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SURVEY-BASED
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Competition, Innovation, and Market Structure in India's AI Ecosystem

AN EMPIRICAL ASSESSMENT

AUGUST 2026

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The Dialogue is a public policy think tank with a vision to drive a progressive narrative in India's policy discourse. Founded in 2017, we believe in facilitating well-researched policy debates at various levels to help develop a more informed citizenry, on areas around technology and development issues. The Dialogue has been ranked as the world's Top 10 think tanks to watch out for, by the Think Tank and Civil Societies Programme (TTCSP), University of Pennsylvania in their 2020 and 2021 rankings.

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Foreword

India does not stumble into transformation. We plan for it.

The story of how our country has approached artificial intelligence is, at its core, a story of purposeful governance. While much of the world spent the early 2020s debating whether AI was a threat to be contained or an opportunity to be cautiously embraced, India made a choice, a choice to lead. That choice did not happen by accident. It was the product of sustained political direction, far-sighted institutional design, and government institutions willing to invest in the future of its people.

The IndiaAI Mission, approved by the Union Cabinet with an outlay of over ₹10,372 crore, is the clearest expression of this resolve. Planned across seven strategic pillars, which include compute infrastructure, datasets, the India AI Innovation Centre, application development, skilling, safety and trust, and startup financing, the Mission is one of the most comprehensive national AI programmes anywhere across the globe. Its subsidized compute infrastructure, which now makes over 38,000 high-performance GPUs available to Indian startups and researchers at just ₹65 per hour, has done more to democratize access to AI development infrastructure than any comparable initiative in the Global South.

We can see the results now. India's AI market has grown from USD 3.2 billion in 2020 to over USD 6 billion in 2024, and is projected to reach nearly USD 32 billion by 2031. India is now home to over 8,900 active AI startups, and the third-largest digital ecosystem in the world. AI startup funding in the first half of 2026 alone surged more than four times compared to the same period the previous year. Global technology majors have committed tens of billions of dollars in India-facing investments, drawn by a combination of digital infrastructure, policy certainty, and a government that has demonstrated, consistently, that it means what it says about making India an AI powerhouse.

In February 2026, India hosted the AI Impact Summit, the first summit in this series to be held in a Global South nation. It was a recognition of the global standing we have built through deliberate effort. The Summit was a platform for India to not merely participate in the global AI governance conversation, but to shape it, and to offer the world a model of how an emerging economy can build AI capability at scale, responsibly, and in a manner that serves its own citizens and its own development priorities.

The study prepared by The Dialogue arrives at a timely moment in this journey. Its empirical findings offer an independent data-backed assessment of where India's AI ecosystem stands, and they reflect well on the choices our government has made. Nearly 85% of business users report that AI has had a moderate to highly positive impact on their competitiveness. Open-source AI tools are now essentially universal among Indian developers, and the downstream application market is characterised by strong entry, experimentation, and

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product diversity, precisely the kind of competitive dynamism that the Mission's startup pillar was designed to foster.

The paper also lays down the groundwork for what's next. As a member of the Parliamentary Standing Committee on Communications and Information Technology, I am cogent of the role that parliamentary functionaries will play in providing the next-steps for AI governance. The government has laid the foundation, and the stakeholders are responding. What India's AI story now requires is the continued partnership of researchers, industry, and Parliament working together, each contributing its part to an ambition that is, by any measure, among the most exciting our country has ever set for itself.

Overall, I commend The Dialogue for this timely and carefully empirical contribution. Good governance begins with good evidence, and good evidence about India's AI markets is precisely what policymakers, regulators, and legislators need more of.

Dr. Rabindra Narayan Behera , Hon'ble Member of Parliament

New Delhi

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Date: 18th August, 2026

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Foreword

We are living through a moment of technological transformation that rivals, and may well surpass, the industrial revolutions that reshaped the global economic order in centuries past. Artificial Intelligence is no longer a technology of the horizon, it is here, and it is reshaping the contours of markets, investment, and economic power with a speed that demands serious and sustained attention from policymakers, regulators, and legislators alike.

For India, this moment carries exceptional promise. Our AI market has more than doubled in just four years from USD 3.2 billion in 2020 to USD 6.05 billion in 2024, and is projected to reach nearly USD 32 billion by 2031. The IndiaAI Mission, backed by an allocation of over ₹10,372 crore, has catalysed the creation of subsidised public compute infrastructure and positioned India as a serious actor in the global AI race. The India AI Impact Summit in February 2026, the first such summit in the series to be hosted by a Global South nation, was a statement of intent from India to the world: that we are not merely consumers of this technology, but architects of its future. Major global players have responded with investment commitments running into tens of billions of dollars. India's AI startup ecosystem, too, is on a steep upward trajectory, with funding in the first half of 2026 alone surging over four times compared to the same period the previous year.
Yet the history of transformative technologies also teaches us that the rewards of innovation are not self-distributing. Markets that are not watched, structured, and where necessary, corrected, can concentrate power in ways that ultimately constrain the very dynamism they appear to generate. It is precisely this question, how to ensure that India's AI boom translates into a competitive, innovative, and inclusive digital economy that has rightfully occupied our regulators and policymakers in recent years.

In October 2025, the Competition Commission of India published its landmark Market Study on Artificial Intelligence and Competition, the first comprehensive analysis of how AI is reshaping market structures and competitive behaviour in India. The study was a welcome and necessary intervention. It documented the promise of AI adoption across banking, healthcare, retail, and logistics, while raising measured concerns about concentration at the upstream layers of the AI stack, the potential for algorithmic collusion, and the barriers facing smaller firms in accessing proprietary data and compute. It was, above all, a call for evidence-based regulation vigilant but proportionate, attentive to harm but respectful of innovation.
This paper published by The Dialogue is a significant contribution to this evolving conversation. Where the CCI study surveyed the competitive landscape from the regulator's perspective, this paper brings us the view from within the market itself from the businesses using AI tools, the startups building it, and the consumers experiencing its effects. Its findings are striking in their nuance.

As a member of the Parliamentary Standing Committee on Finance, I am acutely conscious of the stakes involved. The choices India makes today, on regulation, on public investment, on the architecture of data and compute governance will determine whether the extraordinary capital now flowing into our AI ecosystem builds lasting productive capacity or accumulates in the hands of a few.

Yours sincerely,

(Lavu Sri Krishna Devarayalu)

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Foreword

Artificial Intelligence is rapidly becoming a defining technology of our time. It has the potential to transform productivity, innovation, public services and the way businesses operate. For India, this presents a significant opportunity, but also an important responsibility to ensure that the benefits of AI are broad-based and accessible.

Building a strong AI ecosystem requires more than technology alone. It requires access to compute, data, skills, capital and markets, along with an environment that encourages innovation and competition. The Government of India's efforts in these areas are aimed at creating the foundations for a vibrant and inclusive AI ecosystem.

Competition will be an important part of this journey. Open and contestable markets can encourage new ideas, enable startups to challenge established models, improve choice and ensure that innovation continues to deliver value to businesses and citizens. At the same time, the rapidly evolving AI value chain, from compute and data to models and applications, calls for a nuanced understanding of how these markets are developing.

Evidence and informed discussion will therefore be important as India shapes its approach to AI. Perspectives from businesses, startups, developers and consumers, along with lessons from international experience, can help inform this conversation while recognising that India's approach must reflect its own priorities and circumstances.

It is in this context that I welcome The Dialogue's study on competition and AI in India. Based on primary research with business users, AI startups and developers, and consumers, the study moves the discussion beyond assumptions and towards evidence.

As India seeks to build a globally competitive and inclusive AI ecosystem, continued dialogue between government, industry, academia and civil society will be essential. I hope this study contributes to that larger conversation and encourages further thinking on how India can foster AI innovation while preserving competition, choice and trust.

Ms. Kavita Bhatia
AI & Emerging Technologies
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Government of India
New Delhi

The views expressed in this Foreword are personal.

Founder's Vision

The Dialogue was founded in July 2017 on a simple but ambitious belief: good policy is not made in isolation. It emerges from conversation, between institutions and citizens, research and lived experience, the state and those affected by its decisions.

That belief has shaped our work from the beginning. Our mission has been to bring policy closer to people and connect people with the issues that matter, particularly at a time of rapid technological and social change.

This paper is part of that continuing effort. Artificial intelligence presents India with significant economic and technological opportunities, but it also raises important questions about how its markets are structured and how the benefits of innovation will be shared. These questions cannot be answered through assumptions or by relying entirely on the experiences of other countries. They require evidence rooted in India's own market conditions.

Our research therefore examines competition across the AI value chain, from compute and data, to models, applications, and consumer-facing services. These layers are closely connected. Infrastructure providers, model developers, startups, and downstream businesses increasingly depend on one another, even as the tech ecosystem continues to evolve through new investment, experimentation, and market entry.

A central strength of this study is its primary research. By drawing on evidence from business users, AI startups and developers, and consumers, the paper brings the experiences of market participants into the policy debate. It considers not only how AI markets are organised, but also how businesses access and adopt AI, how developers build and compete, and how consumers experience choice.

The comparative analysis shows that many jurisdictions are approaching competition in AI with care. Given the pace of technological change, regulators have generally placed emphasis on monitoring, transparency, and continued assessment. For India, this offers an important lesson: competition policy should respond to evidence from our domestic sector while preserving the investment and experimentation needed for it to mature.

Through this paper, our team has sought to deepen the discussion on AI value chains, competitive conditions, innovation, and consumer choice. We do not regard this study as the final word. Rather, we hope it provides a stronger foundation for continued engagement among policymakers, regulators, industry, researchers, startups, and civil society.

I am proud of the rigour and commitment with which our team has undertaken this work. I hope the paper leads to sharper questions, better-informed debate, and policy choices that support an open, innovative, and competitive AI landscape in India.

Mr. Kazim Rizvi

Founding Director | The Dialogue

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The acknowledgement of any individual or institution in this report does not imply their endorsement of its findings, analysis, conclusions or recommendations. Any views expressed and interpretations made in this report should not be attributed to any individual or institution acknowledged herein.

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Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
AIGEG	AI Governance and Economic Group
AIKosh	AIKosh (IndiaAI's Datasets Platform)
ASIC	Application-Specific Integrated Circuit
API	Application Programming Interface
AWS	Amazon Web Services
BIS	Bureau of Indian Standards
CCI	Competition Commission of India
CDCL	Committee on Digital Competition Law
CMA	Competition and Markets Authority (United Kingdom)
CPU	Central Processing Unit
DCB	Draft Digital Competition Bill
DPDP Act	Digital Personal Data Protection Act, 2023
DPI	Digital Public Infrastructure
EC	European Commission
EU	European Union
FTC	Federal Trade Commission (United States of America)
GCP	Google Cloud Platform
GPU	Graphics Processing Unit
LLM	Large Language Model
MCA	Ministry of Corporate Affairs
MeitY	Ministry of Electronics and Information Technology
MLOps	Machine Learning Operations
MSMEs	Micro, Small and Medium Enterprises
MTIA	Meta Training and Inference Accelerator
OCC	Open Cloud Compute
OECD	Organisation for Economic Co-operation and Development
R&D	Research and Development
RAG	Retrieval-Augmented Generation
RBI	Reserve Bank of India
SEBI	Securities and Exchange Board of India
SSDEs	Systemically Significant Digital Enterprises
TPEC	Technology and Policy Expert Committee
TPU	Tensor Processing Unit
TRAI	Telecom Regulatory Authority of India
UK	United Kingdom
UPI	Unified Payment Interface

Executive Summary

Artificial intelligence ('AI') is reshaping economic activity worldwide, with AI applications projected to contribute USD 13 trillion by 2030. India is well positioned in this transformation, supported by the INR 10,371.92 crore IndiaAI Mission. Alongside this expansion, the Competition Commission of India ('CCI') published its Market Study on AI and Competition (October 2025), examining how the structural characteristics of AI markets intersect with competition policy.

This study builds on existing literature, and examines the evolving structure of India's AI ecosystem, the competitive dynamics across its value chain, and the implications for competition policy. It draws on a structured literature review as well as original evidence gathered through three stakeholder surveys conducted for this research: a **Business User Survey (Survey 1)** targeting **102** businesses across financial services, healthcare, logistics, manufacturing, and retail; an **AI Startups and Developers Survey (Survey 2)** targeting **106** AI startups and developers; and a **Consumer Survey (Survey 3)** targeting **100** consumers exploring everyday AI use, trust perceptions, and choice behaviour. Collectively, these surveys capture perspectives across the AI value chain and provide an empirical basis for evaluating how the structural concerns raised in AI competition literature are presently materialising within India's ecosystem.

Our study arrives at the following conclusions:

India's AI Ecosystem Offers Competitive Access to Compute Infrastructure

At present, access to compute infrastructure is widely recognised as a foundational determinant of participation in AI markets. Despite concerns about concentration in this layer, survey evidence from Indian AI developers suggests that cloud-based compute is broadly accessible, competitively priced, and not characterised by the exclusionary dynamics that might justify regulatory intervention.

Infrastructure Access

Approximately **85%** of Indian AI developers reported relying predominantly on public cloud infrastructure, while only **27%** reported using proprietary hardware for AI model development and deployment.

Affordability and Provider Options

Only **38.7%** of respondents considered compute affordability to be a significant issue, while **74.5%** believed that sufficient compute provider options exist. Looking at affordability, provider options and accessibility together, it is pertinent to note that respondents perceive compute markets to be competitive, affordable with readily available choices.

Switching Between Cloud Providers

Of the survey respondents who had switched or attempted to switch cloud providers, only **12.5%** found it challenging to do so. The principal barriers cited were data transfer constraints **(51.2%)**, compatibility issues **(46.3%)**, and service disruption risks **(41.5%)**. By contrast, only **14.6%** identified a lack of alternative providers as a significant obstacle.

Open-Source AI is Deeply Embedded and Meaningfully Reduces Entry Barriers

Open-source AI has emerged as an important mechanism for broadening access to AI capabilities and reducing barriers to entry at the application and fine-tuning layers of the AI stack. Survey evidence indicates that open-source ecosystems are deeply embedded within India's AI development community with respondents citing reliance on Llama, Hugging Face etc.

Reliance on Open Source

A striking **96.2%** of AI startup and developer respondents indicated at least some reliance on open-source models, frameworks, or tooling, with **62.3%** reporting 'high' reliance**.** Open-source adoption is concentrated at the model fine-tuning and alignment stage, where **68.9%** of respondents reported reliance on open-source tools.

Substitutability with Proprietary Models

More than **79%** of respondents reported that open-source models serve as at least a partial substitute for proprietary frontier models, while approximately **20**% considered them fully viable alternatives. This suggests that firms see open source as a viable solution for most applications, but not across all use cases.

AI Inputs Are Generally Accessible, with Data Standardisation as the Principal Challenge

Data access, talent availability, and relationships with infrastructure providers shape the ability of Indian firms to participate across different layers of the AI value chain. Survey evidence indicates that while these inputs are broadly accessible, specific structural challenges, particularly around data standardisation and talent availability exists.

Data Sources and Accessibility

Indian AI firms rely on a diverse range of data sources: proprietary data **(68%)**, public datasets **(64%)**, synthetic data **(32%)**, and licensed datasets **(25%)**. Around **60%** of respondents agreed that high-quality data is generally available, and only **32%** considered it unaffordable. However, perceptions were markedly negative with respect to public-sector data: only **15%** believed government datasets are readily accessible.

Primary Data Challenge: Standardisation, Not Scarcity

Lack of standardisation **(63.2%)** emerged as the most significant data-related challenge, ahead of more commonly assumed barriers such as copyright concerns **(44%)**, data scarcity **(42%)**, and privacy restrictions **(41%).** This indicates that most barriers remain due to technical complexities rather than structural concerns.

Talent Availability

Nearly half of respondents **(49.1%)** identified skilled talent as a key enabler of product development, third among all enablers, just behind data access **(53.8%)** and partnerships **(52.8%).** At the same time, 47.2% identified talent availability as a significant barrier to competitiveness, ranking it jointly first alongside customer adoption and ahead of compute costs.

Relationship with Infrastructure Providers

75.5% of AI startup respondents agreed that access to infrastructure providers is essential to their ability to compete. **62.3%** of respondents disagreed that they had been required to purchase additional services to access infrastructure, and only **9.4%** reported experiencing forced bundling. **63.2%** found provider pricing transparent. Further concerning their relationship with infrastructure providers, only **32.1%** of the respondents felt that they were able to negotiate commercial terms with infrastructure providers, while **42.5%** respondents remained neutral to the question.

AI Adoption Generates Broad and Commercially Viable Benefits for Businesses

AI technologies are being adopted across a wide range of business sectors in India, and businesses overwhelmingly report positive competitive effects. The survey evidence indicates that AI is reshaping business operations and users broadly view AI adoption as commercially viable.

Sectoral Adoption

AI adoption levels vary across sectors, with digitally mature industries leading deployment. Technology firms reported broad deployment at **74%**, professional services firms at **80%**, and retail/e-commerce firms at **100%**. Manufacturing and healthcare sectors reported significant pilot-stage adoption, suggesting that diffusion is underway but uneven across industries.

Use Cases and Perceived Impact

Data analysis and business intelligence emerged as the most common AI use case, identified by **70%** of business respondents, followed by customer service and chatbots **(54%),** product and service development **(53%)**, and marketing and advertising **(49%).** Overall, **85%** of business respondents rated AI's impact as moderate to highly positive, while only **15%** expressed a low-impact perception.

Key Business Benefits

Businesses primarily associate AI adoption with the following benefits: Decision-making improvements (identified by **61%** of respondents); Faster product and service delivery (**55%)**; Streamlined internal operations (**47%)**; Increased customer personalisation (**45%)**.

Commercial Viability and Satisfaction

Approximately **67%** of respondents agreed that the cost of AI solutions is proportionate to the benefits they provide. Around **65%** expressed satisfaction with the quality and range of AI solutions currently available in the market, with **22%** of the respondents strongly agreeing with the statement. Importantly, **71%** of business respondents disagreed that AI services had not significantly affected their operations, confirming that AI is meaningfully reshaping business processes even where adoption remains at early or experimental stages.

Transparency and Ability to Switch Providers

Upon being queried on the transparency of AI providers on pricing and data usage terms, **38%** respondents rated AI providers as transparent, **34%** highlighted transparency as a concern, and **28%** remain neutral to this inquiry. In terms of the ease of switching providers, among the respondents who felt switching was difficult, **56%** identified high implementation and switching costs and the need for improved reliability concerns as the main barrier, followed by integration challenges and industry-specific customisation gaps which was identified by **44%**.

Barriers to Adoption

Despite broad based adoption, some barriers do persist. Data privacy and security concerns represent the most significant barrier, identified by **56%** of respondents. Other barriers include lack of technical expertise **(38%)**, integration difficulties **(35%)**, limited understanding of AI applications **(34%)**, and high implementation costs **(29%).** Respondents also identified better privacy and security protections

(60%), easier integration **(54%)**, and lower costs with flexible pricing **(53%)** as the factors most important to making AI solutions more useful and accessible.

Consumer Experience with AI is Largely Positive

Consumers are increasingly interacting with AI-enabled services across digital platforms. Survey evidence indicates that AI has broadly improved user experience and consumers perceive meaningful choice within AI markets.

Reliance on AI-Enabled Services

Approximately **85%** of consumer respondents reported moderate to very high reliance on AI-enabled services, reflecting the growing embeddedness of AI across everyday digital activities. AI-enabled chatbots and virtual assistants are the most widely used AI-powered services, identified by **77%** of consumer respondents, followed closely by AI-powered search engines (**76%**) and social media platforms **(44%)**.

Positive Consumer Experience

Approximately **79%** of respondents reported that AI had significantly or somewhat improved their consumer experience, while only **9%** reported a worsening. Parallely, **40%** of respondents found it easy to opt-out of AI-powered features, and **33%** felt that it was not easy to opt-out of the AI-powered feature.**74%** agreed that AI integration has improved their overall user experience. **65%** agreed they have several alternatives to choose from among AI services, **62%** agreed they can easily switch between AI services, and **62%** reported using multiple AI services simultaneously. A further nuance noted here is that **78%** of respondents stated that the type of task determined whether they used a stand-alone AI tool or an embedded tool.

AI Generated Pricing

On being asked about pricing controlled by algorithms, **71%** of respondents reported to be aware that vary by timing, demand or profile. Concerning the reasonability of those prices, **25%** of respondents found them to be not reasonable, while **38%** of respondents remained neutral on that issue.

Satisfaction, Personalisation and Control

When asked about their sense of control over AI-driven personalisation in the digital services they use, **43%** agreed that they had a sense of control over AI service personalisation while **30%** remained neutral. Further, **51%** were satisfied with the range of AI enabled services available to them, **30%** remained neutral, and only **19%** were not satisfied. On the issue of integration, **57%** preferred AI features that are integrated within an existing digital service, and only **23%** did not have this preference. Concerning data usage, **78%** reported being either very aware or somewhat aware of how their personal data is used by AI systems.

Certain Concerns exists as Identified by Consumers

Data-related concerns represent the most significant issue experienced by consumer respondents, identified by **64%** of users. Ecosystem lock-in or dependence was identified by **48%,** while concerns relating to unclear terms, high pricing, and limited provider choice were each identified by between **35%** and **38%** of respondents. Upon being queried as to how to improve competitiveness and fairness in AI-enabled services, **70%** of respondents identified clearer information on AI recommendations, **65%** identified greater control over personal data, **54%** identified increased choice through more competing AI services, **47%** supported industry standards for transparency and safety, **38%** marked easier switching between services, and **39%** identified limits on enterprise AI integration as key factors.

Overall, quality or accuracy **(63%)**, and ease of use **(73%)** were identified as the factors which influence continued use of a particular AI-enabled service.

Way Forward

The findings of this study suggest that India's AI ecosystem is currently in a developmental and expansionary phase characterised by broad access to cloud compute infrastructure, a deeply embedded open-source culture, and growing AI adoption across business sectors generating measurable performance benefits. While certain upstream layers, particularly compute infrastructure and frontier model development exhibit higher levels of concentration due to large-scale investment requirements, downstream markets continue to display substantial experimentation, entry, and product differentiation.

Importantly, the principal concerns identified in this study relate less to market access or exclusionary conduct than to data standardisation, talent availability, pricing transparency, and data governance. In light of the foregoing, we recommend the following:

- **Maintain an innovation-oriented, proportionate regulatory approach towards AI markets.** AI markets remain technologically fluid, and premature or overly prescriptive intervention risks constraining investment, reducing experimentation, and limiting ecosystem development.

- **Invest in expanding access to compute infrastructure,** particularly through public compute initiatives, AI-focused cloud credits, and public-private collaboration models such as the IndiaAI Mission, to support startup participation and downstream innovation.

- **Support open ecosystems and interoperability standards** that enable portability and flexibility across providers, while recognising that both open-source and proprietary innovation models contribute to AI development in complementary ways.

- **Monitor strategic partnerships, investments, and ecosystem integration arrangements involving AI firms and cloud infrastructure providers,** given that such arrangements may influence access to infrastructure, distribution channels, and technological capabilities across the ecosystem. While partnerships have played an important role in enabling smaller firms to access compute resources, engineering expertise, and distribution networks, the CCI should observe arrangements involving strategically significant AI infrastructure or capabilities as the ecosystem matures.

- **Strengthen institutional capacity and inter-regulatory coordination,** given that AI-related governance questions intersect across competition, privacy, financial regulation, and consumer protection. Closer coordination between the CCI, MCA, and sector-specific regulators will be important as AI markets mature.

- **Institutionalise multi-stakeholder engagement and improve regulatory awareness** by undertaking regular consultations with industry players, startups, academia, civil society, and technical experts into the AI governance process, ensuring that regulation remains evidence-based, proportionate, and responsive to evolving market dynamics. Our survey evidence indicates that awareness of AI-related regulatory frameworks remains uneven across India's developer ecosystem, underscoring that effective governance depends not only on the quality of rules but on their visibility to the firms they are intended to govern.

1 | Introduction

1.1 Background

The last decade has seen Artificial Intelligence ('AI') take monumental strides, emerging as one of the most consequential technological developments of the era. Advances in machine learning, data processing, and computing infrastructure now enable increasingly capable AI systems to perform a wide variety of functions across industries and use-cases.[1] These tools are now being integrated across diverse sectors such as finance, logistics, healthcare, manufacturing, and digital services.[2] The recent acceleration of generative AI has proved a further catalyst: tools capable of producing text, images, video, and even code in response to natural language prompts have brought AI from the research laboratory into everyday commercial and consumer use.[3]

The economic scale of this transformation is significant.[4] Estimatedly, generative AI alone could add between USD 2.6 trillion and USD 4.4 trillion annually to global economic output across use cases, with broader AI contributing a potential USD 13 trillion in cumulative additional output by 2030.[5] The Organisation for Economic Co-operation and Development ('OECD') documents substantial productivity and innovation potential across sectors.[6] Both government and private investment in AI research, infrastructure, and applications is correspondingly accelerating worldwide.[7]

India sits at a strategically significant juncture in this transformation. The country possesses a constellation of structural advantages: a large and growing pool of technically trained talent, a proven track record in software services and technology exports,[8] an expanding domestic digital market of over 900 million internet users,[9] and a pioneering Digital Public Infrastructure ('DPI') stack that has rapidly brought digital payments, identity, and commerce to hundreds of millions of citizens.[10] The Stanford University Global Vibrancy Ranking 2025 ranks India third globally in AI competitiveness by growth and innovation trajectory from 2017 to 2024.[11] The country recorded over 8900 active AI

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[8] Office of Principal Scientific Advisor to the Government of India. (2025, September). *Shaping AI for India and the world.* https://psa.gov.in/CMS/web/sites/default/files/psa_custom_files/VIGYAN%20DHARA%20MAGAZINE%20AUGUST%20EDITION%20-%2008%20Sept.pdf.
[9] The Economic Times. (2025, January 16). India to have over 900 million internet users in 2025: report. https://economictimes.indiatimes.com/tech/technology/india-to-cross-900-million-internet-users-this-year-says-iamai-report/articleshow/117290089.cms?from=mdr&utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst.
[10] Press Information Bureau, Government of India. (2026, March 6). India's Digital Public Infrastructure – Setting a global benchmark for population-scale DPI. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2235812&reg=3&lang=2.
[11] Press Information Bureau, Government of India. (2026, February 12). AI@Work: Driving Productivity, Jobs, and Innovation. https://www.pib.gov.in/PressNoteDetails.aspx?id=157310&NoteId=157310&ModuleId=3&reg=44&lang=1.

startups as of 2026,[12] with the ecosystem raising approximately USD 856 million in 2025 and USD 626 million from January to February 2026, in AI funding.[13]

This rapid growth has drawn increasing attention from policymakers across the globe. Similar to other jurisdictions like Europe and the United Kingdom ('UK'), India has also begun examining the structure of emerging AI markets and the potential implications for the future of competition policy and enforcement.[14] The underlying questions are substantive: How concentrated are different layers of the AI value chain? Do the economics of AI development create durable barriers to entry? Are AI tools and infrastructure easily accessible to smaller firms, developers, and Micro, Small and Medium Enterprises ('MSMEs').[15] The inquiry has also included questions on the adequacy of existing competition frameworks to address emerging market failures, and the appropriate calibration of regulatory responses at a stage when the technology is still rapidly evolving and the benefits of continued innovation remain substantial.[16]

In light of these concerns, the study contributes to the discussion by examining the evolving structure of AI markets and their implications for the future of competition policy. In our research, we draw on existing literature, as well as original evidence gathered through stakeholder surveys conducted as part of this research. These surveys capture the perspectives of AI startups and developers, business users of AI tools, and consumers.

1.2 AI Governance: A Priority for India

India's AI governance landscape is evolving with notable speed. The IndiaAI Mission, approved by the Union Cabinet in March 2024 with a total outlay of INR 10,371.92 crore over five years, represents the most ambitious government intervention intervention in India's AI development to date.[17] The Mission encompasses seven pillars: compute capacity (with a target of 10,000+ Graphics Processing Units [‘GPUs’] available at subsidised rates), an AI Innovation Centre for indigenous foundation model development, a Datasets Platform (AIKosh), an Application Development Initiative, FutureSkills for AI talent development, Startup Financing for deep-tech AI companies, and a Safe and Trusted AI governance framework. By late 2025, approximately 38,000 GPUs had been onboarded under the Mission, significantly exceeding the original target, and GPUs have been made available to startups at subsidised rates of INR 65 per hour.[18]

On the competition side, the Ministry of Corporate Affairs' (‘MCA’) Committee on Digital Competition Law (‘CDCL’) released its report and the Draft Digital Competition Bill (‘DCB’) in February 2024,

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[12] Aumiqx Research. (March 2026). State of AI in India 2026. https://aumiqx.com/india-ai/report/.

[13] Kumar, C. (2026, February 19). India’s sovereign AI push gains momentum as funding crosses $5.5 bn. *Fortune India.* https://www.fortuneindia.com/business-news/indias-sovereign-ai-push-gains-momentum-as-funding-crosses-55-bn/130565.

[14] Martens, B. (2024, July). Why artificial intelligence is creating fundamental challenges for competition policy. *Policy Brief 16/2024, Bruegel.* https://www.bruegel.org/sites/default/files/2024-07/PB%2016%202024.pdf.

[15] Thun, M.V., & Hanley, D.A. (2024). Stopping Big Tech from Becoming Big AI: A Roadmap for Using Competition Policy to Keep Artificial Intelligence Open to All. *Open Markets Institute.* https://static1.squarespace.com/static/5e449c8c3ef68d752f3e70dc/t/67100db89a1e511e8f734a36/1729105337383/Stopping+Big+Tech+from+Becoming+Big+AI.pdf.

[16] Carugati, C., Guerra, M.P. (2024, May 30). Antitrust in the Age of Artificial Intelligence : Lessons from “I, Robot”. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4851821.

[17] Press Information Bureau, Government of India. (2025, October 12). Transforming India with AI – Over ₹10,300 crore investment & 38,000 GPUs powering inclusive innovation. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2178092&reg=3&lang=2.

[18] *Ibid.*

proposing ex-ante obligations on Systemically Significant Digital Enterprises ('SSDEs').[19] More recently, the Competition Commission of India ('CCI') released its Market Study on AI and Competition in 2025, the most systematic regulatory analysis of India's AI ecosystem to date.[20]

Sector-specific regulators including the Reserve Bank of India ('RBI') (FREE-AI guidelines, 2024),[21] the IndiaAI Governance Guidelines published by the IndiaAI Mission,[22] and Securities and Exchange Board of India ('SEBI') (consultation papers on algorithmic trading and AI/ML in securities markets)[23] have also engaged actively with AI-specific regulatory concerns. The Digital Personal Data Protection Act ('DPDP Act'), 2023 adds a data governance layer that interacts directly with AI training and deployment practices. More recently, the Ministry of Electronics and Information Technology ('MeitY') has constituted the AI Governance and Economic Group ('AIGEG') as the central inter-ministerial body for coordinating AI governance and policy.[24] It has also constituted the Technology and Policy Expert Committee ('TPEC') to provide the AIGEG with ongoing technical, policy, and strategic advice.[25]

These developments indicate that AI governance is now an active regulatory priority in India. The key challenge is to ensure that policy responses are calibrated to India's market realities, AI innovation ecosystem, and global competitiveness objectives.

1.3 Why AI Markets Raise Distinctive Questions for Competition Policy?

AI markets exhibit several distinctive characterisitics that make them particularly relevant for our analysis.[26]

First, AI is a general-purpose technology. General-purpose technologies are characterised by their ability to be deployed across multiple industries while enabling complementary innovations and productivity improvements throughout the economy.[27] Historically, technologies such as electricity, the

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[19] Ministry of Corporate Affairs, Government of India. (2024, February 27). Report of the Committee on Digital Competition Law. https://www.mca.gov.in/bin/dms/getdocument?mds=gzGtvSkE3zIVhAuBe2pbow%253D%253D&type=open

[20] Competition Commission of India & MDI Gurgaon. (2025, September). Market Study on Artificial Intelligence and Competition. https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

[21] Reserve Bank of India. (2025, August). *FREE-AI Committee Report – Framework for Responsible and Ethical Enablement of Artificial Intelligence.* https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/FREEAIR130820250A24FF2D4578453F824C72ED9F5D5851.PDF.

[22] Ministry of Electronics and Information Technology, Government of India. (2025, November). *India AI Governance Guidelines – Enabling Safe and Trusted AI Innovation.* https://static.pib.gov.in/WriteReadData/specificdocs/documents/2025/nov/doc2025115685601.pdf.

[23] Securities and Exchange Board of India. (2025, June 20). *Consultation Paper on "Guidelines for Responsible Usage of AI/ML In Indian Securities Markets".* https://www.sebi.gov.in/reports-and-statistics/reports/jun-2025/consultation-paper-on-guidelines-for-responsible-usage-of-ai-ml-in-indian-securities-markets_94687.html.

[24] Press Information Bureau, Government of India. (2026, April 16). Government Constitutes AI Governance and Economic Group (AIGEG) to Lead India's National AI Governance Strategy. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2252739&reg=3&lang=2

[25] Press Information Bureau, Government of India. (2026, April 18). Government Constitutes Technology and Policy Expert Committee (TPEC) to Provide Expert Advisory Support to India's AI Governance Architecture. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2253322&reg=3&lang=2

[26] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.

[27] Organisation for Economic Co-operation and Development. (2023). Competition and Innovation: A Theoretical Perspective – OECD Competition Policy Roundtable Background Note. https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/05/competition-and-innovation-a-theoretical-perspective_6e330b82/4632227c-en.pdf.

internet, and semiconductors have transformed not only individual markets but also the broader competitive landscape by creating new industries, lowering entry barriers in some sectors, and reshaping relationships between upstream infrastructure providers and downstream users.[28] AI exhibits similar characteristics, with its capabilities being integrated across sectors. As a result, competition issues arising in AI are unlikely to be confined to a single market or industry. Instead, they have the potential to influence competition across a wide range of sectors that increasingly rely on AI as a foundational input.[29]

Second, AI markets are multi-layered[30] and involve a high degree of interdependence between different players within the AI stack.[31] Cloud infrastructure providers supply the compute resources required to train and deploy AI models. Model developers build foundation models that can be integrated into software applications. Application developers then deploy these models across a wide range of consumer-facing or business-facing services.[32] This structure gives rise to a layered AI value chain, which can be understood as comprising interconnected segments, and is explained as follows:

- The **compute layer** includes semiconductors, cloud infrastructure, and data storage systems required to train and operate AI models. Access to such infrastructure is often highlighted to be costly and concentrated, creating potential entry barriers for smaller firms.[33]

- The **data layer** provides the raw material for training AI systems. The quality, diversity, and scale of data directly influence model performance, making access to data a critical competitive parameter.[34] At the same time, legal and economic constraints, including copyright and privacy considerations, may limit access to high-quality datasets.[35]

- The **model development layer** involves the creation of foundation models and other AI systems through processes such as pre-training and fine-tuning. Larger and more complex models often deliver superior performance but require significant investment in data and computational resources.[36]

- The **application layer** includes the deployment of AI systems in specific use cases, such as recommendation systems, pricing algorithms, and generative tools. This layer typically exhibits

[28] Organisation for Economic Co-operation and Development. (2023). Competition and Innovation: A Theoretical Perspective – OECD Competition Policy Roundtable Background Note. https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/05/competition-and-innovation-a-theoretical-perspective_6e330b82/4632227c-en.pdf.

[29] Marar, S. (2024, February). Artificial Intelligence and Antitrust Law: A Primer. Mercatus Special Study, Mercatus Center at George Mason University. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4745321.

[30] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

[31] Thun, M.V., & Hanley, D.A. (2024). Stopping Big Tech from Becoming Big AI: A Roadmap for Using Competition Policy to Keep Artificial Intelligence Open to All. *Open Markets Institute.* https://static1.squarespace.com/static/5e449c8c3ef68d752f3e70dc/t/67100db89a1e511e8f734a36/1729105337383/Stopping+Big+Tech+from+Becoming+Big+AI.pdf.

[32] *Ibid.*

[33] Martens, B. (2024, July). Why artificial intelligence is creating fundamental challenges for competition policy. *Policy Brief 16/2024, Bruegel.* https://www.bruegel.org/sites/default/files/2024-07/PB%2016%202024.pdf.

[34] Marar, S. (2024, February). Artificial Intelligence and Antitrust Law: A Primer. *Mercatus Special Study, Mercatus Center at George Mason University.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4745321.

[35] Martens, B. (2024, July). Why artificial intelligence is creating fundamental challenges for competition policy. *Policy Brief 16/2024, Bruegel.* https://www.bruegel.org/sites/default/files/2024-07/PB%2016%202024.pdf.

[36] Marar, S. (2024, February). Artificial Intelligence and Antitrust Law: A Primer. *Mercatus Special Study, Mercatus Center at George Mason University.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4745321.

greater entry and diversity, as firms can build on existing models without developing them from scratch.[37]

- Finally, the **distribution and ecosystem layer** connects AI systems to users through platforms, cloud services, and integrated digital ecosystems. Control over these channels can influence market access, interoperability, and user switching.[38]

Third, access to key inputs is fundamental to AI development. The development and scaling of large-scale AI models requires substantial compute power and access to large datasets.[39] These inputs may influence competitive conditions in AI markets, particularly in the development of large-scale foundation models.[40] These characteristics have prompted legislators and competition regulators worldwide to examine how existing competition frameworks apply to emerging AI markets.

1.4 Research Objectives and Methodology

Against the above backdrop, our study examines the evolving structure of AI markets and their implications for competition policy in India. The core objective of the study is to develop an evidence-based understanding of how AI ecosystems function and how different stakeholders participate in AI markets.

Specifically, the study examines the structure of India's AI value chain and the manner in which firms participate across different layers of the value chain, assesses how AI adoption is influencing businesses, consumers, and competition across sectors; evaluates access to key inputs such as compute, data, talent, and AI infrastructure; analyses the role of open-source models, cloud services, and technological innovation in shaping market participation; examines India's position within the current AI innovation cycle; and considers the role of India's competition and technology policy frameworks, drawing on comparative international experience to identify policy considerations for fostering competitive and innovation-oriented AI markets.

The study adopts a dual-track research methodology. Primary research was conducted across three cohorts through structured surveys:

First, a **Business User Survey (Survey 1)** targeted 102 businesses across sectors including financial services, healthcare, logistics, manufacturing, and retail, assessing the extent and nature of AI adoption, its competitive effects, barriers to adoption, provider satisfaction and switching behaviour, and views on the policy landscape.

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[37] *Ibid.*
[38] Thun, M.V., & Hanley, D.A. (2024). Stopping Big Tech from Becoming Big AI: A Roadmap for Using Competition Policy to Keep Artificial Intelligence Open to All. *Open Markets Institute.* https://static1.squarespace.com/static/5e449c8c3ef68d752f3e70dc/t/67100db89a1e511e8f734a36/1729105337383/Stopping+Big+Tech+from+Becoming+Big+AI.pdf.
[39] Olabiyi, W., Akinyele, D. & Joel, E. (2025, January). The Evolution of AI: From Rule-Based Systems to Data-Driven Intelligence. https://www.researchgate.net/publication/388035967_The_Evolution_of_AI_From_Rule-Based_Systems_to_Data-Driven_Intelligence. Also see: Martens, B. (2024, July). Why artificial intelligence is creating fundamental challenges for competition policy. *Policy Brief 16/2024, Bruegel.* https://www.bruegel.org/sites/default/files/2024-07/PB%2016%202024.pdf.
[40] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.

Second, an **AI Startups and Developers Survey (Survey 2)** targeted 106 AI startups and developers, examining their positioning across the AI value chain, access to compute and data inputs, use of open-source tools, experiences with infrastructure providers, and perceptions of the regulatory environment.

Third, a **Consumer Survey (Survey 3)** covered 100 end-consumers of AI tools and explored everyday AI use, choice and switching behaviour, trust and transparency perceptions, experiences of algorithmic pricing and lock-in, and views on competition concerns and remedies.

Collectively, these surveys and interviews provide insights into how AI technologies are being developed, deployed, and used across different parts of the economy.

Furthermore, the sample stratification and standard deviations for the three surveys are provided in Annexures 1 and 2, respectively.

Secondary research drew on a structured literature review covering academic economics and competition literature; regulatory market studies from the CCI, OECD, Competition and Markets Authority ('CMA'), Federal Trade Commission ('FTC'), and European Commission ('EC'); policy documents from Indian government bodies including NITI Aayog, MeitY, the RBI, SEBI, and the CDCL; industry and institutional reports from NASSCOM, McKinsey & Company, Stanford, Bureau of Indian Standards ('BIS'), and others; and recent news and regulatory developments.

1.5 Limitations of the Study

While this study combines primary survey evidence, literature review, and comparative policy analysis to examine AI markets and competition, certain limitations should be acknowledged when interpreting the findings.

a. **Sample Size and Representativeness:** Although the study received responses from 106 AI startups and developers, 102 business users, and 100 consumers, the findings are not intended to be statistically representative of the entire Indian AI ecosystem. Given the diversity and rapidly evolving nature of AI markets, the survey findings should be interpreted as indicative of prevailing trends and stakeholder perspectives rather than precise measures of the broader population.

b. **Sectoral Representation:** AI adoption and development vary significantly across industries and stages of technological maturity. While the surveys received responses from participants across sectors such as technology, financial services, healthcare, manufacturing, education, retail, media, and professional services, certain industries and specialised AI use cases may be underrepresented. Consequently, the findings should not be interpreted as reflecting the experiences of all sectors equally.

c. **Respondent Composition and Selection Bias:** The study draws upon three distinct stakeholder surveys covering AI startups and developers (Survey 2), business users (Survey 1), and consumers (Survey 3). It should be noted that all three surveys were conducted among respondents who were already engaged with AI in some capacity, whether as AI developers, business adopters, or active users of AI-enabled services. As a result, the surveys are subject to a degree of selection bias in favour of AI users and may not fully capture the perspectives, constraints, or reasons for non-adoption among individuals or organisations that do not currently use AI. Accordingly, the findings should be interpreted as reflecting the experiences and perceptions of active participants within India's AI ecosystem rather than the broader population.

d. **Perception-Based Responses:** Several survey questions sought respondents' perceptions regarding competition, switching costs, transparency, barriers to AI adoption, and market dynamics. These responses reflect stakeholder experiences and perceptions at the time of the survey and should not be interpreted as conclusive evidence of market conditions or anti-competitive conduct. Throughout the study, these findings are considered alongside secondary literature, comparative policy developments, and established economic research to provide a broader analytical context.

e. **Rapidly Evolving Technology and Markets:** AI technologies, business models, and regulatory approaches continue to evolve rapidly. New foundation models, infrastructure investments, strategic partnerships, and policy initiatives may emerge after the completion of this research. Accordingly, the findings represent a snapshot of the AI ecosystem during the study period and should be interpreted within the context of continuing technological and market evolution.

f. **Scope of the Competition Analysis:** The study focuses on the competition implications of AI markets rather than undertaking a comprehensive assessment of AI governance, safety, intellectual property, cybersecurity, or data protection frameworks. These issues are discussed only to the extent necessary to understand their interaction with competition and market dynamics.

g. **Cross-Sectional Nature of the Study:** The surveys capture stakeholder perspectives at a single point in time. The surveys were designed and conducted through 2025-26. As AI adoption, competitive dynamics, and policy frameworks continue to evolve, future longitudinal research may identify changes in market structure, business behaviour, and consumer experiences that are not captured in the present study.

To improve transparency and assist readers in distinguishing between different respondent cohorts, all survey findings are identified throughout the paper by their respective survey number (Survey 1, Survey 2, or Survey 3). This distinction is intended to ensure that the empirical findings are interpreted within the appropriate respondent context.

1.6 Structure of the Paper

The remainder of the study is structured as follows.

Chapter 2 maps the structure of the AI value chain, covering the upstream layer of compute infrastructure, data, and hardware; the intermediate layer of model development and training; and the downstream layer of deployment and applications. The chapter also examines how major AI firms are integrating vertically across the stack and considers what that integration means for competition. ***Chapter 3*** examines the economics of the three critical inputs underlying AI development in the Indian context, namely compute infrastructure, data access, and human capital. It draws on original survey findings from AI developers and startups to assess whether these inputs are currently acting as barriers to entry or drivers of innovation, and also considers the role of open-source ecosystems and startup-infrastructure provider relationships.

Chapter 4 analyses the competitive dynamics of India's AI ecosystem from the perspective of business users. It examines AI adoption patterns across sectors, the benefits and competitive effects of AI deployment, barriers to adoption, provider satisfaction, and switching behaviour. *Chapter 5* extends this analysis to consumers, examining how consumer users interact with AI-enabled services and what their experiences reveal about choice, switching, transparency, pricing, and competition. It provides the demand-side complement to the business evidence examined in Chapter 4. *Chapter 6* synthesises the foregoing evidence to consider the implications for competition policy. It assesses whether existing theories of harm, including foreclosure of inputs, tying and bundling, and ecosystem lock-in, are supported by the survey evidence; identifies the policy considerations that follow; surveys comparative regulatory approaches across major jurisdictions; and sets out a way forward for India. *Chapter 7* concludes the study.

2 | Understanding the AI Value Chain

2.1 Different Layers of the AI Ecosystem: Current Literature

In order to understand the structure of AI markets, it is necessary to examine how AI systems are developed, refined, and deployed across different stages of the value chain. AI does not constitute a single product market. Instead, it functions as a layered and interdependent ecosystem, in which distinct stages of production are linked through flows of data, compute, and model outputs. This understanding is reflected across jurisdictions.[41] The CCI in their Market Study on AI and Competition[42] recognises that AI markets are structured through interdependent layers, while the EC defines generative AI ecosystems as multi-layered systems involving infrastructure, models, and downstream applications.[43]

The UK CMA similarly characterises AI ecosystems as interconnected 'stacks' or 'supply chains' rather than isolated markets, emphasising the relationships between infrastructure, model development, and downstream deployment activities.

At a functional level, the lifecycle of modern AI systems, particularly foundation models, consists of architecture design, data preprocessing, pre-training, fine-tuning, and deployment, each of which introduces distinct technical constraints and competitive dynamics.[44]

The OECD's work notes that AI systems are not static products but evolving systems, where deployment generates new data that feeds back into model improvement.[45] These feedback loops may strengthen the position of firms capable of operating across multiple stages of the AI lifecycle, particularly where scale advantages in deployment generate additional data and model improvements. Different firms participate across different stages of this value chain. Although these functions are distinct, they are also economically interdependent, creating a value chain in which activity at one stage influences outcomes across others.

2.2 The AI Stack: Upstream, Intermediate and Downstream Layers

The AI ecosystem can be conceptualised as a stack comprising upstream, intermediate, and downstream layers.[46] The upstream layer includes the foundational inputs required to develop AI

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[41] Organisation for Economic Co-operation and Development. (2025, November 14). *Artificial intelligence and competitive dynamics in downstream markets.* https://www.oecd.org/en/publications/artificial-intelligence-and-competitive-dynamics-in-downstream-markets_ccf0624a-en/full-report/component-5.html.

[42] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

[43] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.

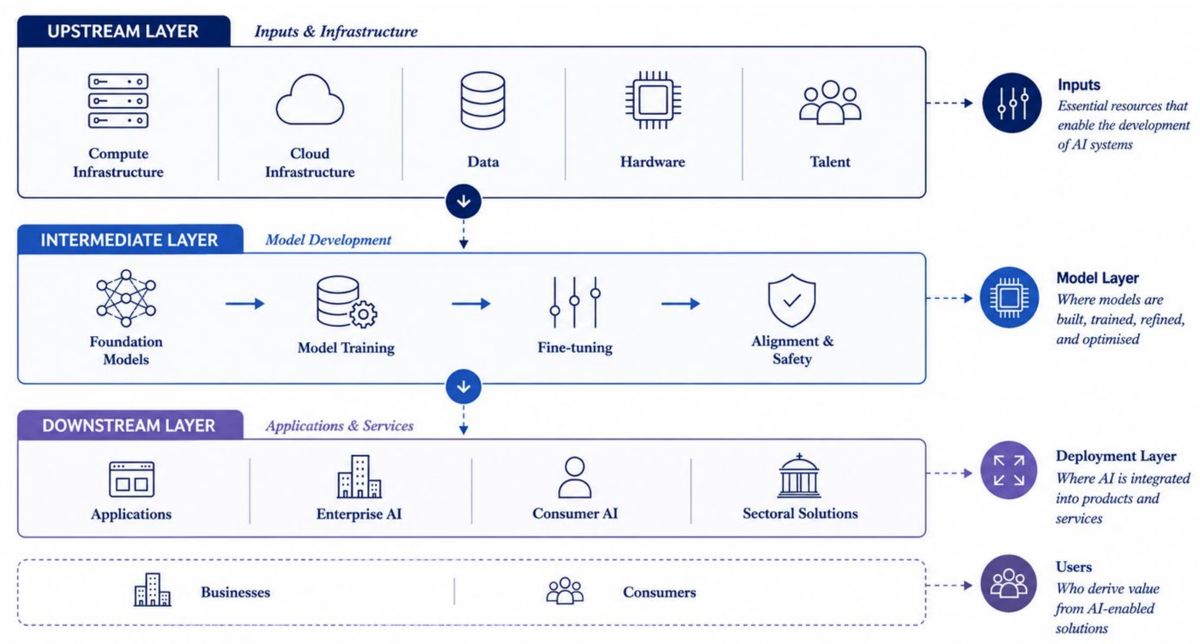
[44] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

[45] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

[46] Susnjara, S., Flinders, M. & Smalley, I. (2026, April 8). *What is AI infrastructure?.* IBM. https://www.ibm.com/think/topics/ai-infrastructure.

systems.[47] The intermediate layer consists of model development, which includes the training of foundation models, as well as adapting these models for specific use cases.[48] The downstream layer consists of applications and services that integrate AI systems into products which are used by businesses and often by consumers directly.[49]

Figure 1: The AI Stack: Upstream, Intermediate and Downstream Layers



2.2.1 Upstream Layer: Compute, Data, and Hardware

The upstream layer consists of the foundational inputs required for AI development, including computational infrastructure, datasets, and specialised hardware. These inputs are critical for the training and deployment of foundational models and are characterised by significant scale requirements.

a. Compute Hardware

The development of foundation models depends on high-performance computing resources capable of executing large volumes of parallelised mathematical operations. As the UK CMA explains, AI training relies on accelerator chips such as GPUs and Tensor Processing Unit ('TPUs'), which are optimised for parallel computation and enable efficient processing of neural network operations.[50]

The hardware layer is the most structurally concentrated segment of the AI supply chain. For example, semiconductors have been structurally concentrated almost from inception. The industry remains

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[47] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.
[48] Huang, J. et. al. (2025). Foundation models and intelligent decision-making: Progress, challenges, and perspectives. *The Innovation, Volume 6 Issue 6.* https://doi.org/10.1016/j.xinn.2025.100948.
[49] Organisation for Economic Co-operation and Development. (2025, December 1). *Artificial Intelligence and Competitive Dynamics in Downstream Markets – Background Note.* https://one.oecd.org/document/DAF/COMP/GF(2025)4/en/pdf.
[50] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

capital intensive with multi-year research and development ('R&D') cycles, and access to a handful of choke-point inputs. Central Processing Units ('CPUs') remain effectively an Intel-AMD duopoly even after decades,[51] with ARM-based entrants (Arm Holdings, Qualcomm, and others) carving out adjacent niches rather than displacing the core structure.[52]

On the other hand, NVIDIA's GPUs, originally designed for the gaming market but uniquely suited to the parallel computation required for AI training, dominate the AI accelerator market.[53] NVIDIA's market share in AI accelerators is estimated at 70-80%, declining from approximately 86% in 2024.[54] However, recent years have seen the rapid scaling of custom AI chips, Application-Specific Integrated Circuits (ASICs), designed by hyperscalers themselves.[55] Google's TPUs have undergone multiple generations of development, with the 2025 Ironwood TPUs reported to offer nearly 30 times the energy efficiency of the first-generation TPU.[56] Amazon Web Services ('AWS') has developed Trainium (for training) and Inferentia (for inference) chips, with Trainium 2 delivering up to four times the performance of the first generation at 30-40% better price-performance than GPU-based instances for certain workloads.[57] Meta's MTIA ('Meta Training and Inference Accelerator') represents a further internal chip capability. At scale, these custom ASICs offer 40-65% total cost of ownership advantages over equivalent GPU-based systems.[58]

Among venture-backed hardware startups, Cerebras, Groq, and SambaNova have developed specialist architectures optimised for specific AI workloads, particularly inference.[59] Separately, Chinese firms including Huawei (Ascend AI chips), Alibaba (Hanguang series), and Baidu are developing domestic AI accelerators, partly driven by US export control restrictions that limit their access to NVIDIA's most advanced chips, creating a structural incentive to develop competitive domestic hardware.[60]

b. Cloud Computing Infrastructure

Cloud computing infrastructure, comprising data centres, networking systems, and managed compute services, functions as the critical intermediary layer between AI hardware and AI development activities. The EC has emphasised that access to advanced computing infrastructure constitutes a key determinant of participation in generative AI markets, given the substantial capital expenditure required to develop

[51] TOI Tech Desk. (2026, February 25). Nvidia is about to challenge 'Intel Inside' with its own chips for laptops and PCs. *The Times of India.* https://timesofindia.indiatimes.com/technology/laptops-pc/nvidia-is-about-to-challenge-intel-inside-with-its-own-laptop-chips/articleshow/128717252.cms.

[52] Nellis, S. (2024, October 15). Intel, AMD team up to confront rising challenge from Arm. *Reuters.* https://www.reuters.com/technology/intel-amd-team-up-confront-rising-challenge-arm-2024-10-15/.

[53] ByteBridge. (2025, January 20). NVIDIA: From Gaming Pioneer to AI Powerhouse. *Medium* https://bytebridge.medium.com/nvidia-from-gaming-pioneer-to-ai-powerhouse-44cd1c7427f8.

[54] Leswing, K. (2024, June 2). Nvidia dominates the AI chip market, but there's more competition than ever. *CNBC.* https://www.cnbc.com/2024/06/02/nvidia-dominates-the-ai-chip-market-but-theres-rising-competition-.html.

[55] Organisation for Economic Co-operation and Development. (2025, November 14). *Competition in artificial intelligence infrastructure.* https://www.oecd.org/en/publications/competition-in-artificial-intelligence-infrastructure_623d1874-en/full-report/component-5.html.

[56] Vahdat, A. (2025, April 9). *Ironwood: The first Google TPU for the age of inference.* Google. https://blog.google/innovation-and-ai/infrastructure-and-cloud/google-cloud/ironwood-tpu-age-of-inference/.

[57] Amazon Web Services. (n.d.). *AWS Trainium*. https://aws.amazon.com/ai/machine-learning/trainium/.

[58] Cloud News.tech. (n.d.). *ASICs Accelerate AI and Threaten GPU's Absolute Dominance.* https://cloudnews.tech/asics-accelerate-ai-and-threaten-gpus-absolute-dominance/.

[59] Freund, K. (2025, October 21). Cerebras, Groq And SambaNova Line Up To Compete With Nvidia. *Forbes.* https://www.forbes.com/sites/karlfreund/2025/10/21/cerebras-groq-and-sambanova-line-up-to-compete-with-nvidia/.

[60] Reuters. (2025, July 28). Chinese AI firms form alliances to build domestic ecosystem amid US curbs. *The Economic Times.* https://economictimes.indiatimes.com/tech/artificial-intelligence/chinese-ai-firms-form-alliances-to-build-domestic-ecosystem-amid-us-curbs/articleshow/122945505.cms?from=mdr.

and scale models.[61] This also aligns with the CCI Market Study's observation that access to compute infrastructure may act as a structural constraint for smaller firms.[62]

At the cloud infrastructure level, AWS, Microsoft Azure, and Google Cloud lead globally. In India, the same three providers lead. Microsoft has committed significant AI and cloud infrastructure investment in India, reported at USD 3 billion in 2023 with subsequent expansions totalling USD 17.5 billion over several years.[63] Google has established data centre regions in India.[64] Domestic providers including Tata Communications, Yotta (with its Shakti Cloud offering large-scale GPU infrastructure),[65] Neysa {offering managed GPU and Machine Learning Operations ('MLOps') services},[66] and Airtel's AI and cloud services are expanding their base.

Recently, investments in India's AI infrastructure have seen tremendous growth. Adani Group has committed a directed investment of USD 100 billion (INR 10 lakh crore) towards building Sovereign AI infrastructure in India, with an additional USD 150 billion to be put towards manufacturing, servers and sovereign cloud services by 2035.[67] Even the Reliance Group alongwith its digital arm Jio has decided to invest USD 110 billion over the next seven years to drive India's AI transformation specifically with an aim to construct a multi-gigawatt AI-ready data centres in Jamnagar.[68]

The IndiaAI Mission further proposes a shared compute facility targeting approximately 10,000 GPUs for Indian AI startups and researchers.[69] Notably, as of 2026, more than 38,000 GPUs have been onboarded, which are provided at a subsidized and affordable rate.[70] Additionally, initiatives such as the Open Cloud Compute ('OCC') initiative, a public-interest project developing DPI-style shared compute infrastructure through interoperable open protocols, represents an innovative approach to democratising compute access in the spirit of India's Unified Payment Interface ('UPI') and Aadhaar models, though it remains at an early stage.[71]

[61] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.

[62] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

[63] Butts, D. (2025, December 9). Microsoft to invest $17.5 billion in India's AI infra as Big Tech bets on country's growth potential. *CNBC.* https://www.cnbc.com/2025/12/10/microsoft-india-investment-ai-infra-as-big-tech-google-aws.html.

[64] Kurian, T. (2025, October 14). *Our First AI Hub in India, Powered by a $15 Billion Investment*. Google India Blog. https://blog.google/intl/en-in/company-news/our-first-ai-hub-in-india-powered-by-a-15-billion-investment/.

[65] Yotta. (2025, February 17). *Yotta Empaneled in India AI Mission to Accelerate AI Adoption with Advanced GPU & AI Cloud Services.* https://yotta.com/press-releases/yotta-empaneled-in-india-ai-mission-to-accelerate-ai-adoption-with-advanced-gpu-ai-cloud-services/.

[66] Neysa.AI. (n.d.). https://neysa.ai/.

[67] Adani. (2026, February 17). *Adani commits USD 100 bn to sovereign AI infrastructure.* https://www.adani.com/newsroom/media-releases/adani-commits-usd-100-bn-to-sovereign-ai-infrastructure.

[68] DD News. (2026, February 19). Reliance and Jio to invest Rs. 10 lakh crore over several years ofr India's AI transformation: Mukesh Ambani. *DD News.* https://ddnews.gov.in/en/reliance-and-jio-to-invest-rs-10-lakh-crore-over-seven-years-for-indias-ai-transformation-mukesh-ambani/.

[69] Press Information Bureau, Government of India. (2026, March 25). IndiaAI Mission Expands AI Ecosystem with Affordable Compute and Startup Support – Semicon India Programme Boosts Domestic Chip Manufacturing and Design Ecosystem. *Press Information Bureau.* https://www.pib.gov.in/PressReleasePage.aspx?PRID=2245069&reg=3&lang=2.

[70] *Ibid.*

[71] Swathi Moorthy. (2024, December 3). Open cloud compute: a UPI moment for AI?. *The Economic Times.* https://economictimes.indiatimes.com/tech/artificial-intelligence/open-cloud-compute-a-upi-moment-for-ai/articleshow/115910167.cms?from=mdr.

c. Data

Data is the most fundamental determinant of AI model quality. During pre-training, models are trained on large-scale datasets comprising text, images, code, and other forms of data. These datasets are converted into tokens, which function as the basic units through which models identify patterns and statistical relationships.[72]

The OECD's literature notes that model performance scales with increases in data, compute, and model size, creating a reinforcing relationship between these inputs.[73] However, concerns persist regarding the availability of high-quality data, with increasing reliance on proprietary datasets potentially shaping competitive dynamics.[74] The CCI's Market Study identifies access to relevant and high-quality datasets as a key factor influencing the ability of firms to develop and compete in AI markets.[75]

Estimatedly, effective supply of human-generated public text data amounts to approximately 300 trillion tokens, an enormous quantity, but one that current AI training paradigms may fully exhaust between 2026 and 2032, with 2028 estimated as the median exhaustion year, under current scaling trajectories.[76] Low-quality language data may last until 2030-2050; low-quality image data potentially until 2030-2060. The implications of this constraint are significant and still emerging.[77] The industry is responding through several strategies, each with its own competition implications. Synthetic data generation, using AI models to create training data for other AI models, is now widespread,[78] with Microsoft's Phi-4,[79] Google's Gemma,[80] Meta's Llama, and Anthropic's Claude models all incorporate synthetic training data.[81] [82]

India's training data landscape presents challenges that compound the global data constraints with India-specific structural features. Government initiatives are partially addressing this gap. The IndiaAI Mission's AIKosh platform had accumulated over 5,500 datasets and 251 AI models across 20 sectors by December 2025, with over 385,000 platform visits.[83] The Bhashini[84] initiative is developing Indian language AI tools and datasets, enabling real-time translation and voice-first interfaces for non-English

[72] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.
[73] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.
[74] *Ibid.*
[75] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.
[76] Villalobos, P. et al. (2024, June 4). Will we run out of data? Limits of LLM scaling based on human-generated data. https://arxiv.org/html/2211.04325v2.
[77] Matulionyte, R. (2023, November 9). Researchers warn we could run out of data to train AI by 2026. What then?. *The Hindu.* https://www.thehindu.com/sci-tech/science/researchers-warn-we-could-run-out-of-data-to-train-ai-by-2026/article67516326.ece.
[78] Abdalla, H.B. et al. (2025, June 9). The Future of Artificial Intelligence in the Face of Data Scarcity. *Computers, Materials and Continua*, Volume 84, Issue 1. https://doi.org/10.32604/cmc.2025.063551.
[79] Masood, A. (2025, May 3). Small Language Models: The Rise of Compact AI and Microsoft's Phi Models. *Medium.* https://medium.com/@adnanmasood/small-language-models-the-rise-of-compact-ai-and-microsofts-phi-models-cdc7cf20ea2d.
[80] Davidson, T.R. & Harkous, H. (2026, April 16). *Designing synthetic datasets for the real world: Mechanism design and reasoning from first principles.* Google Research. https://research.google/blog/designing-synthetic-datasets-for-the-real-world-mechanism-design-and-reasoning-from-first-principles/.
[81] Meta AI, Introducing Llama 3.1: Our Most Capable Models to Date (July 2024), https://ai.meta.com/blog/meta-llama-3-1/
[82] Anthropic, Claude's New Constitution (2025), https://www.anthropic.com/news/claude-new-constitution; Anthropic Alignment
[83] AIKosh. (n.d.), *India AI Kosh, Government of India.* https://aikosh.indiaai.gov.in/home.
[84] Bhashini, National Language Translation Mission. (n.d.). *Bhashini, Government of India.* https://bhashini.gov.in/.

speakers.[85] BharatGen, selected under the IndiaAI Innovation Centre, is developing multilingual foundation models using Indian data.[86] Private sector efforts including Sarvam AI (Indian language models),[87] Gnani AI (speech recognition in Indian languages),[88] and AI4Bharat (open-source Indian language AI resources) are expanding the indigenous training data and the model ecosystem.[89]

d. Human Capital

The development and deployment of AI systems depends on a specialised talent base including machine learning engineers, data scientists, and AI researchers who are capable of designing model architectures, managing training processes, and deploying systems in production environments. Talent is a cross-cutting input: it is required at the upstream stage for model development, at the intermediate stage for fine-tuning and alignment, and at the downstream stage for application development and integration. As discussed further in Chapter 3, the availability of this talent in India shapes where domestic firms are able to compete within the AI value chain.

2.2.2 Intermediate Layer: Model Development and Training

The intermediate layer comprises the development of AI models, particularly foundation models that can be adapted to multiple downstream tasks. At this stage, firms focus on building the core systems that enable AI functionality across applications. Most foundational models today are based on transformer architectures, which are a class of neural networks specifically designed to process sequential data such as text, images, or code.[90] These models operate by breaking input data into smaller units known as "tokens", which may represent words, parts of words, or other data elements.[91]

Model development typically involves two stages: first, pre-training and second fine-tuning. Pre-training establishes general-purpose capabilities using large-scale datasets and requires[92] substantial computational resources. Fine-tuning adapts these models to specific tasks or domains using smaller, curated datasets. Fine-tuning may also involve alignment processes, such as reinforcement learning from human feedback, to improve the reliability and safety of outputs.[93]

The distinction between these stages is economically significant. The UK CMA and OECD both note that pre-training is capital-intensive and concentrated among a limited number of firms, whereas fine-tuning enables broader participation by smaller firms and startups.[94] The CCI's Market Study similarly observes

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[85] Press Information Bureau, Government of India. (2026, March 27). Over 10,000 contributors onboarded on Bhashini Samudaye, a digital platform supporting the development of multilingual AI ecosystem. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2246222&reg=3&lang=1.

[86] BharatGen- India's Sovereign GenAI Ecosystem. (n.d.). *BharatGen, Government of India.* https://bharatgen.com/.

[87] Sarvam – India's Sovereign AI Platform. (n.d.). *SarvamAI.* https://www.sarvam.ai/.

[88] Gnani. (2025, August 20). *Voice AI for Indian Languages: Developing Speech Models.* https://www.gnani.ai/resources/blogs/voice-ai-for-indian-languages-developing-speech-models-36b9f.

[89] Data Management Unit, Bhashini (AI4Bharat, and IIT Madras) (2022, May). *Building an open data infrastructure for Indian languages.* https://indicnlp.ai4bharat.org/static/documents/DMU_Data_Report_May_2022.pdf.

[90] Vaswani, A. et al. (2017). *Attention is All You Need.* https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

[91] Kaplan, G. (2025). *From tokens to words: On the inner lexicon of LLMs.* https://arxiv.org/pdf/2410.05864

[92] Adusumilli, P., Strancener, C. & Touma, M. (n.d.). *Foundation models at the edge.* IBM. https://www.ibm.com/think/insights/edge-ai-strategy.

[93] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

[94] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

that Indian firms are more active in downstream adaptation and application development rather than large-scale model training, reflecting these cost asymmetries.[95]

The leading frontier model developers are: OpenAI (GPT series), Google DeepMind (Gemini), Anthropic (Claude), Meta AI Llama, and Qwen (Alibaba Group). The competitive dynamics within the foundation model layer have evolved rapidly. DeepSeek's R1 release in early 2025 was a structural development.[96] By demonstrating that frontier-competitive models could be developed at approximately USD 5-6 million in training costs, DeepSeek challenged the premise that unlimited capital was a prerequisite for frontier AI participation.[97] Mistral AI has demonstrated a similar approach from Europe.

India has nascent but growing indigenous foundation model development. Under the IndiaAI Mission's Innovation Centre pillar, four startups were selected in the first phase, Sarvam AI, Soket AI, Gnani AI, and Gan AI, and eight additional organisations including IIT Bombay (BharatGen consortium), Zenteiq, Fractal Analytics, and Tech Mahindra's Maker's Lab were added in the second phase, bringing the total to twelve organisations developing indigenous foundation models with government support.[98] These developments are significant in demonstrating that India can build competitive AI capabilities in the Indian language domain.[99] However, India's foundation model capabilities remain substantially behind global frontier developers, a gap that is widening in absolute terms even as it may be narrowing in Indian-language tasks specifically.[100]

2.2.3 Downstream Layer: Deployment and Applications

The downstream layer consists of applications and services that integrate AI models into user-facing or enterprise-facing products. Downstream tasks often involve fine-tuning, where a pre-trained model is trained on a smaller, labelled dataset tailored to a specific purpose, such as medical diagnostics or fraud detection. This layer is characterised by diversity and relatively lower barriers to entry compared to upstream segments.[101]

The ecosystem creates specific applications using pre-trained foundational models that would allow developers to integrate AI capabilities to their products. Google, Anthropic and OpenAI offer Application Programming Interface ('API') access to their models, available to any developer on per-query pricing.[102] API-based access allows third-party developers to use model capabilities without managing

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[95] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

[96] Li, D. (2025, July 3). Impact of the DeepSeek-R1 Model Launch on the Value of Chinese AI Concept Companies. *SHS Web of Conferences, volume 218, 01027* (2025). https://www.shs-conferences.org/articles/shsconf/abs/2025/09/shsconf_icdde2025_01027/shsconf_icdde2025_01027.html.

[97] *Ibid.*

[98] Ministry of Electronics & IT, (2026, February 13). *In less than 24 months, India AI Mission has Set up a Foundation for Development of AI Ecosystem in the Country.* Press Information Bureau. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2227612&reg=3&lang=2.

[99] Ministry of Electronics & IT, PIB Delhi. (2026, March 25). *Government supporting organisations and consortia to develop sovereign foundational model.* Press Information Bureau. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2245063&reg=3&lang=2.

[100] Sayamsiddha. (2026, February 24). India's AI ambition seems to stop at the server room. *Frontline, The Hindu.* https://frontline.thehindu.com/science-and-technology/india-ai-future-data-centers-shift/article70667816.ece.

[101] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

[102] Gemini API. (n.d.). *Gemini Developer API pricing.* https://ai.google.dev/gemini-api/docs/pricing#:~:text=Table_title:%20Gemini%203.%201%20Pro%20Preview%20Table_content:,then%20$14%20/%201%2C000%20search%20queries%20%7C.

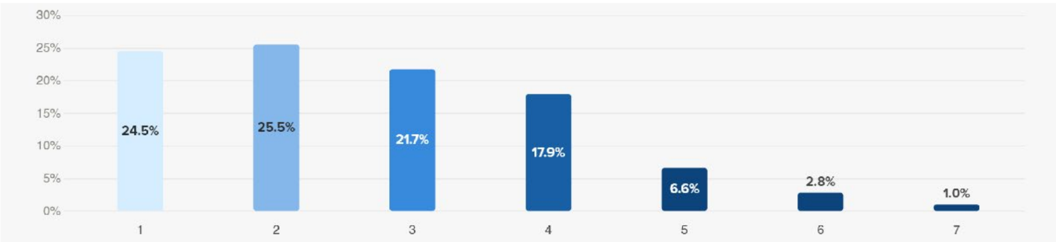
underlying infrastructure, thereby lowering entry barriers for application development.[103] Open-source models have further played an important role in expanding participation across the AI ecosystem. Some of the biggest hyperscalers, such as Meta and Google, offer open-weight models, including Meta's Llama and Google's Gemma, that support greater accessibility and broader participation. By enabling firms to access and adapt existing models, open-source ecosystems support experimentation and innovation, particularly for smaller firms.[104] Hugging Face, which hosts thousands of open-source and commercial model weights, has further democratised access to AI capabilities.[105] Model router services that allow developers to switch between different underlying models based on cost and performance have introduced an additional layer of competitive pressure on foundation model providers.

The EC highlights that such modular deployment structures enable innovation at the application layer, as firms can build services without replicating upstream investments.[106] The CCI's Market Study similarly notes that Indian startups are increasingly leveraging cloud-based AI services and pre-trained models to develop applications across sectors such as finance, healthcare, and digital services.[107] At the same time, deployment generates user interaction data, which can be used to improve models over time.[108]

2.3 Vertical Integration Across the AI Stack

The AI ecosystem is increasingly characterised by vertical integration, where firms operate across multiple layers of the value chain simultaneously rather than remaining confined to a single segment.

Figure 2: Number of Stack Layers Per Firm



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked to identify which layers of the AI value chain (infrastructure– hardware, infrastructure – software, data infrastructure, model development, model fine-tuning & alignment, model deployment, downstream applications) their organisation operates in. The chart shows the number of stack layers each firm operates across, from one layer to three or more.]

[103] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.
[104] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.
[105] Stryker, C. (n.d.). What is Hugging Face. *IBM.* https://www.ibm.com/think/topics/hugging-face.
[106] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.
[107] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.
[108] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

75.5% of respondents operate across two or more layers of the stack. These findings suggest that AI ecosystems are increasingly characterised by layered participation and operational integration, with many firms combining infrastructure, model development, deployment, and application-level activities as part of broader ecosystem strategies. This layered market structure implies that competition cannot be assessed through a single market definition. Competitive conditions differ significantly across layers of the AI stack, requiring any assessment of market power or competitive harm to distinguish between upstream infrastructure markets and downstream application markets.

To assess competitive implications accurately, it is necessary to distinguish how major AI firms are positioned across four dimensions: (i) in-house silicon, (ii) owned data-centre capacity, (iii) model development, and (iv) distribution surfaces through which AI reaches end users.

Firm	In-house silicon capability	Owned data-centre capacity	Model development	Distribution surfaces
Google (Alphabet)	TPU is now in its seventh generation ("Ironwood"), and Google has shifted from purely captive use to selling/leasing TPUs externally including a large Anthropic commitment[109] and reported Meta usage.[110]	A long-standing owned global fleet, now expanded through vendor-financed third-party projects (TeraWulf,[111] FluidStack,[112] and River Bend[113]) that Google backstops to seed chip demand.	Gemini remains closed and frontier,[114] but Gemma (now gen 4) gives Google an open-weight line.[115]	Android, Chrome, Search, YouTube, Workspace, and Google Cloud/Vertex AI give it a significant combined consumer-and-enterprise footprint.[116]
Microsoft	Maia chips mark a real shift from near-total Nvidia dependence. Maia entered mass production in January 2026 and now powers Copilot.[117]	Microsoft's custom Maia chip is deployed across its Azure network[118] which spans over 400 data centres across 70+ regions.[119]	MAI models launched in June 2026,[120] even as the OpenAI partnership continues in parallel with GPT models integrated across Azure AI	Windows, Microsoft 365, GitHub, Teams, and Azure Foundry give Microsoft the deepest enterprise

[109] Vahdat, A. & Lohmeyer, M. (2025, November 7). *Announcing Ironwood TPUs General Availability and new Axion VMs to power the age of inference.* Google Cloud. https://cloud.google.com/blog/products/compute/ironwood-tpus-and-new-axion-based-vms-for-your-ai-workloads.
[110] Reuters. (2026, February 27). Meta signs multi-billion dollar deal to rent Google AI chips, The Information reports. *Reuters.* https://www.reuters.com/business/google-signs-multibillion-dollar-ai-chip-deal-with-meta-information-reports-2026-02-26/.
[111] Subin, S. (2025, August 18). TeraWulf stock gains more than 4% as Google boosts stake in data center operator. *CNBC.* https://www.cnbc.com/2025/08/18/terawulf-stock-google-stake-datacenter.html.
[112] Simply Wall St. (2026, March 15). *Google-Backed Fluidstack Deal And Asset Sale Might Change The Case For Investing In Hut 8 (HUT).* yahoo!finance. https://finance.yahoo.com/news/google-backed-fluidstack-deal-asset-120620060.html.
[113] Dixon, B. (2026, April 29). *Hut 8 selling $3.25bn in bonds to finance Google and Anthropic-backed River Bend AI data center campus.* Data Center Dynamics. https://www.datacenterdynamics.com/en/news/hut-8-selling-325bn-in-bonds-to-finance-google-and-anthropic-backed-river-bend-ai-data-center-campus/.
[114] Glover, E. (2026, May 20). *What is Google Gemini?.* Built In. https://builtin.com/articles/google-gemini.
[115] Farabet, C. & Lacombe, O. (2026, April 2). *Gemma 4: Byte for byte, the most capable open models.* Google. https://blog.google/innovation-and-ai/technology/developers-tools/gemma-4/.
[116] Google. (n.d.). *Helpful products, built with you in mind.* https://about.google/products/?tab=wh&.
[117] Cvetko, J. (2026, January 28). *Microsoft introduces Maia 200 - the next generation of AI technology.* Microsoft. https://news.microsoft.com/source/emea/features/maia-200-microsoft-ai-accelerator-azure/.
[118] *Ibid.*
[119] Microsoft. (n.d.). *Azure global infrastructure.* https://azure.microsoft.com/en-in/explore/global-infrastructure.
[120] Suleyman, M. (2026, June 2). *Building a hill-climbing machine: Launching seven new MAI models.* Microsoft. https://microsoft.ai/news/building-a-hillclimbing-machine-launching-seven-new-mai-models/.

			Services,[121] GitHub,[122] and Microsoft 365 Copilot.[123]	distribution layer.[124]
AWS	Trainium (now gen 3), Inferentia, and Graviton (gen 5) form a mature, multi-purpose in-house chip line, offered to cloud customers at reported cost savings of 30–60% compared to equivalent NVIDIA GPU configurations. AWS continues to purchase large volumes of NVIDIA GPUs in parallel, maintaining a mixed fleet rather than relying exclusively on its own silicon.[125]	AWS's own regional footprint includes Project Rainier, its largest dedicated AI data centre, built and operated in-house to run Anthropic workloads.[126]	AWS does not develop its own frontier foundation models; instead, it has a strategic partnership with Anthropic.[127]	AWS distributes AI through Bedrock,[128] Alexa,[129] and its broader cloud marketplace[130].
Meta	MTIA chip, co-developed with Broadcom, is deployed exclusively within Meta's own data centres for internal workloads[131] whereas general-purpose Large Language Model (LLM)	Large owned build-out (e.g., the 5GW Hyperion campus[133]), alongside leased third-party GPU/TPU capacity[134].	Llama remains the most established open-weight portfolio, though no longer the only major one.[135]	Facebook, Instagram, WhatsApp, Threads, and Ray-Ban Meta glasses give Meta the largest consumer/social reach, but the weakest

[121] Microsoft. (n.d.). *Azure OpenAI in Foundry Models.* https://azure.microsoft.com/en-us/products/ai-foundry/models/openai.
[122] Github Blog. (2026, April 24). *GPT-5.5. is generally available for GitHub Copilot.* https://github.blog/changelog/2026-04-24-gpt-5-5-is-generally-available-for-github-copilot/
[123] Smith, E. (2025, August 7). *Microsoft incorporates OpenAI's GPT-5 into consumer, developer and enterprise offerings.* Microsoft. https://news.microsoft.com/source/features/ai/openai-gpt-5/.
[124] Daigle, K. (n.d.). *Microsoft Build 2026: Be yourself at work.* Microsoft. https://news.microsoft.com/source/asia/2026/06/03/microsoft-build-2026-be-yourself-at-work/.
[125] The Motley Fool. (2026, June 24). *Will Amazon's AI Chip Business Be a Threat to Nvidia?.* yahoo!finance. https://finance.yahoo.com/technology/ai/articles/amazons-ai-chip-business-threat-095000177.html.
[126] Sigalos, M. (2025, October 29). Amazon opens $11 billion AI data center in rural Indiana as rivals race to break ground. *CNBC.* https://www.cnbc.com/2025/10/29/amazon-opens-11-billion-ai-data-center-project-rainier-in-indiana.html
[127] Anthropic. (2026, April 20). *Anthropic and Amazon expand collaboration for up to 5 gigawatts of new compute.* https://www.anthropic.com/news/anthropic-amazon-compute; Amazon News. (2023, September 25). *Amazon and Anthropic Announce Strategic Collaboration to Advance Generative AI.* https://press.aboutamazon.com/2023/9/amazon-and-anthropic-announce-strategic-collaboration-to-advance-generative-ai.
[128] Amazon Web Services. (n.d.). *Amazon Bedrock Marketplace.* https://aws.amazon.com/bedrock/marketplace/.
[129] Amazon Web Services. (n.d.). *Next-Generation Personal Assistant.* https://aws.amazon.com/solutions/amazon/one-amazon-lane/alexa/.
[130] Amazon Web Services. (n.d.). *AWS Global Infrastructure.* https://aws.amazon.com/about-aws/global-infrastructure/?pg=WIAWS.
[131] Broadcom. (n.d.). *Broadcom Announces Extended Partnership with Meta to Deploy Technology to Support Multi-Gigawatts of Meta's Custom Silicon, MTIA.* https://investors.broadcom.com/news-releases/news-release-details/broadcom-announces-extended-partnership-meta-deploy-technology.
[133] Moss, S. (2026, February 9). *Meta purchases additional 1,400 acres for Hyperion mega-data center expansion.* Data Center Dynamics. https://www.datacenterdynamics.com/en/news/meta-purchases-additional-1400-acres-for-hyperion-mega-data-center-expansion/.
[134] Novet, J. & Vanian, J. (2025, August 21). Google scores six-year Meta cloud deal worth over $10 billion. https://www.cnbc.com/2025/08/21/google-scores-six-year-meta-cloud-deal-worth-over-10-billion.html; Butler, G. (2026, July 2). *Meta pushes ahead with plans to launch cloud business - report.* Data Center Dynamics. https://www.datacenterdynamics.com/en/news/meta-pushes-ahead-with-plans-to-launch-cloud-business-report/.
[135] Meta. (n.d.). *Your next build starts with Muse.* https://developer.meta.com/ai/.

	training continues to run on NVIDIA GPUs.[132]			enterprise-cloud presence of the five.
OpenAI	In June 2026, OpenAI and Broadcom unveiled their own custom AI chip design. The partnership was officially announced in October, but OpenAI's chip plans have long been rumored as a way to reduce the company's dependence on Nvidia's GPUs.[136] [137]	Effectively no owned fleet; Stargate has become an umbrella term for separately negotiated leasing deals with Oracle, Microsoft, SoftBank, Amazon, and CoreWeave.[138]	GPT remains closed and frontier, but gpt-oss-120b/20b (August 2025, Apache 2.0) gives OpenAI a smaller, more recent open-weight tier too.[139]	ChatGPT and the API dominate consumer AI usage,[140] but with no proprietary cloud, OpenAI rides on partners' surfaces (Copilot, Bedrock/Frontier) for enterprise reach.
Anthropic	None, entirely dependent on external accelerators. It also uses Google Cloud TPUs for inference and has GPU-based capacity through other providers.[141]	Anthropic is planning to lease and manage its own data centers and is seeking financial backing from Google for the lease payments,[142] and has reportedly signed more than a dozen letters of intent with multiple US data center developers.[143]	Claude remains Anthropic's flagship closed, frontier model family, with the company continuing to scale its capabilities through successive models. The models line-up includes Haiku, Sonnet and Opus, with two models, namely, Mythos and Fable.[144]	Its primary distribution surface is the Claude API with model integration via Bedrock, Google Cloud, and third-party platforms.[145]
xAI	Its compute runs almost entirely on NVIDIA GPUs rather than proprietary silicon.[146]	It built its own data centres rather than relying on hyperscalers. The Colossus complex in Memphis/ Southaven, initially launched in	Grok remains xAI's flagship closed, frontier model family, with successive Grok releases.[148]	Grok is deployed through the X platform, which is both its primary distribution channel and an

[132] Reuter, M. (2026, July 2). *AI investment playbook enters a new phase as chip dominance gives way to application-driven competition.* The Economy. https://economy.ac/news/2026/07/202607289460.
[136] Metz, C. (2026, June 24). OpenAI and Broadcom Unveil Custom A.I. Chip Design. *The New York Times.* https://www.nytimes.com/2026/06/24/technology/openai-broadcom-chip-jalapeno.html.
[137] Brandom, R. (2026, June 24). *OpenAI unveils its first custom chip, built by Broadcom.* TechCrunch. https://techcrunch.com/2026/06/24/openai-unveils-its-first-custom-chip-built-by-broadcom/.
[138] OpenAI. (2025, January 21). *Announcing The Stargate Project.* https://openai.com/index/announcing-the-stargate-project/
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[140] Ermut, S. (2026, July 2). *LLM Market Share: Compare Usage & Adoption.* AI Multiple. https://aimultiple.com/llm-market-share.
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[142] Reuters. (2026, June 11). Anthropic pursues data center leases, seeks financial backing from Google, The Information reports. *Reuters.* https://www.reuters.com/business/anthropic-pursues-data-center-leases-seeks-financial-backing-google-information-2026-06-11/
[143] Butler, G. (2026, June 12). *Anthropic signs "more than a dozen" letters of intent for data center leases - report.* Data Center Dynamics. https://www.datacenterdynamics.com/en/news/anthropic-signs-more-than-a-dozen-letters-of-intent-for-data-center-leases-report/.
[144] Claude Platform Docs. (n.d.). *Models overview.* https://platform.claude.com/docs/en/about-claude/models/overview.
[145] Claude Platform Docs. (n.d.). Features overview. https://platform.claude.com/docs/en/build-with-claude/overview?eicker.news=&fcdaa149_sort_date=desc
[146] NVIDIA. (2024, October 28). *NVIDIA Ethernet networking accelerates world's largest AI supercomputers, Built by xAI.* https://nvidianews.nvidia.com/news/spectrum-x-ethernet-networking-xai-colossus.
[148] SpaceXAI. (n.d.). *Frontier AI models for everything.* https://x.ai/.

		2024, is expanding toward 2 GW of capacity.[147]		integrated downstream application.[149]

Two key observations help contextualise this landscape. First, no major firm relies solely on its own silicon. Google,[150] AWS,[151] and Meta[152], even as they design and deploy their own custom in-house AI chips, all continue to purchase large volumes of NVIDIA GPUs. The custom chip strategies are cost-reduction tools for specific workloads, not wholesale replacements.[153] Second, DeepSeek's V3[154] and V4[155] models, achieving near-frontier performance at a fraction of Western training costs, demonstrate that efficiency-first architectures can meaningfully challenge the assumption that frontier AI requires the infrastructure scale of the major hyperscalers. DeepSeek V4 (released April 2026) has been validated for deployment on Huawei's Ascend AI processors, showing that hardware-software co-design can deliver competitive inference economics even outside the established US hyperscaler ecosystem.[156]

What Vertical Integration Means for Competition

The UK CMA identifies multiple forms of vertical integration, including firms that control compute infrastructure, develop models, and integrate them into downstream applications.[157] The EC similarly highlights that integration across layers may allow firms to leverage advantages in one segment to influence outcomes in others.[158] The CCI's Market Study notes that such integration can generate efficiencies, including improved coordination and faster deployment, but also emphasises the importance of examining how dependencies between firms may arise, particularly where smaller firms rely on integrated platforms for access to essential inputs.[159]

These concerns are real, but the efficiency gains from vertical integration are also tangible. When firms design chips, data centres, and models together, they can optimise across layers in ways that disaggregated supply chains cannot. The most concrete evidence is on inference costs: Meta's MTIA delivers its 44% TCO saving precisely because it was co-designed for Meta's specific workload

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147 Wagner, K. (2025, December 31). Musk's xAI buys building to expand 'Colossus' Data Center. *Bloomberg.* https://www.bloomberg.com/news/articles/2025-12-30/musk-s-xai-to-expand-colossus-data-center-information-reports.

149 Kinsella, B. (2023, November 5). *What is Grok? Is X.ai's Chatbot for Twitter really better than ChatGPT?.* Synthedia. https://synthedia.substack.com/p/what-is-grok-xais-chatbot-on-twitter.

150 Novet, J. (2026, April 22). Google unveils chips for AI training and inference in latest shot at Nvidia. *CNBC.* https://www.cnbc.com/2026/04/22/google-launches-training-and-inference-tpus-in-latest-shot-at-nvidia.html.

151 The Motley Fool. (2026, June 24). *Will Amazon's AI chip business be a threat to Nvidia?.* yahoo!finance. https://finance.yahoo.com/technology/ai/articles/amazons-ai-chip-business-threat-095000177.html/.

152 Reuter, M. (2026, July 2). *AI investment playbook enters a new phase a s chip dominance gives way to application-driven competition.* The Economy. https://economy.ac/news/2026/07/202607289460.

153 Novet, J. (2026, April 22). Google unveils chips for AI training and inference in latest shot at Nvidia. *CNBC.* https://www.cnbc.com/2026/04/22/google-launches-training-and-inference-tpus-in-latest-shot-at-nvidia.html; Reuter, M. (2026, July 2). *AI investment playbook enters a new phase a s chip dominance gives way to application-driven competition.* The Economy. https://economy.ac/news/2026/07/202607289460.

154 Liu, A. & al. (2025). *DeepSeek-V3 Technical Report.* https://arxiv.org/abs/2412.19437.

155 Bapista, E., Wang, E. and Pan, C. (2026, April 24). DeepSeek unveils new AI model tailored for Huawei chips as China pushes for tech autonomy. *Reuters.* https://www.reuters.com/technology/chinas-deepseek-returns-with-new-model-year-after-viral-rise-2026-04-24/.

156 *Ibid.*

157 Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

158 Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.

159 Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

patterns;[160] AWS's Inferentia similarly targets cost efficiency for specific inference use cases.[161] The broader consequence is that as inference costs fall, driven by both integrated hyperscaler silicon and open-source model releases, AI deployment becomes economically viable for a wider range of businesses in sectors like healthcare, logistics, and finance.

[160] Ram, S. (2026, March 15). *Meta's new MTIA chips could slash your inference bills by 50% – what AI builders need to know.* Build MVP Fast. https://www.buildmvpfast.com/blog/meta-mtia-chips-inference-cost-ai-builders-2026.
[161] Amazon Web Services. (n.d.). *AWS Inferentia.* https://aws.amazon.com/ai/machine-learning/inferentia/

3 | AI Inputs: Compute, Data, and Talent in India's Ecosystem

3.1 Key Insights from the Chapter

The Chapter examines various competitive parameters for the foundational components required for AI development.

Key Insights on Compute Infrastructure

The survey findings suggest that while compute is a vital and resource-intensive input, it is currently perceived as competitively accessible in India.

- **Dominance of Public Cloud**: Approximately **84.9%** of Indian AI developers rely on public cloud platforms like AWS, Azure, and Google Cloud Platform ('GCP'), while only **27.4%** use proprietary hardware.
- **Affordability and Choice:** Compute affordability is not viewed as a major hurdle for the majority; **38.7%** of respondents consider it a significant issue, and **74.5%** believe there are sufficient provider options in the market.
- **Technical Nature of Switching Costs:** Only **12.5%** found it difficult to switch between cloud providers. The primary barriers remain technical: data transfer constraints **(51.2%)** and compatibility issues **(46.3%)**, rather than a lack of alternatives (cited by only **14.6%**).

Key Insights on Data

Data is identified as the most fundamental determinant of model quality, with developers navigating a complex landscape of source. Firms rely heavily on proprietary data **(67.9%)** and public datasets **(64.2%)**, while the majority **(60.4%)** agree high-quality data is generally accessible. The single greatest barrier to using data is a lack of standardization **(63.2%)**, which outranks concerns about copyright **(44.3%)**, data scarcity **(43.4%)**, and privacy restrictions **(41.5%)**.

Key Insights on Human Capital and Open Source

Talent and open-source ecosystems are highlighted as critical enablers that shape where firms compete in the AI stack. Skilled talent is an asset and also identified as a major constraint. **47.2%** of respondents identified talent availability as a significant barrier to competitiveness.

Respondents show a deep reliance on open source models, over **96%** of the respondents rely heavily on open source models. **79.2%** of developers view open-source models as viable substitutes for proprietary frontier models in most use cases.

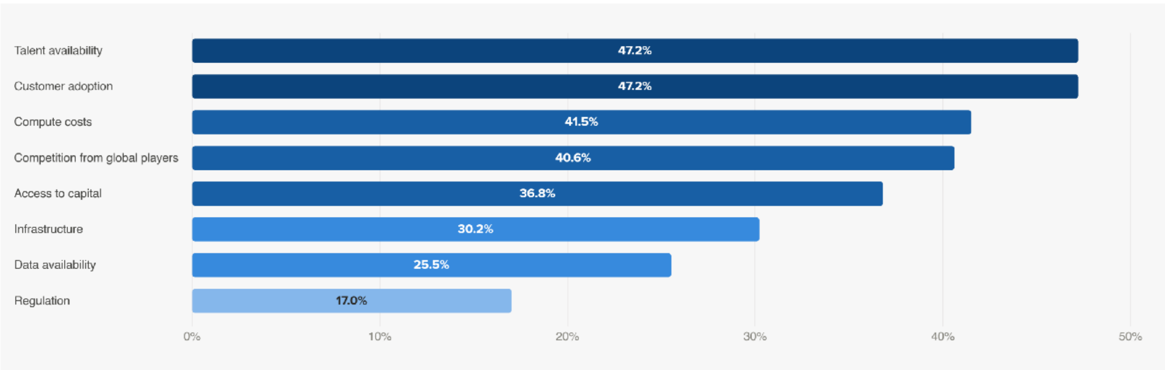
While India's AI ecosystem faces structural challenges, that are, talent shortages and data standardisation, the primary technological inputs like compute and open-source models are currently supporting a dynamic and accessible market.

3.2 The Role of Inputs in AI Markets

AI development depends on three cross-cutting inputs: compute, data, and skilled human resources. While Chapter 2 mapped the full breadth of the AI value chain, these three inputs are examined in depth here because they are the primary determinants of a firm's ability to enter, scale, and innovate at any layer of the stack. Compute and data feature as upstream elements of the value chain; talent, though not confined to a single layer, underpins capability across all stages and is accordingly treated as a foundational input alongside the other two. Economic literature on productivity J-curve recognises these inputs as complementary assets that jointly determine the adoption and productivity of AI.[162] While advances in frontier models are important, productivity gains depend equally on complementary investments in digital infrastructure, organisational capabilities, workforce skills, and deployment systems. Because these inputs determine firms' ability to enter, scale, and innovate, they also shape competitive dynamics across AI markets.[163]

This understanding is reflected in India's policy framework. NITI Aayog's National Strategy for AI,[164] MeitY's IndiaAI Report,[165] and CCI's Market Study,[166] all recognise compute infrastructure, data availability, and skilled talent as foundational enablers of AI development and adoption. The significance of these inputs varies across the AI value chain. Upstream activities, such as training foundation models, are highly resource-intensive, whereas downstream application developers can often build on existing models through APIs and cloud-based services. Consequently, access to critical inputs influences not only whether firms can participate in AI markets, but also the layer of the AI ecosystem in which they are able to compete.[167]

Figure 3: Barriers Affecting Competitiveness of AI Startups



[Source: Survey 2 —AI Startups and Developers, n=106. Respondents were asked which barriers most affect the competitiveness of AI startups in India. Respondents could select multiple options.]

162 Brynjolfsson, E., Daniel, R. & Chad, S. (2021, January). The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics*, *Volume 13, No. 1,* 333–72. https://www.aeaweb.org/articles?id=10.1257/mac.20180386.

163 Acemoglu, D. & Restrepo, P. (2018, January). Artificial Intelligence, Automation, and Work. *National Bureau of Economic Research, NBER Working Paper Series.* https://www.nber.org/system/files/working_papers/w24196/w24196.pdf.

164 NITI Aayog. (2018, June). *National Strategy for Artificial Intelligence*. https://www.niti.gov.in/sites/default/files/2023-03/National-Strategy-for-Artificial-Intelligence.pdf

165 MeitY, IndiaAI. (2023, October 14). *IndiaAI 2023: Expert Group Report – First Edition*. https://indiaai.gov.in/news/indiaai-2023-expert-group-report-first-edition.

166 Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.

167 Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

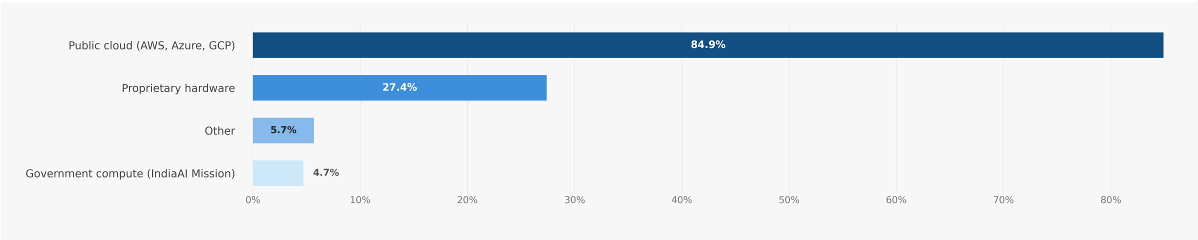
3.3 Access to Compute Infrastructure

Compute infrastructure is a foundational input for AI development as it enables providing necessary infrastructure for the execution of large-scale numerical computations required for training machine learning models.[168] Stanford University's 2025 Artificial Index Report notes that the scale of compute used in training frontier models has increased exponentially in recent years, reflecting both growing model complexity and improvements in hardware capabilities.[169]

Despite these high infrastructure requirements, access to compute has become substantially more accessible through cloud computing. Rather than investing in costly on-premise infrastructure, firms can access compute on demand through cloud providers, reducing upfront capital expenditure, and enabling experimentation, rapid deployment, and scaling.[170]

Our survey establishes the baseline: what compute do Indian developers actually access, do they find it affordable, and what do they experience when they try to switch providers?

Figure 4: Infrastructure Use: What Indian Developers Access

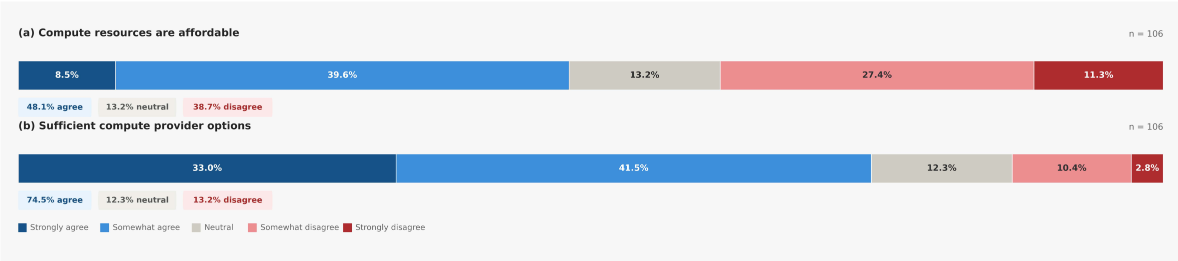


[Survey 2 — AI Startups and Developers, n=106. Respondents were asked regarding which types of compute infrastructure do they currently use for AI development and deployment. Respondents could select multiple options. The chart which shows the share of respondents using each infrastructure type.]

The survey findings indicate that Indian AI developers rely predominantly on public commercial cloud infrastructure for compute access, with approximately **85%** of respondents reporting usage of these platforms. By comparison, **27%** reported using proprietary hardware, while only a small proportion reported reliance on government-supported compute infrastructure. The low uptake of government-supported compute despite the IndiaAI Mission's subsidised GPU facility is a notable finding that warrants further examination, and may reflect limited awareness, access friction, or insufficient capacity relative to commercial alternatives.

[168] Susnjara, S., Flinders, M. & Smalley, I. (2024, June 3). *What is AI Infrastructure?* IBM. https://www.ibm.com/think/topics/ai-infrastructure.
[169] Maslej N. et al. (2025, April 8). Artificial Intelligence Index Report 2025. *Stanford University, Human-Centered Artificial intelligence.* https://doi.org/10.48550/arXiv.2504.07139.
[170] MeitY, IndiaAI. (2023, October 14). *IndiaAI 2023: Expert Group Report – First Edition*. https://indiaai.gov.in/news/indiaai-2023-expert-group-report-first-edition.

Figure 5: Compute Affordability and Provider Options

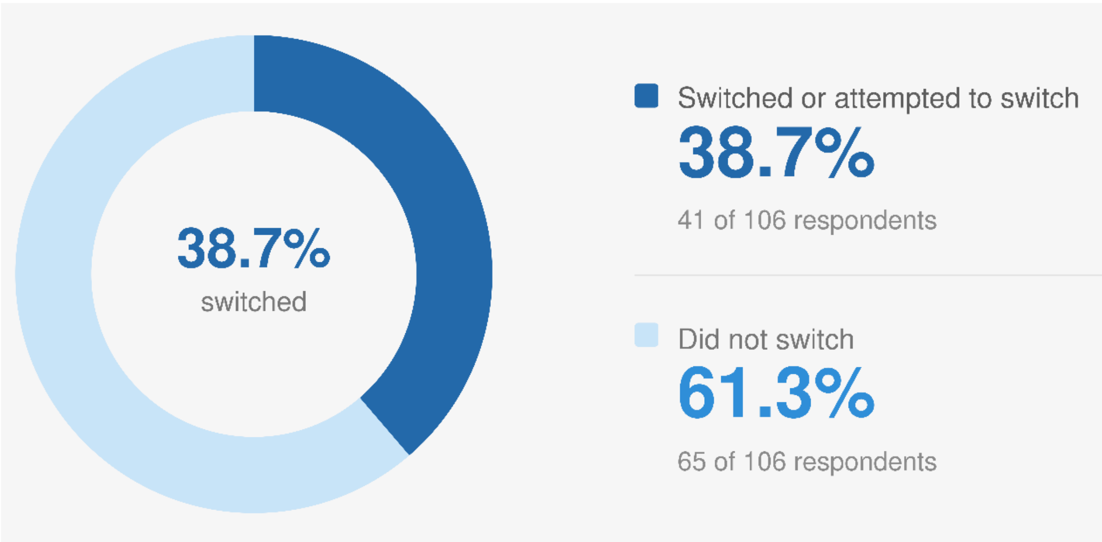


[Survey 2 — AI Startups and Developers, n=106. Respondents were asked to indicate their agreement/disagreement with the following two statements – (a) compute resources are affordable, and (b) there are a sufficient number of compute service provider options available in the market. The chart shows the share of respondents who strongly agree, somewhat agree, neutral, somewhat disagree, and strongly disagree with the statements.]

The respondents largely agree that compute is generally accessible within the market. **38.7%** think affordability is an issue while **74.5%** believe that sufficient provider options exist. Taken together, these findings suggest that respondents generally perceive compute markets to be competitive, with affordability and availability not emerging as significant barriers to participation.

To assess potential lock-in, the survey also examined developers' experiences switching cloud providers.

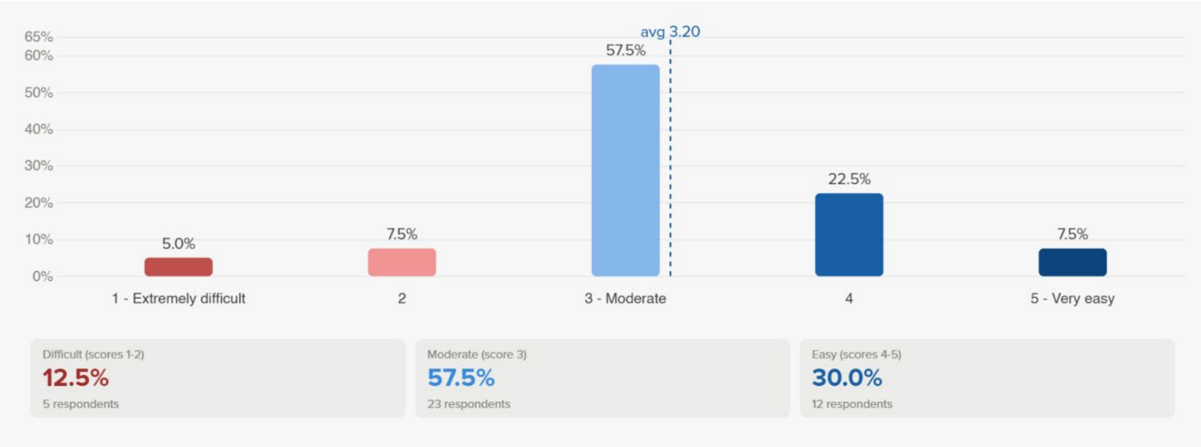
Figure 6: Switching Between Cloud Providers



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked whether they switched or attempted to switch computer or cloud infrastructure providers in the last three years. The chart shows the percentage of people in either category.]

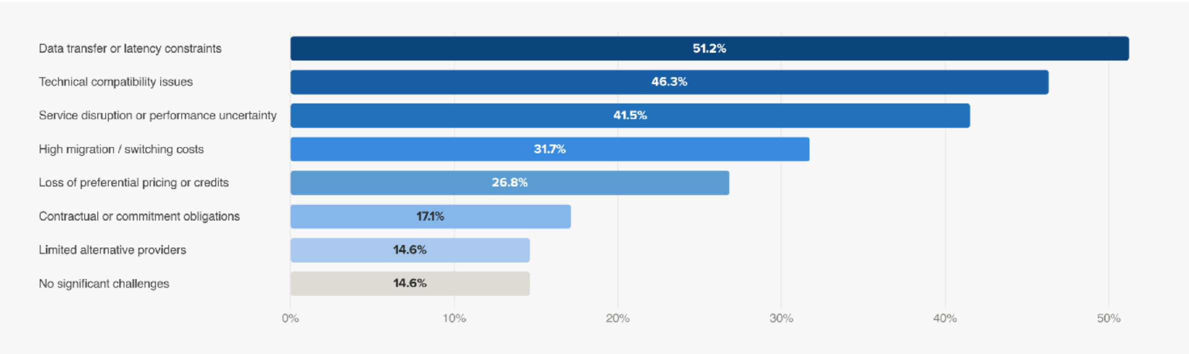
Out of 106 respondents surveyed during Survey 2 (AI startups and developers), 41 respondents had switched or attempted to switch cloud providers. As shown below, out of these 41, only **12.5%** found it challenging to switch providers. The principal challenges were data transfer constraints (**51.2%**), compatibility issues (**46.3%**), and service disruption risks (**41.5%**). By contrast, only **14.6%** identified a lack of alternative providers as a significant obstacle.

Figure 7: For startups that attempted to switch: ease-of-switching score



[Survey 2 — AI Startups and Developers, n=41 (respondents who had switched or attempted to switch cloud providers). Respondents were asked to rate the difficulty of switching to a different cloud provider on a scale of 1 (extremely difficult) to 5 (very easy). The chart shows the distribution of ease-of-switching scores across this sub-cohort.]

Figure 8: For startups that attempted to switch: distribution of switching challenges



[Survey 2 — AI Startups and Developers, n=41 (respondents who had switched or attempted to switch cloud providers). Respondents were asked: "Which challenges did you face when switching cloud providers?" Respondents could select multiple options. The chart shows the share of respondents citing each type of switching challenge.]

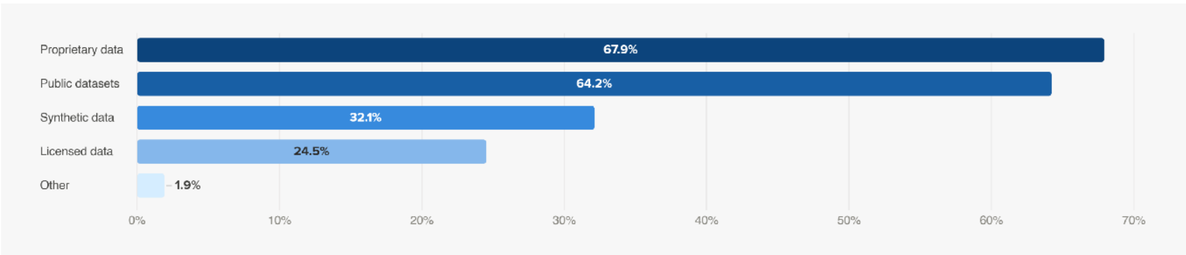
One of the survey's key findings is that switching costs stem primarily from the technical complexity of migrating workloads rather than a lack of competitive alternatives. This suggests that the main barriers to switching are technical, not structural, with little evidence that limited provider choice currently constrains competition in India's cloud compute market. Instead, challenges relate to interoperability, data portability, and migration costs, which may be better addressed through targeted technical or regulatory measures than structural competition remedies.

3.4 Access to Data

Data is a critical input for AI development. However, its competitive value depends not only on access, but also on a firm's ability to organise, process, and deploy it effectively alongside complementary inputs such as compute and technical expertise. The quality, diversity, and relevance of training data are key determinants of model performance, particularly during pre-training, while domain-specific datasets are essential for fine-tuning models for specialised applications.[171] Following deployment, user interactions generate additional data that can be used to refine models, creating feedback loops that support continuous improvement.

Accordingly, competition concerns have shifted from the mere possession of large datasets towards firms' ability to effectively leverage data. Advances in transfer learning, Retrieval-Augmented Generation ('RAG'), synthetic data generation, and open-source foundation models have reduced reliance on proprietary datasets, enabling firms to build competitive AI applications with more limited data resources. As a result, the competitive significance of data increasingly lies in its quality, relevance, and integration into AI systems, rather than its volume alone. From a competition policy perspective, this suggests that barriers to AI innovation are more likely to arise from unequal access to complementary capabilities including compute infrastructure, engineering talent, and deployment tools than from data ownership itself.

Figure 9: Training Data Sources

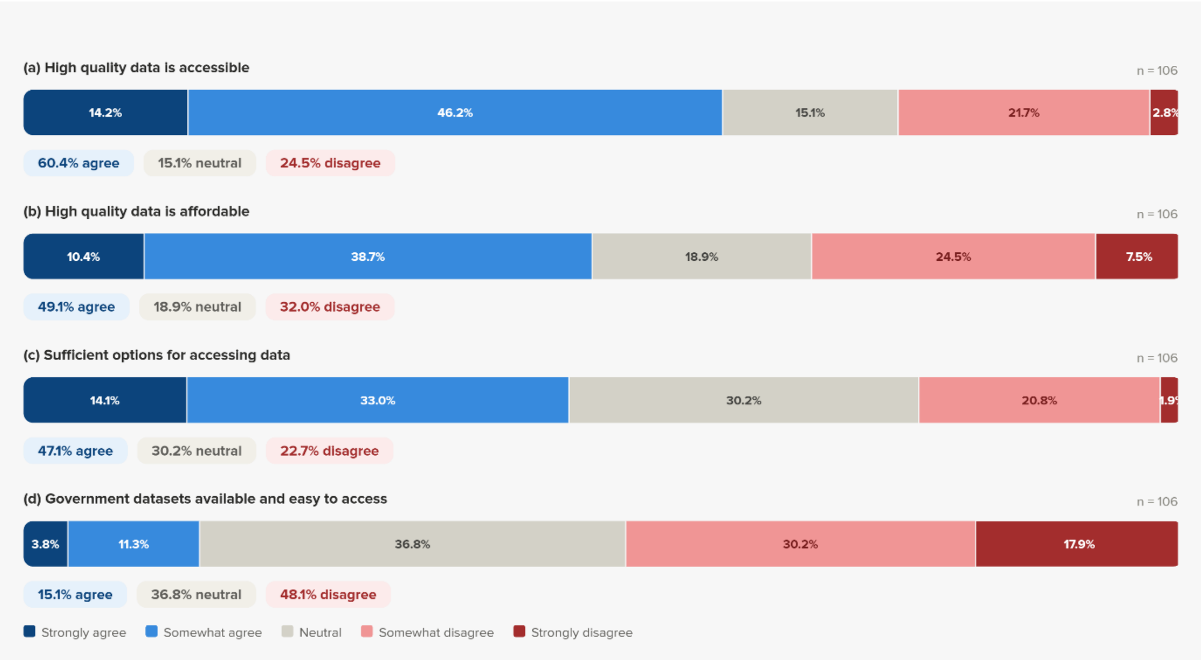


[Survey 2 — AI Startups and Developers, n=106. Respondents were asked regarding the main sources of data used for AI model training and development. Respondents could select multiple options. The chart shows the share of respondents using each data source type, including proprietary data, public datasets, synthetic data, and licensed datasets.]

Proprietary data emerged as the most commonly used source by AI startups at approximately **68%,** followed closely by public datasets (including open-access repositories such as Common Crawl and Hugging Face datasets, government open data portals, and publicly available web-scraped data) at **64%,** while synthetic and licensed datasets were used by **32%** and **25%** of respondents respectively.

[171] Organisation for Economic Co-operation and Development. (2024, May). Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

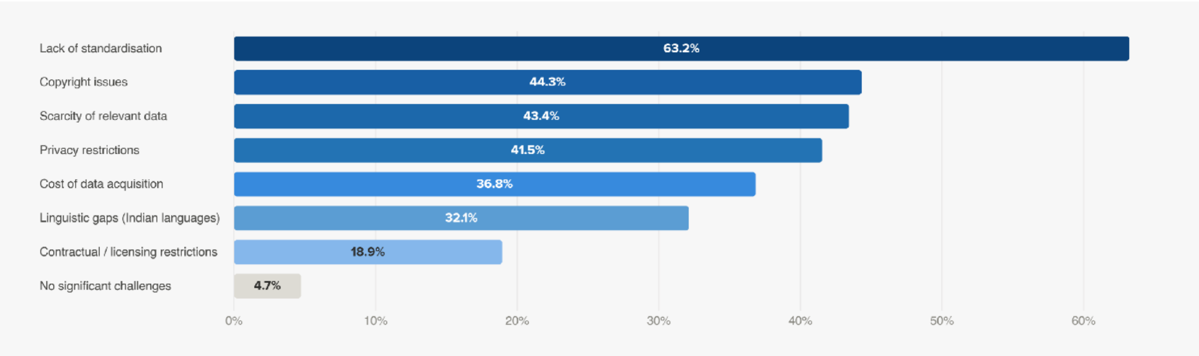
Figure 10: Accessibility, Affordability and Diversity of Datasets



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked a series of statements about data availability, affordability, and accessibility. Respondents indicated agreement on a 5-point scale. The chart shows the share of respondents agreeing with each statement.]

Respondents generally viewed high quality data as accessible. Around **60%** agreed that high-quality data is available, while only **32%** considered it unaffordable. However, perceptions were markedly different for government-held datasets. Only **15%** of respondents believed that government datasets are readily accessible, while nearly half expressed disagreement. This indicates that although firms can often obtain data through commercial and proprietary sources, improving the accessibility and usability of public datasets remains an important opportunity to strengthen AI innovation.

Figure 11: Challenges in Accessing Data



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked regarding the challenges they face with accessing high-quality data. Respondents could select multiple options. The chart shows the share of respondents identifying each data access challenge.]

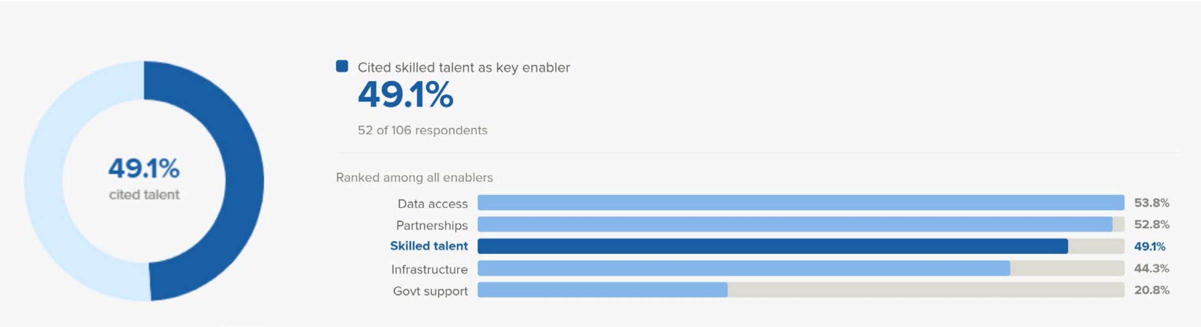
The survey also examined the principal barriers to accessing and using data. Lack of standardisation (**63.2%)** emerged as the most significant challenge, exceeding concerns relating to more commonly assumed barriers of data scarcity and cost. Copyright concerns, scarcity, and privacy restrictions all cluster closely between **41 to 44%**, suggesting that Indian AI developers are navigating several overlapping data challenges at once rather than a single dominant constraint.

3.5 Access to Human Capital

The third critical input is human capital. The development of AI systems requires specialised human resources, including machine learning engineers, data scientists, and researchers. These roles involve designing model architectures, optimising training processes, and deploying AI systems in real-world settings.[172] MeitY's IndiaAI Report highlights that talent availability remains a key constraint in the Indian AI ecosystem, particularly for advanced research and model development.[173]

The survey provides insights into how firms rank talent availability relative to compute infrastructure and data access, both as an enabling factor for AI development and as a potential competitive constraint.

Figure 12: Skilled Talent: A Key Enabler for AI Development



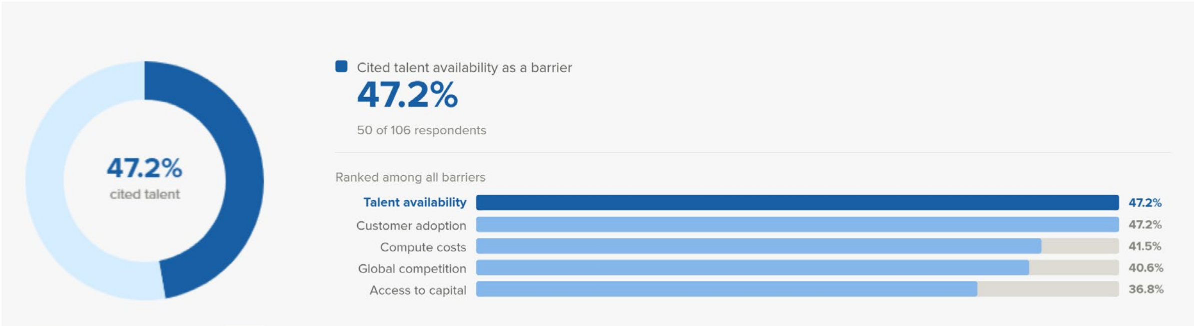
[Survey 2 — AI Startups and Developers, n=106. Respondents were asked: "Which factors have most supported your product development?" Respondents could select multiple options. The chart shows the share of respondents identifying different factors as key enablers.]

Nearly half of respondents (**49.1%**) identify skilled talent as a key enabler of their product development, ranking it third across all enablers, just behind data access (**53.8%**) and partnerships (**52.8%**). This highlights that technical expertise is regarded as a core competitive asset alongside other critical inputs.

[172] Organisation for Economic Co-operation and Development. (2024, May). Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificialintelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

[173] MeitY, IndiaAI. (2023, October 14). *IndiaAI 2023: Expert Group Report – First Edition*. https://indiaai.gov.in/news/indiaai-2023-expert-group-report-first-edition.

Figure 13: Talent Availability: A Significant Barrier Affecting Competitiveness



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked regarding the barriers that most affect competitiveness of AI startups in India. Respondents could select multiple options. The chart shows the share of respondents identifying each factor as a significant barrier to competitiveness.]

At the same time, **47.2%** of respondents identified talent availability as a significant barrier to competitiveness, ranking it jointly first with customer adoption and ahead of compute costs, access to capital, and competition from global firms. Taken together, these findings suggest that while firms with access to skilled talent are better positioned to innovate and scale, talent shortages remain a significant constraint for a substantial share of the ecosystem.

Shortages of skilled workers primarily reflect labour market dynamics, education systems, and the maturity of the AI ecosystem. Smaller firms may face greater challenges in attracting and retaining specialised talent than larger firms with greater financial resources and global reach. Addressing these constraints is therefore likely to depend on broader innovation and skills policies including AI education, workforce development, and international talent mobility.

3.6 Role of Open-Source AI in Lowering Entry Barriers

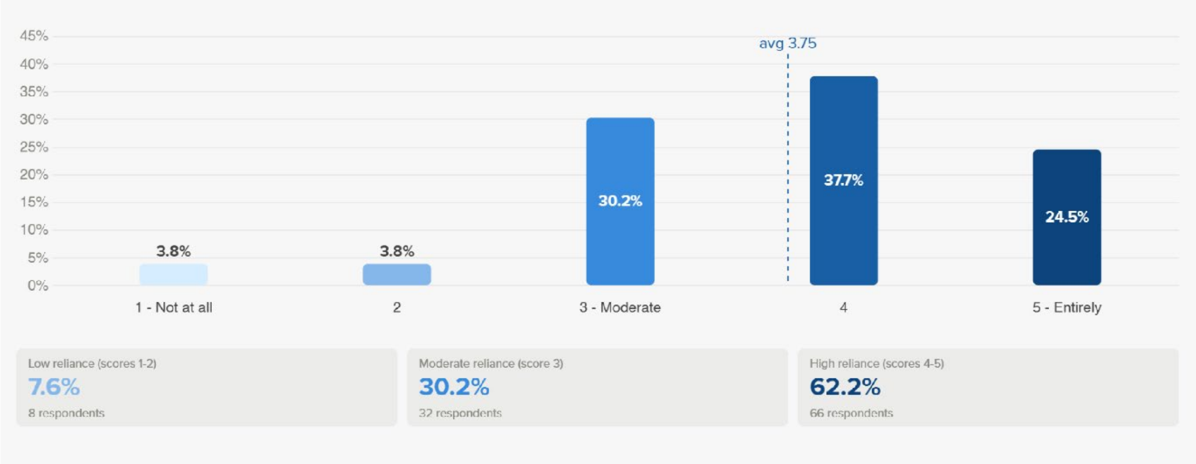
Open-source AI has emerged as an important mechanism for broadening access to AI capabilities and reducing barriers to innovation. By making model weights, development frameworks, and tooling publicly available, open-source ecosystems enable firms to build, fine-tune, and deploy AI systems without incurring the substantial costs of training foundation models from scratch.[174] Academic literature increasingly recognises open-source AI as an important driver of innovation and competition.[175] Rather than replacing proprietary models, open-source models expand the range of technological options available to developers, reduce development costs, promote experimentation, and accelerate downstream innovation.

Recent developments illustrate this trend. Meta's Llama family of open-weight models significantly broadened developer access to advanced language models. This was followed by open-weight releases from Mistral AI, DeepSeek, Google (Gemma), and Microsoft (Phi), which have collectively expanded the availability of high-performing models across a range of capabilities. These models have also

[174] Shashidhar, S. et al. (2023, October 11). Democratizing LLMs: An Exploration of Cost-Performance Trade-offs in Self-Refined Open-Source Models. https://arxiv.org/abs/2310.07611.
[175] Bommasani, R. et al. (2021, August 16). On the Opportunities and Risks of Foundation Models, *Center for Research on Foundation Models (CRFM) Stanford Institute for Human-Centered Artificial Intelligence (HAI) Stanford University.* https://crfm.stanford.edu/assets/report.pdf.

contributed to shared tooling, benchmarks, and technical standards that support wider participation in AI development.

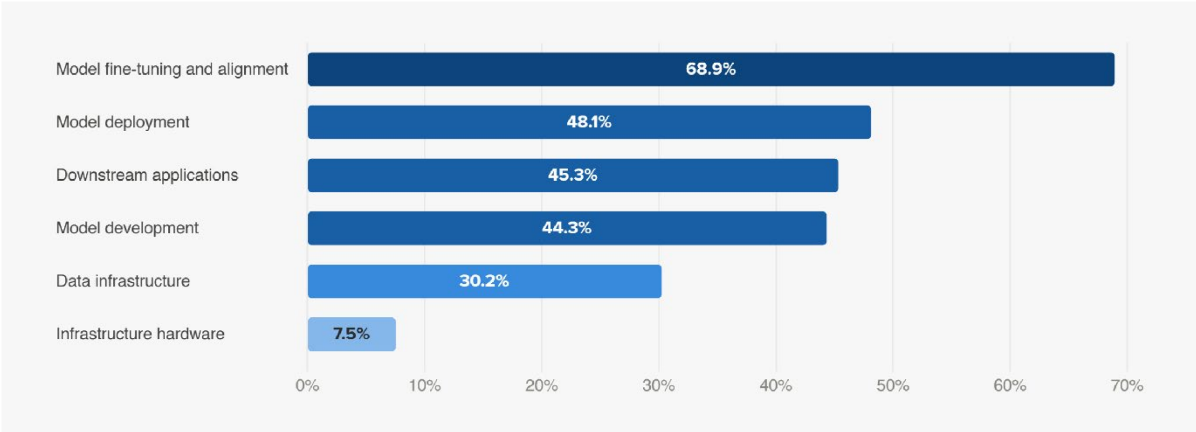
Figure 14: Reliance on open source



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked: "How reliant is your organisation on existing open-source AI tools for the development of your own AI tools?" Respondents selected a level of reliance (none, low, medium, high, or entirely). The chart shows the distribution of responses across reliance levels.]

The survey demonstrates that open source is deeply embedded within India's AI ecosystem. **96.2%** of respondents indicated at least some kind of reliance on open source with **62.2%** indicating 'high' reliance.

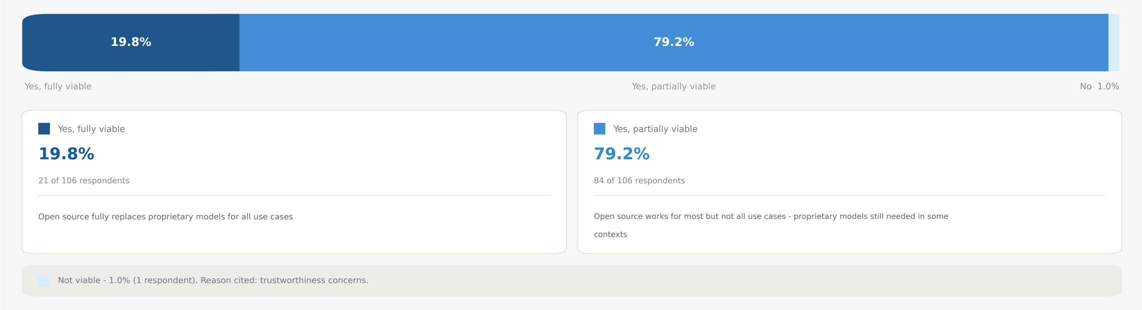
Figure 15: Layers of the AI stack where respondents rely on open source most



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked: "Across which layer of the AI are you relying on open source tools the most?" Respondents could select multiple options. The chart shows the share of respondents reporting open-source reliance at each layer of the AI stack.]

Reliance on open source varies significantly across the AI stack. Model fine-tuning and alignment emerged as the primary area of adoption, with **68.9%** of respondents relying on open-source models at this stage. By contrast, only **7.5%** reported using open source at the infrastructure layer, confirming that physical compute remains a proprietary or commercial dependency that open-source software cannot substitute.

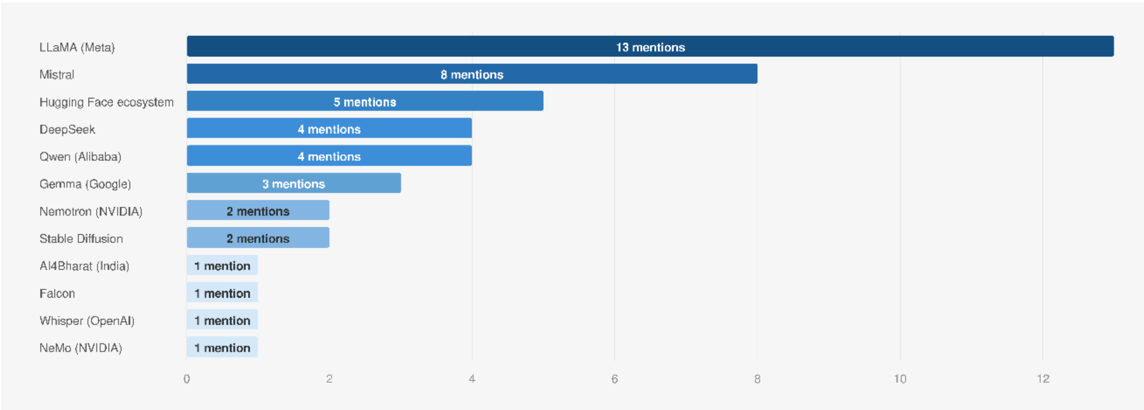
Figure 16: Viability of Substituting Proprietary Models with Open-Source



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked: "Do you consider open-source a viable substitute for proprietary models?" Respondents selected from options ranging from "yes, fully", "yes, partially", and' "no"' The chart shows the distribution of views on open-source substitutability for proprietary models.]

The survey also highlights the complementary relationship between open-source and proprietary models. More than **79%** of respondents reported that open-source models are at least a partial substitute for proprietary frontier models, while around **20%** viewed them as fully viable. This suggests that firms see open source as a viable solution for most applications, but not across all use cases.

Figure 17: Most Commonly Used Open-Source Models



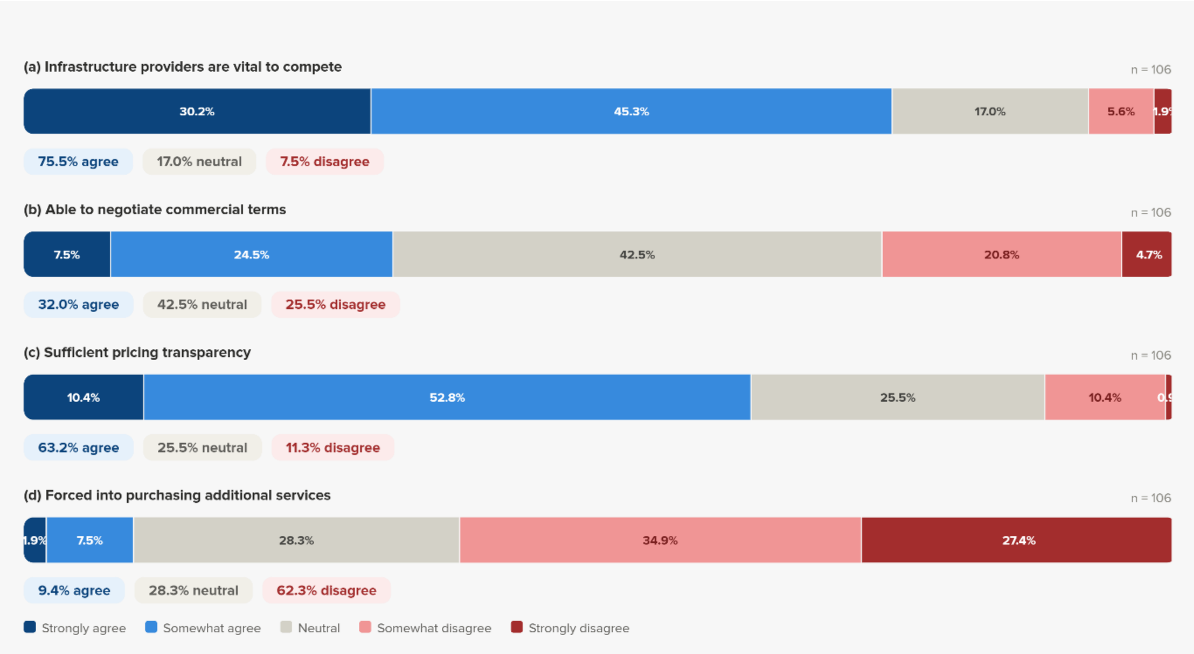
[Survey 2 — AI Startups and Developers, n=106. Respondents were asked: "If your organisation relies on open-source AI models, please list the main open-source models you use". The chart shows the share of respondents using each open-source model family.]

Among respondents, Llama was the most widely used open-source model, followed by Mistral, Hugging Face models, and DeepSeek. These findings suggest that open-source AI acts as an important competitive parameter by lowering entry barriers and expanding developer choice.

3.7 Relationship between Startups and Infrastructure Providers

The survey asked 106 AI startups and developers to assess their relationship with infrastructure providers across four dimensions: competitive necessity, ability to negotiate commercial terms, pricing transparency, and forced bundling. Taken together, the findings suggest that while infrastructure providers are indispensable to AI development, respondents generally do not perceive their relationships to be characterised by coercive commercial practices.

Figure 18: Assessing the Relationship between AI Startups/Developers and Infrastructure Providers



[Survey 2 — AI Startups and Developers, n=106. Respondents were asked a series of statements about their commercial relationship with AI infrastructure providers and asked to indicate their level of agreement on a 5-point scale (strongly disagree to strongly agree). The chart shows the distribution of agreement levels across the four dimensions: competitive necessity, ability to negotiate terms, pricing transparency, and forced bundling.]

The strongest finding relates to the importance of infrastructure providers. **75.5%** of respondents agreed that access to infrastructure providers is essential to their ability to compete, with **30.2%** strongly agreeing. Only **7.5%** disagreed. This reflects the central role of cloud compute and AI infrastructure in enabling startups to develop, fine-tune, and deploy AI applications.

Responses on commercial negotiations were more mixed. Only **32.1%** agreed that they had been able to negotiate contractual terms with infrastructure providers, while **42.5%** responded 'neither agree nor disagree'. A potential reason for this maybe that many firms rely on standard commercial offerings rather than individually negotiated arrangements.

Perceptions of pricing transparency were comparatively positive. **63.2%** of respondents agreed that pricing was sufficiently transparent. The survey provides the clearest evidence on bundling practices. **62.3%** of respondents disagreed that they had been required to purchase additional services in order to access infrastructure offerings, while only **9.4%** reported experiencing such practices. This suggests that tying and forced bundling, issues that have attracted regulatory attention in several jurisdictions, are not currently perceived as widespread concerns among Indian AI startups.

Taken together, the findings indicate that AI startups operate in a market where infrastructure providers are indispensable but generally viewed as accessible and transparent. The principal challenges identified by respondents relate less to exclusionary conduct than to the limited scope for negotiating commercial terms and the technical realities of relying on shared infrastructure.

4 | Competition Dynamics in the AI Ecosystem: Evidence from Business Users

4.1 Key Insights from this Chapter

This chapter examined how the structural characteristics of India's AI market translates into real-world adoption patterns and competitive effects. Key Insights from surveys:

- **Uneven Sectoral Adoption**: Survey results reveal that AI deployment is most advanced in digitally mature industries. Retail or E-commerce firms reported **100%** broad deployment, followed by professional services at **80%** and technology firms at **74%.** In contrast, sectors like manufacturing and healthcare reported only **29%** broad deployment, though they show significant pilot-stage activity.
- **Strategic Use Cases:** The most common functional use for AI is data analysis and business intelligence **(70%)**, followed by customer service or chatbots **(54%)** and then product development **(53%)**.
- **Positive Competitive Effects:** Businesses overwhelmingly perceive AI as a strategic enabler rather than just an automation tool. **85%** of business respondents rated AI's impact as moderate to highly positive, and **71%** disagreed with the notion that AI-enabled services have not significantly impacted their business.
- **Tangible Benefits and Commercial Viability**: The primary competitive benefits cited include improved decision-making **(61%)** and faster product delivery **(55%)**. Furthermore, **67%** of firms agreed that the cost of AI solutions is proportionate to the benefits they provide, suggesting high commercial satisfaction.
- **Barriers to Implementation:** Despite positive outcomes, firms face significant hurdles. Data privacy and security concerns were identified as the top barrier **(56%)**, followed by a lack of technical expertise **(38%)** and integration difficulties **(35%)**.

4.2 From Market Structure to Market Outcomes

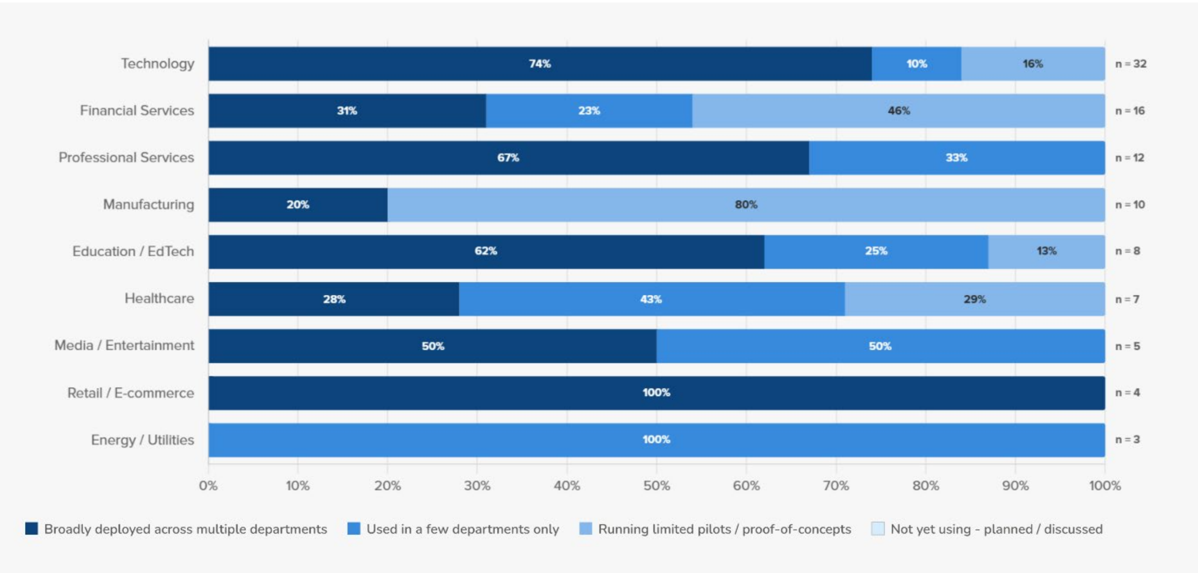
The structural characteristics of AI markets examined in preceding chapters translate into observable outcomes through the adoption and deployment of AI technologies across sectors. Firms respond to the availability of AI tools by integrating them into production processes, decision-making systems, and customer-facing services. The relationship between market structure and outcomes is mediated by adoption. Analysing adoption patterns provides insight into how AI is reshaping both supply-side and demand-side dynamics.

Economic literature on general-purpose technologies emphasises that the impact of such technologies emerges through gradual and uneven adoption. Brynjolfsson, Rock, and Syverson note that productivity gains often follow a "J-curve", where initial investments in new technologies are followed by delayed but substantial efficiency improvements as firms adapt organisational processes.[176] Similarly, Acemoglu and Restrepo highlight that the economic effects of AI depend on how it is deployed across tasks, particularly in terms of automation versus augmentation.[177] Both frameworks suggest that early adoption data will understate AI's long-run competitive impact, and that uneven adoption across firm sizes and sectors will shape who captures those long-run gains.

4.3 AI Adoption Across Various Sectors

AI technologies are being adopted across a wide range of sectors, including finance, retail, healthcare, logistics, manufacturing, and professional services. Firms are deploying AI tools for tasks such as customer support, data analysis, forecasting, process automation, and content generation.

Figure 19: Sector-wise AI Adoption



[Survey 1 — Business User Survey, n=102. Respondents were asked: "How much is AI currently used in your organisation?" Respondents selected from broad deployment, pilot stage, exploratory, being discussed but not yet adopted, and no plans.]

The survey findings indicate that AI adoption levels currently vary across sectors. Technology firms reported broad deployment levels of **74%**, professional services firms **80%**, and retail/e-commerce firms **100%**, while manufacturing and healthcare firms reported significantly lower levels of broad deployment alongside higher levels of pilot-stage adoption.

These patterns suggest that AI adoption is progressing somewhat unevenly across industries, with digitally mature sectors integrating AI systems more rapidly, while other sectors continue to experiment with use cases and deployment models before broader implementation. These survey results also

[176] Brynjolfsson, E., Daniel, R. & Chad, S. (2021, January). The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics*, *Volume 13, No. 1,* 333–72. https://www.aeaweb.org/articles?id=10.1257/mac.20180386.

[177] Acemoglu, D. & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives, Volume 33, Issue 2,* 3-30. https://www.aeaweb.org/articles?id=10.1257/jep.33.2.3

suggest that AI adoption is not confined to technology firms but is diffusing across the broader economy.

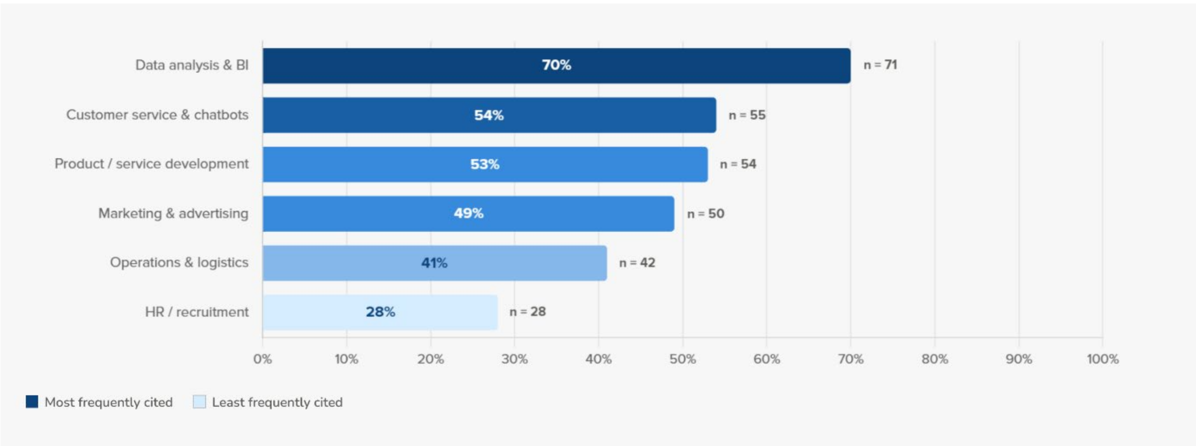
However, adoption is uneven across sectors. Differences in digital maturity, regulatory requirements, and data availability influence the extent to which firms are able to integrate AI into their operations. For instance, sectors such as finance and e-commerce, which generate large volumes of structured data, are more conducive to AI adoption compared to sectors with fragmented or unstructured data environments.[178]

In the Indian context, the RBI and SEBI have noted that AI adoption in financial services is driven by use cases such as risk assessment, fraud detection, and customer analytics, but is also shaped by regulatory and data governance considerations.[179]

4.4 Impact on Business Performance and Competitive Effects

Businesses are deploying AI technologies across a wide range of functional areas, reflecting the general-purpose nature of AI systems.

Figure 20: AI Use Cases and Functionality



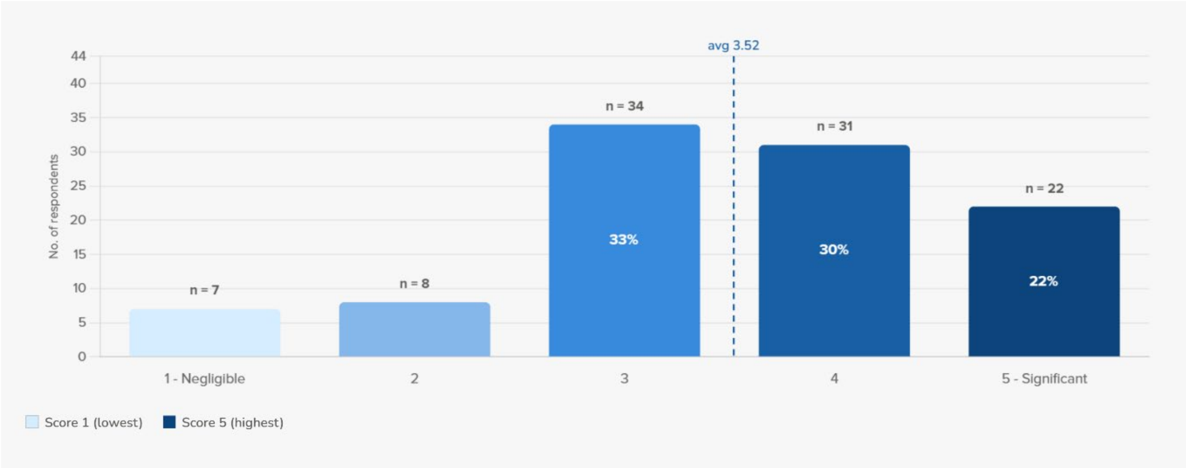
[Survey 1 — Business User Survey, n=102. Respondents were asked regarding the purpose for which AI is used by their organisation. Respondents could select multiple options. The chart shows the share of business respondents deploying AI for each functional use case.]

The survey findings indicate that businesses are deploying AI technologies across a wide range of operational and customer-facing functions. Data analysis and business intelligence emerged as the most common use case at **70%,** followed by customer service and chatbots at **54%**, product and service development at **53%**, and marketing and advertising at **49%**. The breadth of these use cases reflects the capabilities of foundation models, which can be adapted to multiple tasks through fine-tuning or API-based access.

[178] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

[179] Reserve Bank of India. (2025, August). *FREE-AI Committee Report – Framework for Responsible and Ethical Enablement of Artificial Intelligence*. https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/FREEAIR130820250A24FF2D4578453F824C72ED9F5D5851.PDF.

Figure 21: Business Users Perception Regarding the Impact of AI Adoption on Business Operations and Competitiveness



[Survey 1 — Business User Survey, n=102. Respondents were asked: "How would you rate the impact of AI on your organisation's ability to compete". Scores 1–2 indicate low impact; scores 3–5 indicate moderate to highly positive impact. The chart shows the distribution of impact ratings across all business respondents.]

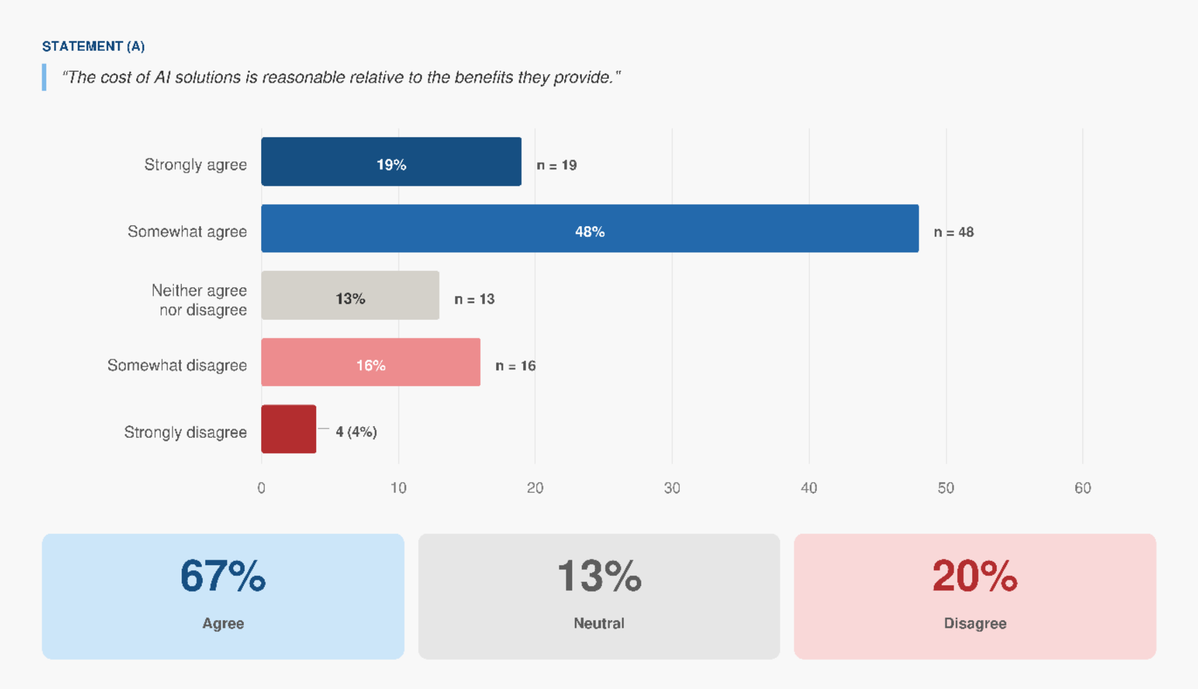
The results demonstrate a generally positive perception of AI adoption among respondents. Overall, **85%** of respondents rated AI's impact on their ability to compete as moderate to highly positive (scores 3–5), while only **15%** expressed a low-impact perception (scores 1–2). These findings suggest that the majority of respondents recognize AI as an important driver of improved efficiency, innovation, productivity, and competitive advantage.

Figure 22: Benefits of AI Adoption

[Survey 1 — Business User Survey, n=102. Respondents were asked: "In what ways has AI helped your business compete more effectively?". Respondents could select multiple options. The chart shows the share of respondents reporting each category of benefit, led by decision-making improvements, faster delivery, and operational efficiency.]

The survey findings indicate that firms primarily associate AI adoption with improvements in decision-making, identified by **61%** of respondents, followed by faster product and service delivery at **55%**, streamlined internal operations at **47%**, and increased customer personalisation at **45%.** These findings suggest that firms increasingly view AI systems not only as automation tools, but also as strategic enablers capable of improving efficiency, responsiveness, and business performance across multiple operational functions.

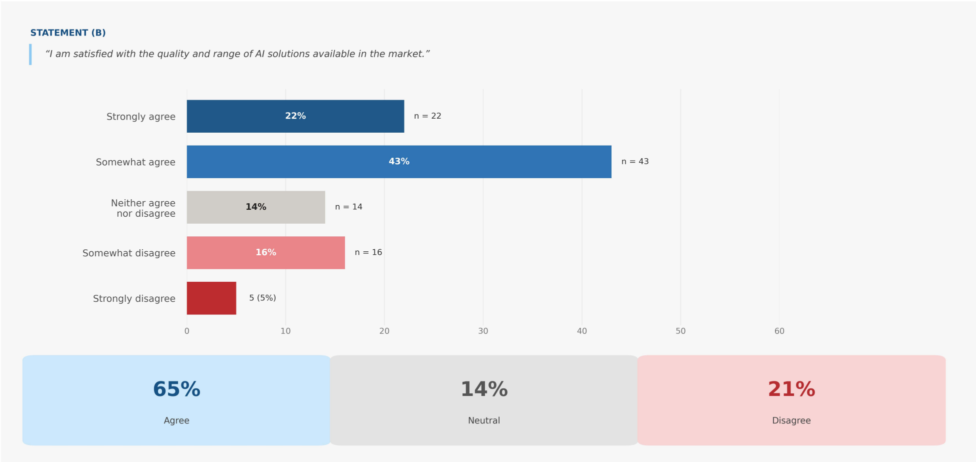
Figure 23: Reasonableness of the Cost of AI Solutions Compared to the Benefits They Provide



[Survey 1 — Business User Survey, n=102. Respondents were asked to indicate their level of agreement with the following statement – "The cost of AI solutions is reasonable relative to the benefits they provide to my business". Respondents indicated agreement on a 5-point scale. The chart shows the distribution of agreement levels, with a majority viewing AI costs as proportionate to the benefits received.]

The survey findings indicate that a majority of respondents view the cost of AI solutions as proportionate to the benefits they provide. Approximately **67%** of respondents agreed with the statement, including **19%** who strongly agreed, while **20%** expressed disagreement. These findings suggest that firms increasingly perceive AI adoption as commercially viable, with many businesses viewing the operational and strategic benefits of AI systems as outweighing implementation and deployment costs.

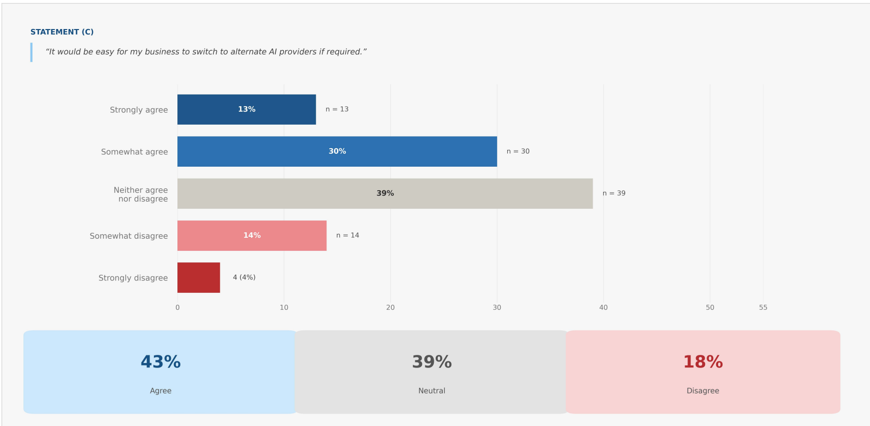
Figure 24: Business Users Satisfaction Regarding the Quality and Range of AI Solutions Available in the Market



[Survey 1 — Business User Survey, n=102. Respondents were asked to indicate their level of agreement with the following statement – "I am satisfied with the quality and range of AI solutions available in the market." Respondents selected from levels of satisfaction on a 5-point scale. The chart shows the distribution of satisfaction levels among business users.]

The survey findings indicate that respondents are generally satisfied with the quality and range of AI solutions currently available in the market. Approximately **65%** of respondents agreed with the statement, including **22%** who strongly agreed, while **21%** expressed dissatisfaction. These findings suggest that the growing availability of AI tools, models, and cloud-based services has expanded the range of commercially viable solutions available to businesses across sectors.

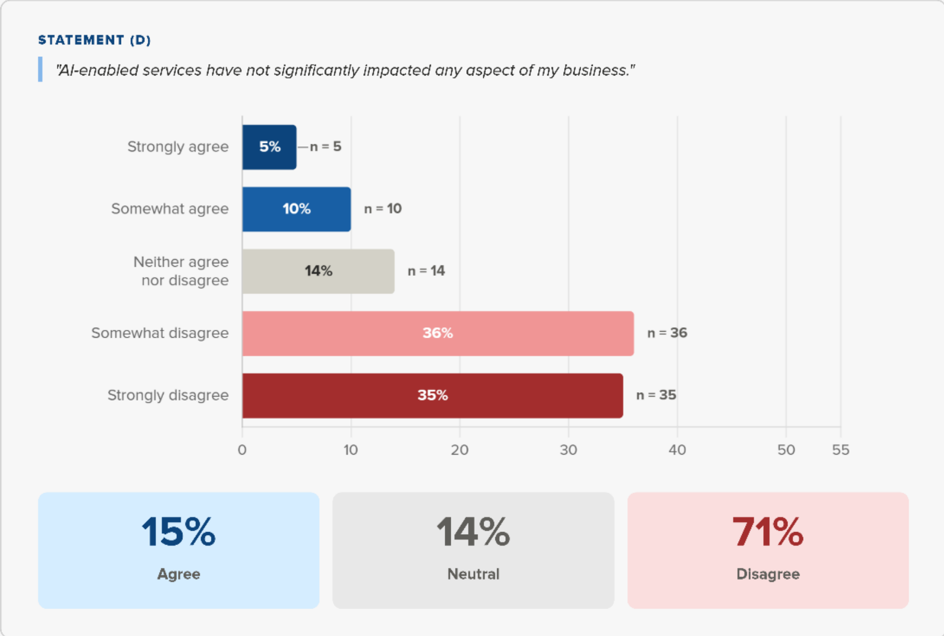
Figure 25: Ease of Switching between AI Providers



[Survey 1 — Business User Survey, n=102. Respondents were asked to indicate their level of agreement with the following statement – "It would be easy for my business to switch to alternate AI providers if required". Respondents indicated ease on a 5-point scale from very difficult to very easy. The chart shows the distribution of responses, with notable dispersion across all levels of difficulty.]

The survey findings indicate mixed views regarding the ease of switching between AI providers. Approximately **43%** of respondents agreed that switching providers would be relatively easy, while **40%** remained neutral and **18%** expressed disagreement.

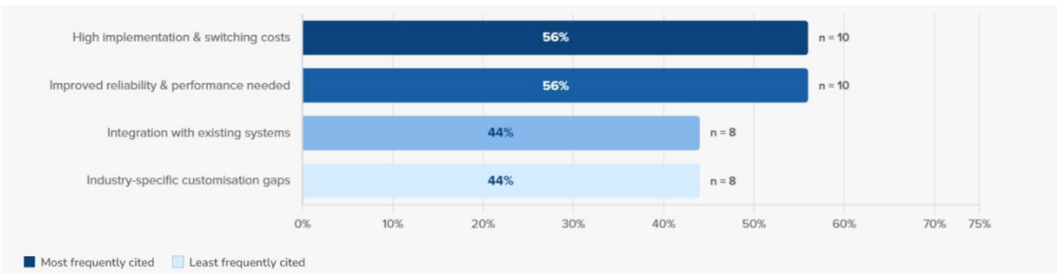
Figure 26: Impact of AI on Businesses



[Survey 1 — Business User Survey, n=102. Respondents were asked to indicate their level of agreement with the following statement – "AI-enabled services have not significantly impacted any aspect of my business." Respondents indicated agreement on a 5-point scale. The chart shows the proportion of business respondents who agreed, disagreed, or remained neutral on AI's operational impact.]

The survey findings indicate that a substantial majority of respondents believe AI-enabled services have had a meaningful impact on their businesses. Approximately **71%** of respondents disagreed with the statement that AI services had not significantly affected their operations, while only **15%** agreed with it. These findings suggest that AI technologies are increasingly influencing business processes, operational efficiency, and service delivery across firms, even where adoption may still be at relatively early or experimental stages.

Figure 27: For Respondents that Found Switching AI Providers as Difficult: The Most Common Barriers



[Survey 1 — Business User Survey, n=102 (subset who indicated switching AI providers would be difficult). Respondents were asked: "What are the primary barriers to switching AI providers?" Respondents could select multiple options. The chart shows the share of respondents identifying each type of switching barrier, with high switching costs and reliability concerns ranking highest.]

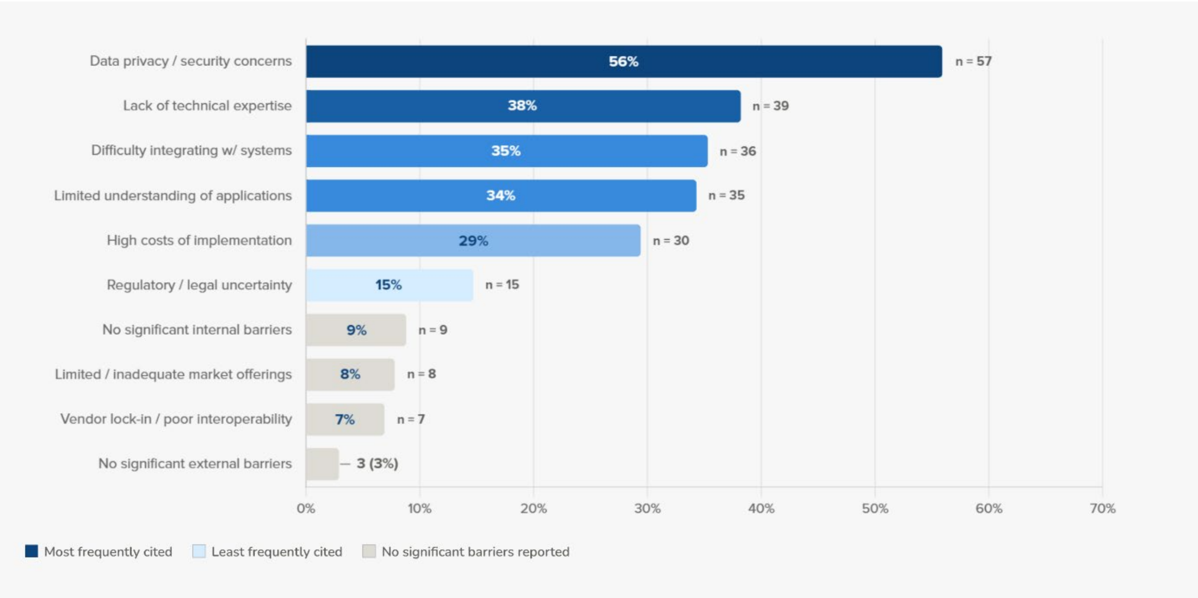
Among respondents who indicated that switching AI providers would be difficult, the most commonly cited barriers were high implementation and switching costs and the need for improved reliability and performance, each identified by **56%** of respondents. Integration challenges and industry-specific customisation gaps were also identified by **44%** of respondents.

These findings suggest that switching constraints in AI markets may arise not only from technical integration costs, but also from concerns relating to performance reliability, workflow compatibility, and the operational complexity of transitioning between AI systems.

4.5 Barriers to AI Adoption

Despite increasing adoption, firms continue to face several barriers in implementing AI solutions. Common challenges include: high costs of implementation, technical complexity, lack of skilled personnel, concerns around data availability and quality.

Figure 28: Various Barriers to AI Adoption

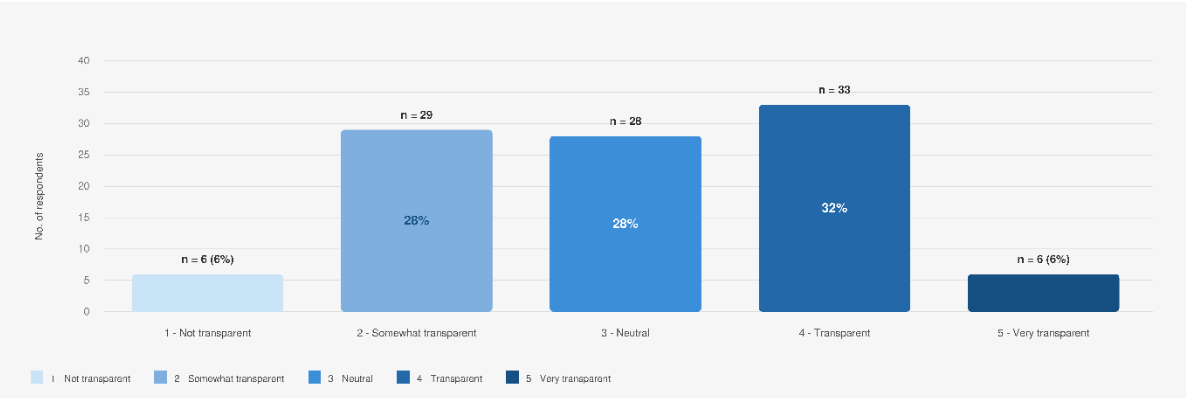


[Survey 1 — Business User Survey, n=102. Respondents were asked: "What are the biggest challenges your organisation faces when adopting AI?" Respondents could select multiple options. The chart shows the share of respondents identifying each adoption barrier, with data privacy and security concerns emerging as the leading constraint.]

The survey findings indicate that data privacy and security concerns represent the most significant barrier to AI adoption, identified by **56%** of respondents. Other major constraints include lack of technical expertise at **38%**, integration difficulties at **35%**, limited understanding of AI applications at **34%**, and high implementation costs at **29%**.

These findings suggest that barriers to AI adoption extend beyond infrastructure access alone and increasingly involve organisational readiness, technical capability, integration complexity, and trust-related concerns associated with deploying AI systems within business environments.

Figure 29: Transparency about Pricing and Data Usage Terms

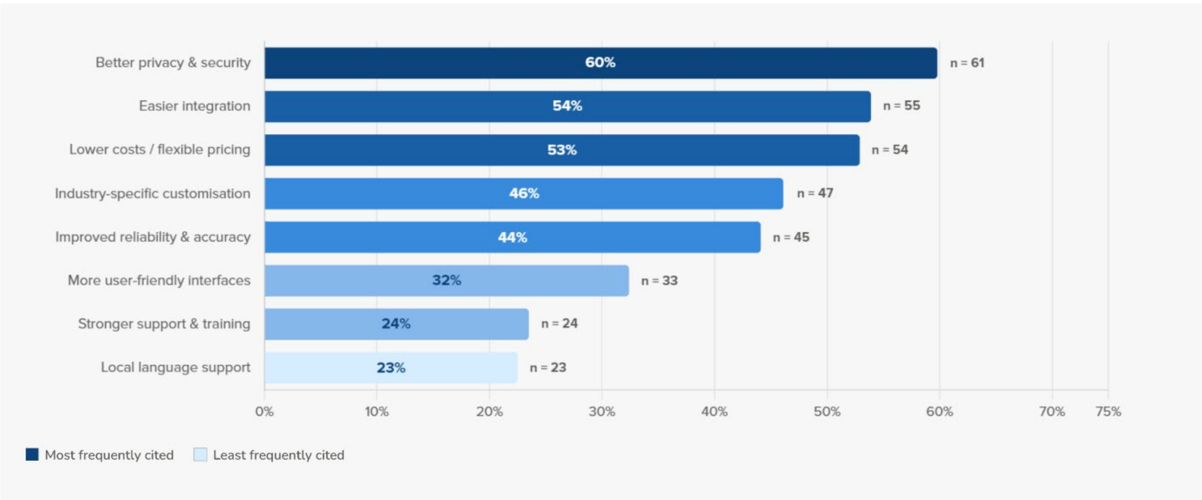


[Survey 1 — Business User Survey, n=102. Respondents were asked: "On a scale of 1 to 5, how transparent are AI providers about pricing and data usage terms?" Scores 1–2 indicate low transparency; scores 4–5 indicate high transparency. The chart shows the distribution of transparency ratings, with roughly equal proportions across the three bands — satisfied, neutral, and concerned.]

The survey findings indicate mixed perceptions regarding the transparency of AI providers in relation to pricing and data usage terms. Approximately **34%** considered transparency to be an issue while **38%** of respondents rated providers at level 4 and 5 on transparency, **28%** remained neutral.

These findings suggest that although many firms perceive current AI providers as reasonably transparent, concerns regarding pricing clarity, data governance, and contractual terms continue to shape user confidence and provider relationships within AI markets.

Figure 30: Factors Making AI Solutions More Useful and Accessible



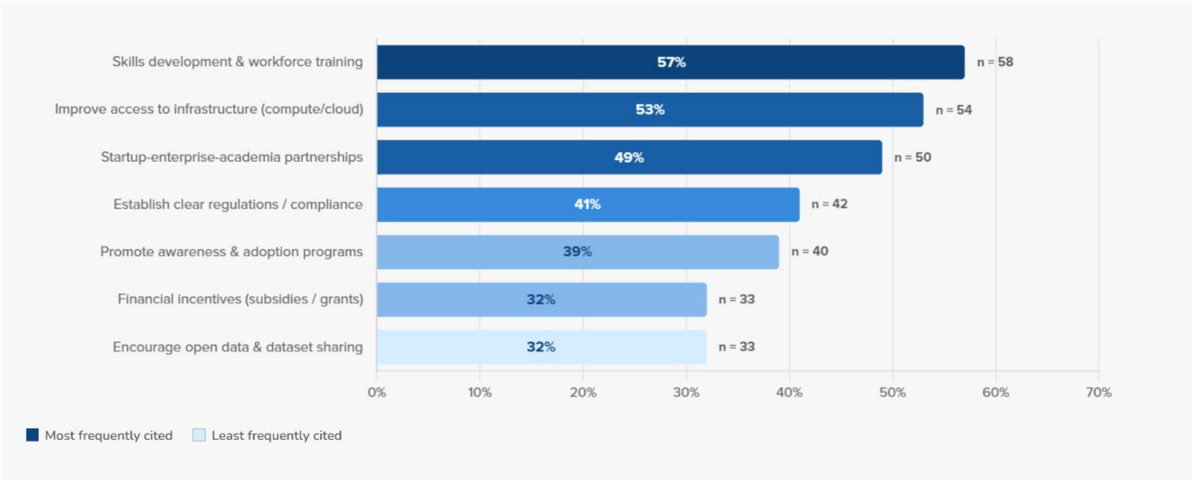
[Survey 1 — Business User Survey, n=102. Respondents were asked: "What changes would make AI solutions more useful and accessible for businesses like yours?" Respondents could select multiple options. The chart shows the share of respondents identifying each factor, led by better privacy and security protections, easier integration, and lower costs with flexible pricing.]

The survey findings indicate that respondents view better privacy and security protections as the most important factor in making AI solutions more useful and accessible, identified by **60%** of respondents. Easier integration (**54%**), lower costs and flexible pricing (**53%**), and industry-specific customisation (**46%**) were also identified as major priorities.

These findings suggest that businesses increasingly value AI solutions that are secure, interoperable, cost-effective, and adaptable to sector-specific operational requirements, highlighting the importance of usability and integration alongside technological capability.

The survey also examined business users' views on the role that government and industry bodies should play in addressing these barriers and improving AI adoption.

Figure 31: Role of Government and Industry in Improving AI Adoption



[Survey 1 — Business User Survey, n=102. Respondents were asked: "What role should government or industry bodies play in improving AI adoption for businesses?" Respondents could select multiple options. The chart shows the share of respondents identifying each factor, led by skill development and workforce training, improving access to infrastructure, partnerships, and clear regulations and compliance requirements.]

The findings indicate that respondents view regulatory clarity, infrastructure access, and skills development as complementary and broadly co-equal priorities rather than a single dominant ask. This suggests that the business community perceives AI adoption constraints as multi-dimensional, requiring a layered policy response rather than a single-point intervention. These preferences are reflected in the policy considerations examined in Chapter 6, which addresses compute access, open ecosystems, institutional capacity, and regulatory design as interconnected pillars of an enabling environment for AI adoption.

4.6 Key Implications for Market Dynamics from the Perspective of Business Users

The evidence presented in this chapter demonstrates that AI is increasingly becoming a general-purpose business technology that is improving productivity, innovation, and competitiveness across a wide range of sectors. Businesses reported deploying AI across functions such as data analytics, customer service, product development, marketing, and operations, with a majority indicating that AI has improved organisational performance. At the same time, adoption remains shaped by complementary inputs including access to skilled talent, technical expertise, implementation capabilities, and integration with existing systems.

From a competition perspective, these findings suggest that the principal constraints facing business adoption are currently linked more closely to capabilities and implementation than to the absence of competitive alternatives. Businesses generally reported satisfaction with the range and quality of AI solutions available, while concerns relating to switching were primarily associated with data privacy issues, lack of technical expertise and legal uncertainty. At the current stage of market development, measures that strengthen capabilities, improve access to infrastructure, and lower implementation costs may have a greater impact on market participation than interventions aimed solely at addressing market concentration.

5 | Consumer Choice and Competition in the AI Ecosystem: Evidence from Consumers

5.1 Key Insights from this Chapter

This chapter examines how consumers have interacted with AI markets, and how that translates into real-world adoption patterns and competitive effects. Key insights from survey include:

Consumer Reliance and Usage

- Approximately **85%** of consumer respondents reported moderate to very high reliance on AI-enabled services (**30%** moderate, **34%** high, **21%** very high).
- AI-enabled chatbots and virtual assistants are the most widely used AI-powered service, identified by **77%** of respondents, followed by AI-powered search engines **(76%)** and social media platforms **(44%)**.

Consumer Experience and Satisfaction

- Approximately **79%** of respondents reported that AI had significantly or somewhat improved their overall consumer experience; only **9%** reported a worsening.
- **72%** agreed that AI integration has improved their overall user experience, and **74%** agreed that AI integration into existing products has improved their experience.

Choice, Switching, and Multi-Homing

- **65%** of respondents agreed that they have several alternatives available when using AI-enabled services.
- **62%** agreed that they can easily switch between services offering similar AI features, and **61%** reported using multiple AI services simultaneously.
- **78%** reported that the nature of task drives their selection between standalone and embedded AI services.

Pricing and Service Availability

- **71%** of respondents agreed that the prices or offers shown to them may vary based on timing, demand, or their user profile. Only **37%** considered algorithmically generated pricing to be generally reasonable; **25%** actively disagreed and **38%** remained neutral.
- **51%** expressed satisfaction with the range of AI-enabled services currently available.
- **57%** expressed a preference for AI features integrated within existing digital services rather than standalone tools.

Data Awareness and Competition Concerns

- **78%** of respondents reported being very aware **(30%)** or somewhat aware **(48%)** of the types and volume of personal data used by AI systems.
- Data-related concerns represent the most significant competition concern experienced by respondents, identified by **64%** of users.
- Ecosystem lock-in or dependence was identified by **48%** of respondents; unclear terms, high pricing, and limited provider choice were each identified by between **35%** and **38%**.

Consumer Priorities

- Clearer information about how AI recommendations are generated was identified by **70%** of respondents as the most important improvement to competition and fairness.
- Greater control over personal data was identified by **65%** of respondents, followed by more competing AI services **(54%)** and industry standards for transparency and safety **(47%)**.

5.2 Consumer Perspective: A Demand-Side Analysis

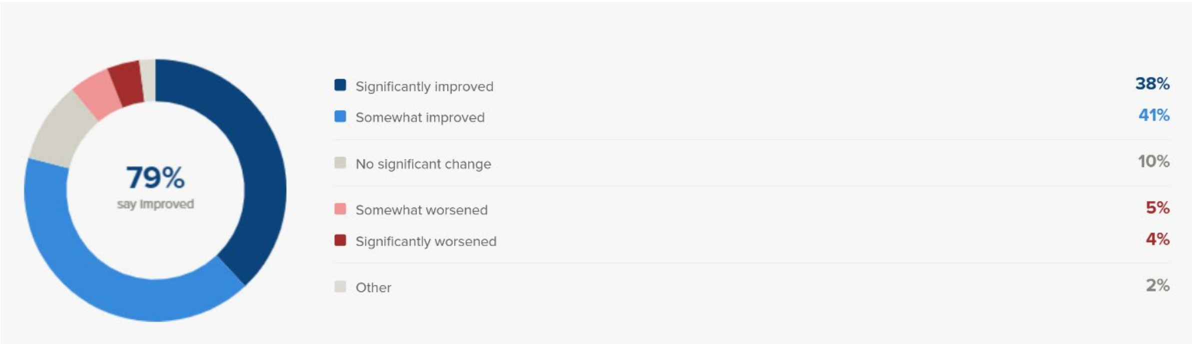
The preceding chapter examined AI adoption from the perspective of businesses, focusing on how firms deploy AI technologies, the competitive benefits they derive, and the constraints that influence adoption. Since competition policy seeks to promote consumer welfare alongside innovation and fair market outcomes, understanding consumer experiences with AI is equally important in assessing the evolving dynamics of AI ecosystems. Consumers increasingly interact with AI across a wide range of digital services, including search engines, virtual assistants, e-commerce platforms, financial services, navigation applications, content recommendation systems, and generative AI tools. Their choices, preferences, and perceptions influence adoption patterns, competitive incentives, and the direction of innovation. Consumer experiences also provide valuable evidence regarding switching behaviour, transparency, personalisation, trust, and the availability of alternatives, all of which are relevant to the assessment of competition in AI-enabled markets.

Accordingly, this chapter complements the preceding analysis of business adoption by examining AI from the demand side of the market. Drawing on findings from Survey 3 (Consumer Survey, n=100), it explores how consumers interact with AI-enabled services, the factors influencing their adoption and continued use, and their perceptions regarding choice, transparency, pricing, and competition. Together with the business user survey, these findings provide a more comprehensive understanding of AI market outcomes by incorporating both enterprise and consumer perspectives.

5.3 Consumer Interaction with AI Systems

Consumers are increasingly interacting with AI-enabled services across digital platforms, including chatbots, recommendation systems, voice assistants, and generative AI tools.

Figure 32: Improvements in Consumer Experience through AI Adoption

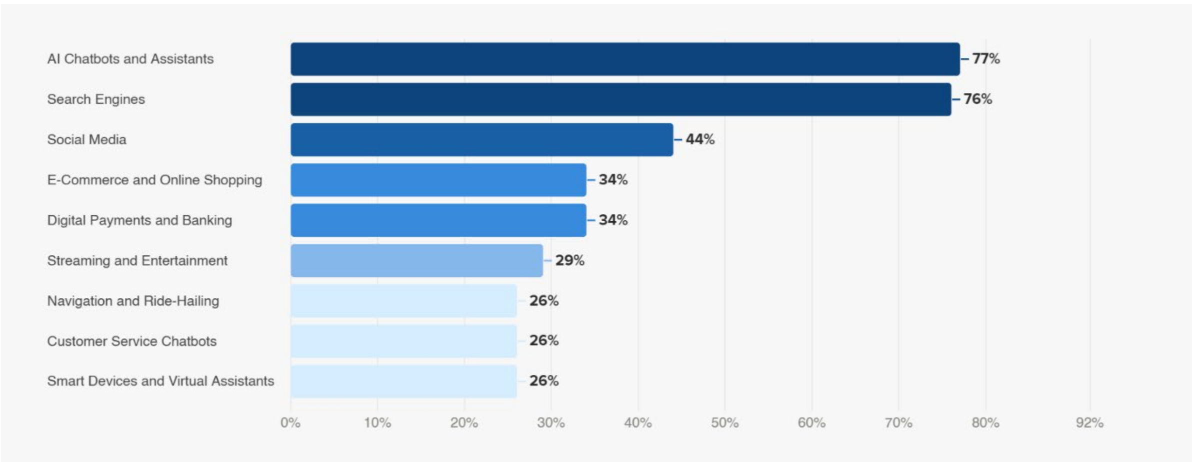


[Survey 3 — Consumer Survey, n=100. Respondents were asked: "Overall, do you believe AI has improved or worsened your experience as a consumer?". Respondents selected from significantly improved, somewhat improved, no change, somewhat worsened, or significantly worsened. The chart shows the distribution of consumer responses, with a substantial majority reporting improvement in their overall experience.]

The survey findings indicate that a substantial majority of respondents believe AI has improved their overall consumer experience. Approximately, **79%** of respondents reported that AI had either significantly improved or somewhat improved their experience, while only **9%** reported a worsening of experience.

These findings suggest that consumers generally associate AI-enabled services with improvements in convenience, personalisation, efficiency, and usability across a wide range of digital platforms and services.

Figure 33: Most Widely Used AI-Powered Services

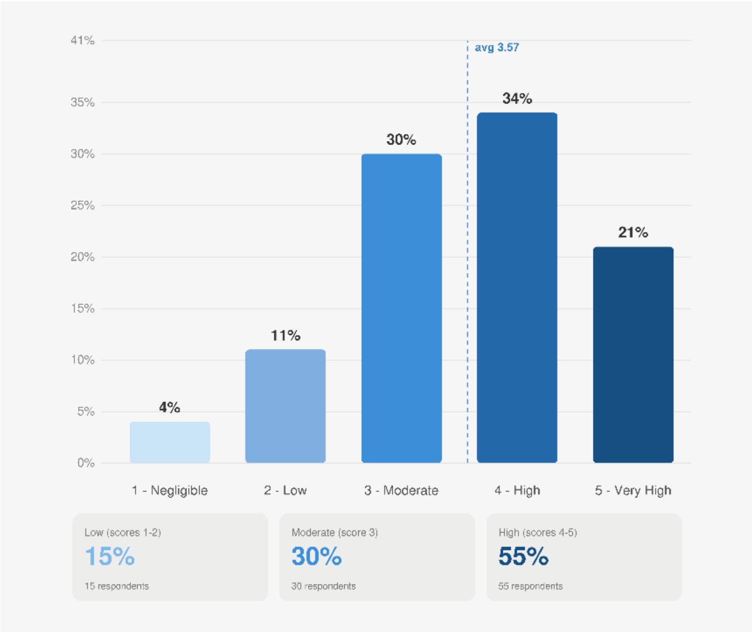


[Survey 3 — Consumer Survey, n=100. Respondents were asked: "In which of the following types of digital services do you use AI-powered features?" Respondents could select multiple options. The chart shows the share of consumer respondents using each AI-powered service category, with chatbots and assistants and AI-powered search engines leading across all categories.]

The survey findings indicate that AI-enabled chatbots and assistants represent the most widely used AI-powered services among respondents, identified by **77%** of users, followed closely by search engines at **76%**. Social media platforms were identified by **44%** of respondents, while digital payments, e-commerce, and streaming services reflected comparatively lower but still significant levels of AI-enabled usage.

These findings suggest that consumer interaction with AI is currently concentrated in digitally embedded and high-frequency services, particularly search, conversational interfaces, and online platforms where AI systems are integrated directly into everyday user experiences.

Figure 34: Reliance on AI-Enabled Services



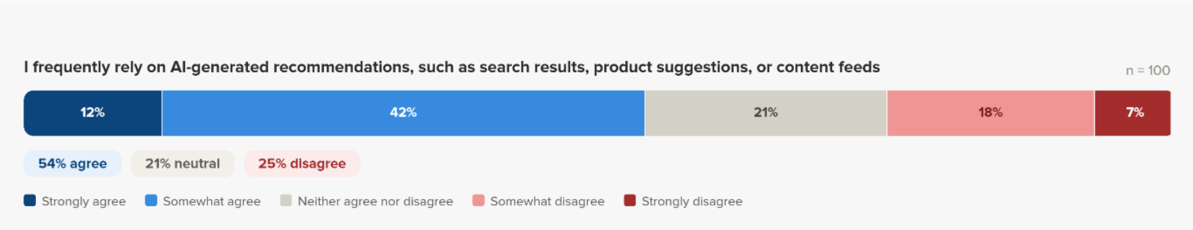
[Survey 3 — Consumer Survey, n=100. Respondents were asked: "How extensively do you rely on AI tools in your daily use?" Respondents selected from none, low, moderate, high, or very high reliance. The chart shows the distribution of reliance levels across the consumer respondent cohort, with a substantial majority reporting moderate to very high reliance.]

The survey findings indicate that a substantial majority of respondents report moderate to very high reliance on AI-enabled services. Approximately **30%** of respondents reported moderate reliance, **34%** reported high reliance, and **21%** reported very high reliance, collectively accounting for **85%** of respondents.

These findings suggest that AI-enabled services are increasingly becoming integrated into routine consumer activities, reflecting the growing embeddedness of AI systems across digital markets and everyday operational workflows.

Beyond aggregate reliance on AI-enabled services, the survey also examined the specific degree to which consumers depend on AI-generated recommendations, including search results, product suggestions, and content feeds as part of their everyday digital activity.

Figure 35: Frequency in relying on AI-generated recommendations by consumers



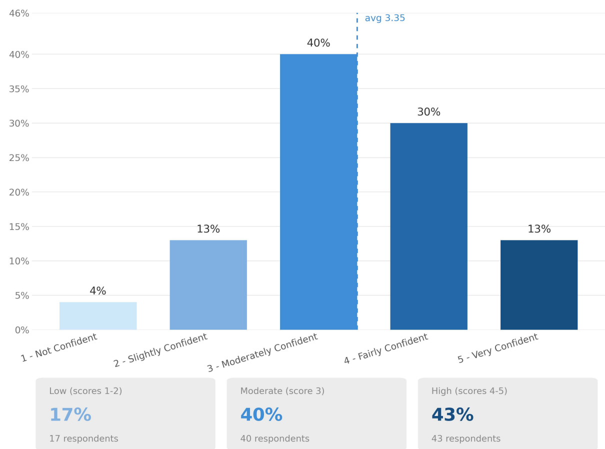
[Survey 3. Consumer Survey, n=100. Respondents were asked to indicate their level of agreement with the following statement about AI-generated recommendations and personalisation: "I frequently rely on AI-generated recommendations, such as search results, product suggestions, or content feeds.'" Responses were recorded on a five-point scale ranging from Strongly disagree to Strongly agree. The chart shows the distribution of agreement levels across the consumer respondents.]

The findings indicate that a substantial majority of respondents report frequent reliance on AI-generated recommendations. This points to the deep integration of AI-driven personalisation into everyday consumer behaviour and is relevant to understanding how market structure at the upstream and intermediate layers of the AI stack ultimately manifests in consumer-facing experiences. Recommendation systems are the primary interface through which many consumers engage with AI-enabled services, which means that competitive conditions in recommendation markets directly shape consumer outcomes.

5.4 Consumer Experiences with Choice, Transparency, Pricing, and Market Concerns

A prerequisite for exercising meaningful choice in AI-enabled markets is the ability to recognise when one is interacting with AI-generated content or recommendations. The survey examined consumer confidence in making this distinction, providing a baseline measure of AI literacy that contextualises the trust and choice findings discussed throughout this section.

Figure 36: Consumer Confidence in Identifying AI-Generated Content

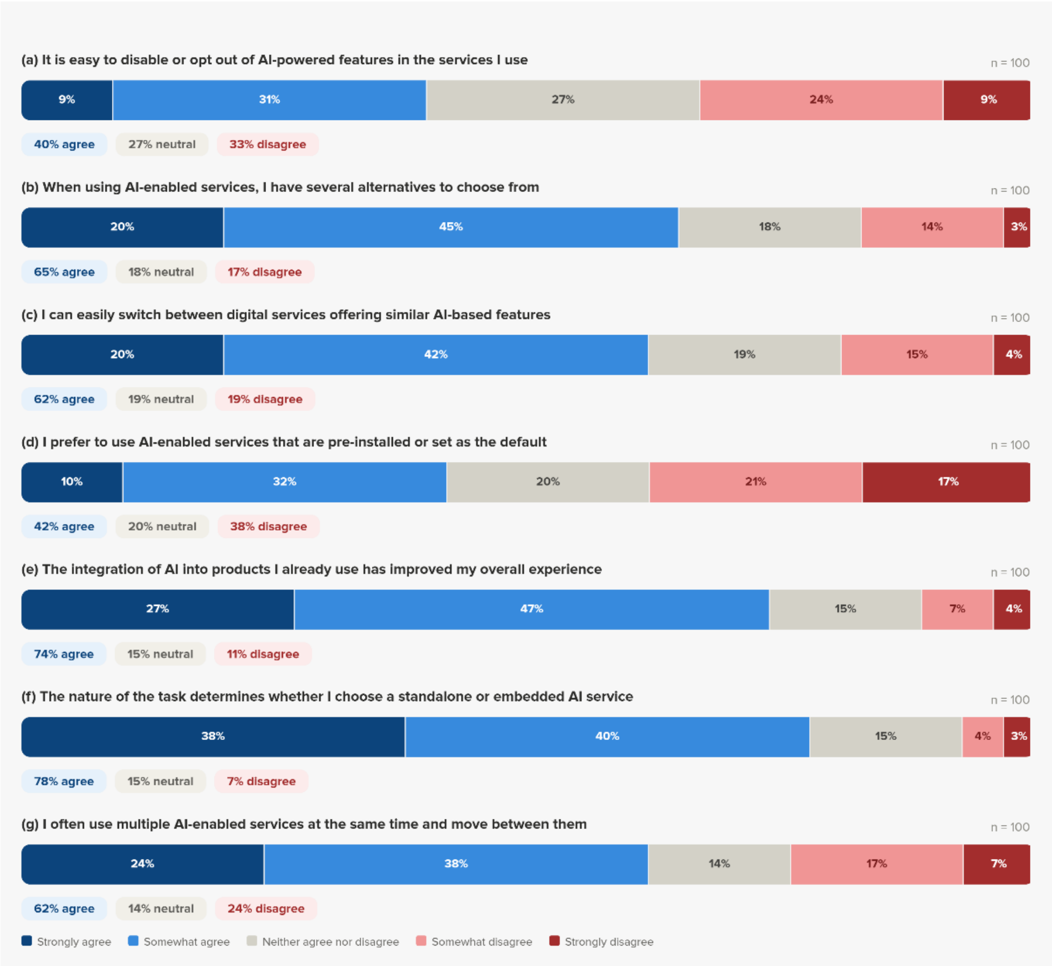


[Survey 3. Consumer Survey, n=100. Respondents were asked: "How confident are you that you can tell when a digital service is showing AI-generated content rather than human-created content?" Responses were recorded on a five-point scale ranging from Not Confident to Very Confident. The chart shows the distribution of agreement levels across the consumer respondents.]

The findings indicate that consumer confidence in identifying AI-generated content varies considerably, with a significant proportion of respondents reporting low to moderate confidence. This asymmetry between how AI systems function and how users perceive them is analytically significant: where consumers cannot reliably distinguish AI-generated outputs from human-created content, the exercise of informed choice is constrained regardless of how many alternatives are available. This finding is relevant to how transparency obligations in AI-enabled markets should be calibrated, an issue addressed in the policy considerations in Chapter 6.

Consumer perceptions play a critical role in shaping adoption and usage patterns. Key factors include transparency, reliability and accuracy, ease of use, and the availability of alternatives which influences consumer experience.

Figure 37: Consumer Experiences with Choice, Switching, and AI Integration



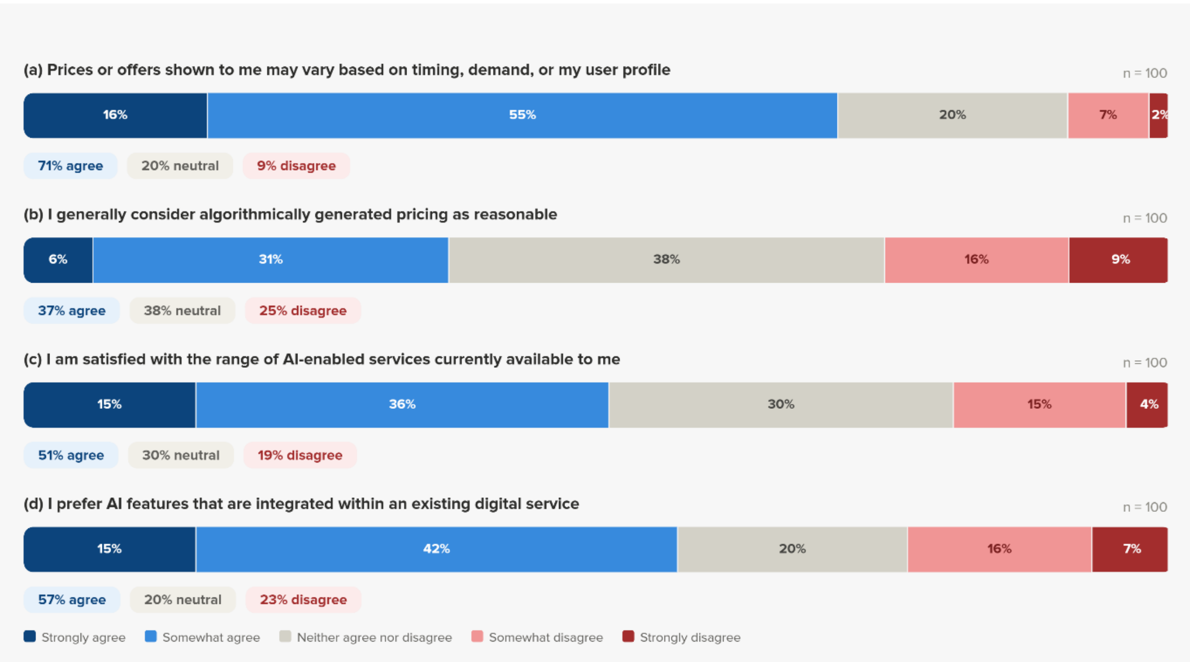
[Survey 3 — Consumer Survey, n=100. (a) Respondents were presented with seven statements covering: ease of opting out of AI-powered features; (b) availability of alternative AI service providers; (c) ease of switching between services offering similar AI features; (d) preference for default or pre-installed AI services; (e) perceived impact of AI integration on overall user experience; (f) task-driven selection between embedded and standalone AI services; and (g) simultaneous use of multiple AI services, i.e. multi-homing. Respondents indicated their level of agreement on a five-point scale ranging from Strongly Disagree to Strongly Agree. The chart shows the share of respondents agreeing or disagreeing with each statement.]

The above infographic presents consumer perceptions across seven dimensions of choice, switching behaviour, and AI service integration, and the findings collectively paint a picture of a relatively dynamic consumer-side market operating alongside meaningful structural constraints.

On provider choice and portability, a substantial majority of respondents agreed that they have several alternatives when using AI-enabled services **(65%, statement b)** and that they can easily switch between services offering similar AI features **(62%, statement c)**, while **62%** also reported actively multi-homing across multiple AI services simultaneously (statement g). These figures are consistent with a market where competition on the demand side remains operative.

However, the opt-out dimension tells a more qualified story: only **40%** of respondents agreed that it is easy to disable or opt out of AI-powered features in the services they use (statement a), with **33%** actively disagreeing, a finding that suggests meaningful constraints on consumer agency at the feature level, even where service-level switching appears accessible. The preference for pre-installed or default AI services was also notably divided, with **42%** agreeing and **38%** disagreeing (statement d), indicating that defaults and pre-installation are influential for a significant share of the consumer cohort but not determinative across the board. Positively, **74%** agreed that AI integration into existing products has improved their overall experience (statement e), and **78%** indicated that the nature of task drives their choice between standalone and embedded AI services (statement f), reflecting a nuanced, use-case-led approach to AI service selection.

Figure 38: Consumer Perceptions of AI-Enabled Market Features



[Survey 3. Consumer Survey, n=100. Respondents were asked to indicate their level of agreement with four statements relating to AI-enabled personalisation, pricing, service availability, and product integration. Responses were recorded on a five-point scale ranging from Strongly disagree to Strongly agree.]

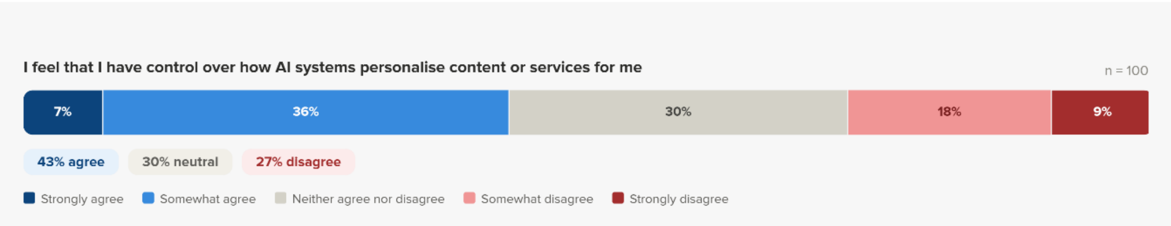
The figure above extends the analysis of consumer satisfaction and service preferences across four further dimensions, and its findings complement the switching and choice dynamics discussed in the preceding figure. Most strikingly, a large majority of respondents **(71%)** agreed that prices or offers shown to them may vary based on timing, demand, or their user profile (statement a), with only **9%** disagreeing. This high level of awareness of algorithmic or personalised pricing is analytically significant: it suggests that consumers broadly recognise that the prices and offers they receive are not uniform, which is a prerequisite for any meaningful exercise of informed choice. Yet recognition does not translate into acceptance; views on the reasonableness of algorithmically generated pricing were sharply divided, with only **37%** considering such pricing generally reasonable while **25%** actively disagreed and a substantial **38%** remained neutral (statement b). This three-way split indicates that algorithmic pricing remains a contested and unresolved dimension of the consumer experience in AI-enabled markets, and one where transparency obligations could play a meaningful role.

On service availability, a bare majority of **51%** expressed satisfaction with the range of AI-enabled services currently available (statement c), with **30%** neutral and **19%** dissatisfied, a more qualified verdict than the positive experience scores recorded in the previous figure, and one that may reflect unmet demand for more specialised or domain-specific AI applications.

Finally, **57%** expressed a preference for AI features integrated within existing digital services rather than standalone tools (statement d), consistent with the broader pattern of consumers favouring embedded, low-friction AI experiences over separate product adoption.

Taken together, the two figures present a consumer-side picture characterised by meaningful choice and generally positive experience at the service level, but accompanied by unresolved concerns around pricing transparency, opt-out friction, and the scope of available alternatives concerns.

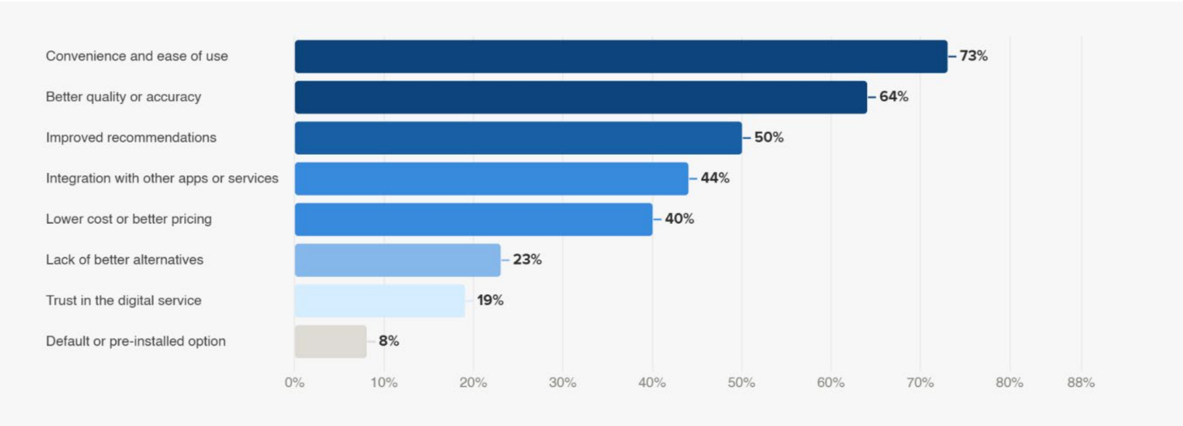
Figure 39: Consumer Perception on Control over AI Driven Personalisation



[Survey 3 — Consumer Survey, n=100. Respondents were asked about their sense of control over AI-driven personalisation in the digital services they use. Respondents indicated their level of agreement on a 5-point scale. The chart shows the distribution of responses regarding perceived agency over AI personalisation systems, with a significant proportion reporting limited or no sense of control.]

The findings indicate that perceptions of control over AI personalisation are limited for a significant share of respondents. Taken together with the findings on content recognition, this suggests that a meaningful proportion of consumers engage with AI-driven personalisation systems without clear visibility into how those systems operate or confidence in their ability to influence the outputs they receive. This information asymmetry between platforms and users is relevant both to competition analysis where it may limit the effectiveness of demand-side discipline and to the design of transparency and consent mechanisms in AI-enabled digital markets.

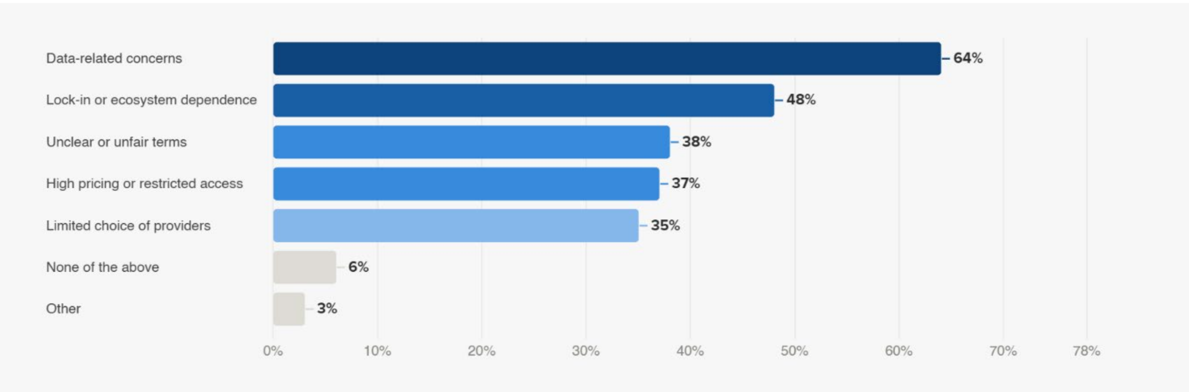
Figure 40: Factors Influencing Continued Use of an AI-Enabled Service



[Survey 3. Consumer Survey, n=100. Respondents who reported using AI-enabled services were asked: "What factors most influence your continued use of a particular AI-enabled service?" Respondents could select multiple options. The chart shows the share of respondents selecting each factor influencing their use of AI-enabled services, highlighting the relative importance of convenience, performance, cost, and integration-related considerations.]

The findings indicate that quality, accuracy **(64%)**, and ease of use **(73%)** are the primary drivers of continued service use, consistent with quality-based competition. However, a notable share of respondents also cited lack of better alternatives and default or pre-installed status as influential factors. This distinction between preference-driven and constraint-driven retention is significant for competition analysis. Where users remain because of service quality, this reflects effective market competition and consumer satisfaction. Where users remain primarily due to defaults and absence of alternatives, it may indicate that competitive forces are not fully operative on the demand side, and that structural features of the market including default-setting, pre-installation arrangements, and switching costs are shaping outcomes in ways that warrant closer scrutiny.

Figure 41: Competition-Related Issues Experienced within AI-Enabled Digital Markets



[Survey 3 — Consumer Survey, n=100. Respondents were asked: "Which of the following concerns, if any, have you experienced with AI-enabled digital services?" Respondents could select multiple options. The chart shows the share of consumer respondents identifying each competition concern, with data-related issues and ecosystem lock-in ranking as the most widely experienced.]

The survey findings indicate that data-related concerns represent the most significant competition-related issue experienced by respondents, identified by **64%** of users. Lock-in or ecosystem dependence was identified by **48%** of respondents, while concerns relating to unclear terms, high pricing, and limited provider choice were identified by between **35%** and **38%** of respondents.

These findings suggest that user concerns within AI-enabled digital markets are increasingly shaped by issues relating to data governance, ecosystem dependence, pricing transparency, and platform interoperability, particularly as AI services become more deeply integrated into digital ecosystems.

A further dimension of consumer experience in AI-enabled markets concerns awareness of the personal data that AI systems draw upon to deliver personalised services. The survey examined the extent to which consumers are aware of the types and volume of data such as browsing history, location, purchase behaviour, and interaction history that AI systems use to shape their digital experiences.

Figure 42: Consumer Awareness of Personal Data Used by AI Systems

[Survey 3. Consumer Survey, n=100. Respondents were asked: "How aware are you of the types and amount of personal data used by AI systems to personalise digital services (for instance — browsing history, location, purchase behaviour, or interaction history)?" Respondents selected one of five options ranging from Very aware to Not aware at all.]

The findings suggest that most consumers have at least a basic awareness of how AI systems use personal data. A combined **78%** of respondents reported being either very aware **(30%)** or somewhat aware **(48%)** of AI-related data collection and usage practices, while **17%** reported being not very aware. Only a small proportion indicated that they were either not sure **(3%)** or not aware at all **(2%)**. These findings suggest that although awareness of AI data practices is relatively widespread, the predominance of respondents reporting only moderate levels of awareness indicates continued scope for improving transparency and consumer understanding regarding how personal data is collected, processed, and used within AI-enabled services.

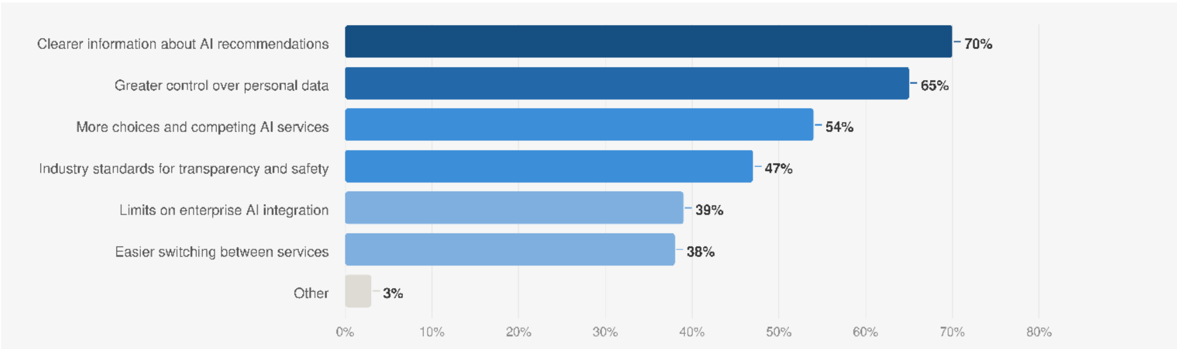
Academic literature highlights that trust is a key determinant of AI adoption. Users are more likely to engage with AI systems that are perceived as reliable, transparent, and fair.[180] At the same time, while limited perceived choice or higher switching costs may affect competitive dynamics in some contexts, integrated ecosystems may also improve usability, interoperability, security, and consumer convenience.

[180] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

5.5 Key Implications for Market Dynamics from the Perspective of Consumers

Before drawing together the implications of the evidence examined in this chapter, it is useful to consider how consumers themselves assess the current state of AI-enabled markets and what improvements they view as most pressing. The survey asked respondents to identify what, in their view, would most improve competition and fairness in the services they use. These responses provide demand-side evidence that directly informs the policy considerations examined in Chapter 6.

Figure 43: Factors Relevant to Competition and Fairness



[Survey 3. Consumer Survey, n=100. Respondents were asked: "What, in your view, would most improve competition and fairness in AI-enabled services?" Respondents could select multiple options. The chart shows the proportion of respondents selecting each measure that they believe would strengthen confidence in AI-enabled services, highlighting consumer priorities relating to transparency, control, competition, and governance.]

The findings suggest that consumers place the greatest emphasis on transparency and user empowerment as mechanisms for building trust in AI-enabled services. Clearer information about how AI recommendations are generated emerged as the most frequently selected measure **(70%)**, followed by greater control over personal data **(65%)**. More than half of respondents also identified increased choice through more competing AI services **(54%)** as an important factor, while nearly half supported industry standards for transparency and safety **(47%)**. Easier switching between services **(38%)** and limits on enterprise AI integration **(39%)** were selected less frequently but remained important considerations for a substantial proportion of respondents. Overall, the results indicate that consumer confidence is shaped not only by the availability of AI services but also by greater transparency, meaningful user control, and the ability to exercise informed choice within competitive digital markets.

6 | Implications for Competition Policy: India and Global Lessons

The preceding chapters examined the structure of AI markets, the role of key inputs, and evidence from AI developers, business users, and consumers regarding adoption, market participation, and competitive outcomes. Together, these findings provide an empirical foundation for considering the circumstances in which competition concerns may arise within AI ecosystems. Rather than assuming that concentration or vertical integration necessarily results in competitive harm, competition policy requires an evidence-based assessment of whether market characteristics are capable of restricting competition, reducing consumer welfare, or limiting innovation.

AI markets exhibit several characteristics that are relevant to competition analysis, including concentrated upstream infrastructure, increasing vertical integration, strategic partnerships, strong network effects, and ecosystem complementarities. However, the survey findings presented in this study also suggest that many observed market outcomes continue to reflect technological and commercial realities rather than clear evidence of market failure. Accordingly, theories of harm should be assessed carefully against the available evidence and in the context of AI markets' continuing evolution.

6.1 Assessing Theories of Harm in AI Markets

The structural characteristics of AI ecosystems have prompted competition authorities globally to examine whether increasing concentration and vertical integration may give rise to new forms of competitive harm. Existing literature identifies a few broad areas of concern: foreclosure of access to critical inputs, tying and bundling, ecosystem lock-in, algorithmic pricing, and investments, partnerships, and restrictive agreements. The survey findings provide an opportunity to assess whether these concerns are presently reflected in the experience of Indian AI firms.

a. Foreclosure through control of inputs

Firms that control key inputs such as compute infrastructure or proprietary datasets may influence access conditions for downstream firms. However, such control may also reflect the need for large-scale investment and coordination in developing AI systems.[181]

The survey provides limited evidence that such concerns have materialised in the Indian AI ecosystem. Over **75%** of business user respondents believed that compute access was important for their business. Respondents generally reported that compute infrastructure was accessible, multiple provider options were available, and data could be obtained through a combination of proprietary, public, licensed, and synthetic sources. Over **74%** of business user respondents believed that compute access was affordable and the market remained competitive. Infrastructure providers were regarded as

[181] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

indispensable, and respondents did not identify lack of access to compute or data as their principal competitive constraint.

While access to compute, data, and specialised talent remains important, the survey evidence suggests that barriers differ across inputs. Among AI developers, **84.9%** reported relying on public cloud infrastructure, while only **4.7%** used government-supported compute, indicating the central role of commercial cloud services in enabling AI development. At the same time, respondents identified interoperability, migration complexity, and technical compatibility as more significant constraints than a lack of provider choice, suggesting that technical frictions currently play a greater role than outright exclusion from essential infrastructure.

With respect to data as an input, survey evidence suggests that the primary barrier is not access per se but usability: **63.2%** of AI developer respondents identified lack of standardisation as the most significant data-related challenge, ahead of data scarcity **(43.4%)** and privacy restrictions **(41.5%)**. Notably, only **15%** of respondents believed that government-held datasets are readily accessible, indicating that while commercial and proprietary data sources remain broadly available, the accessibility of public-sector data represents a meaningful structural gap. Regarding human capital as a third form of critical input, **47.2%** of respondents identified talent availability as a significant barrier to competitiveness, ranking it jointly first alongside customer adoption and ahead of compute costs. These findings collectively suggest that elements of foreclosure concerns that may arise in India's AI ecosystem, are more likely to stem from structural deficits in data standardisation and talent availability than from anti-competitive conduct from firms.

b. Tying and Bundling

Integrated AI ecosystems may create incentives for providers to bundle cloud infrastructure, AI models, developer tools, and complementary services in ways that disadvantage competitors.

The survey, however, indicates limited evidence of such practices forced bundling. More than **62%** of respondents disagreed that they had been required to purchase additional services in order to access AI infrastructure, while fewer than **10%** reported experiencing forced bundling. From the consumer perspective, **57%** had agreed that they preferred AI products that were integrated within another digital service.

This suggests that tying and bundling, although recognised internationally as potential theories of harm, are not currently perceived as widespread concerns by Indian AI startups. However, the survey did not examine a related but distinct practice: the provision of cloud credits, which are discounts and usage subsidies offered by larger technology companies that incentivise adoption of their bundled suite of AI, storage, and compute services.

c. Ecosystem Lock-in and Switching Costs

A third concern relates to switching costs and ecosystem lock-in. Dependencies on specific platforms or providers may make it more difficult for firms to switch, particularly where systems are tightly integrated. However, the extent of such lock-in may vary depending on the availability of alternatives and interoperability standards.[182]

Survey findings suggested that **43%** of businesses believed that it was easier to switch between infrastructure providers however they believed that switching costs do exist. Through the surveys it was indicated that constraints primarily existed due to technical rather than commercial factors. **51.2%** of Respondents identified migration complexity like data transfer constraints, compatibility issues **(46.3%)** service disruption risks, as the principal barriers to switching cloud providers. Concerning this issue and in the spirit of completeness, we would add a slight caveat here which is that the survey did not specifically examine egress fees, which are charges levied by cloud providers for transferring data out of their platforms. By contrast, relatively few respondents viewed the absence of alternative providers as the primary obstacle. Similarly, respondents generally reported having access to multiple AI services and indicated that multi-homing was common.

Evidence from the consumer survey similarly suggests that ecosystem participation is driven primarily by perceived utility rather than default settings or limited alternatives. Consumers most frequently cited convenience **(73%)**, better quality or accuracy **(64%)**, and improved recommendations **(50%)** as reasons for continuing to use AI-enabled services, whereas only 8% identified pre-installed defaults as a significant factor. These findings suggest that ecosystem expansion may often reflect product quality and innovation alongside any competitive advantages associated with integrated platforms.

Business users reported relatively mixed views regarding switching AI providers, with **43%** agreeing that switching would be easy, **40%** remaining neutral, and **18%** disagreeing. Among developers experiencing switching difficulties, the principal barriers related to data transfer, technical compatibility, and migration costs rather than limited provider availability. These findings indicate that switching frictions may currently be driven more by technical complexity than by structural market constraints.

d. Algorithmic Pricing

A further competitive concern specific to AI markets is the potential for algorithmic pricing systems to facilitate collusion, whether through explicit coordination or through autonomous learning dynamics in which competing algorithms independently converge on supracompetitive pricing equilibria. Unlike traditional collusion, algorithmic pricing may arise without any direct communication between firms, making it difficult to detect and prosecute under conventional competition law frameworks that require proof of concerted practice. Global competition authorities, including the OECD,[183] have begun developing frameworks for examining algorithmic pricing, but enforcement remains nascent. Survey evidence from Survey 3 provides relevant empirical context. A large majority of respondents **(71%)** agreed that the prices or offers shown to them may vary based on timing, demand, or their user profile, indicating that consumer awareness of differential or personalised pricing is already widespread. However, this awareness does not translate into acceptance: only **37%** of respondents considered algorithmically generated pricing to be generally reasonable, while **25%** actively disagreed and a substantial **38%** remained neutral. This three-way split indicates that algorithmic pricing remains a contested dimension of the AI-enabled consumer experience, and that consumer recognition of the

[182] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

[183] OECD (2023), Algorithmic Competition, OECD Competition Policy Roundtable Background Note. Available at: www.oecd.org/daf/competition/algorithmic-competition-2023.pdf

practice is not equivalent to satisfaction with it. These findings suggest that as AI systems become more deeply embedded in pricing mechanisms across sectors, the adequacy of existing transparency and enforcement frameworks will warrant closer scrutiny.

e. Investments, Partnerships and Restrictive Agreements

A distinct structural concern is the growing web of cross-equity investments between major AI developers and cloud infrastructure providers, often accompanied by preferential compute access, distribution agreements, or model exclusivity arrangements. The EC and the CMA have each examined whether such arrangements constitute de-facto mergers or give rise to coordination concerns. Survey 2 reinforces this view from the supply side as **52.8%** of AI startup respondents identified partnerships as a key enabler of product development, ranking it second among all enablers and just ahead of skilled talent **(49.1%)**. Taken together, these findings underscore the dual character of strategic partnerships in AI markets, while they raise concerns at the ecosystem level, they simultaneously function as important mechanisms through which smaller firms gain access to compute resources, engineering expertise, and distribution channels that they could not otherwise secure independently. This duality suggests that any prospective assessment of partnership arrangements should be attentive to their pro-competitive dimensions and should not presume harm from integration alone.

6.2 From Market Analysis to Policy Considerations

The preceding chapters of our study have demonstrated that AI markets are characterised by multi-layered value chains, substantial long-term investment requirements, strong complementarities across inputs, and increasing collaboration between infrastructure providers, model developers, and downstream application firms.[184] These characteristics have enabled the emergence of highly interconnected AI ecosystems in which different firms contribute specialised capabilities across the stack.[185] Taken together, these dynamics shape how firms participate within AI markets, support innovation across layers of the ecosystem, and influence the evolution of competition and technological development over time.

At the same time, our analysis through this paper suggests that AI markets remain very dynamic and technologically fluid.[186] While certain upstream layers such as compute infrastructure and frontier model development exhibit relatively higher concentration due to the scale of investment and technical expertise required in their operations, downstream markets continue to display substantial experimentation, entry, and product differentiation.[187] The increasing availability of open-source models, cloud-based AI services, and API-based deployment mechanisms have enabled a broad range

[184] Competition and Markets Authority, Government of UK. (2023, September 18). AI Foundation Models: Initial Report. https://www.gov.uk/government/publications/ai-foundation-models-initial-report.

[185] Organisation for Economic Co-operation and Development. (2025, November 14). *Competition in artificial intelligence infrastructure.* https://www.oecd.org/en/publications/competition-in-artificial-intelligence-infrastructure_623d1874-en/full-report/component-5.html.

[186] Competition and Markets Authority, Government of UK. (2024, April 11). AI Foundation Models: Updated paper. https://www.gov.uk/government/publications/ai-foundation-models-update-paper.

[187] Stanford University Human Centered AI. (2025). *Artificial Intelligence Index Report, 2025*. https://hai.stanford.edu/ai-index/2025-ai-index-report.

of startups and application developers to participate within the ecosystem without undertaking full-scale model development.[188]

At the same time, AI markets also exhibit features that warrant more attention. Access to compute infrastructure, specialised talent, and high-quality datasets may influence participation across different layers of the AI value chain.[189] Similarly, dependencies arising from cloud infrastructure, model access, and ecosystem integration may shape how firms compete and innovate over time.[190] These dynamics have prompted increasing engagement by competition regulators globally, many of whom have initiated market studies and consultations focused on AI ecosystems.[191]

In the Indian context, this calibrated approach is especially relevant, particularly since India's AI ecosystem is in a developmental and expansionary phase.[192] A phase which is characterised by increasing startup participation, growing enterprise adoption, and expanding public and private investment in digital infrastructure. Competition policy in this context must therefore balance multiple objectives simultaneously, which include preserving incentives for investment and innovation, enabling access to critical inputs, supporting startup participation, and ensuring that market structures remain sufficiently open to permit continued experimentation and downstream innovation.

6.3 Global Lessons and Comparative Regulatory Approaches

Across the globe, antitrust regulators have increasingly recognised that AI markets possess certain structural characteristics that differ from traditional digital markets.[193] As a result, competition authorities across jurisdictions have initiated market studies, consultations, partnership reviews, and policy discussions examining how existing competition frameworks should engage with AI ecosystems, particularly in relation to foundation models, cloud infrastructure, data access, and vertical integration.

The UK's CMA through its work on foundation models, has emphasised that AI ecosystems should be seen and analysed as interconnected systems comprising compute infrastructure providers, model developers, and downstream application firms.[194] The CMA has repeatedly emphasised the importance of continued market monitoring, evidence-led assessment, and preserving dynamic competition within the ecosystem.[195] The CMA has also recognised that open-source models, modular deployment

[188] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.
[189] Competition Commission of India & MDI Gurgaon. (2025, September). *Market Study on Artificial Intelligence and Competition.* https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf.
[190] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.
[191] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.
[192] MeitY, IndiaAI. (2023, October 14). *IndiaAI 2023: Expert Group Report – First Edition.* https://indiaai.gov.in/news/indiaai-2023-expert-group-report-first-edition.
[193] Organisation for Economic Co-operation and Development. (2025, November 14). *Competition in artificial intelligence infrastructure.* https://www.oecd.org/en/publications/competition-in-artificial-intelligence-infrastructure_623d1874-en/full-report/component-5.html.
[194] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.
[195] Competition and Markets Authority, Government of UK. (2024, April 11). *AI Foundation Models: Updated paper.* https://www.gov.uk/government/publications/ai-foundation-models-update-paper.

structures, and API-based access mechanisms may support downstream innovation and broaden participation by startups and smaller firms.[196]

The European Union ('EU') through its antitrust regulator the EC has examined the relationship between generative AI, cloud infrastructure, and digital ecosystems. Discussions have highlighted the importance of monitoring dependencies that may arise from integration across different layers of the AI stack, particularly where firms simultaneously operate as infrastructure providers, model developers, and downstream service providers.[197]

In the United States, regulatory attention has focused on strategic partnerships, infrastructure access, and investments involving AI firms and cloud providers. The FTC and the Department of Justice have both highlighted the importance of preserving competition in emerging AI markets while simultaneously recognising the dynamic and evolving nature of the ecosystem.[198]

Other jurisdictions have similarly adopted exploratory and consultative approaches. The French Competition Authority,[199] the Bundeskartellamt (the German Competition Regulator),[200] and the Japanese Fair Trade Commission,[201] have all emphasised the importance of continued market monitoring, interoperability, and access to infrastructure while recognising that AI markets remain technologically fluid and innovation-driven. Singapore's Competition and Consumer Commission has similarly stressed that AI regulation should remain proportionate and should avoid discouraging innovation or investment in emerging technologies.[202]

Across jurisdictions, several broader lessons emerge from regulatory engagement with AI markets:

- First, regulators increasingly recognise that AI ecosystems are vertically interconnected and cannot be analysed through narrow market definitions alone. Competition authorities across jurisdictions have therefore focused on ecosystem-level relationships involving compute infrastructure, models, cloud services, and downstream applications.[203]
- Second, antitrust regulators have acknowledged the central role of compute infrastructure, data access, and specialised talent in shaping participation within AI ecosystems. Many competition authorities have recognised that the development of frontier AI systems requires substantial

[196] Competition and Markets Authority, Government of UK. (2023, September 18). *AI Foundation Models: Initial Report.* https://www.gov.uk/government/publications/ai-foundation-models-initial-report.
[197] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue. 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.
[198] Khan, L.M. (2024, July 23). Joint Statement on Competition in Generative AI Foundation Models and AI Products. *Federal Trade Commission, Government of United States of America*. https://www.ftc.gov/legal-library/browse/joint-statement-competition-generative-ai-foundation-models-ai-products
[199] Autorité de la concurrence. (2024, June 28). *Generative artificial intelligence: the Autorité issues its opinion on the competitive functioning of the sector.* https://www.autoritedelaconcurrence.fr/en/press-release/generative-artificial-intelligence-autorite-issues-its-opinion-competitive.
[200] Bundeskartellamt. (2025, June 24). *Expert Group on AI and Competition.* https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2025/24_06_2025_Expertenkreis_KI.html.
[201] Japan Fair Trade Commission. (2026, April 16). *Report Regarding Generative AI Version 2.0.* https://www.jftc.go.jp/en/pressreleases/yearly-2026/April/260416.html.
[202] Xinhua. (2026, May 13). Singapore PM calls for balance between AI safety, innovation*. Xinhua Net News.* https://english.news.cn/20260513/278f930f95ef4cf3b9ba3bb0dd237ea7/c.html.
[203] Organisation for Economic Co-operation and Development. (2024, May). *Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.

investment and technical capabilities, which may naturally lead to varying levels of concentration across layers.[204]

- Third, competition authorities have generally distinguished between structural risk and demonstrated harm. While regulators have identified potential concerns relating to foreclosure, self-preferencing, or ecosystem lock-in, most authorities have refrained from concluding that current market structures necessarily justify broad ex-ante intervention. Instead, the prevailing approach has emphasised evidence-based assessment, market observation, and targeted scrutiny where necessary.
- Fourth, several regulators have highlighted the importance of open-source ecosystems and interoperability in expanding access and supporting downstream innovation. Open models, shared tooling frameworks, and API-based deployment have been viewed as important mechanisms for broadening participation and reducing technical barriers for smaller firms.[205]
- Finally, many jurisdictions around the world have emphasised that competition policy alone may not be sufficient to address all AI-related challenges. Several antitrust regulators have therefore stressed the need for coordination between competition regulators, digital regulators, sectoral authorities, standards bodies, and governments more broadly.[206]

These comparative developments can help provide important takeaways, in terms of international best practices that India may draw from. This suggests that regulatory approaches towards AI markets are still evolving globally and that most jurisdictions continue to prioritise flexibility, institutional learning, and evidence-based policymaking rather than immediate structural intervention.

6.4 Way Forward

The findings of this paper, together with emerging international approaches, suggest several policy considerations for India as AI markets continue to evolve.

6.4.1 Maintaining an Innovation-Oriented Regulatory Approach

Understanding the current stage of development of India's AI ecosystem and the overall AI value chain in India, regulatory approaches should remain innovation-oriented and proportionate. AI markets are still evolving rapidly, with significant experimentation occurring across models, applications, infrastructure, and deployment mechanisms. India's policy approach should therefore continue to prioritise ecosystem development, innovation incentives, and technological diffusion. This includes supporting research and development, facilitating startup participation, encouraging public-private partnerships, and expanding digital infrastructure. In particular, policy drivers need to distinguish between conduct that reflects the economics of large-scale technological development and conduct that demonstrably restricts competition. The existence of scale advantages or ecosystem integration alone

[204] Organisation for Economic Co-operation and Development. (2024, May). Artificial Intelligence, Data, and Competition – OECD Artificial Intelligence Papers. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/artificial-intelligence-data-and-competition_9d0ac766/e7e88884-en.pdf.
[205] Bommasani, R. et al. (2021, August 16). On the Opportunities and Risks of Foundation Models, *Center for Research on Foundation Models (CRFM) Stanford Institute for Human-Centered Artificial Intelligence (HAI) Stanford University.* https://crfm.stanford.edu/assets/report.pdf.
[206] Organisation for Economic Co-operation and Development. (2023, September 7). *G7 Hiroshima Process on Artificial Intelligence (AI).* https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/09/g7-hiroshima-process-on-generative-artificial-intelligence-ai_8d19e746/bf3c0c60-en.pdf.

may not necessarily imply anti-competitive outcomes, particularly in markets characterised by rapid innovation and evolving business models.[207]

6.4.2. Expanding Access to Compute Infrastructure

Access to compute infrastructure is likely to remain a central determinant of participation within AI markets. As discussed in earlier chapters, the training and deployment of advanced AI systems require substantial computational resources, particularly for frontier model development. In this context, continued investment in digital infrastructure and cloud capacity will be important for expanding participation within the ecosystem. Potential public policy initiatives aimed at expanding domestic compute access may include support for shared research infrastructure, public compute initiatives, AI-focused cloud credits, and public-private collaboration models. The IndiaAI Mission already reflects movement in this direction through proposals relating to compute infrastructure and AI ecosystem development.[208]

6.4.3. Supporting Open Ecosystems and Interoperability

Open-source models, interoperable tools, and modular deployment systems have played an important role in broadening participation within AI markets. As noted earlier in this paper, many firms operating at the application layer rely on open-source frameworks and cloud-based APIs to develop and deploy AI-enabled services. Regulatory and policy approaches may therefore benefit from supporting open ecosystems and interoperability standards. This may reduce technical frictions for startups and downstream firms while preserving incentives for innovation and investment.[209]

6.4.4. Monitoring Partnerships, Investments, and Ecosystem Integration

Globally, antitrust regulators have increasingly examined partnerships and investment arrangements involving AI firms, cloud providers, and model developers. Such arrangements may influence access to infrastructure, distribution channels, and technological capabilities across the ecosystem.[210] At the same time, partnerships have also played a significant role in accelerating AI development and deployment. Collaboration between infrastructure providers, model developers, and downstream firms has enabled access to compute resources, engineering expertise, and distribution networks that might otherwise be difficult for smaller firms to obtain independently. In the Indian context, the CCI may therefore benefit from continued monitoring of major partnerships, investments, and integration arrangements involving strategically significant AI infrastructure or capabilities.

6.4.5. Strengthening Institutional Capacity and Inter-Regulatory Coordination

AI markets raise technical and economic questions that often extend beyond traditional competition analysis. Assessing AI ecosystems may require understanding machine learning architectures, cloud infrastructure, data governance systems, interoperability standards, and model deployment mechanisms. Accordingly, strengthening institutional capacity within competition authorities and

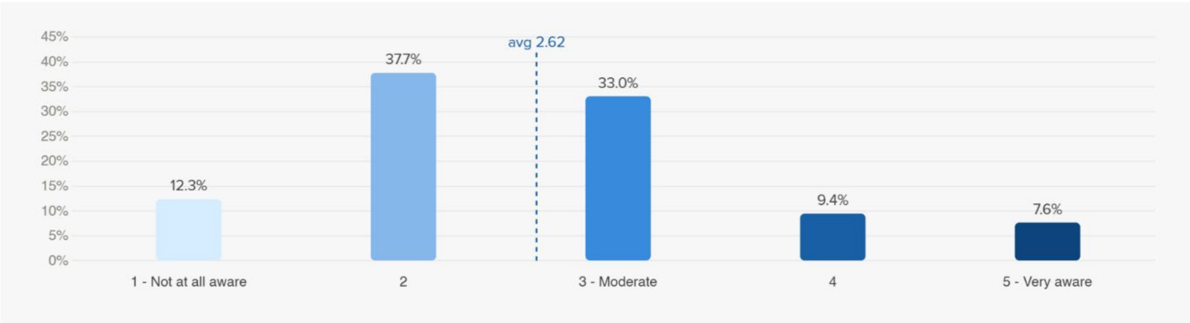
[207] Acemoglu, D. (2024, May 28). The Simple Macroeconomics of AI. *NBER*. https://ssrn.com/abstract=4843046.
[208] MeitY, IndiaAI. (2023, October 14). *IndiaAI 2023: Expert Group Report – First Edition*. https://indiaai.gov.in/news/indiaai-2023-expert-group-report-first-edition.
[209] *Ibid.*
[210] Kowalski, K., Volpin, C. & Zombori, Z. (2024, September). Competition in Generative AI and Virtual Worlds. *Competition Policy Brief, European Commission.* Issue 3. https://competition-policy.ec.europa.eu/document/download/c86d461f-062e-4dde-a662-15228d6ca385_en.

sectoral regulators may become increasingly important. This could include technical expertise development, interdisciplinary research capabilities, and closer engagement with academic institutions and technical experts.

6.4.6 Strengthen Multi-Stakeholder Engagement and Regulatory Awareness

Policymakers should institutionalise regular multi-stakeholder consultations involving industry, startups, academia, civil society, and technical experts to ensure AI regulation remains evidence-based, proportionate, and responsive to evolving market dynamics. At the same time, regulators should strengthen awareness and capacity-building. The survey provides direct evidence on the extent to which India's AI startup ecosystem is currently aware of the regulatory frameworks that govern their activities. Effective regulation depends not only on the quality of rules but also on their visibility to the firms they are intended to govern.

Figure 44: Awareness of laws and regulations governing AI



[Source: Survey 2 —AI Startups and Developers (n=106). Respondents were asked: "How aware are you of the laws, regulations, or regulatory authorities that currently oversee or affect the use of AI in India?". Respondents indicated their awareness on a 5-point scale, where 1 indicated 'not aware at all' and 5 indicated 'very aware'.]

The findings indicate that awareness of AI-related laws and regulatory authorities remains uneven across India's developer ecosystem, with a meaningful share of respondents reporting limited familiarity with existing frameworks. This has two implications for institutional design. First, it underlines the importance of improving regulatory outreach, communication, and sandboxing mechanisms so that startups can navigate the regulatory environment with confidence. Second, it suggests that capacity building should be understood as a two-way task: regulators need deeper technical understanding of AI systems, and developers need clearer visibility into the regulatory landscape in which they operate.

In addition, several AI-related issues intersect with broader domains such as privacy, cybersecurity, financial regulation, telecommunications, and consumer protection. Effective governance may therefore require greater coordination between the CCI, MCA, MeitY, RBI, SEBI, Telecom Regulatory Authority of India ('TRAI'), and sector-specific regulators.

7 | Conclusion

AI and allied markets represent a significant technological and economic transition, with implications that extend across infrastructure, innovation, productivity, and competition. As this paper has demonstrated, AI ecosystems are characterised by layered market structures, substantial investment requirements, strong complementarities across inputs, and increasing interdependence between infrastructure providers, model developers, and downstream application firms. At the same time, the ecosystem remains highly dynamic, with rapid experimentation, evolving business models, and growing participation by startups and downstream developers across sectors.

The findings of our study and accompanying analysis suggests that competition analysis in AI markets requires a broader and more contextual framework than traditional static approaches centred solely on concentration indicators or market shares. Certain upstream segments of the AI stack, particularly compute infrastructure and frontier model development, exhibit higher levels of concentration due to the economics of scale, technical complexity, and long-term investment requirements associated with these activities. However, downstream layers continue to display significant entry, experimentation, interoperability, and product differentiation, supported by open-source ecosystems, cloud-based infrastructure, and API-driven deployment models. These dynamics highlight the importance of assessing AI markets through the lens of dynamic competition, technological evolution, and ecosystem-level interactions.

The comparative analysis undertaken in this paper further demonstrates that competition regulators across jurisdictions have generally adopted cautious, evidence-led, and innovation-oriented approaches towards AI markets. Rather than relying on immediate structural intervention or broad ex-ante obligations, regulators have largely focused on market monitoring, institutional learning, interoperability, transparency, and continued assessment of ecosystem developments. These approaches reflect a broader recognition that AI markets remain technologically fluid and that regulatory responses must remain proportionate to evolving market realities.

In the Indian context, these considerations are particularly significant given the developmental stage of the country's AI ecosystem. India's growing digital infrastructure, startup ecosystem, public digital architecture, and expanding enterprise adoption create substantial opportunities for innovation and technological diffusion. Going forward, competition policy in AI markets may therefore be most effective where it preserves incentives for investment and innovation while simultaneously ensuring that market conditions remain sufficiently open, contestable, and interoperable to support long-term participation, experimentation, and downstream innovation across the ecosystem.

Annexure 1: Sample Stratification

The study draws on primary survey data collected across three distinct respondent groups - Business Users, Consumers, and AI Developers/Startups in order to examine the market dynamics in India’s emerging AI ecosystem. The study comprises **308 completed responses across the three surveys**, representing a diverse cross-section of industries, company sizes, professional backgrounds, and positions along the AI value chain. An overview of each survey's sample composition is set out below.

Survey	Total Respondents
Business Users	102
AI Developers/Startups	106
Consumers	100
Combined Users	308

Section A: Business Users Survey

The Business Users survey targeted professionals and decision-makers at companies actively using or evaluating AI tools in their operations. A total of 102 complete responses were received. Respondents represented organisations ranging from early-stage startups to large multinational enterprises, spanning a wide range of sectors. The survey was distributed digitally, and responses were collected between February and May 2026.

Industry / Sector

Sector	Respondents	Percentage (%)
Technology (Software / Hardware / Services)	32	31%
Financial Services / FinTech	16	16%
Professional Services (Consulting, Legal, etc.)	12	12%
Manufacturing / Industrial	10	10%
Education / EdTech	8	8%
Healthcare / HealthTech / Pharma	7	7%
Media / Entertainment / Advertising	5	5%
Retail / E-commerce	4	4%
Energy / Utilities	3	3%
Logistics / Transportation / Supply Chain	2	2%
Real Estate / Construction / PropTech	2	2%
Hospitality / Travel	1	1%
Total	102	100%

Note: Percentages are calculated based on 102 respondents and rounded to one decimal place.

Technology (Software / Hardware / Services) was the dominant sector at 31% of responses, consistent with the sector's high baseline rate of AI adoption. Financial Services / FinTech (16%) and Professional Services (12%) were the second and third-largest cohorts respectively. The remaining nine sectors collectively accounted for 41% of responses, underscoring the breadth of AI deployment across the Indian economy.

Company Size (Full-Time Employees)

Company Size	Respondents	Percentage (%)
1-10 employees	22	22%
11-50 employees	20	20%
51-250 employees	11	11%
251-1,000 employees	16	16%
1,001–5,000 employees	18	18%
5,001+ employees	15	15%
Total	102	100%

Note: Percentages are calculated based on the 102 respondents who answered this question and rounded to one decimal place.

Micro and small organisations (1–50 employees) together account for 42% of the sample, indicating that AI adoption is not limited to large enterprises. Mid-size organisations (51–1,000 employees) represent 27% of the sample. Large and very large enterprises (1,001+ employees) constitute the remaining 33%, with the 5,001+ band including respondents from companies such as Walmart India, TCS, Capgemini, Cognizant, HCL, Accenture, and HSBC.

Years in Operation

Years in Operation	Respondents	Percentage (%)
Less than 1 year	12	12%
1-3 years	24	24%
4-7 years	26	25%
8-15 years	20	20%
15 + years	20	20%
Total	102	100%

Note: Percentages are calculated based on the 102 respondents who answered this question and rounded to one decimal place.

Early-stage organisations (under 3 years) account for 36% of the sample, reflecting active AI experimentation among India's startup and new-venture ecosystem. Growth-stage organisations (4–7 years) are the single largest cohort at 25%. Mature and established organisations (8 years and above) together constitute 40% of the sample, consistent with enterprise AI deployment typically requiring institutional maturity and capital.

Geographical Distribution

Respondents were located across fifteen cities and four regional clusters.

Region	Respondents	Percentage (%)
North	34	33%
South	32	31%
West	30	29%
East	6	6%
Total	102	100%

Note: Percentages are calculated based on the 102 respondents who answered this question and rounded to one decimal place.

The North and South regions account for the largest shares at 33% and 31% respectively, followed by West at 29%. East India is relatively underrepresented at 6%. At the city level, Bangalore (17%) and Mumbai (15%) lead the distribution, reflecting their status as India's primary technology and financial services hubs. The national capital region i.e., Delhi, Noida, and Gurgaon combined accounts for a further 28% of responses.

Depth of AI Integration

Respondents were asked to characterise the extent of AI deployment within their organisation. Respondents with no AI use and no plans to adopt were screened out of the substantive survey.

- Broad deployment: A majority of respondents reported AI is used across multiple departments.
- Partial deployment: A meaningful proportion reported AI limited to a few departments only.
- Pilot stage: A smaller cohort indicated limited pilots or proof-of-concepts are underway.
- Planned adoption: The smallest qualifying group reported AI adoption is planned but not yet in use.

Section B: Consumer Survey

The Consumer survey was designed to capture individual users' experiences with AI-enabled digital services, their switching behaviour, and their perceptions of competition and fairness in AI markets. A total of 100 valid responses were received, with data collection running between February and May 2026.

Age Group

Age data were collected across five bands.

Age Group	Count	Percentage (%)
18-24	24	24%
25-34	52	52%
35-44	20	20%
45-54	1	1%
55+	3	3%
Total	100	100%

Note: Age data were available for 100 respondents. Percentages are calculated based on respondents who provided age information.

The 25–34 age band is the dominant cohort, accounting for 52% of respondents which captures early-career professionals, entrepreneurs, and graduate students who are intensive users of AI-enabled platforms. The 18–24 band forms the second-largest group at 24%, reflecting strong AI tool adoption among younger users. Together, the two younger bands account for 76% of the sample. Respondents aged 35–44 represent 20%, while those above 45 are minimally represented (4% combined), a demographic limitation acknowledged in the paper.

Geographical Distribution

Consumer respondents were spread across 34 cities and four regional clusters.

Region	Count	Percentage (%)
North	52	52%
South	27	27%
West	13	13%
East	8	8%
Total	100	100%

Note: Percentages are calculated based on the 100 consumer respondents who provided geographical information.

City	Respondents	Percentage (%)
Delhi	22	22%
Bangalore	16	16%
Lucknow	7	7%
Gurgaon	5	5%
Chennai	4	4%
Agra	3	3%
Hyderabad	3	3%
Trivandrum	3	3%
Pune	3	3%
Ahmedabad	3	3%
Kolkata	3	3%
Other cities (24 cities)	24	24%
Total	100	100%

Note: Percentages are calculated based on 100 consumer respondents. "Other cities" comprises respondents across 24 additional cities.

North India dominates the consumer sample at 52%, driven primarily by Delhi (22%), the largest single-city concentration and Gurgaon (5%). South India accounts for 27%, led by Bangalore (16%) and Chennai (4%). The geographic spread across 34 cities, including smaller centres such as Bhimtal, Pilibhit, and Senapati, provides some regional diversity, though the sample skews toward Tier-1 cities.

Professional Background

Respondents self-identified their primary professional status. Students and private sector employees together constituted the large majority of the sample, consistent with the survey's digital distribution channels and the age skew toward the 25–34 and 18–24 bands. Government and public sector employees, self-employed individuals, homemakers, and retired persons were also represented in smaller proportions.

AI Reliance

Respondents rated the extent to which they rely on AI tools in their daily use on a scale of 1 (negligible) to 5 (very high). The mean reliance score across the sample was 3.56, with a median of 4, indicating a moderately high level of AI integration into daily digital routines.

Types of AI-Enabled Services Used

Respondents identified, on a multi-select basis, the types of digital services in which they use AI-powered features.

- General-purpose AI chatbots / assistants (e.g., ChatGPT, Claude, Gemini) — cited most frequently, indicating widespread adoption of standalone AI tools.
- Search engines (e.g., Google Search, Microsoft Bing) — near-universally used, reflecting AI's deep integration into internet search.
- Social media (e.g., Instagram, Facebook, X, LinkedIn).
- E-commerce and online shopping (e.g., Amazon, Flipkart, Myntra).
- Digital payments and banking apps (e.g., Paytm, PhonePe, Google Pay).
- Streaming and entertainment services (e.g., Netflix, YouTube, Spotify).
- Navigation and ride-hailing apps (e.g., Uber, Rapido, Ola).
- Customer service chatbots embedded in enterprise platforms.
- Smart devices and virtual assistants (e.g., Amazon Echo with Alexa, Google Nest).

Section C: AI Developers and Startups Survey

The AI Developers survey targeted founders, engineers, product leads, and strategy professionals at companies building or deploying AI products and services. The survey attracted responses from pure-play AI startups, AI-enabled SaaS companies, and large enterprises with dedicated AI development capabilities. Data collection ran between February and May 2026.

Sector	Mentions (a respondent can select multiple sector)	Percentage (%)
IT Services & Technology	28	26.4%
BFSI	17	16%
Media & Entertainment	15	14.2%
Education	15	14.2%
Healthcare	14	13.2%
Retail / E-commerce	14	13.2%
Manufacturing	11	10.4%
Public Sector / Government	7	6.6%
Logistics	6	5.7%
Telecommunications	5	4.7%
Legal & Professional Services	4	3.8%
Agriculture	2	1.9%
Travel, Hospitality & Mobility	2	1.9%
Total	140	-

Note: Percentages are calculated based on 106 respondents. Respondents could select more than one sector; therefore, the total number of mentions (140) exceeds the number of respondents, and percentages do not sum to 100%.

IT Services & Technology was the most commonly targeted sector (26.4%), followed by BFSI (16.0%). Media & Entertainment and Education each attracted 14.2% of respondents, while Healthcare and Retail / E-commerce were each cited by 13.2%. The distribution across thirteen sectors reflects the horizontal nature of AI product development in India, with few developers targeting a single vertical exclusively.

Geographical Distribution

Region	Count	Percentage (%)
North	44	41.5%
South	38	35.8%
West	23	21.7%
East	1	0.9%
Total	106	100%

Note: Percentages are calculated based on 106 respondents and rounded to one decimal place. Totals may not sum to exactly 100% due to rounding.

Bangalore dominates the AI developer sample at 23.6%, consistent with its position as India’s premier technology and startup hub. The Delhi-NCR cluster, which comprises Gurgaon (17.0%), Delhi (11.3%), and Noida (8.5%) collectively accounts for 36.8% of the sample, making it the largest regional concentration. Mumbai (13.2%), Hyderabad (6.6%), Chennai (5.7%), and Ahmedabad (5.7%) round out the primary centres.

Core AI Technologies and Applications

Respondents identified, on a multi-select basis, the AI technologies and applications they are currently developing or deploying.

- LLMs for services and tools: The most frequently cited technology, consistent with the recent wave of generative AI deployment.
- Predictive Analytics and Forecasting: The second most common, reflecting its established position across enterprise verticals.
- Generative AI (images, video, audio) and AI Infrastructure / Tooling: Also widely cited.
- Natural Language Processing (excl. LLMs), Computer Vision, and Speech Recognition / TTS: Reported by a meaningful subset.
- Foundation Model development and Robotics / AI for physical systems: Less commonly cited but present, indicating an emerging base of frontier AI activity in India.

Position Along the AI Value Chain

Respondents identified the layers of the AI stack at which their organisation operates.

- Downstream Applications: The most commonly cited layer (chatbots, analytics, sector-specific AI products), indicating that the majority of Indian AI developers are deploying at the application layer.
- Model Deployment (APIs, SaaS platforms) and Model Fine-tuning and Alignment: The next most common operational layers.
- Data Infrastructure (warehouses, pipelines, curation, synthetic data): Cited by a significant share.
- Infrastructure — Software and Tools (cloud platforms, MLOps): Reported by a smaller cohort.
- Infrastructure — Hardware (chips, accelerators, servers): The least commonly cited layer, consistent with India's current reliance on imported compute hardware.

Compute Infrastructure

Public cloud services dominated as the primary compute infrastructure, with a large majority of respondents relying on providers including AWS, Google Cloud, Microsoft Azure, and NVIDIA-hosted offerings. Proprietary hardware and on-premises infrastructure were used by a smaller proportion, typically larger or more specialised organisations. Government compute infrastructure was cited by a minimal number of respondents, reflecting the early stage of India's public AI compute initiatives.

Open-Source Reliance

Respondents rated their reliance on open-source AI tools for internal development on a scale of 1 (not reliant at all) to 5 (very reliant), with results indicating a high degree of dependence on open-source tooling across the developer community. Commonly cited open-source models and frameworks included LLaMA (Meta), Mistral, Qwen (Alibaba), DeepSeek, Gemma (Google), Falcon, and the Hugging Face Transformers ecosystem. A majority of respondents indicated that open-source tools are at least partially viable substitutes for proprietary models.

Awareness of AI Regulation in India

Respondents rated their awareness of laws, regulations, or regulatory authorities currently governing AI in India on a scale of 1 (not aware at all) to 5 (very aware). The mean awareness score was 2.64, with a median of 3, indicating a below-average level of regulatory awareness across the sample — a finding of direct relevance to the paper's assessment of the Indian regulatory landscape for AI competition.

Methodology Note

All three surveys were administered digitally via SurveyMonkey and distributed through targeted outreach to industry networks, professional associations, and academic communities. Sampling followed a purposive approach, targeting individuals with direct experience of AI use, deployment, or development in the Indian context. Responses were cleaned to remove duplicates and incomplete submissions prior to analysis. Percentage distributions for individual demographic variables are presented in the tables above. As with any purposive sample, the findings are not statistically representative of the full population of Indian businesses, consumers, or AI developers; they are intended to provide directional empirical grounding for the qualitative and comparative analysis in the paper.

Annexure 2: Key Metrics and Standard Deviation

AI Startups & Developers Survey

Metric	Coding	n	Mean	SD	Interpretation
Switching-ease score (switchers only)	1–5 (5=easy)	41	3.2	0.87	Switching leans slightly easy on balance, but most sit near neutral with moderate spread
Reliance on open-source AI tools	1–5 (5=high)	106	3.75	0.99	Reliance is high on average, with broad agreement but moderate variation in intensity
Awareness of AI laws/regulators	1–5 (5=high)	106	2.62	1.06	Awareness sits below the midpoint (limited) and is the most divided of the native-scale items
Open-source a viable substitute	−1..+1	106	0.19	0.42	Near-unanimous that open-source is at least a partial substitute; tightest consensus in the table
High-quality data is accessible	−2..+2	106	0.47	1.07	Mild net agreement that quality data is accessible, but opinion is moderately divided
High-quality data affordable	−2..+2	106	0.2	1.15	Barely net-positive on affordability, with wide disagreement across respondents
Sufficient options for high-quality data	−2..+2	106	0.37	1.03	Slight net agreement that options exist, with opinion moderately split
Govt datasets available & easy to access	−2..+2	106	−0.47	1.03	Net disagreement that government datasets are accessible, moderate spread
Compute resources are affordable	−2..+2	105	0.09	1.2	Essentially neutral on compute affordability, and the most divided item in the set
Sufficient compute provider options	−2..+2	106	0.92	1.06	Clear net agreement that provider options are sufficient, with moderate spread
Infra providers vital to compete	−2..+2	106	0.96	0.94	Strong net agreement that infra providers are vital, with relatively tight consensus
Able to negotiate commercial terms	−2..+2	105	0.1	0.98	Near-neutral on ability to negotiate; a large share sit on the fence

Sufficient pricing transparency	−2..+2	105	0.61	0.85	Net agreement that pricing is transparent, and the tightest consensus among the Likert items
Forced into buying additional services	−2..+2	106	−0.78	1	Net disagreement that they were forced into extra purchases (a favourable result), moderate spread

AI Business User Survey

Metric	Coding	n	Mean	SD	Interpretation
AI adoption stage	1–4 (4=broad)	102	3.13	1.03	Adoption sits between "few departments" and "broad", fairly advanced on average, with moderate spread along the ladder
Competitive impact score	1–5 (5=positive)	102	3.51	1.13	Impact rated clearly positive on balance, with moderate spread
Cost of AI is reasonable	−2..+2	102	0.62	1.08	Net agreement that cost is reasonable, moderate spread
Satisfied with quality & range	−2..+2	102	0.61	1.14	Net agreement on satisfaction, but the most divided of the Q5 statements
Easy to switch AI providers	−2..+2	102	0.34	1	Only mild net agreement that switching is easy; many sit neutral (40 "neither")
AI has not significantly impacted	−2..+2	102	−0.87	1.15	Strong net disagreement, i.e. AI has meaningfully impacted their business (favourable), though opinion is spread
Provider transparency score	1–5 (5=very)	102	3.03	1.04	Transparency rated right at the midpoint (neutral), with moderate spread

AI Consumer Survey

Metric	Coding	n	Mean	SD	Interpretation
Reliance on AI tools	1–5 (5=high)	100	3.57	1.07	Reliance above midpoint (fairly high), moderate spread
Confidence identifying AI content	1–5 (5=high)	100	3.35	1	Confidence modestly above midpoint, moderate spread
Trust AI to meet goal	1–5 (5=high)	100	3.18	0.95	Trust just above neutral, tightest of the three native scales
Easy to opt out of AI features	−2..+2	100	0.07	1.13	Essentially neutral on opting out; opinion split
Several alternatives available	−2..+2	100	0.65	1.05	Net agreement that alternatives exist, moderate spread

Easy to switch services	−2..+2	100	0.59	1.09	Net agreement switching is easy, moderate spread
Prefer pre-installed / default AI	−2..+2	100	−0.03	1.27	Neutral on default preference, among the most divided items
Integration improved experience	−2..+2	100	0.86	1.03	Clear net agreement that integration improved experience
Task determines standalone/embedded	−2..+2	100	1.06	0.98	Strongest agreement in the set. task drives choice, relatively tight consensus
Use multiple AI services, move easily	−2..+2	100	0.55	1.23	Net agreement but widely spread
Rely on AI recommendations	−2..+2	100	0.34	1.12	Mild net agreement on reliance, spread
Control over personalisation	−2..+2	100	0.14	1.08	Near-neutral on feeling in control, divided
Prices may vary by timing etc	−2..+2	100	0.76	0.88	Net agreement prices vary; tightest consensus among Likert items
Algo pricing is reasonable	−2..+2	100	0.09	1.04	Neutral on whether algorithmic pricing is reasonable, divided
Satisfied with range available	−2..+2	100	0.43	1.05	Mild net satisfaction with range
Prefer integrated AI features	−2..+2	100	0.42	1.14	Mild net preference for integrated features, spread
AI uses more of my data	−2..+2	100	0.79	1.12	Net agreement AI uses more data than other services
Personalisation benefits reasonable	−2..+2	100	0.29	1.16	Mild net agreement benefits justify data use, divided
Enterprises transparent on AI	−2..+2	100	−0.38	1.14	Net disagreement that enterprises are transparent (unfavourable), spread
Comfortable w/ cross-service data	−2..+2	100	−0.08	1.29	Neutral overall, but the single most divided item, comfort with cross-service data splits respondents sharply
Data awareness	1–4 (4=very)	100	3.09	0.75	Awareness between "somewhat" and "very aware," tightest consensus in the table
Overall experience	−2..+2	100	1.06	1.03	Net positive: most say AI improved their experience, moderate spread

Authors

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Bhoomika Agarwal is a Programme Manager at The Dialogue, working across competition law and AI policy, where she has played a key role in strengthening the organisation's competition policy vertical. She has authored and contributed to several research reports, white papers, and policy briefs addressing regulatory challenges in the technology ecosystem, with her work spanning digital markets, e-commerce, and data protection. With a strong legal background and experience through voluntary engagements with organisations such as Amnesty International and the United Nations, Bhoomika is driven by a deep commitment to advancing informed and forward-looking tech policy discourse.

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