artificial intelligence - Data life cycle framework, which was established as an Indian Standard on 26 March 2024. This standard defines the stages of the data life cycle and identifies associated actions for data processing throughout that cycle in AI systems [15].

(b) Standards on AI Data Quality

In parallel, BIS has adopted the IS/ISO/IEC 5259 series – Artificial intelligence — Data quality for analytics and machine learning (ML), which provides a comprehensive toolkit for specifying and managing data quality in AI contexts [16]. While IS/ISO/IEC 5259-5:2025 is currently circulated as a draft Indian Standard, it will be adopted by the BIS as an identical Indian Standard on the recommendations of the LITD 30 with the approval of the Electronics and Information Technology Division Council. This extends India's adoption of the ISO/IEC 5259 series from data-quality concepts and processes to a full governance framework for analytics and ML data [17].

Standard	Title	Scope & Purpose
IS/ISO/IEC 5259-1:2024	Part 1: Overview, terminology, and examples	Establishes the conceptual foundation for data quality in analytics and ML. Defines core terminology and key concepts. Provides examples illustrating data quality issues.

IS/ISO/IEC 5259-2:2024	Part 2: Data quality measures	Specifies a data quality model. Defines data quality measures relevant to analytics & ML. Provides guidance for reporting data quality. It helps organisations define and monitor their data quality objectives.
IS/ISO/IEC 5259-3:2024	Part 3: Data quality management requirements and guidelines	Describes requirements and guidelines for managing data quality across the data life cycle. It covers organisational responsibilities and internal controls. Provides guidance for establishing quality management processes for ML data.
IS/ISO/IEC 5259-4:2024	Part 4: Data quality process framework	Provides a process framework for implementing data quality activities. Outlines processes for operating and maintaining data quality across the data life cycle. Supports systematic, repeatable data quality workflows for ML.
IS/ISO/IEC 5259-5:2025 (Yet to be adopted, in Draft)	Part 5: Data quality governance framework	Provides a data-quality governance framework for analytics and ML, enabling governing bodies of organisations to direct and oversee data-quality measures, management, and related processes across the full data life cycle. Focuses on organisational oversight and controls rather than day-to-day management or process specifications and is intended to be used together with ISO/IEC 5259-3 and ISO/IEC 5259-4, which define those elements in detail.

Table 2: ISO standards for Data Management for AI

3.2.3 Human Capital:

Building data-preparedness for AI demands a coordinated effort across institutions, human talent, and technology. It is not simply about accumulating datasets but ensuring that the workforce is equipped to manage every dimension of readiness, from accessibility and structure to quality, bias, and governance[13]. It means annotators, data curators, and operations teams must not only collect and clean raw information but also assess completeness, representativeness, feature relevance, documentation, and ethical alignment [18].

India's strategy for data preparedness deeply intertwines with its human capital development agenda. Unlike compute or hardware, which depend on capital and imports, data preparedness for AI depends on a skilled workforce, like annotators, validators, and curators who transform raw information into AI-ready assets. This makes data work a powerful lever for employment generation, skills development, and inclusion across India's digital economy.

As data annotation and curation become integral to AI pipelines, India is witnessing the rise of new digital occupations:

- Data Annotators and Labellers
- Linguistic Validators and Translators
- Data Curators and Auditors
- Dataset Engineers and Tooling Developers

Several national initiatives are now integrating data annotation and AI data management into India's broader skill development framework:

- 570 AI Data Labs will be set up across India to promote regional AI innovation, data annotation, and skills development under the IndiaAI Mission by MeitY[14].
- Private sector Initiatives such as NASSCOM FutureSkills Prime: Offers micro-certifications in AI data operations, dataset curation, and responsible AI practices. Co-funded by MeitY, it connects learners to employment pipelines in annotation firms[15].

[13] Data Readiness Dimensions for AI, Source: Hiniduma, K., Byna, S., & Bez, J. L. (2024). Data readiness for AI: A 360-degree survey. arXiv.
[14] https://www.pib.gov.in/PressReleasePage.aspx?PRID=216,8319
[15] https://www.futureskillsprime.in

- The Directorate General of Training (DGT), under the Ministry of Skill Development & Entrepreneurship (MSDE), has introduced a dedicated NSQF Level-3.5 trade titled "Data Annotation Assistant" under the Craftsmen Training Scheme (CTS). The curriculum includes text, image, audio, and video annotation techniques, dataset quality practices, and ML-readiness workflows[16].
- The digital platform under Skill India lists a course, "Data Annotator" (data entry and classification), among its catalogue. This supports the pipeline for data-related skills[17].

State-Government-Level Initiatives:

NIELIT Patna (Bihar) launched a course titled "Fundamentals of Data Curation using Python" under the IndiaAI Mission on 22 August 2025. The course covers data collection & cleaning, structuring datasets, and preparing data for AI/ML applications[18]. The Telangana State Government, under an agreement with Bangalore-based Tika Data, established a data-annotation cluster in rural districts, aimed at building annotation capacity in non-metropolitan areas[19]. India's opportunity, however, should not be limited to creating a large pool of data annotators, translators, and curators. The focus needs to be on building AI process knowledge that enables existing technical and domain expertise to generate, structure, validate, and govern high-quality data for AI systems. Data annotation and curation should therefore be developed as sub-skills within broader AI and domain expertise, rather than as end skills in themselves. This is particularly important for developing specialised capabilities in areas such as sensor, geospatial, space, and underwater data, which can support the development of niche and high-value AI systems.

3.2.4 Role of Private Sector in India's Data for AI Ecosystem

Traxcn data analysed on Indian firms working in the field of AI shows four broad functional categories. These firms illustrate how the private sector complements public initiatives in making Indian data usable for AI development:

[16] https://dgt.gov.in/sites/default/files/2024-02/Data%20Annotation%20Asst._CTS1.0_NSQF 3.5.pdf
[17] https://www.skillindiadigital.gov.in/courses/detail/c7bcbb29-2465-45c5-a5e5-160179ed10e6
[18] https://www.nielit.gov.in/patna/nielit-news-gallery?gallery=26224
[19] https://timesofindia.indiatimes.com/city/hyderabad/t-aims-for-data-annotation-clusters-in-state-inks-mou-with-tika-data/articleshow/89651044.cms

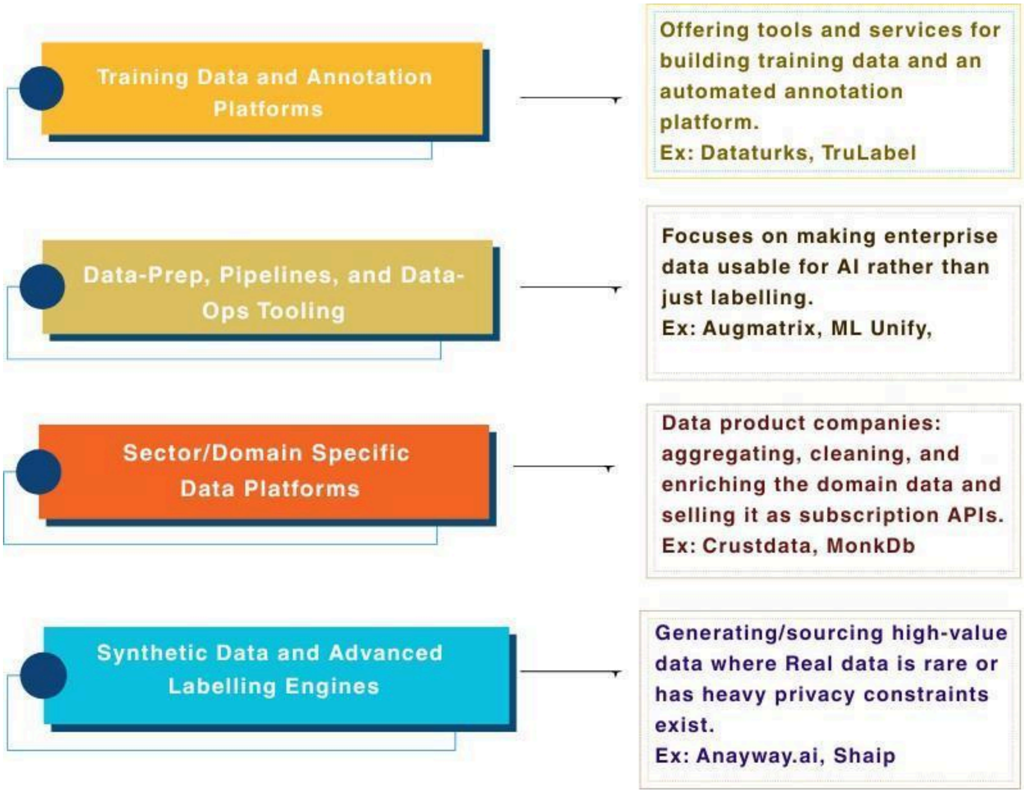

Fig. 5: Key categories of work areas in India's data ecosystem

- **Data platforms, engineering & integration tools:** A second cluster of firms focuses on data engineering, integration, and search platforms that sit between raw data and model development. Companies such as Augmatrix, ML Unify, InfraHive, WitHub, and YouData.ai provide data pipelines, unstructured-data processing, search and analytics layers, and “data-aware” copilot infrastructure. These tools help enterprises and developers clean, connect, and operationalise disparate datasets, making it easier to plug organisational data into AI systems.

- **Domain- and sensor-specific AI/data solutions:** Some of the firms are building AI solutions tightly coupled to particular domains or data sources, turning specialised datasets into applied intelligence. Examples include Crustdata, MonkDB, and ThereliableAI. These companies show how sectoral data, commerce, mobility, healthcare, and industrial IoT can be transformed into AI products that address concrete business and public-service problems.

- **Synthetic Data and Labelling:** Companies, such as Anyway.ai and Shaip, focus on synthetic data generation and compliance training datasets. These categories of companies address two critical challenges in India’s AI development: data scarcity and data sensitivity. They curate and annotate highly regulated data, particularly in domains like healthcare and speech, with a strong emphasis on privacy, consent, and compliance. This segment plays an enabling role in making high-value, hard-to-access data available for AI training in a manner that is both technically useful and aligned with regulatory and ethical requirements.

How private-sector work differs from public-sector initiatives on Data:

Aspect	Public-sector Data Initiatives	Private Sector Data Initiatives
Primary Data Source & Ownership	Work mainly with government-generated data (administrative, statistical, geospatial, language, and sectoral datasets). Ownership typically rests with the state, with mandates for openness and public benefit.	Work primarily with enterprise and platform data (customer interactions, operational logs, proprietary content, sensor streams). Data is controlled by clients or the company and is generally not open.
Core Purpose	It is designed as a digital public infrastructure to democratise access, improve transparency, and enable broad-based research and innovation.	Designed as commercial services and products that monetise data preparation, annotation, curation, synthetic data, and domain solutions for specific clients.
Access Model	Emphasise open or regulated public access (open data, tiered access, registration-based access), with common schemas and documentation for reuse.	Provide restricted, contract-based access, where data and pipelines are built for specific organisations and are usually confidential or proprietary.

Level of Customisation	Offer generic, standardised datasets that users adapt for their own use cases; customisation is limited and usually not client-specific.	Deliver highly bespoke pipelines (custom schemas, labels, workflows) tailored to a bank, hospital, logistics firm, and platform.
Governance & Standards Focus	Prioritise standardisation, interoperability, and equitable access under common rules and public accountability frameworks.	Prioritise compliance with contracts, sectoral regulations, and client requirements, often adding proprietary quality and governance layers for competitive advantage.
Pace of Change & Experimentation	Operate at the pace of policy, budgeting, and inter-agency coordination; updates and new features are periodic and process-driven.	Can iterate rapidly, testing new labelling schemes, quality metrics, workflows, and integrations as AI architectures (RAG, agents, and multimodal) evolve.
Role in the AI Ecosystem	Provide a baseline, shared data infrastructure for the country as a common floor of AI-relevant datasets available to many actors.	Convert organisation-specific, often sensitive data into AI-ready assets, closely integrated with products, models, and enterprise workflows.

Table 3: Comparative Understanding of India Compute Initiatives

3.2.5 Key Gaps in India's Data Readiness for AI

(a) Limited volume &coverage of AI-ready datasets, despite a strong early push:

AI Kosh, NDAP, and other public data portals are important first steps, but they still represent only a fraction of the datasets needed to train robust AI models. Training competitive foundational and domain models typically requires thousands of high-quality, well-documented datasets across sectors. Many key ministries and departments have not yet contributed their priority datasets in an AI-ready form (structured, cleaned, documented, and machine-readable). As a result, large volumes of valuable administrative, sectoral, and operational data remain locked in silos or in formats (PDFs, unstandardised CSVs, and legacy systems) that are difficult to use for model training and evaluation.

Potential Measures:

- Mandate that current and upcoming centrally and state-sponsored schemes and digital public infrastructures publish standardised, well-documented, AI-ready datasets.

- Providing technical support and shared toolkits so line ministries can convert legacy data into structured, annotated, and machine-readable formats.

(b) Fragmented governance and slow institutional capacity-building:

India's policy framework has begun to recognise the need for systematic data governance (e.g., NDGFP, AI Kosh design, BIS standards), but institutional capacity remains uneven. The proposed India Data Management Office (IDMO) has yet to fully take shape as a central "data regulator" with clear authority, staffing, and budget. In the absence of a strong coordinating institution, ministries, states, and public agencies face uncertainty about what to share and how to anonymise and document it.

Potential Measures:

- The NDGFP needs to be notified and operationalised at the earliest, with clearly assigned institutional responsibilities for coordinating AI-relevant data governance.

- Defining minimum metadata, documentation, and quality requirements for datasets to qualify as "AI-ready" under national programmes.

- Coordinate across ministries, states, and regulators to harmonise rules for non-personal data sharing, anonymisation practices, and consent-based reuse.

(c) Gaps in human capital for data curation and stewardship:

While India has launched some important initiatives (e.g., AI Data Labs, DGT's Data Annotation Assistant, FutureSkills Prime), the scale of trained data annotators, curators, and stewards is still small relative to national need. Many public-sector bodies and smaller institutions lack dedicated teams who understand both domain context and AI data requirements (bias, representativeness, documentation, consent, reuse conditions). Human capital gaps also extend to the limited legal and institutional protections for workers engaged in data labelling and annotation, particularly in relation to worker safety, working conditions, and employment stability.

Potential Measures:

- Creating funded data steward positions in major departments and state governments, linked to the IndiaAI Mission and NDGFP implementation

- Link initiatives such as AI Data Labs, DGT's Data Annotation Assistant trade, and NASSCOM FutureSkills Prime to government demand and private-sector demand so that trained workers can be deployed on real annotation and curation projects, not just classroom exercises.

(d) Disconnect between public data infrastructure and private data-for-AI activity:

Public initiatives focus on open or shared datasets, while private firms increasingly work with high-value, organisation-specific, and often sensitive data (e.g., financial, health, mobility, and platform logs). There are few incentives or mechanisms for private actors to contribute derived datasets, documentation practices, or synthetic data back into the public corpus.

Potential Measures:

- Sectoral data partnerships or data trusts where enterprises can contribute anonymised, aggregated or synthetic datasets (or model-ready features) for regulated public-interest use.

- Incentives (e.g., recognition, access to IndiaAI compute, or targeted tax benefits) for firms that open-up derived datasets, benchmarks, or tools under appropriate licences.

(e) Uneven implementation of standards and safeguards across sectors:

Technical standards for data life-cycle management and quality (e.g., IS/ISO/IEC 8183, 5259 series) are now available, but adoption is patchy. Many datasets lack basic metadata, provenance information, quality indicators, or explicit licensing terms. At the same time, the capacity to implement privacy-preserving techniques (anonymisation, differential privacy, secure aggregation) varies widely across ministries, states, and private actors. This creates a dual risk: underutilisation of data because agencies are unsure how to share it safely, and overexposure to sensitive data where safeguards are weak.

Potential Measures:

- Requiring that projects funded under IndiaAI (compute, models, and pilots) follow BIS data life cycle and quality standards and publish data documentation cards or schemas where feasible.
- Encourage states and ministries that meet data-readiness milestones (e.g., number and quality of AI-ready datasets) through incentives and recognition in national rankings.

(f) Need for Data Commons for AI

India's data ecosystem remains fragmented across ministries, states, research institutions, and private actors, limiting the ability to discover, combine, and reuse high-quality datasets for AI development. A national Data Commons could provide a trusted framework for pooling, cataloguing, standardising, and governing access to diverse datasets while preserving appropriate privacy, security, and licensing safeguards.

Potential Measures:

- A federated national data commons may be created that connects existing public and sectoral data platforms through common metadata, interoperability standards, access protocols, and governance safeguards, rather than creating another standalone centralised repository.

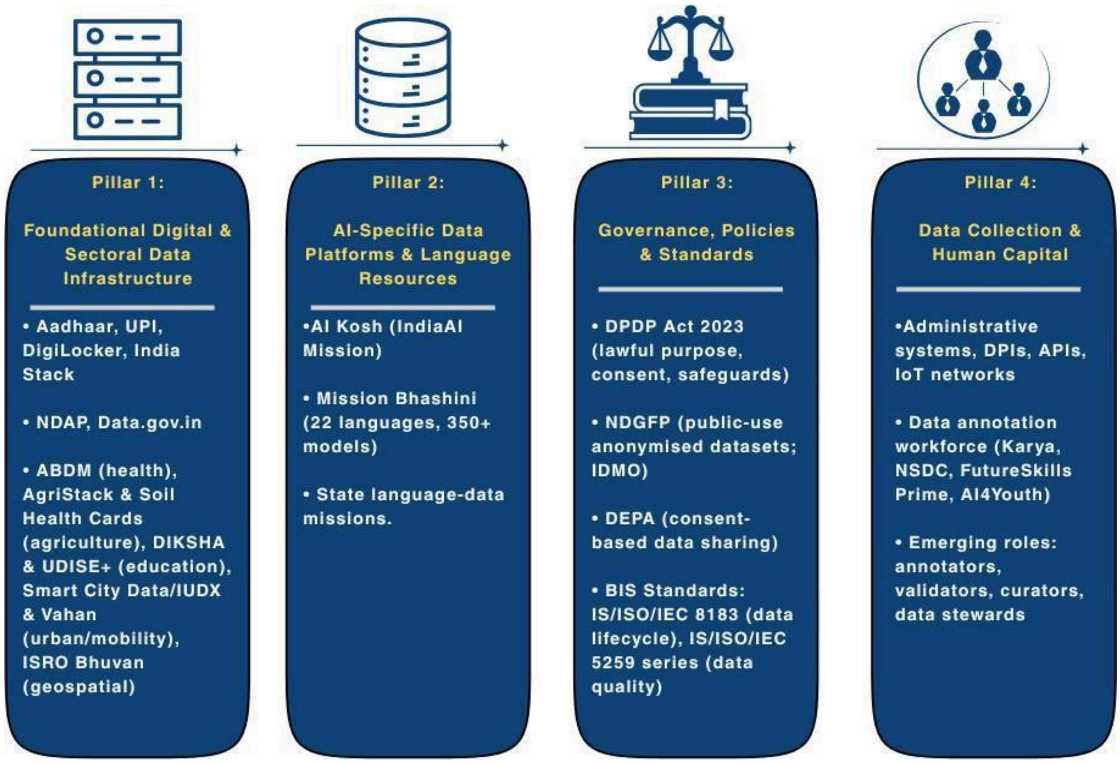

Fig. 6: Snapshot of India's Data Ecosystem for AI

3.3 AI Model Capacity

The objective of this section is to assess India's capacity to develop, train, sustain, and govern indigenous AI models. Model capacity determines whether AI systems deployed in India can encode Indian languages, knowledge systems, economic priorities, and public values. It is therefore evaluated through the lenses of sovereignty (who controls core models), equity (whose linguistic and cultural realities models represent), and scalability (whether models can be maintained and improved over time). A simple taxonomy of various widely used AI models is below:

- Foundation Models (FMs): Broadly trained, adaptable models (text, speech, vision, multimodal) that can be fine-tuned for many downstream tasks. India's public programs are funding domestic FM training runs (e.g., Sarvam AI under IndiaAI)
- LLMs (Large Language Models): Text-centric FMs (often tens/hundreds of billions of parameters). Used in Indian enterprises, GovTech pilots, and startups; global LLMs (e.g., Gemini, Llama, OpenRouter ecosystem) are widely integrated in India-built solutions.

- SLMs (Small Language Models): Compact models (sub-20B typical) for edge or low-latency; strong push in India for Indic-aware SLMs for affordability and sovereign constraints.
- Domain/Task-specialised models: E.g., bilingual/multilingual translation and speech models for Indic languages, traffic/cyclone forecasting models, code and RAG models for BFSI/governance.

3.3.1 AI models Development Landscape

Across the world, governments are debating the strategic importance of developing sovereign AI models, foundation models that are trained, governed, and adapted within national borders. In India, this debate is driven by concerns over long-term dependence on foreign model providers, limited availability of models trained on Indian languages and socio-economic contexts, risks related to data security, intellectual property, and geopolitical vulnerability.

Fig. 7: Key components to build a Sovereign AI Model

Policymakers, industry leaders, and researchers argue that India requires sovereign models to ensure autonomy in critical sectors such as governance, finance, healthcare, education, agriculture, and national security. Building sophisticated AI models, especially FM, is a resource-intensive and demanding task. In India, model development capacity is emerging through a network of collaborations; it is defined by a distributed architecture in which government missions, academic research labs, startups, industry R&D units, and global partnerships each perform complementary and interdependent roles in the model development pipeline.

The table below summarises the principal actors, their focus areas, and coordination mechanisms shaping India's emerging model capacity.

Actor Category	Focus	Key Examples
Government & Public Missions	National infrastructure, model funding, and open repositories	IndiaAI Mission functions as a national coordination and accountability hub.
Academic & Research Institutions	Open-source model development, benchmarks, and domain R&D	IIT Madras / AI4Bharat (IndicBERT, ULCA); IISc; IIIT Hyd; BharatGPT Consortium
Private Sector & Startups	Training and deployment of sovereign LLMs / SLMs; commercial AI solutions	Sarvam AI, Krutrim, Hanooman, CoRover (BharatGPT)
Global Partnerships	Compute and tooling for training and fine-tuning; benchmark collaboration	Google Gemini, Azure OpenAI, Meta Llama 3 for Indic languages
Industry Associations & Standards Bodies	Coordination of model safety protocols and evaluation frameworks	NASSCOM GenAI Foundry.

Table 4: Overview of Model Ecosystem Actors

3.3.2 Indigenous Foundation Models:

Under the IndiaAI Mission's pillar, a flagship programme is underway to fund and foster Indian-led foundation models. As of November 2025, the government has selected 12 teams comprising startups, academic groups, and industry labs to develop large AI models. These include:

Model	Developer	Domain	Highlights
Sarvam AI	Sarvam AI Pvt. Ltd.	Multilingual reasoning, voice-first	Developing a 105B-parameter sovereign LLM, alongside 30B models for Indian languages; anchor project with 4,096 NVIDIA H100 GPUs and a focus on governance, public services, and high-stakes deployment.
Soket AI	Soket AI Labs	Text-based multilingual foundation model	Developing a 120B-parameter open-source multilingual foundation model tailored to India's linguistic diversity.
Gnani.ai	Gnani Innovations Pvt. Ltd.	Speech and dialogue understanding	Developing a 14B-parameter multilingual Voice AI foundation model for real-time speech processing and advanced reasoning.
Gan.ai	Gan Systems / Gan.ai	Video + speech generation (TTS)	Developing a 70B-parameter multilingual TTS foundation model targeting high-performance text-to-speech capabilities.
Avataar AI	Avataar AI Pvt.	Avatars / embodied AI agents	Developing specialised AI Avatar models of up to 70B parameters, optimised for Indian languages and domains such as agriculture, healthcare, and governance.
BharatGen (IITB Consortium)	IIT Bombay + Jio + research consortium	General-purpose, multilingual, multimodal	Developing multilingual and multimodal models ranging from 2B to 1T parameters, with an open-source approach supporting applications in agriculture, finance, legal, health, and education.
Fractal Analytics FM	Fractal Analytics	STEM / medical reasoning	Developing a large reasoning model of up to 70B parameters for structured reasoning, STEM disciplines, and medical problem-solving.

Tech Mahindra Maker's Lab FM	Tech Mahindra	Indic language model/government applications	Developing an efficient 8B-parameter model for Indic languages, with a focus on Hindi dialects, alongside the Orion agentic AI platform for government applications.
ZenteiQ.ai – BrahmAI	ZenteiQ.ai	Scientific & R&D foundation model	Developing BrahmAI, a science-driven multimodal foundation model ranging from 8B to 80B parameters for engineering intelligence, scientific computing, and industrial innovation.
GenLoop (Yukti, Varta, Kavach)	Consortium project	Small language model suite	Developing 2B-parameter small language models—Yukti, Varta, and Kavach—to support all 22 scheduled Indian languages with native reasoning and content moderation capabilities.
IntelliHealth	HealthTech startup	Biomedical / health-signal foundation model	Proposing a 20B-parameter foundation model for EEG signal analysis, neurological disorder screening, and brain–computer interface research.
Shodh AI	Academic consortium	Scientific discovery model	Developing a 7B-parameter model for material discovery, integrating AI into experimental workflows to accelerate scientific research.

Table 5: Foundation Model Projects Under IndiaAI Mission

Through the above projects, India is investing in the capacity to create its own sovereign models. Many of these models, once developed, are expected to be made available for use and adaptation. There is an emphasis on openness and support for Indian languages, which should help spur innovation by enabling startups and students to build on top of these foundation models rather than always relying on foreign APIs. The challenge ahead will be ensuring these efforts result in competitive, well-maintained models and that the different teams share knowledge and avoid duplicating work.

3.3.3 AI Model-Focused Startups/Companies in India's AI Ecosystem

As per Tracxn data analysed, there are nearly 276 India-based companies directly or indirectly engaged in AI model development and the surrounding tooling stack. Together, they form the core of India's model layer, building foundation models, domain-specific models, generative applications, and the MLOps and developer tools required to train, fine-tune, evaluate, and deploy these systems at scale. Karnataka, and particularly Bengaluru, emerged as the dominant hub. Delhi-NCR (Delhi, Gurugram, and Noida) forms the second major cluster, followed by Hyderabad, Pune, Chennai, Mumbai, and emerging centres such as Indore, Thiruvananthapuram, and Prayagraj.

In terms of sectoral focus, the dataset classifies around 240 firms as Developer Tools & MLOps companies. They build platforms for data preparation, training orchestration, model evaluation, monitoring, deployment pipelines, and inference optimisation. In practice, these tools convert raw compute and datasets into usable modelling capacity for enterprises, startups, and public projects, allowing many organisations to work with AI without maintaining deep in-house infrastructure teams.

Alongside this, a smaller but strategically important subset of firms works on LLMs and foundation models, contributing directly to India's indigenous model capacity, including domain-specific LLMs, specialised reasoning systems, and multilingual models. The remaining companies primarily focus on applying models within sectors such as finance, retail, manufacturing, logistics, and public services. Together, these segments strengthen India's ability to build, adapt, and operate AI systems that work with Indian languages, local datasets, and domestic regulatory requirements.

Functional profile

The ecosystem also invests in enabling infrastructure and tools, as well as general-purpose foundation model builders. Around one-third of the companies, nearly 80, categorise themselves under generative AI, reflecting activity around text, code, image, and multimodal generation. Another 98 firms fall under machine learning (ML), focusing on predictive and analytical models embedded into vertical solutions. Few companies are positioned as LLM / foundation-model developers in the dataset; most others contribute to the model ecosystem through task-specific models, agents, or orchestration layers rather than frontier-scale base models.

Contribution to India’s model capacity

Viewed through the lens of capacity, these companies contribute to India’s model development in four main ways:

(a) **Core model development and adaptation:** A small, important subset of firms is building large language models (LLMs) and domain-specific foundation models, trained or fine-tuned on Indian data, multilingual corpora, or sectoral datasets. These actors broaden the range of indigenous models that can align with Indian languages, regulatory constraints, and normative priorities. Examples include firms developing Indic LLMs and multilingual assistants. Their work increases India’s ability to host, govern, and iterate models domestically rather than relying exclusively on foreign APIs.

(b) **Tooling, MLOps, and infrastructure abstraction:** The largest share of companies builds the “tools and platforms” layer rather than focusing solely on pure model research. They build training pipelines. evaluation suites, monitoring dashboards, deployment platforms, and API gateways. This layer plays a force-multiplier role: it lowers the technical barrier for enterprises, startups, and public agencies to experiment with, fine-tune, and deploy models without having deep in-house infrastructure or research teams.

(c) **Domain and vertical models:** Many companies in the ML, vision, and NLP categories specialise in sector-specific use cases (finance, healthcare, retail, logistics, and governance). They create domain-tuned models, evaluation datasets, and workflows that convert raw modelling capabilities into productivity and service-delivery gains across the economy.

(d) **Ecosystem experimentation and spillovers:** The large number of early-stage firms reflects active experimentation in architectures (agents, retrieval-augmented systems, and multimodal models), interfaces (no-code model builders, API gateways), and pricing models. Even when individual ventures exit, their talent, open-source artefacts, and learning spill over into larger firms, research labs, and subsequent startups, cumulatively strengthening India’s model-development know-how.

Contribution to model capacity	Definition	Companies
Core model development & adaptation	Training or heavily fine-tuning LLMs / large domain models on Indian data and languages	Sarvam AI, Krutrim/BharatGPT, BharatGen, OpenHathi, Bhabha AI, Odia Generative, LLUMO, Soket AI
Tooling, MLOps & infra abstraction	Platforms for training, evaluation, deployment, monitoring, and orchestration on top of compute.	Composio, DhiWise, Smarter.codes, Assurtiv, Actionpackd, QuickSmart AI
Domain & vertical models	Sector-specific models and data pipelines for health, mobility, logistics, etc.	Kaaenaat, Maruth Labs, Medvolt.
Ecosystem experimentation & spillovers	Mostly unfunded/seed firms exploring new architectures, agents, UX, and pricing models	1Bot, Loop, Dr Code, ReplyMaster, Nhancio

Table 6: Categories of India's Model Development Ecosystem

Key Findings:

1. **Distributed Ecosystem:** The public sector intends to focus on encouraging the development of homegrown, India-specific large language models (LLMs) and multimodal models (LMMs) that are trained on diverse Indian datasets to capture unique linguistic and cultural nuances. The private sector tends to focus more on building applied models, generative applications, and the surrounding tools and MLOps platforms that make these capabilities usable at scale for enterprises, startups, and public projects.

2. **Strong tilt toward tools, platforms, and applied ML:** Our analysis shows that the model ecosystem in India is developing more as developer tools and MLOps

providers. A strategic group of companies is focused on core LLM/foundation model development. The majority work on training orchestration, evaluation, monitoring, deployment, agents, and vertical solutions, which lowers barriers for enterprises, startups, and public agencies to use models without building in-house research infrastructure.

3. **Growing Opportunity around SLM and Domain-Specific Models:** An opportunity is emerging around SLMs/domain-specific models. They are compact, purpose-built models that are significantly cheaper and faster to train than large-scale LLMs. Because SLMs require far fewer resources, they are accessible to startups, universities, and corporate innovation teams, enabling a wider set of actors to participate in India's AI development. Their small size also enables enterprises, especially in regulated domains such as finance, healthcare, and governance, to deploy them securely on private servers or at the edge. Indian startups are already demonstrating the potential of this approach by building multilingual, voice-first, enterprise-ready SLMs tailored to Indian languages and use cases.

3.3.4 Key Gaps in India's Model Capacity

(a) Structural imbalance between tools/MLOps and core model R&D

Our analysis indicates that out of nearly 276 model-layer companies, around 240 are positioned as Developer Tools & MLOps providers. At the same time, only a small subset focuses on training or heavily fine-tuning base models. This tilt towards orchestration, evaluation, and deployment tooling is valuable. Still, it also means that deep expertise in training large or specialised models remains concentrated in a few firms and academic groups. Without deliberate effort, India risks becoming primarily a "model application and tooling" hub rather than a centre of core model innovation.

Proposed Measures

- Introduce targeted R&D incentives, grants, and anchor-customer arrangements for firms and labs that undertake base-model training (e.g., domain LLMs, multilingual FMs).

- Couple these with requirements for India-relevant evaluation, safety documentation, and structured collaboration with tool/MLOps providers so that core model know-how diffuses more widely.

(b) Limited integration between publicly funded models and private innovation

While the IndiaAI Mission and public research institutions are investing in foundation models, and the private sector is rapidly building applied solutions, agents, and tooling, the interfaces between these layers are still evolving. Benchmarking evaluation practices for publicly funded models are not yet fully standardised, and there is no single, unified integration layer for these models.

In practice, many Indian startups and enterprises continue to rely heavily on foreign foundation models (such as OpenAI, Gemini, or Llama), whose APIs and tooling ecosystems are currently more mature and easier to integrate. Strengthening documentation, access frameworks, and interoperable evaluation protocols for India-funded models will be essential to deepen their uptake in the domestic innovation ecosystem.

(c) Under-exploited opportunity around SLMs and domain-specific models

Policy and public narrative emphasise large LLMs, even though India's compute constraints and market structure favour small, purpose-built models. SLMs and domain models are cheaper and faster to train, can be deployed on-premise or at the edge, and are better suited to regulated sectors and bandwidth-constrained environments. While several startups are already demonstrating multilingual, voice-first, enterprise-ready SLMs, there is no dedicated national track, benchmarking regime, or procurement preference for such models.

Proposed Measures

- Create a dedicated IndiaAI "Small and Sectoral Models Track" with lighter-touch grants, access to subsidised compute, and fast-cycle evaluations for SLMs and domain models (e.g., for BFSI, health, agriculture, justice, and education).
- Develop public benchmark suites for Indic SLMs and encourage open-weight releases, so that states, MSMEs, and smaller institutions can adopt and adapt them at low cost.

(d) Uneven capacity to adopt and adapt models outside major hubs

Model-layer activity is concentrated in Bengaluru and Delhi-NCR, with smaller clusters in a few other cities. Many state departments, Tier-2 and Tier-3 institutions, and MSMEs lack the technical depth to fine-tune or safely deploy models, even when tools and APIs are available. Without targeted support, this may exacerbate regional and institutional inequities in AI capability.

Proposed Measures

- Develop regional AI application centres, linked to leading institutes and IndiaAI, that provide hands-on support for states, smaller universities, and MSMEs to fine-tune SLMs, integrate domain models into workflows, and comply with safety and data-governance norms.

- Pair model access with structured training for public officials and local developers so that sovereign model capacity translates into broad-based adoption.

3.4 Data Centre

Data centres form the physical backbone of the AI ecosystem. The training and deployment of large AI and GenAI systems require massive computational power, high-performance servers, and access to large, well-organised datasets, driving an unprecedented surge in demand for data-centre capacity worldwide. As of November 2025, the United States leads with 4,165 data centres, followed by the United Kingdom (499), Germany (487), and China (381), while India hosts around 274 facilities [19]. Despite generating nearly 20 per cent of the world's data and supporting more than 2100 AI companies and startups, India accounts for just about 3 per cent of global data centres [20].

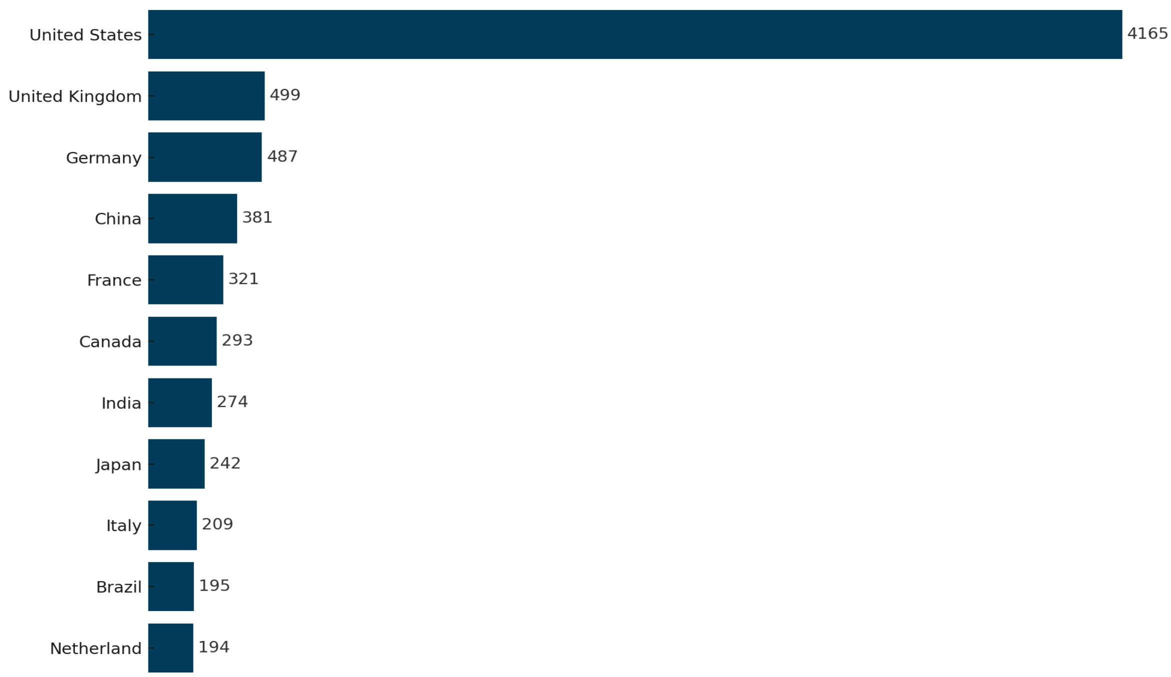

Fig. 8: Number of data centres worldwide, by country (November 2025),
Source:[**https://www.statista.com/statistics/1228433/data-centers-worldwide-by-country/**](https://www.statista.com/statistics/1228433/data-centers-worldwide-by-country/)

India is rapidly positioning itself as a major global hub for AI innovation, and this growth is closely mirrored in the expansion of its data-centre industry. Over the past five years, India's data-centre capacity has grown 2.5 times, at a robust CAGR of around 24 per cent [21]. The sector is now on an accelerated growth trajectory, with future capacity expected to expand in the coming years, driven by the rise of AI and large-scale adoption of GenAI across industries. As of 2025, India has roughly 274 operational data centres, and a report titled 'Racks to Riches' estimated that currently India has an IT load capacity of 1.4 GW, with another 1.4 GW under construction and a further 5 GW in the planning stage[20]. Projections indicate this capacity will rise to 8 GW by 2030 [22].

3.4.1 Emerging Data Centres Hub in India:

India's major metropolitan regions, Mumbai, Chennai, Bengaluru, Hyderabad, Delhi-NCR, and Pune, have emerged as the country's dominant data centre hubs, together accounting for roughly 73% of operational data centres nationwide [23]. These cities benefit from strong fibre connectivity, reliable power availability, mature IT/ITeS ecosystems, and sustained enterprise demand. Coastal hubs such as Mumbai and Chennai also benefit from multiple submarine cable landing stations, giving them a natural advantage in international connectivity and making them preferred locations for hyperscale data centre deployments.

- Mumbai remains India's largest data centre market, hosting 47 facilities, the highest in the country. Its strategic coastal location, access to multiple subsea cable landing points, mature BFSI demand, and resilient infrastructure make it the anchor of India's data-centre industry. Navi Mumbai, with 21 centres, is rapidly consolidating its position as the next major hotspot within the Mumbai Metropolitan Region and is expected to drive substantial future capacity addition.

- Chennai, with 35 data centres, has become India's second major coastal hub. It benefits from multiple submarine cable gateways, a stable power supply, and proactive state-level policies. It is expected to contribute a significant share of upcoming capacity additions as AI and cloud demand accelerate.

- Hyderabad (32 centres) and Bengaluru (30 centres) continue to grow as high-demand regions, driven by their strong presence in IT, cloud services, and enterprise workloads. Both cities host hyperscaler availability zones and are witnessing increased interest from AI-driven infrastructure developers.

[20] https://timesofindia.indiatimes.com/business/india-business/digital-surge-ahead-indias-data-centres-to-grow-fivefold-by-2030-says-report/articleshow/124879397.cms

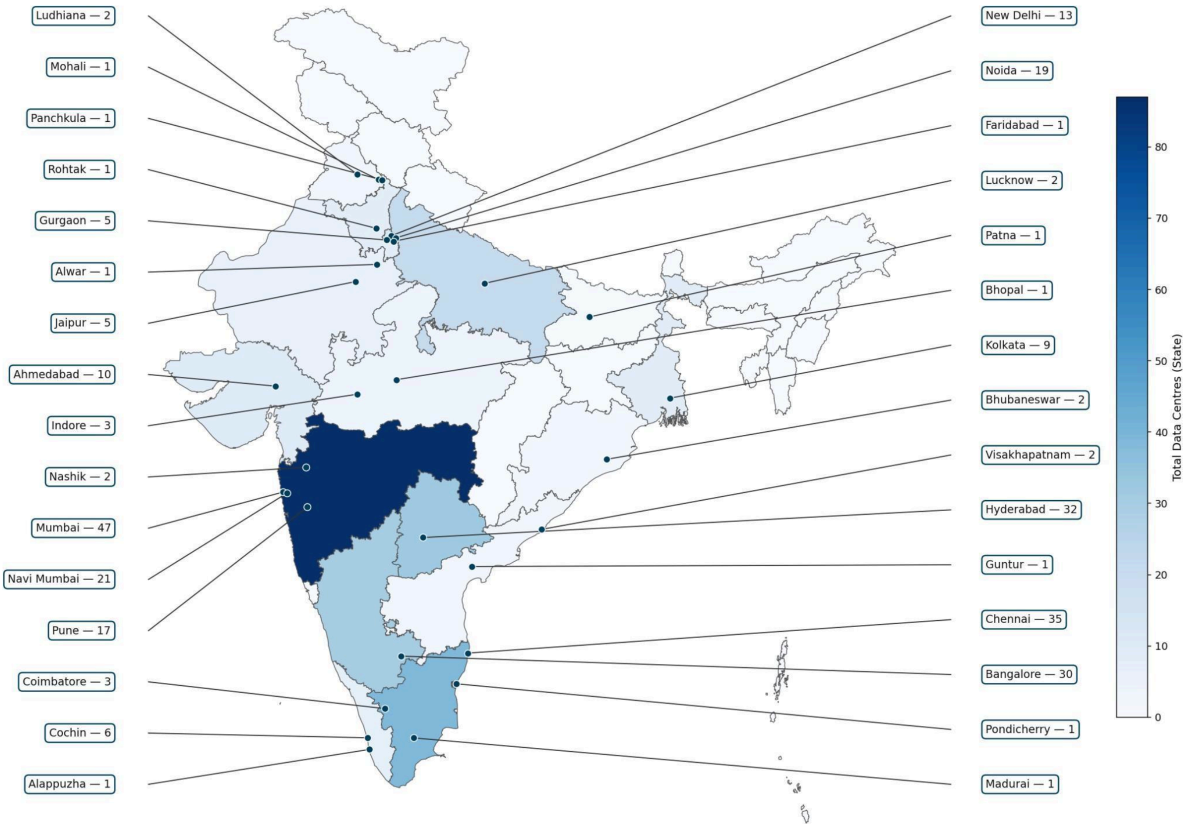

Fig 9: Number of Data Centres in India, City-wise (November 2025),
Source: https://www.datacentermap.com/

- Delhi-NCR, covering Delhi (13 centres), Noida (19), Gurgaon (5), Faridabad (1), and Rohtak (1), forms the largest landlocked data centre cluster in India, benefiting from policy incentives, large consumer markets, and proximity to government and public sector workloads.

- Pune (17 centres), Cochin (6), Ahmedabad (10), Jaipur (5), and Visakhapatnam (2) reflect the rise of Tier-II hubs, supported by local enterprise demand, smart-city initiatives, and emerging AI workloads. Cities such as Indore, Coimbatore, Ludhiana, Nashik, Guntur, Madurai, Alappuzha, and Bhopal, each hosting 1–3 data centres, indicate the beginning of wider regional dispersion.

As we have seen above, large metropolitan hubs continue to concentrate most of India's data centre capacity, raising questions about equitable access to AI infrastructure. Therefore, public policy and market developments increasingly focus on extending the benefits of this capacity beyond Tier-1 cities. At the national level, the IndiaAI Compute pillar and other cloud-based public digital infrastructures are designed so that researchers, startups, and public agencies in any part of the country can remotely access GPU and storage resources over high-speed networks, regardless of their physical proximity to a major data centre. In parallel, several states are using dedicated data centre policies and industrial incentives to encourage facilities in emerging locations with lower land costs and stronger power availability. For example, the Haryana State Data Centre Policy (2022)[21], Uttar Pradesh Data Centre Policy (2021)[22], Telangana Data Centre Policy (2016)[23], and the Karnataka Data Centre Policy (2022)[24], all of which aim to attract investments through fiscal incentives, power subsidies, single-window clearances, and infrastructure support. Private operators are also beginning to deploy edge and micro data centers in Tier II and Tier III markets. For example, CtrlS has announced and commissioned edge facilities in cities such as Patna, Lucknow, Bhopal, and Bhubaneswar and planned sites in other smaller hubs to bring compute closer to where data is generated and consumed. Together, this model of dense hyperscale clusters in metros complemented by a growing ring of regional and edge facilities allows India to keep the economic advantages of large coastal and metro hubs while gradually widening low-latency, affordable access to compute and storage for institutions, governments, and enterprises across the country.

3.4.2 Key Enablers of India Data Centre Ecosystem:

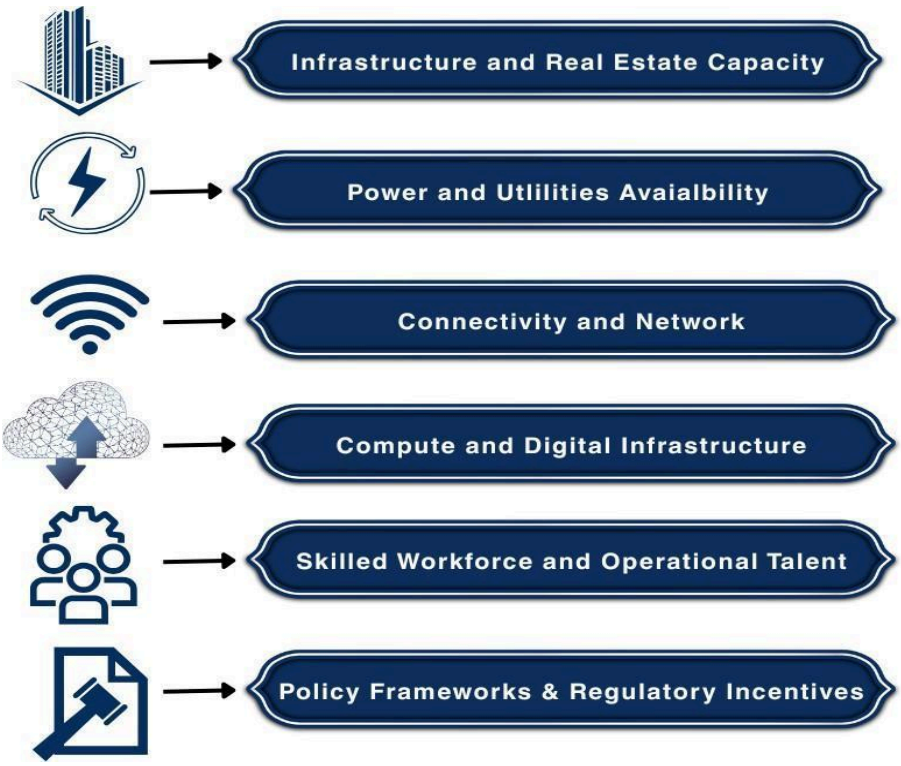

Fig. 10: Key Enablers of India's Data-Centre Ecosystem

[21] https://cdnbbsr.s3waas.gov.in/s35352696a9ca3397beb79f116f3a33991/uploads/2022/07/2022071110.pdf
[22] https://invest.up.gov.in/wp-content/uploads/2022/11/DC-Policy-2021_091122.pdf
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[24] https://eitbt.karnataka.gov.in/it/public/uploads/media_to_ucentrespload1727071046.pdf

India's data-centre ecosystem is anchored in seven foundational enablers that determine its ability to support the next generation of AI and digital services:

- The first enabler is infrastructure and real estate capacity, which form the physical foundation of data centres' operations. As AI workloads push the boundaries of density, cooling, and equipment weight, data centres increasingly require large, contiguous land parcels, purpose-built facilities, high floor loading, and specialised structural design. While India offers cost advantages in land and construction, the sector continues to face prolonged land acquisition cycles, fragmented multi-agency approvals, and limited availability of designated data-centre zones. Addressing these challenges will require expanding pre-approved data centre parks, adopting single-window clearances, and developing tailored building codes for data centre construction.

- A second enabler is power and utilities availability, which is central to sustaining high-density compute environments. AI training clusters require uninterrupted grid supply, redundant substations, and access to large volumes of renewable energy as sustainability mandates grow stronger. However, power constraints persist across several urban clusters, along with high operational costs due to reliance on diesel backup and limited renewable integration. Strengthening open-access renewable energy frameworks, investing in dedicated feeders for large DC hubs, and incentivising low power usage effectiveness (PUE) designs can significantly enhance India's power resilience.

- The third enabler, connectivity and network backbone, determines the efficiency and latency of digital operations. High-speed fibre, redundant terrestrial paths, carrier-neutral access, and proximity to Internet exchange points form the backbone of data movement. Coastal hubs such as Mumbai and Chennai benefit naturally from submarine cable landings, while inland hubs rely heavily on expanding terrestrial infrastructure. Challenges remain around last-mile redundancy in Tier II and III cities and the slow growth of neutral internet exchange points (IXPs). Accelerated fibre expansion, mandated route diversity, and strengthened IXPs will be critical for supporting distributed AI applications.

- The fourth enabler is compute and digital infrastructure, which now defines the strategic capabilities of data centres. The shift toward GPU clusters, HPC systems, liquid cooling, and AI-optimised architectures has redefined the design of modern facilities. India's challenges lie in its reliance on imported GPUs, the high cost of AI-grade rack deployments, and the limited availability of sovereign compute. Scaling the IndiaAI Compute pillar, incentivising AI-optimised retrofits, and supporting indigenous hardware ecosystems will be essential to building long-term strategic capability.

- A fifth enabler is a skilled workforce and operational talent that underpin reliable 24×7 data centre operations. As data centres evolve from traditional colocation facilities to AI-first infrastructure hubs, the need for advanced roles, HPC operators, GPU cluster managers, cooling specialists, and cybersecurity engineers has increased sharply. While India has a strong digital talent base, there is a clear shortfall in specialised AI infrastructure skills. Expanding targeted skilling programmes under NSDC, NASSCOM FutureSkills, and sector-specific academies, alongside standardised national certifications, is critical for sustaining operational excellence.

- The sixth enabler is policy frameworks and regulatory incentives, which shape the overall investment climate. States such as Uttar Pradesh (2021), Haryana (2022), Karnataka (2022), Maharashtra (2023), Tamil Nadu (2021), and Telangana (2016) have introduced dedicated data centre policies that provide benefits such as stamp duty waivers, capital subsidies, infrastructure support, electricity duty exemptions, and power tariff concessions. However, uneven incentive structures, regulatory complexity in land and building permissions, and ambiguity in the intellectual property rights framework for AI-generated models continue to pose barriers. In addition, regulatory clarity[25] on dark fibre access[26] and related digital connectivity infrastructure remains a policy issue for data centre development, particularly where low latency and resilient network capacity are critical.

- The seventh enabler is water availability and sustainable water management, which is increasingly important for data-centre siting and operations. Data centres can require significant volumes of water for cooling, depending on their scale, cooling technology, and local climate. A typical 100 MW hyperscale data centre using water-intensive cooling systems can consume around 2 million litres of water per day

[25] https://trai.gov.in/sites/default/files/2024-11/BIF_14022022%20%281%29.pdf
[26] https://www.trai.gov.in/sites/default/files/2025-02/Recommendations_17022025.pdf

for on-site cooling[27]. This raises particular concerns where data centre growth is concentrated in urban regions already facing competing demands for water. Water availability should therefore be integrated into data-centre siting decisions alongside power, land, connectivity, and climate risks.

3.4.3 Key Gaps in India's Data Centre Ecosystem

1. **High Growth, but narrow geographic concentration and uneven access**

India's data-centre capacity has expanded rapidly and is projected to reach 8 GW by 2030. However, our analysis shows that most operational and pipeline capacity is concentrated in a few metropolitan hubs, especially Mumbai, Chennai, Bengaluru, and Delhi-NCR, which together account for the bulk of the national inventory. Tier-II and Tier-III cities are only beginning to see small clusters and edge deployments. This spatial concentration raises questions about equitable access to low-latency, affordable AI infrastructure for institutions, startups, and governments located outside major metros.

Potential Measures:

- Encourage data centre development in emerging hubs through targeted fiscal incentives; land allotment in pre-approved industrial and IT parks; and priority infrastructure (power, fibre, last-mile connectivity, green incentives, and stamp duty exemption).
- Use IndiaAI and other national digital platforms as "virtual equalisers", ensuring that institutions in any state can reliably access compute and storage resources over high-speed networks, irrespective of physical proximity to a large data centre.
- Support edge and micro data centre deployments in Tier-II and Tier-III cities, especially where new AI-driven public services (health, agriculture, and mobility) are being rolled out.

2. **Land, real estate, and approvals are not fully aligned with AI-grade requirements**

AI-optimised data centres require large contiguous land parcels, specialised building design, higher floor loading[28], advanced cooling, and integrated power infrastructure. While India offers relative cost advantages, developers still face prolonged land acquisition cycles, fragmented multi-agency approvals, and limited availability of designated data-centre zones.

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[27] https://www.ceew.in/sites/default/files/ceew-data-centre-study-web-ready-final.pdf

[28] In a data centre, floor loading (or floor load capacity approvals for data land acquisition centreacity) refers to the maximum amount of weight per unit area that the floor structure can safely support requirements.

This adds time and uncertainty to AI-graded data centre projects, especially in new locations.

Potential Measures

- Expand pre-notified "data centre parks" and integrate them into broader industrial and IT corridors with pre-cleared land, trunk infrastructure, and single-window clearances.
- Develop standardised national guidelines and building codes for AI-oriented data centres (including high-density racks, liquid cooling, fire safety, and redundancy norms) to reduce approval ambiguity for both developers and regulators.
- Encourage states to align local planning and zoning regulations with national data-centre
- standards to shorten project timelines.

3. Power reliability, grid integration, and sustainability pressures

AI workloads are power-intensive and require an uninterrupted power supply, redundant substations, and a growing share of renewable energy. Several urban clusters still face grid constraints, high dependence on diesel backup, and limited integration of green power. This raises operational costs and complicates long-term sustainability commitments, even as international clients and investors increasingly demand low-PUE and low-carbon facilities.

Potential Measures

- Create dedicated, high-capacity power corridors and feeders for major data centre hubs, with guaranteed reliability standards and time-bound upgrade plans.

- Strengthen renewable energy and enable long-term green power purchase agreements (PPAs)[29] tailored to data centre requirements.

- Introduce incentive schemes for low-PUE designs and retrofits (e.g., accelerated depreciation or capital subsidies for energy-efficient cooling, waste-heat reuse, and on-site renewables).

4. Network backbone and interconnection gaps beyond major hubs

Coastal hubs such as Mumbai and Chennai benefit from multiple submarine cable landings and strong backbone connectivity. Still, inland and emerging locations face challenges

[29] Green power purchase agreements (PPAs) are long-term contracts where data centres buy renewable energy to power their facilities, ensuring a stable, predictable cost while meeting sustainability goals.

around route diversity, last-mile redundancy, and neutral internet exchange points (IXPs)41. For distributed AI applications and edge inference, weak interconnection increases latency and vulnerability to outages.

Potential Measures

- Prioritise fibre expansion and mandated route diversity42 in and between upcoming data-centre hubs, including Tier-II cities.
- Support access to dark fibre networks, growth of neutral IXPs and carrier-neutral facilities to improve traffic exchange, reduce latency, and lower bandwidth costs for AI workloads.
- Integrate network-resilience benchmarks into state data-centre policies and national infrastructure programmes.

5. Fragmented and uneven policy incentives, with limited guidance on AI-readiness

As we have shown in our analysis, several states have introduced dedicated data-centre policies with fiscal incentives, but incentive structures, approval processes, and interpretations of regulatory requirements vary significantly. At the same time, there is limited national-level guidance on what constitutes an "AI-ready" data centre (in terms of compute density, cooling, sustainability, and security).

Potential Measures

- Develop a light-touch national reference framework for AI-ready data centres, covering minimum benchmarks for compute density, energy efficiency, connectivity, and security, which states can adapt in their own policies.

- Harmonise and simplify incentive regimes across states by identifying a core set of common benefits (e.g., stamp duty waivers, power tariff concessions, and infrastructure support) and publishing comparative guidelines.

6. Water availability and sustainability risks in data-centre siting

As AI workloads increase, data centre siting without adequate assessment of local water availability could increase pressure on local resources and create long-term operational risks for the facilities themselves. Current state-level approaches also provide limited common standards for water-use reporting, water usage effectiveness (WUE), and the use of alternative water sources.

Potential Measures

- Encourage the use of treated wastewater, recycled water, rainwater harvesting, closed-loop cooling, and other water-efficient cooling technologies, particularly in water-stressed regions.
- Develop common reporting and performance benchmarks for Water Usage Effectiveness (WUE), including disclosure of water sources and consumption by large data-centre facilities.
- Encourage states to undertake cumulative assessments of data-centre water demand at the regional level, rather than evaluating water requirements only on a project-by-project basis.

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List of Abbreviations

AI – Artificial Intelligence

ABDM – Ayushman Bharat Digital Mission

ABHA – Ayushman Bharat Health Account

AIRAWAT-PSAI – Performance Supercomputing AI Platform

API – Application Programming Interface

BFSI – Banking, Financial Services, and Insurance

BIS – Bureau of Indian Standards

C-DAC – Centre for Development of Advanced Computing

DEPA – Data Empowerment and Protection Architecture

DPDP Act – Digital Personal Data Protection Act

DPI – Digital Public Infrastructure

FM – Foundation Model

GPU – Graphics Processing Unit

HPC – High Performance Computing

IISc – Indian Institute of Science

IIT – Indian Institute of Technology

IUDX – India Urban Data Exchange

LLM – Large Language Model

ML – Machine Learning

MeitY – Ministry of Electronics and Information Technology

MSME – Micro, Small, and Medium Enterprises

NDAP – National Data and Analytics Platform

NDGFP – National Data Governance Framework Policy

NIELIT – National Institute of Electronics & IT

NSM – National Supercomputing Mission

NSQF – National Skills Qualification Framework

OSM – OpenStreetMap

PMEC – Programme Monitoring & Evaluation Committee

PUE – Power Usage Effectiveness

RAG – Retrieval-Augmented Generation

SLM – Small Language Model

TPU – Tensor Processing Unit

UPI – Unified Payments Interface

WRIS – Water Resources Information System

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