WHITE PAPER

GenAI for Business: Insights from India

Authors:
Dr. Lina Sonne Vyas
Vrushank Arur

Desai Sethi School of Entrepreneurship (DSSE),
Indian Institute of Technology – Bombay.

January, 2026

Executive Summary

Generative Artificial Intelligence (GenAI) has rapidly transitioned from a futuristic concept to a foundational business imperative for Indian organisations, driving a strategic necessity for immediate implementation. This white paper documents the practical strategies, key enablers, and critical barriers faced by Indian firms as they move GenAI from experimentation into scalable production. Grounded in 30 in-depth stakeholder interviews and a review of contemporary literature, this research aims to equip business leaders and policymakers with clear guidance to navigate this AI transition

The Context and Landscape

The Government of India is strengthening the ecosystem through the IndiaAI Mission, prioritising massive public investment to build AI Sovereignty and ensure compute power is accessible. India's Sovereign AI push is focused on developing indigenous Large Multimodal Models to cater to the country's language diversity. Currently, there is no dedicated AI Act; instead the regulatory framework relies on a number of existing laws related to digital privacy and information technology.

Drivers and Implementation

The primary motivations for GenAI adoption are operational improvement, cost savings, and remaining competitive. Implementation is generally concentrated in functional areas that offer immediate efficiency gains.

Critical Barriers to Scaling

Implementation of GenAI is hampered by significant practical barriers:

1. **Data Deficiencies**: Poor data quality and the inaccessibility of data locked in fragmented silos
2. **Infrastructure and Cost**: The high cost of required GPUs and specialised cloud computing
3. **Talent Shortage**: Lack of AI engineers and those that know intersection of business and AI
4. **Organisational Resistance**: Resistance to change stalls implementation
5. **Regulatory Ambiguity**: Evolving legal landscape creates compliance risks and uncertainty.

Responsible AI

Establishing robust AI governance is a critical component to mitigate risks like bias, opacity, and IP exposure. This requires maintaining a "Human-in-the-Loop" to continuously monitor outputs and ensure the maxim of "Delegate, but Validate" is strictly enforced. Governance structures should include ethical policies, accountability through dedicated AI team and mechanisms.

Framework for Implementation

We provide a six-step hands-on guide to walk businesses through the implementation of AI solutions from initial preparation to long-term maintenance: **Prepare:** Align strategy with business goals and assess data, skill, and financial readiness; **Identify:** Gather insights across all levels of the organisation to pinpoint bottlenecks and potential use cases; **Validate:** Score projects based on business value versus technical and regulatory feasibility; **Select:** Choose a priority pilot project with clear success criteria and define the tech stack; **Deploy:** Focus on change management, educating employees, and initiating an iterative rollout; **Optimise:** Monitor performance, quantify ROI, and expand.

Implications for Policy, Practice and Academia

To drive GenAI success in India, stakeholders must collaborate to strengthen digital infrastructure, skilling, and ethical governance. Key priorities include launching MSME-specific support, incentivising R&D for local challenges, and overhauling curricula to bridge the talent gap. Implementing clear regulatory frameworks and industry-led knowledge networks will help ensure an inclusive transition.

About Authors

Dr. Lina Sonne Vyas

Dr. Lina Sonne Vyas is Associate Professor of Innovation & Entrepreneurship at the Desai Sethi School of Entrepreneurship, IIT Bombay, Mumbai India. She teaches and researches on innovation and entrepreneurship for societal good; digitisation & AI in business & society, and entrepreneurial ecosystems. She was previously Associate Professor at FLAME University, Pune, and at O.P. Jindal Global University, NCR. Before that she set up and ran Inblick Innovation Advisory in Mumbai 2017-2021, where she undertook consulting and advisory projects on digitisation, social innovation and entrepreneurship. Earlier, she built a research and consulting portfolio on innovation and entrepreneurship for social impact at Okapi Research & Advisory, Mumbai, co-led research at Intellecap, Mumbai; and was Assistant Professor at Azim Premji University, Bengaluru. Prior to moving to India, she was a researcher on innovation and technology policy with UNU-MERIT, the Netherlands. She holds a PhD in Economics of Innovation from UNU-MERIT, Maastricht University, Netherlands; an MSc in Business Economics from City, University of London; and a PG Diploma in Modern & Contemporary Indian Art History from the Bhau Daji Lad Museum, Mumbai. She has led cross-sectoral projects in multiple Asian countries and collaborated with partners across academia, government, think-tanks, nonprofits, industry and multilateral organisations.

Corresponding Author: linasonnevyas@iitb.ac.in

Vrushank Arur

Vrushank Arur is a Project Research Assistant at the Desai Sethi School of Entrepreneurship (DSSE) at IIT Bombay. His research focuses on the adoption and practical industry impact of Artificial Intelligence and Generative AI on Indian enterprises. Holding a B.E. in Electronics and Computer Science, he is committed to pursuing a long-term academic and research career focused on the dynamic intersection between technology and business strategy. Vrushank has also contributed to technology discourse as a panellist at the Agile Mumbai 2025 conference and was involved in organising and anchoring TEDx events for multiple years.

Acknowledgments

We extend our sincere gratitude to all those who contributed to this white paper. Our deepest thanks go to the Desai Sethi School of Entrepreneurship (DSSE) for providing continuous institutional support, and especially to the DSSE Administration and HOD Prof. Trupti Mishra, whose endorsement were invaluable to this project. We are thankful to Prof. Ramesh Kuruva for generously providing essential contacts. We also deeply appreciate the research participants (interviewees) for dedicating their time and sharing their insights. Finally, we acknowledge the support from IIT Bombay and thank the Industrial Research & Consultancy Centre (IRCC) for providing the research internship opportunity that kick-started the study on which this paper is based.

Table of Contents

1. Introduction 4
2. Context: The AI Landscape in India 6
   2.1. History – An AI Timeline 6
   2.2. AI Infrastructure: A Taxonomy 7
   2.3. The Government Regulation and Policy 9
      2.3.1. Regulatory 9
      2.3.2. IndiaAI Mission 10
      2.3.3. India's Sovereign AI Push 11
   2.4. India's Dual Ecosystem: Global vs. Local Infrastructure 12
3. How Businesses are Thinking about AI 13
   3.1. AI Awareness, Knowledge and Digital Literacy 13
   3.2. Motivations and Drivers of AI Adoption 15
   3.3. Decision-Making Regarding GenAI Strategy and Implementation 16
   3.4. AI Readiness 16
4. AI Solutions Businesses are Implementing 18
   4.1. What do we know about what Indian businesses are implementing? 18
   4.2. GenAI Touch Points: What Can Businesses Implement? 19
   4.3. Types of AI Solutions 23
5. Responsible AI: Importance of Governance and Ethics 25
   5.1. Responsible AI: Insights from Interviews 25
   5.2. Responsible AI: Best Practices 26
6. Barriers and Challenges 28
7. Framework: AI Implementation Journey 30
8. Implications for Policy, Practice and Academia 33
   8.1. For Government and Policymakers 33
   8.2. For Industry Bodies and Ecosystem Stakeholders 34
   8.3. For Research, Education, and Skilling 35
9. Conclusion 36
References 37
Appendices 40
   Appendix 1: Interviewee Description 40
   Appendix 2: List of Figures, Boxes and Tables 41
   Appendix 3: IndiaAI Mission Pillars (Additional Information) 42

1. Introduction

In the rapidly evolving landscape of the global economy, Generative Artificial Intelligence (GenAI) has transcended its status as a futuristic concept to become a foundational business imperative. For Indian enterprises, the conversation has moved beyond experimentations and proof of concepts to immediate operational implementation. Across India's diverse industrial and business fabric, companies are no longer merely exploring GenAI; they are actively deploying it to automate customer engagement, hyper-personalise marketing, and accelerate software development.

As India positions itself as a global digital powerhouse, the strategic adoption of GenAI offers a singular opportunity to unlock unprecedented productivity, foster indigenous innovation, and sharpen the country's competitive edge. Given India's unique business landscape, defined by its complexity, vast scale, and diversity, AI implementation is fundamentally shaped by the need to navigate intricate local contexts, achieve massive scalability, and cater to the market's distinct preference for frugal, value-driven solutions.

Central to this transformation is the urgent need for Sovereign AI. For Indian businesses, developing and maintaining control over local data, indigenous models, and domestic infrastructure is not just a matter of technological pride but a strategic necessity to ensure data security and cultural relevance. Understanding AI at this critical juncture is no longer optional; it is the dividing line between market leadership and obsolescence.

The primary objective of this white paper is to take stock and provide a clear and practical understanding of how Indian businesses are currently thinking about and approaching the implementation of GenAI.

In addition, a key contribution is the introduction of a step-by-step framework designed to guide Indian business leaders through the complexities of AI integration. This practical "how-to" guide serves as a manual for navigating the transition from discovering AI implementation use cases to deploying and optimising AI solutions.

By blending theoretical depth with practice-relevant insights, this paper serves three core functions:

1. Delivering deep insights into what Indian businesses are implementing and the specific hurdles they face.
2. Providing a unique implementation framework that acts as a strategic roadmap for enterprises at any stage of their AI journey, together with an introduction and overview of AI technology and implementation solutions.
3. Informing policy and practice by equipping enablers and policymakers with a clear-eyed view of the foundational challenges within the Indian context.

This paper bridges the gap between academic rigour and industrial practice. It is grounded in a robust qualitative methodology, with 30 in-depth interviews with a representative sample of stakeholders involved in AI implementation in businesses, including implementation agencies, consultants, startup founders, business leaders, and policy architects. These interviews provide rich and granular, behind-the-scenes insights into the implementation paths being carved out and the challenges encountered on the ground. By combining these first-hand accounts with secondary data from literature published in 2024 and 2025, this research offers a sophisticated, nuanced view of the ecosystem that a purely quantitative study might overlook.

The research draws on a comprehensive review of contemporary literature on the deployment of AI in Indian business context, drawing on work from government like NITI Aayog (2025a, 2025b) and MeitY (2025), key industry agencies such as NASSCOM (2025a, 2025b) and CII (2024), major consultancies (Boston Consulting Group [BCG], 2025c; Ernst & Young [E&Y], 2025), and think-tanks like ORF (Nandi et al., 2025) and the World Economic Forum (WEF, 2025).

The mixed methods approach enabled us to explore what businesses know about GenAI, how they are strategically considering it, their current implementation status, and the associated challenges they face. While the review of recent literature combined with the in-depth interviews offer rich, granular insights, they are intended to provide a qualitative depth rather than a statistical generalisation of the entire Indian industry. This white paper serves as the inaugural output of a larger, ongoing study; as such, these findings represent an initial yet vital exploration of a rapidly evolving landscape, with further comprehensive papers and other output to follow as the research matures.

In conducting our research, we also leveraged GenAI tools to assist in transcribing recorded interviews, analysing a portion of the qualitative data, and editing the final text. While leveraging GenAI tools, the heart of this work remains the nuanced interview data gathered from the field.

The rest of the paper is structured as follows: Section 2 sets out context, history and landscape of GenAI in India. Section 3 discusses AI awareness, literacy levels, and the motivations and decision-making drivers of GenAI adoption. Section 4 details what Indian businesses are implementing, and offers an overview of AI solutions across business functions. Section 5 discusses the importance of responsible AI, while Section 6 reviews barriers and challenges to implementing GenAI. Section 7 provides a practical "how-to" guide for thinking through GenAI, while Section 8 offers recommendations for industry, academia and policymakers.

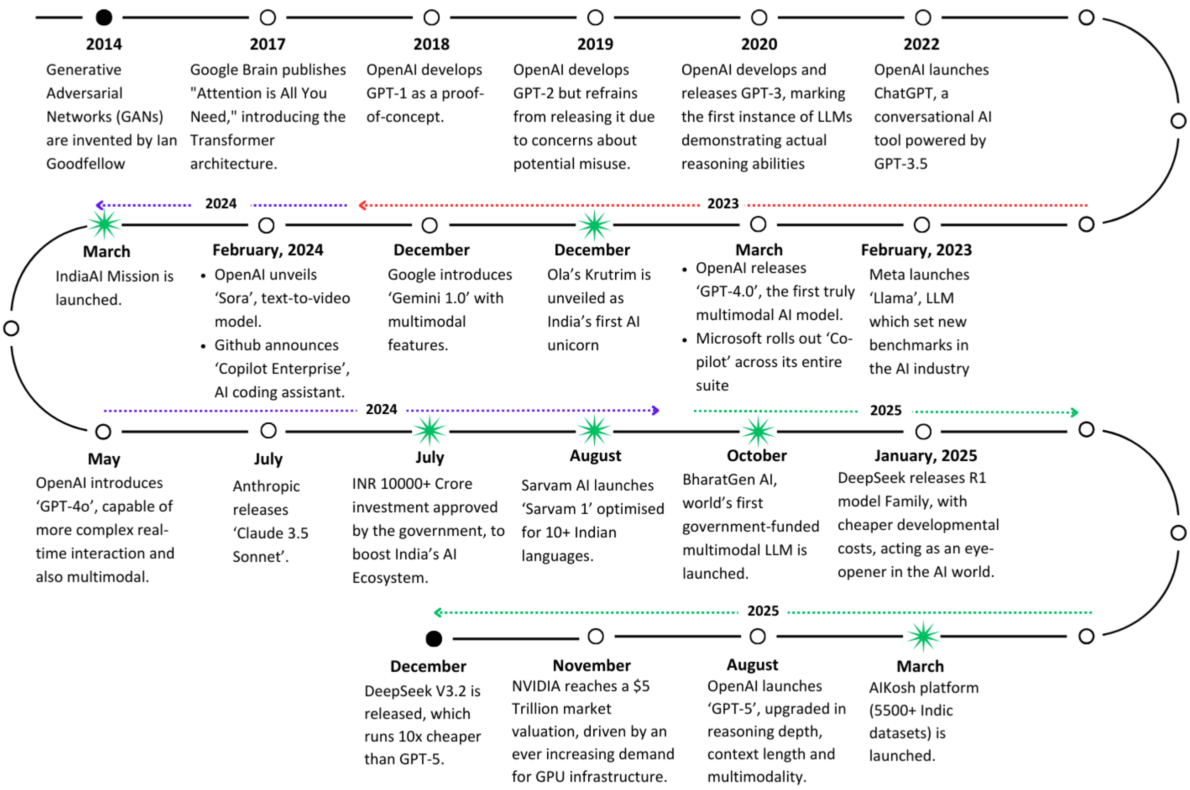
2. Context: The AI Landscape in India

In this section we provide the context to GenAI in India. We describe the evolution of GenAI before explaining the GenAI tech-stack, and discussing the GenAI landscape in India including the role and focus of the government.

2.1. History – An AI Timeline

The rapid evolution of GenAI stems from a foundational push in the last decade. In 2014, Ian Goodfellow invented Generative Adversarial Networks (GANs), which served as the first robust building blocks for models that could create entirely new, realistic content, providing a critical early framework (Goodfellow et al., 2014). The genuine acceleration point for modern GenAI came in 2017 with a Google research paper titled “Attention is All You Need” (Vaswani et al., 2017). That paper introduced the Transformer architecture. This innovative framework, which efficiently processes data in parallel and leverages 'attention mechanisms', is the key technological foundation behind all the powerful new models like GPT, Claude, and Gemini. OpenAI was the first to fully grasp the importance of scaling these Transformer models. By continually increasing the size of the architecture and, critically, feeding them vast amounts of data and computing power, they made a profound discovery: the models suddenly developed advanced, emergent skills. This realisation that scale unlocks capability completely changed the future trajectory of AI development.

Figure 1: AI to GenAI – A Timeline



Source: Author’s own

Following this discovery, the Large Language Model (LLM) era formally began. Companies focused on making the Transformer architecture immense, utilising massive datasets and processing power. This effort resulted in models possessing astonishing abilities: they could write creatively, generate functional computer code, and handle complicated questions requiring deep contextual understanding. When models like the GPT series were released, the general public saw that AI could hold natural, fluid conversations, follow complex and detailed instructions, and perform many different jobs from a single request. This momentous public release brought AI out of the research lab and directly into the hands of millions. This accessibility led to huge investments and intense industry competition, causing the quality, size, and speed of these models to rapidly improve.

The success of the GPT models created a highly competitive environment dominated by proprietary systems, but this quickly spurred a new wave of major players. Anthropic, founded by former OpenAI researchers in 2021, joined the race, launching its Claude model in March 2023. Google, a founding father of the Transformer, formally entered the flagship race with its Gemini models, the first of which was announced in late 2023.

This period also saw a significant and deliberate shift from purely proprietary to an increasingly open-source landscape. While companies like OpenAI and Anthropic largely kept their most powerful models closed behind APIs, the momentum for open-source AI gained critical mass with Meta's release of the LLaMA models (Touvron et al., 2023). LLaMA was released under a permissive license, allowing researchers and developers to freely access, modify, and deploy the model. This move democratised LLM technology, enabling global communities and smaller startups to innovate rapidly without the enormous computational cost of training a model from scratch. DeepSeek rose to prominence in early 2025 by releasing models that matched the performance of frontier systems while being openly accessible. They achieved this with lowered computational costs, thus challenging the idea that only Silicon Valley's massive capital could build top-tier AI.

The focus then quickly expanded beyond just text to multimodal AI. These newer models can work smoothly to create and process text, images, code, and video, all within a single architecture. Currently, the biggest leap is into agentic AI. This signifies a shift where the AI systems are becoming increasingly autonomous, including gaining the capability to plan complex actions, and carry out multi-step tasks across different applications.

As we hint at in Figure 1, India has seen significant development with respect to AI in the last couple of years, something that we will discuss in some detail in sections 2.3 and 2.4.

2.2. AI Infrastructure: A Taxonomy

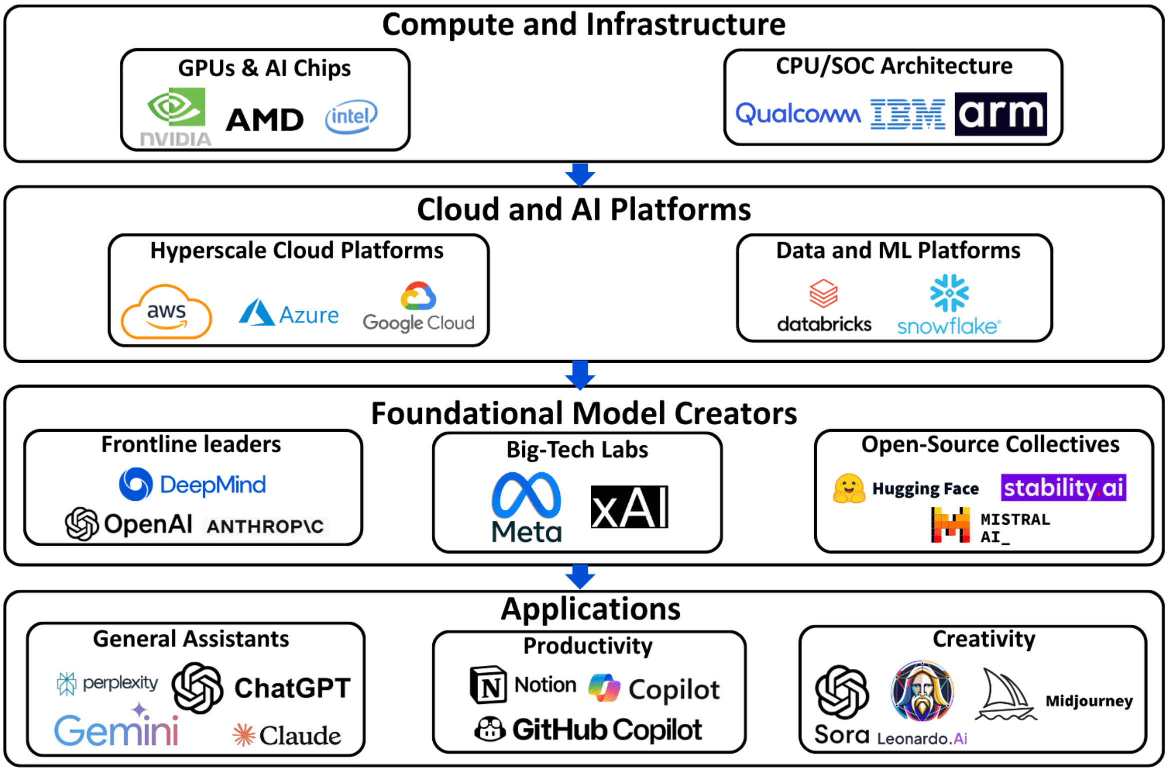
The GenAI ecosystem is best understood through a layered, stack-like taxonomy, ranging from the foundational hardware at the back to user-facing applications at the front. This structure illustrates how various technologies and companies collaborate to deliver GenAI capabilities. While a deep dive into the technicalities may not be necessary for everyone, businesses must grasp the fundamental layers of the AI solutions they deploy. Each layer carries significant cost implications; understanding this hierarchy is essential for evaluating the unit economics of AI, whether you are opting for an off-the-shelf, "plug-and-play" solution or a fully custom-built one. Recognising where these costs reside within the tech-stack allows for more accurate budgeting and strategic implementation. We will explore implementation models and tech-stack options further in Section 4.

The foundation of the entire ecosystem is the Compute and Infrastructure layer. This layer provides the raw processing power required to train and run large AI models and is segmented into three main components. First, there are the Graphics Processing Units (GPUs) and AI Chips, manufactured by companies like NVIDIA and AMD. These specialised processors are essential for parallel processing in deep learning. Parallel processing in AI is a technique that breaks down a complex computational task into many smaller parts, which are executed simultaneously across multiple processing units, such as GPU cores, to achieve dramatically faster computation. Second is the Central Processing Unit (CPU) or

System on Chip (SoC) Architecture, involving firms like Intel and ARM, which design the central architecture that coordinates the entire system's operations.

Moving forward, the next layer is Cloud and AI Platforms, which makes the underlying infrastructure accessible and scalable for widespread use. This layer is broadly divided into two segments. The first is Hyperscale Cloud Platforms, such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud, which provide massive and on-demand computing power, often hosting the GPUs discussed in the previous layer. Hyperscale refers to the ability of a computing infrastructure to massively and seamlessly scale resources, including processing, memory, and storage, to meet huge and rapid increases in demand. These platforms offer essential resources to companies that cannot afford to build or maintain their own data centres. Complementary to this are Data and Machine Learning (ML) Platforms from companies like Snowflake and Databricks. These platforms specialise in managing the vast datasets required to train AI models and provide the specialised tools necessary for ML workflows, model governance, and deployment.

Figure 2: GenAI Infrastructure Taxonomy



Source: Author's own.

Next are the Foundational Model Creators, who are the core innovators developing the AI itself. This is the layer where the largest, general-purpose models, often called Foundation Models, are built and trained. This segment includes: Frontline Leaders like OpenAI, Anthropic, and DeepMind, who pioneer state-of-the-art closed models; Big-Tech Labs such as Meta (with LLaMA) and xAI (with Grok, pioneered by Elon Musk), who leverage vast internal resources to develop competitive models; and Open-Source Collectives like Mistral, Hugging Face and Stability AI, which foster a community-driven approach to model development and sharing. These foundational models are essentially the 'brains' that drive the final user applications.

The final layer is Applications, which is what end-users interact with daily. This layer utilises the foundational models to create tangible products tailored for specific uses. It is commonly categorised by function. General Assistants like ChatGPT, Gemini, and Perplexity serve as broad conversational and research tools. Productivity applications from entities like Notion and Coda integrate AI into work streams, often assisting with summarisation, writing, or coding (for example, GitHub Copilot). Finally, Creativity applications, including tools like Sora, Leonardo.AI and Midjourney, focus on generating new images, video, and other multimedia content. This front layer represents the value delivery point for the entire GenAI ecosystem.

2.3. The Government Regulation and Policy

The Government of India's foundational strategy for AI is driven by the vision of positioning the country as a global AI leader and leveraging technology for economic growth, governance, and societal progress, aligning with the goal of *Viksit Bharat* by 2047.
The government's AI strategy is two-fold: Massive public investment in foundational infrastructure and an AI ecosystem where computing power, GPUs, and research opportunities becomes accessible at an affordable cost.

There is focus on a pragmatic AI regulation which balances innovation and accountability.
The strategy is anchored by the IndiaAI Mission and the coordinated efforts of various governmental institutions (Ministry of Electronics and Information Technology [MeitY], 2025a).

2.3.1. Regulatory

Currently, India does not have a dedicated law regulating AI. Instead, regulation of AI relies on a patchwork of existing laws and forward-looking policy frameworks. The Digital Personal Data Protection Act (DPDPA), 2023 and the Information Technology (IT) Act, 2000 are the primary legal pillars through which regulation is enforced. IT Rules, 2021, passed under the IT Act, regulate social media platforms and other intermediaries (which include GenAI platforms).

The IT Act is India’s primary legislation that governs electronic transactions, digital governance, and cybersecurity. Although it was enacted before AI technologies came to the forefront, several provisions in the IT Act apply to AI related activities.

Box 1: Sections Relevant to AI

- **Section 43A:** This section allows for compensation if a breach of data privacy occurs due to careless management of sensitive personal data. AI systems handling user data must comply with this rule to prevent legal liability.
- **Section 66D**: This section imposes penalties on individuals who commit fraud through impersonation using a computer resource. It applies significantly to AI-powered deepfakes and other digitally generated fraudulent material.
- **Section 67:** This provision forbids the electronic publication or transmission of obscene material. AI tools that can produce inappropriate or damaging content may be covered by this section.

Source: Author's own, based on information from India Code (Parliament of India, n.d.).

The DPDPA, which was notified on August 11, 2023, is being rolled out in a phased manner. It lays down a complete set of rules for protecting personal data across India. It holds significant importance for AI systems as it governs how personal data can be collected, stored, processed, and shared. The DPDPA's most substantial influence is on the data utilised for training AI models. As part of the DPDPA, the Data Protection Board of India (DPBI) will be constituted. The DPBI will function as the central enforcement authority and will be vested with powers of inquiry and investigation equivalent to those of a Civil Court. In addition, prominent regulators like the Reserve Bank of India (RBI), the Securities and Exchange Board of India (SEBI), and the Insurance Regulatory and Development Authority of India (IRDAI) have formulated internal and external policies to bring in sectoral regulation concerning AI.

Lastly, Intellectual Property (IP) and the use of proprietary data, information, and images remain significant grey areas in the context of GenAI. This ambiguity persists across two fronts: first, the legality of using proprietary datasets to train or fine-tune AI models; and second, the ownership and copyright status of the content generated by these systems. Under the Copyright Act, 1957, Indian law traditionally attributes authorship to a "natural person," leaving the status of AI-generated works unsettled. We discuss this and other aspects of responsible AI in further detail in Section 5.

2.3.2. IndiaAI Mission

The IndiaAI Mission is India's flagship initiative designed to accelerate growth of a responsible and inclusive AI ecosystem and position India as a global AI powerhouse (E&Y, 2025). The Mission is spearheaded by the Ministry of Electronics and Information Technology (MeitY, 2025a).

India's massive digital leap and widespread adoption of its digital public infrastructure have laid a robust foundation for an advanced AI ecosystem. With foundational platforms like Aadhaar, UPI, DigiLocker, and the Open Network for Digital Commerce (ONDC), the country already possesses an interconnected technological backbone (MEITY, 2025a). Coupled with over a billion internet users and extensive smartphone penetration (Telecom Regulatory Authority of India [TRAI], 2025), India generates an immense volume of data—the essential fuel needed for training sophisticated AI models.

The IndiaAI Mission, launched with the clear objective of positioning India as a global leader in AI, adopts a collaborative, partnership-based approach to minimise entry barriers for developing and deploying 'Made in India' AI solutions.

As noted in Table 1, the IndiaAI Mission is structured around seven core pillars which are critical components necessary for establishing a complete AI ecosystem (NITI Aayog, 2025a; NASSCOM, 2025a). These pillars include the IndiaAI Compute Capacity, which focuses on building scalable and affordable high-end computing infrastructure using GPUs via public-private partnerships; the IndiaAI Innovation Centre, dedicated to developing and deploying indigenous Large Multimodal Models (LMMs) and domain-specific foundational models tailored for Indian languages and context; and the AIKosh (Datasets Platform), which serves as a unified hub for high-quality, non-personal datasets essential for training innovative AI models.

Table 1: IndiaAI Mission Pillars

Pillar	**Objective**
IndiaAI Compute Capacity	Democratises access to high-end, scalable AI computing infrastructure for startups, academia, and researchers.
IndiaAI Innovation Centre	Focuses on developing and deploying indigenous Large Multimodal Models and domain-specific foundational models
AIKosh (Dataset Platform)	Streamlines access to high-quality, non-personal datasets for research and innovation.
IndiaAI Application Development Initiative	Develops, scales, and promotes impactful AI solutions for India-specific challenges.
IndiaAI FutureSkills	Builds a skilled AI workforce by enhancing educational programs and attracting top talent.
IndiaAI Startup Financing	Provides risk capital and financial support to accelerate deep-tech AI startups.
Safe & Trusted AI	Ensures responsible AI adoption by establishing strong governance and ethical guardrails.

For a more detailed table please see Appendix 3.
Source: Author's own, based on the IndiaAI Mission website (MeitY, n.d.).

Furthermore, the IndiaAI Application Development Initiative promotes the creation and scaling of impactful AI solutions for critical sectors like healthcare and agriculture by addressing problem statements from various government bodies, while the IndiaAI FutureSkills pillar is focused on building a large pool of AI-skilled professionals by expanding AI education and setting up Data and AI Labs, especially in Tier 2 and Tier 3 cities.

The mission also includes the IndiaAI Startup Financing pillar to support deep-tech AI startups with access to capital; and finally, the Safe & Trusted AI pillar, ensuring responsible development and deployment through governance frameworks, ethical guidelines, and indigenous tools.

Collectively, these pillars should enable large-scale, inclusive, and sovereign AI deployment across India, ensuring that AI development is both technologically advanced and socially responsible.

2.3.3. India's Sovereign AI Push

India's substantial investments in its AI infrastructure and ecosystem are fundamentally rooted in the pursuit of AI Sovereignty. This objective is designed to ensure that India maintains strategic and technological autonomy, reducing over-reliance on foreign nations or multinational tech giants for critical compute resources, digital infrastructure, and foundational models. As illustrated in Figure 2, the GenAI landscape is currently dominated by American and, to a lesser extent, Chinese entities. Consequently, the push for Sovereign AI is not merely a technical goal but a vital necessity to safeguard India's long-term interests and national security in the digital age.

A primary focus is on developing indigenous Large Language Models specifically engineered to navigate India's exceptionally complex multilingual landscape. Given that a vast majority of India's population does not speak English, the goal is to make AI fully accessible via voice interfaces in all 22 official languages (E&Y, 2025). These native LLMs are vital for ensuring true digital sovereignty, granting India local control over its vast and sensitive data, while also effectively mitigating the performance issues and cultural biases inherent in global, English-centric models that often fail in the Indian context. To accelerate this development, the government has introduced a strategic "GPU-for-equity" mechanism, wherein it provides subsidised compute resources, particularly high-end GPUs, to pioneering deep-tech AI startups in exchange for a minority equity stake (typically in the 2–4% range) (NASSCOM, 2025a). This has rapidly expanded India's compute muscle; India's capacity has already exceeded the initial 10,000 GPUs target, with over 38,000 GPUs successfully onboarded from key service providers such as Yotta Data Services, CyFuture India, and Netmagic IT Services (PIB, 2025a; MeitY, 2025d).

Table 2: Contributors to India's Sovereign AI Vision.

Initiative/Entity	Lead by	Key Objective	Notable Projects/Models
IndiaAI Mission	Government of India (MeitY)	Catalyse a comprehensive, sovereign AI ecosystem.	GPU Infrastructure (34,000+), Startup Fund (INR 2,000 Cr)
Sarvam AI	Private Startup (Govt. Backed)	Build Indian foundation models & full-stack GenAI platform.	Sarvam-1, Sarvam-M, Amartya TTS, 120B parameter Indic LLM
Ola Krutrim	Private Startup	Develop India's own family of AI models and compute chips.	Krutrim (supports 10 Indian languages)
AI4Bharat	Academic (IIT Madras)	Build open-source datasets and models for Indian languages.	IndicBERT, IndicTransv2, IndicWav2Vec models
Bhashini Mission	Government of India	Create a national public digital platform for languages.	Large-scale data collection for 22 languages

Source: NASSCOM (2025) GenAI Startup Landscape 2025

Beyond technological capacity, AI is also proving instrumental in enhancing digital inclusivity across India by integrating voice and regional language interfaces into existing, popular platforms like UPI and the UMANG application, which onboards citizens with lower digital literacy (E&Y, 2025). Likewise, AI-driven tools on platforms like e-Shram are set to empower informal workers by adapting content and interfaces to their specific literacy levels, thereby bridging the digital divide (Niti Aayog, 2025a).

Indian startups and academics are working in the area of language models: Sarvam AI is focused on building models that support 10 major Indian languages, while Ola's Krutrim is developing its models with capabilities for 22 official Indian languages. Additionally, there are academic projects such as AI4Bharat, an open-source initiative creating models for all 22 scheduled Indian languages including the IndicBERT model and IndicTransv2 model. Furthermore, the government-run Bhashini Mission aims to create a national digital platform for languages by engaging in large-scale data collection for 22 languages (NASSCOM, 2025a).

Krutrim, which became India’s first AI unicorn with a USD 1 billion (INR 8,870 Crore) valuation has developed an LLM for 22 Indian languages. The conversational AI sector is particularly robust, with companies like Uniphore raising over USD 727 million (INR 6,500 Crore) and Observe.AI securing USD 213 million (INR 1,889 Crore) to revolutionise customer service. Indian AI startups are driving innovation in industries such as healthcare, where Qure.ai provides AI-powered diagnostics for millions of patients; and NIRAMAI provides AI-driven breast cancer screening and detection. In fintech ventures like Razorpay use AI for fraud detection and risk assessment (NASSCOM, 2025a).

2.4. India’s Dual Ecosystem: Global vs. Local Infrastructure

While the Government is making a concerted effort to build sovereign AI in India, global companies remain dominant in AI infrastructure in the country. Indian companies and startups remain reliant on the large international AI giants for infrastructure, foundation models and user interfaces.

Global technology giants and hyper-scalers are making substantial commitments to India's AI infrastructure and ecosystem development. Microsoft announced a USD 3 billion (INR 26,610 Crore) investment in India to boost AI and cloud infrastructure (Nandi et al., 2025). They collaborate with Indian partners to integrate GenAI for industry solutions (Confederation of Indian Industry [CII], 2024), and have invested in land in Pune for (NASSCOM, 2024). NVIDIA is also actively involved in supplying critical compute capacity and supporting ecosystem development. Leading Indian corporations like Reliance, Tata Group, Tech Mahindra, and Wipro have partnered with Nvidia to procure advanced GPU infrastructure (E&Y, 2025).

International tech companies are making multi-billion-dollar commitments, primarily to build the foundational infrastructure necessary for advanced AI, cloud computing, and LLMs in India. Google recently announced a USD 15 billion (INR 1.33 trillion) investment over five years (2026-2030) to establish an AI hub in Visakhapatnam, Andhra Pradesh. The project will feature gigawatt-scale data centre operations, a new international subsea gateway, large-scale energy sources, and an expanded fibre-optic network (Doval, 2025). The US-based AI company, Anthropic, has announced plans to open a Bengaluru office in 2026 and begin hiring in India, signalling a strategic focus on the country's talent pool (Anthropic, 2025). In addition, in IT services, and consulting, global firms such as Accenture, Cognizant, Capgemini, and the Big Four (Deloitte, E&Y, PwC, McKinsey) are scaling AI services for enterprise clients globally, with India as their primary hub for talent and development. Their interest in the Indian AI market is primarily driven by hiring local workforce and building on local infrastructure to deliver solutions for global enterprise clients. Investments focus on launching capability centres in India including Accenture's GenAI Studio (Economic Times, 2023) and Deloitte's Global AI Simulation CoE (Deloitte, 2025) in Bengaluru.

3. How Businesses are Thinking about AI

In this section we discuss AI awareness and literacy levels before discussing drivers of adoption, and decision-making with respect to implementation and deployment of AI. However, before doing so, we must recognise that 'Indian business' is complex and very diverse. Drawing on a World Economic Forum report (WEF, 2025) it is clear that India's micro, small and medium enterprises (MSME) ecosystem is far from a homogenous group, presenting a unique challenge for AI implementation. With over 63 million enterprises, the sector spans a vast spectrum- from micro-units like local repair shops operating on cash and paper ledgers to medium-sized industries integrated into global supply chains. This diversity means that businesses operate at very different stages of digital maturity.

While medium enterprises may utilise ERP software and are ready for industrial automation, microenterprises, which constitute over 99% of the sector, often lack basic digital infrastructure and formal data history. Consequently, a 'one-size-fits-all' approach to AI adoption is impractical for the Indian context. Strategies must be tailored to meet enterprises where they are; for instance, while a medium unit might deploy predictive maintenance sensors, a micro-entrepreneur's journey might begin with simple, mobile-based AI tools for basic productivity or credit access. Therefore, unlocking the significant economic potential of AI requires recognising these nuances and adopting a tiered approach to transformation and AI implementation. Keeping this diversity in mind, we note that the MSMEs in India have potential to grow the sector by over 45% and add around USD 490-685 billion (INR 44-62 lakh crores) to the Indian economy, if they utilise AI in their workflows, according to the report by World Economic Forum (WEF, 2025).

3.1. AI Awareness, Knowledge and Digital Literacy

The launch of tools like ChatGPT and Gemini served as an inflection point in awareness about GenAI. As one of our interviewees noted "Now thankfully what happened with ChatGPT, it gave the power of AI to individuals' hands, and that's when people realised that AI is there for real. Everybody used to think that AI is only for corporates, AI is only for large companies, and I will see when it will come. But when ChatGPT came, they realised that it is for real, it's right in your hand, you can use AI and you can do a lot of stuff" (Interviewee 30).

The workforce in India has high exposure to AI and GenAI, and according to a study by Microsoft (2024) on Indian knowledge workers, 92% of Indian professionals are leveraging AI at work, surpassing the global average of 75%. Microsoft defines these professionals as those who typically work at a desk, whether in an office or remotely at home (Microsoft, 2024).

Similarly, a MeitY (2025a) report indicated that seven in 10 Indian employees used AI at work in 2024, an increase from five in 10 a year earlier. These high numbers are due increasing adoption of tools, like ChatGPT, Gemini and Copilot. According to a survey by E&Y (2025), AI expertise is a key need for most enterprises. This conclusion was drawn from interviewing 125 senior (CXO) executives across diverse Indian sectors, including Financial Services, Retail, Life sciences, Technology, Automotive, Industrials, Energy, and Media and Entertainment. However, expertise is severely limited, with only 3% of surveyed Indian enterprises possessing the knowledge and resources required for effective GenAI deployment. Around 35% of executives agreed that their organisation has some skills but needs heavy investment to actually see a measurable outcome, while about one fifth of leaders had not thought about specific GenAI skill requirements (E&Y, 2025).

Taken together, this suggests that while awareness and basic use of GenAI tools is widespread, significant gaps exist when it comes to deeper technical knowledge and use of domain specific specialised tools.

Our interviews suggest that AI knowledge is concentrated within firms. It primarily resides within specialised technical teams including developers and product engineering, and the leadership. Other employees lag behind in AI literacy. One interviewee from a fintech organisation said, “I think everyone is in a rush tagging it as AI, but I think in reality only 20% I would say are actually utilising it in the right way. A lot of them are just paintballing it as AI, whereas it's not really the case” (Interviewee 5).

This lack of literacy often leads to outsized and unrealistic expectations of what AI solutions can do, as noted in several interviews. One interviewee stated “I keep telling this to people, it's not a magic wand” (Interviewee 25), whilst another one said that “a few organisations are in a stage where they think that any problem, anything, can be solved by using AI/ML” (Interviewee 28).

This lack of AI literacy also leads to scepticism and confusion among businesses with respect to AI’s role and potential. Some employees resist the change, perceiving AI as a threat to their job.

The level of AI knowledge differs based on the size and maturity of the company. Startups, particularly those that have a younger workforce tend to be the early adopters and exhibit high AI literacy among their core teams. According to one interviewee, a significant share of founders are advanced users or are upskilling themselves in AI and continually engaging with new tools, especially in the education, healthcare, and SaaS sectors (Interviewee 11). Startups founded on an AI first approach view the core problem through an AI lens, leading to faster adoption of GenAI for tasks like automating candidate screening, content creation and leveraging LLMs for internal knowledge management. Hence startups generally have higher AI literacy and are rapid adopters.

According to the report by WEF (2025) microenterprises (with annual turnover up to INR 10 crore), face the highest barriers to technology adoption due to limited automation and informal operation. Small businesses (with annual turnover of up to INR 100 crore), typically have more structured operations and utilise common business tools (like accounting applications). Medium enterprises (with annual turnover limits of INR 500 crore) are the most suitable for new technology adoption as they often utilise Enterprise Resource Planning (ERP) software and operate at higher stages of digital maturity (WEF, 2025).

In our interviews, we found that MSMEs face substantial challenges regarding awareness and budget allocation. This generally suggests lower implementation knowledge compared to startups and large enterprises. They often require a consultative approach as they lack intrinsic knowledge of relevant solutions (Interviewee 30).

Large firms recognise AI as a core strategic priority. They generally have a formal strategy but have slow scaling. Implementations are typically defined by functional or enterprise-wide AI strategy. However, according to E&Y (2025), adoption is slow: only 15% have deployed GenAI in production while 36% are budgeting and investing, and 24% are experimenting and piloting.

3.2. Motivations and Drivers of AI Adoption

There are several common drivers of AI adoption for Indian companies.

Operational Efficiency and Cost Savings

For the majority of companies in India, the primary motivation for AI adoption is to achieve direct operational improvement and substantial cost savings (Interviewee 26). The chief driver for many businesses is the automation of repetitive and time-consuming tasks. In sectors like manufacturing, AI is applied for tangible, physical enhancements, such as using predictive maintenance to minimise downtime and smartly manage maintenance schedules (CII, 2024).

In IT workflows, AI is leveraged to assist in code development, automate test case creation, and generally improve software quality (NASSCOM, 2025b). According to reports published in 2025, for technology services companies, GenAI is projected to deliver 45% productivity boost across numerous roles by 2030, which reinforces India's standing as a technology services leader (E&Y, 2025; NITI Aayog, 2025a). MSMEs, in particular, prioritise pragmatic solutions that lead to enhanced operational efficiency, cost reduction, and increased revenue growth.

Positioning for Future Economic Advantage

A key reason for adopting AI is to strategically position companies in India for future economic advantage, competitiveness, and global leadership (Access Partnership & FICCI, 2023). Large Enterprises primarily implement AI as a core strategic pillar to achieve long-term growth and secure a competitive advantage. Their adoption strategy is typically enterprise-wide, with a focus on measurable return on investment (ROI) (BCG, 2025c). Furthermore, startups are fundamentally driven by the motivation to achieve product innovation, competitive differentiation, and secure patient capital by creating novel solutions. A major objective for them is creating AI-first or agentic AI products that can autonomously plan and execute complex workflows. Startups also use Large Language Models (LLMs) to quickly build companies, accelerating development cycles by combining roles like front-end and back-end developments (NASSCOM, 2025a).

Competitive Necessity

The rapid pace of AI evolution means its adoption is fast becoming a mandatory step for survival and future readiness. Business leaders recognise that if competitors implement successful AI solutions, they must quickly catch up to avoid lagging behind. Companies, especially large ones and Global Capability Centres (GCCs), prioritise AI adoption to drive their digital transformation journey and remain competitive (E&Y 2024). Current and future market pressures are driving this adoption. One interviewee noted that AI adoption becomes a "necessity" when competitors are seen implementing solutions, compelling the organisation to adopt an accelerated, often decentralised, approach to quickly catch up. This utility is expected to become a necessity akin to computers in the early 21st century or mobile apps, cloud technology, and the internet.

Motivation is Problem-Driven

For MSMEs and other businesses, the focus is often pragmatic, seeking simple, scalable tools that solve distinct, measurable business problems. Their central focus is often financial. Similarly, Large Enterprises ensure their adoption strategy is enterprise-wide, focusing on measurable ROI, which means they are looking for clear solutions to specific challenges. Startups often use a "wide and shallow approach", meaning they test many ideas quickly and cheaply, driven by the goal of building novel solutions for specific needs. Across various segments, the motivation is fundamentally problem-driven: identifying and solving concrete business problems, rather than adopting AI merely as a solution looking for a problem.

3.3. Decision-Making Regarding GenAI Strategy and Implementation

Decision-making regarding the deployment of AI solutions can be broadly categorised into three models: Leadership-Driven (top-down), Individual-Led (bottom up), and a Mixed Strategy. Out of our interviews, the Leadership-Driven approach was the most common, reported by half of the respondents, highlighting that AI solutions gain greater acceptance if leaders explicitly support the initiative. The Mixed Strategy was the next most common, followed by a handful reporting an Employee Driven approach.

Pressure from the Top and The CXO Factor

There is significant pressure from the CXO level to implement AI, driven by the strategic need to manage costs and drive automation. This top-down structure, where AI is viewed as a "strategic topic," ensures decisions regarding implementation "will come from the top." In large organisations, AI adoption is often compelled by "top-down pressure to manage costs," with CEOs questioning if "automation" has been explored before approving staff requests. For sectors like healthcare, having a dedicated mandate, often from a specialised leader like a Chief Medical Informatics Officer, is essential. Crucially, unless the CXO drives implementation, the initiative is more likely to fail due to a lack of institutional support.

Grassroots Adoption and Individual Champions

In contrast, the initial push or adoption of specific tools and use cases often starts at the lower levels of the organisation. This is Individual-led (and bottom-up), where the adoption emerges from individual initiative, driven by employees who are personally convinced AI will help them. These individual champions of AI use tools they are comfortable with, such as GenAI platforms to generate content or code snippets. For early-stage companies or in specific teams, reliance is placed on this individual's motivation, with upskilling often taking place through self-learning.

Technology Teams as Use Case Pioneers

The initial idea frequently comes from the "technology team rather than from the business team," as people "close to the resources can find a use case." For example, the Mixed implementation approach often sees AI adoption start initially as a "bottoms up" idea originating from a productive finding within the technical team. This "grass-roots" initiative then gains acceptance "overnight when it comes from top," as leadership reinforces its value. Leadership typically “defines the vision” but execution is often handled by “small teams or the COEs” (Centres of Excellence), including local developers, data scientists, and domain experts.

3.4. AI Readiness

A foundational requirement for successful GenAI and overall AI implementation, as highlighted across our interviews, is ensuring the quality and availability of data used for training and operation. As one interviewee put it, "good input is good output, garbage in means garbage out," meaning that curating the input data with intense care is crucial for achieving sophisticated output. Furthermore, the deployment environment itself must be suitably prepared to support these advanced AI systems effectively.

Successful implementation also critically depends on a clear alignment between the AI initiative and core business goals, alongside strong leadership buy-in. Most business leaders agree that implementers must be absolutely clear about their use-cases and objectives before taking the plunge into the AI race. As one interviewee stated, "I think before industries take a plunge or a business takes a plunge in this AI race, they should be clear about what their use cases are and what their objectives are..." (Interviewee 19). Parallel to this, ensuring talent and workforce readiness is a major prerequisite for success, particularly given the severe lack of home-grown expertise for adopting

GenAI for Engineering and R&D organisations, with over 49% executives (approximately 50 top executives from technology services firms and engineering R&D companies, including CXOs representing GCCs and leading tech companies) agreeing (NASSCOM, 2025b).

WEF (2025) did a deep dive into different kinds of frameworks for assessing a company's readiness for AI. They emphasise that when thinking about AI readiness in the Indian context, it is essential to realise that "one size does not fit all." Organisations operate at very different stages of digital maturity, ranging from "digital awareness"—where data is still maintained in paper ledgers—to "digital integration," where workflows are fully automated. For a micro-enterprise, readiness might simply mean adopting basic smartphone-based tools, whereas for a medium enterprise, it involves integrating complex ERP systems and cloud platforms. Therefore, an organisation must first self-assess its current standing to identify gaps in data infrastructure and workforce skills before jumping into adoption. To help with this "health check," the WEF (2025) report highlights several global frameworks that MSMEs can utilise.[1] Ultimately, an SME should select an index that matches its specific industry and operational goals to chart the right path forward.

[1] Frameworks mentioned in WEF (2025) includes: Cisco AI Readiness Assessment: For checking strategy, talent, and governance preparedness; Smart Industry Readiness Index (SIRI): For manufacturing units to gauge their Industry 4.0 maturity; TDWI and Avanade Assessments: Provide a general view of organisational maturity and readiness steps; AIIM Readiness Assessment: Focuses on preparing unstructured data for AI implementation; Advaiya AI Readiness Assessment: Evaluates infrastructure and culture.

4. AI Solutions Businesses are Implementing

4.1. What do we know about what Indian businesses are implementing?

The deployment of GenAI and broader AI solutions is swiftly moving from exploratory pilots to strategic, product-level deployment across Indian businesses (E&Y, 2025). Enterprises recognise that AI is rapidly becoming a market imperative, with one interviewee stressing, "if you do not use it, someone else will use it and we will be left behind" (Interviewee 29). While many Indian businesses have exposure to GenAI through its integration into existing software, adoption rates vary. According to the E&Y (2025) study, where 125 CXO level executives were surveyed from different sectors like financial services, retail, life sciences, technology, media, etc. across India, approximately a third of enterprises are actively investing and a quarter are engaged in experimentation. Globally, 80% of Indian companies consider AI a core strategic priority, exceeding the global average of 75% (BCG, 2025c; Microsoft, 2024).

Indian fintech platform Razorpay, illustrates this strategic shift by unifying its AI approach across all operations, moving past isolated pilots. They assimilated AI across their entire ecosystem, covering complex areas like merchant onboarding, risk assessment, fraud detection, and customer support. By deploying a unified architecture, they avoided siloed use-cases, opting for a full-stack approach that incorporated AI for Know Your Customer (KYC) automation, conversational onboarding, automated support bots, and fraud/risk monitoring (BCG, 2025c).

Implementation is largely concentrated in functional areas that promise immediate efficiency gains: customer service, operations, Human Resources, and sales and marketing (E&Y, 2025; Interviewee 29; 28). In human resources, AI application extends beyond simple task automation to complex decision support (Interviewee 23; 27). Use cases involve automating candidate screening and profiling by extracting relevant skills, compensation, and location from resumes, which significantly reduces manual effort (Interviewee 10; 23). One example saw candidate screening time reduced from several minutes to just half a minute using GenAI utilities (Interviewee 23). Digital assistants are also being deployed to manage HR domain queries (policies, leave, pay-slips), covering the entire "hire to retire journey" (Interviewee 27; 28).

In sales and marketing, GenAI has become crucial for content generation, optimisation, and hyper-personalisation, which includes creating marketing collateral, drafting initial email responses, and optimising content for Search Engine Optimisation (SEO) (Interviewee 1; 5; 11; 24). As noted by one interviewee: “some founders shared that they're getting good clients out of the LinkedIn space using the AI (Sales Navigator Tool). So, the sales generation has been improved, and the quality of the work has been improved in terms of the client perspectives” (Interviewee 11).

Parsing data for decision-making is another significant area of implementation. To address specific internal data challenges, custom, highly localised GenAI applications are being created. Interviewees noted: “earlier the process was more like you think in your head, you spend a lot of time structuring the data accordingly. And then finally get to see whether this is making sense from a data point of view” (Interviewee 21). “With all these enormous amounts of data, it is completely impossible for a human to understand all this data and make sense of it over the table” (Interviewee 26).

An interviewee pointed out the difficulty in finding small, crucial niche words within massive Standard Operating Procedure (SOP) documents, noting, “SOP documents are huge and is at times it is very difficult to find very small niche words, which is crucial. But at times, they get missed out” (Interviewee 27). Their solution was a custom RAG engine, trained on internal knowledge systems, to quickly extract crucial details from large company documents.

Enterprises frequently prefer GenAI solutions embedded within existing platforms (e.g., SAP, Salesforce) (E&Y, 2025). This deployment choice ensures seamless integration and addresses crucial compliance and privacy needs. Finally, according to the E&Y (2025) report, in IT Services, providers are implementing AI internally, with many firms reporting AI integration in up to 80% of software development tasks (E&Y, 2025).

4.2. GenAI Touch Points: What Can Businesses Implement?

The adoption of GenAI within Indian enterprises is primarily concentrated around functional areas that offer immediate productivity enhancements and efficiency gains. Here we provide examples of AI solutions across several functional domains where businesses are implementing these technologies. While these are not direct insights from interviews, we decided to include this non-exhaustive list as a reference point and to give a sense of what businesses are implementing.
The intent is to use these as an idea generator to identify potential implementation opportunities within your own business setup. As the master of your own business, you are in the best position to understand what AI implementation opportunities exist.

Marketing and Content Creation

The marketing and content creation function is responsible for engaging and attracting customers. The scope of work ranges from the minute details of creating optimised content and visuals to strategic planning, audience targeting and budget allocation. For many businesses, it is an area that essentially drives revenue growth.

Table 3: Solutions and Impact by Functional Task: Marketing and Content Creation

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
Content Prototyping and Ideation	Generating ideas for large campaigns, generate marketing personas and storyboards.	Ideate using GenAI; create visual mock-ups and storyboards from simple prompts based on market data. Serves as a 'conversation starter' to expedite creative process.
Content Production	Mass production of textual and visual content across multiple formats.	GenAI produces draft documents and uses same source to provide content in multiple formats including blogs, social media posts, email newsletters, and website copy. Creates search engine optimised content.
Visual and Video Asset Creation	Designing graphics for social media, generating lifestyle images for e-commerce, creating scripts or voiceovers for videos.	AI-based Text-to-image/Video Models generate unique, brand-specific visuals; creating realistic voiceovers and initial video scripts, sometimes replacing the need for shooting an ad.
Audience Targeting	Analysing customer data to identify new niche trends and creating personalised messaging for customer groups.	AI-Driven tools curate hyper-personalised content (text and visuals) for advertising. Automatically running and monitoring ads based on AI-driven campaigns (e.g., Facebook and Google ads).
Search Engine Optimisation (SEO)	Researching keywords, optimising existing content for better visibility, and analysing competitor content strategies.	GenAI SEO Assistants identify high-potential keywords; suggesting content gaps based on analysis of competitor strategies. Provide complete SEO automation.
Performance Reporting and Analysis	Summarise vast campaign data and translate these into insight reports.	Summarising large volumes of campaign data into executive reports. AI dynamically allocates budget to high-performing ads, maximising ROI.

Administration and Support Functions

This function involves crucial, routine tasks necessary for daily operations. AI implementation here targets high-volume, time-consuming activities to drive cost savings and increase responsiveness.

Table 4: Solutions and Impact by Functional Task: Administration and Support Function

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
Email and Communication	High volume prioritisation of incoming messages and drafting routine responses.	AI-Powered communication co-pilots draft context-relevant replies, summarise email threads, organising email inbox.
Document Generation and Formatting	Manual effort to create and review documents	Content creators & Co-pilots create draft reports, presentations, and summaries from existing data using prompts; produce multiple formats of same content.
Scheduling & Calendar Management	Coordinating meetings across time zones & calendars; avoid conflicts.	Intelligent scheduling assistants schedule meetings and resolve calendar conflicts automatically.
Internal Knowledge Management	Organising, tagging, ensuring compliance with internal policies and SOPs, documents	RAG chatbots provide instant, accurate, summarised answers to complex questions asked in natural language, trained on private company data.
Travel and Expense Reporting	Intense attention required for processing receipts, quotations, claims, and ensuring policy adherence.	Using AI computer vision to read receipts and GenAI to automatically categorise expenses and check policy adherence.
Accounting and Transaction Processing	Invoice Processing, Account reconciliation	Automating invoice data extraction, and reconciliation, leaving only complex discrepancies for human review.
Routine Process Automation	Managing common IT requests & complex issues	Advanced chatbots use GenAI to understand user requests, provide conversational solution steps, and route complex issues to relevant team.

Business Operations

AI solutions in operations improves supply chain management, logistics, and resource optimisation to deliver products or services.

Table 5: Solutions and Impact by Functional Task: Business Operations

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
Purchasing and Supply-Chain	Procurement and sourcing - contract review, vendor quotation comparison	Identifying risk clauses or savings opportunities in vendor contracts. Reviewing large contracts using RAG-based models.
Logistics	logistics and distribution (optimising routes, resource allocation).	Dynamically adjusting shipping routes and resources to reduce fuel costs and ensure on-time delivery.
Enterprise Resource Management	ERM user support and training, manually cleaning and validating data.	GenAI Copilots embedded in ERP interface guide users directly: identifying, flagging, and suggesting corrections.
Resource Utilisation	Optimising allocation and scheduling of staff, machinery, and materials across shifts/projects.	AI optimisation and scheduling dynamically adjust resource levels against inventory; change schedules in real-time to match demand, reduce waste and operating costs, minimise idle time and maximise output

Human Resources

The HR function includes time consuming and administrative tasks across areas including recruitment, onboarding, employee management, exits and training among others.

Table 6: Solutions and Impact by Functional Task: Human Resources

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
Recruitment	Recruitment admin, creating job descriptions, candidate screening, sending offers.	GenAI drafts job descriptions, personalised candidate outreach, and interview questions. AI automates interview scheduling and resume screening. Agentic bots interview and shortlist.
Employee Management and Development	Employee Management from entry to exit – Onboarding, Performance management, appraisal systems, & exit.	GenAI synthesises performance data into review forms; suggests personalised learning pathways; helps set goals. AI-powered skills mapping. AI for optimised onboarding, induction and exit.
HR Policy FAQ and Compliance	Managing HR information monitoring labour laws / compliance.	Chatbots trained on company HR compliance & policy FAQ become conversational AI Assistants for basic employee queries. Automated trackers can flag changes in HR related policy and regulation globally.
Training & Upskilling	Training programme design and roll-out	GenAI for developing tailored programs for employees; execution of online programmes and testing knowledge.

Sales and Customer Resource Management (CRM)

This functional area is divided into revenue generation (sales pipeline) and relationship management activities and tasks where AI is increasingly important. A lot of sales and CRM systems now include AI Co-Pilots or Assistants as optional add-ons.

Table 7: Solutions and Impact by Functional Task: Sales and CRM

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
	Sales Pipeline	
Lead Identification	Finding new prospects, assessing potential value (lead scoring) and verifying fit for target profile.	AI predictive scoring prioritise highest-value leads or highest conversion rate.
Proposal Generation	Creating proposals and quotations, navigating through the sales cycle.	GenAI drafts customised proposals, contracts and quotes, and entering customer specific details.
Sales Generation Activity	Logging daily activities, managing calendar; provide information.	Copilots / AI Agents summarise sales calls, logging activities, update deal stages; provide information and suggest next step to salesperson directly within the CRM interface.
	Relationship Management	
After Sales	Handling post-sale customer issues, service requests across different mediums; documenting ticket-to-resolution journey.	GenAI handles simple support inquiries 24/7; AI classifies and flags complex issues for human agent intervention.
Customer Usage Monitoring & Education	Monitoring customer usage and satisfaction, offering information, FAQ and training.	Chatbot offering customer interface for all the information related to service/product, and maintenance; FAQ and tutorials.

Data Analysis for Decision-Making & Forecasting

Decision-making and forecasting can be improved across organisational areas through GenAI's ability to analyse vast amounts of diverse data. Data analysis drives the strategic decisions across businesses and includes data processing; analysis and prediction; and insights & communication.

Table 8: Solutions and Impact by Functional Task: Data Analysis for Decision-Making & Forecasting

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
Data Cleaning and Quality	Identifying, locating, cleaning, organising raw data. (e.g. correcting errors, filling gaps)	AI automatically detects, flags, and proposes corrections for data errors, ensuring data accuracy and readiness
Visualisation and Dashboards	Translating complex results into dashboards and pinpointed business insights	Produce clear dashboards and visuals using plain language prompts and pre-made AI templates.
Strategic Reporting	Combining findings from multiple internal and external data in reports in short time.	Synthesise data from multiple sources such as internal data and external market research to generate consolidated, context-specific reports.
Strategic Forecasting and Risk	Analysing historical data to generate revenue forecasts; predict customer attrition.	Predictive AI analysing historical sales and service data to generate revenue forecasts. Analysing customer data to forecast customer retention and highlight risks.
Demand Forecasting	Demand Forecasting using historical sales data	AI predictive modelling providing demand forecasts using external data sets and historical sales data.
Financial Planning & Analysis	Budgeting, forecasting, financial reporting, scenario modelling	AI predictive modelling provides financial forecasts by analysing company history. Run "what-if" scenarios for decision-making.

Physical & Shop-Floor Operations

AI Technology is integrated into this manufacturing shop floors to automate routine tasks, ensure quality control, enforce safety and security, and drive efficiency.

Table 9: Solutions and Impact by Functional Task: Physical Operations

Functional Area	Time-Consuming Tasks	AI Solution, Impact and Use Case
Safety and Security	Monitoring the worksite for worker safety compliance and physical security breaches.	AI-powered computer vision automatically monitors workers to ensure adherence to safety protocols (wearing hard hats, gloves, not entering dangerous spaces), providing real-time alerts for immediate corrective action and emergencies.
Maintenance	Manually inspect machinery and sensor data logs, conducting preventative maintenance checks.	AI-powered analysis from computer vision proactively identifies equipment failure signs (unusual sounds or vibrations) combined with data logs to identify issues and schedule maintenance before breakdown happens.
Product and Process Quality Assurance	Manually inspecting products for defects, ensuring adherence to standards, and verifying process consistency.	AI-powered computer vision provides continuous, fast inspection of every product, identifying minute defects. Improves quality control and reduces waste.
Inventory and Asset Tracking	Manually tracking the location and status of high-value assets. and training employees on complex physical systems using hands-on methods.	Internet of things (IoT) sensors combined with Digital Twin simulation provides real-time, accurate location and count assets and stock within a large facility. Allows for risk-free simulation and remote training on complex, workplace systems like factories, power plants).

4.3. Types of AI Solutions

A wide range of AI solutions are available in the market. The choice of solution depends on the individual company requirement based on matters such as customisation, data security and privacy, cost effectiveness, infrastructure requirements, to name a few.

Organisations or individuals also have the choice of open-source products which have publicly accessible source code, can be viewed, modified, and shared; as well as closed source software products which have its source code private, accessible only to the original developer or company. Below we discuss types of AI tech solutions that companies may consider. This is not an exhaustive list, rather, it is an indicative and included to give those new to AI an understanding of the options.

General Purpose Tools (Horizontal AI)

AI solutions designed to address a broad range of tasks across domains and industries. Tools such as Open AI's ChatGPT focus on common tasks like generating text, summarising information, or writing code. Basic tiers are often free while more advanced tiers come at a cost.

- Focus: Versatile across different business functions (Marketing, HR, Sales, IT).
- Examples: LLMs and tools like Gemini, ChatGPT, and NotebookLM.
- Business Application: Prototyping, content generation and productivity enhancement.

Vertical Specialisation Solutions

AI solutions built for, and trained on, data from a specific industry or specialised domain. They leverage domain-specific knowledge to provide accurate and contextualised results.

- Focus: Deep expertise in a single vertical (e.g., Legal, Healthcare, Finance, or Logistics).
- Examples: AI platforms specialising in contract review and legal research (Harvey Legal), or diagnostic tools trained on medical imagery.
- Business Application: Automating complex and highly technical tasks where specialised knowledge is important.

Pure Off-the-Shelf Products (Packaged AI)

Ready-to-use applications that address a well-defined problem. They require minimal setup and function like traditional software applications with an embedded AI component.

- Focus: Solving discrete business problems with immediate utility and easy integration.
- Examples: AI-powered translation applications, text-to-video converters, chatbots.
- Business Application: Quick adoption for common tasks, such as customer service automation, internal document translation, or basic marketing tasks.

Customisation and Build Solutions

AI solutions that are custom built from the ground up, or heavily customisable applications that are tweaked to meet a business's unique requirements. This typically involves partnering with AI agencies, consultants, or hiring internal tech teams to get the best fit.

- Focus: Customising to integrate with proprietary data, legacy systems, or provide a unique competitive advantage.
- Process: Ranges from utilising open-source models and fine-tuning them with proprietary data, to creating entirely new AI system.
- Business Application: Developing intellectual property, solving problems with company-specific data, or integrating AI into highly contextual workflow.

Cloud Platform Solutions

Major cloud providers offer AI tools and services that businesses can access and pay for on a subscription or use basis. They provide the necessary computing power and pre-built components and resources (e.g., APIs for Computer Vision or NLP).

- Focus: Providing the tools and scalable infrastructure required to build, deploy, and manage AI models.
- Examples: Services and solutions offered by Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP).
- Business Application: Lowering the barrier to entry for developing custom AI applications without huge upfront hardware investment.

AI Enhancement of Existing Software Services (Feature Integration)

Integrating AI capabilities directly into established, non-AI software platforms that businesses already use daily (e.g., ERP, CRM, or Productivity Suites). The AI functionality appears as an add-on feature.

- Focus: Improving the functionality of existing enterprise software by embedding predictive analytics, automation, or generative tools.
- Examples: Microsoft Co-pilot integrated into Microsoft 365, Salesforce Einstein AI, Zoho Zia.
- Business Application: Providing AI features to employees in their familiar interfaces, leading to minimal disruption to existing workflow.

5. Responsible AI: Importance of Governance and Ethics

The deployment of GenAI requires organisations to be aware of potential risks, mandate data security, and establish robust governance mechanisms.

5.1. Responsible AI: Insights from Interviews

The overall discussion on Responsible AI is heavily influenced by the organisation's context and maturity, with the general sentiment revealing several significant gaps in comprehensive adoption.

Primary Focus is Data Privacy and Data Leakage

For many organisations, the conversation around Responsible AI is currently not a major point of discussion beyond avoiding data leakage and managing immediate security risks. The primary concern across the interviewee pool and industry reports is risk mitigation. Data privacy is consistently cited as the biggest barrier to AI adoption, with half of the senior executives surveyed by NASSCOM agreeing (NASSCOM, 2025c). As one of our interviewees noted, "The biggest problem is actually not understanding the solution; but it is essentially data privacy that most people are concerned about" (Interviewee 25).

Lack of Clarity

There is a noticeable lack of understanding and clarity of what Responsible AI is and how to engage effectively with crucial aspects like privacy, bias, and security beyond basic data protection. As one interviewee observed, "I think everybody is talking about responsible AI, but I don't know necessarily whether the startups that we deal with have come to that point. They have to be operating at a particular maturity to actually go there" (Interviewee 18).

No Emphasis on Governance and Monitoring

There is a limited emphasis on the governance mechanisms of GenAI implementation and on continuous monitoring. The focus remains largely on initial risk, rather than long-term systemic controls to manage bias, fairness, and accountability. This reactive, risk-focused approach overlooks the necessary governance frameworks that ensure GenAI systems operate ethically and securely. Our interviews suggest that putting in place AI governance policies and teams is not routinely done in Indian businesses. An interviewee noted, “Frankly, in India, I have not seen many AI governance teams so far, though I've seen, in general, if they have their governance team, they do get involved but not all the time” (Interviewee 30).

Limited Conversations around Organisational Impact

Discussions remain heavily technical (data privacy, IP) and risk-focused, with limited discussion about the human-in-the-loop model or the impact on organisational structures or culture. The current maturity level in many organisations means that the broader societal and internal changes necessitated by AI adoption are not yet a primary point of debate. An interviewee said, “I would say we are still like very early in terms of even understanding the specificity of the effectiveness of AI.” (Interviewee 10)

Another interviewee found out, “We haven't looked at changing the team composition based on AI. It's just that it's good to have AI as one of the skillset, or something that could be built over time as well. But yeah, I don't think we've kind of already looked to change the team composition already basis just that." (Interviewee 5)

5.2. Responsible AI: Best Practices

Below we explain what Responsible AI entails and offer some best practices. Overall, best practices in responsible AI include being aware of the inherent risks of GenAI, and establishing a strong, transparent governance framework are the key prerequisites for the sustainable and responsible adoption of AI.

Understanding the Inherent Risks in GenAI

There are inherent risks involved in deploying GenAI models that can impact legal standing, reputation, and security. To mitigate such risks, organisations should treat AI as an assistant or co-pilot, not as the final authority. A 'human-in-the-loop' must be maintained for validation and oversight.

- Data and Intellectual Property Risks: Models can inadvertently expose personal, private, or proprietary data. Furthermore, the data that models have been trained on raises concerns about potential copyright infringement in model outputs.
- Opacity and Reliability: Many GenAI models function as "black boxes," making it difficult to audit how a specific result was derived. This is coupled with the risk of incorrect or unreliable responses (called hallucinations), which poses a significant reputational threat.
- Reliance on Poor Quality Data: The quality of input data remains paramount; low-quality data inputs will invariably lead to low-quality outputs.
- Application and Code Vulnerabilities: Low-code or no-code applications where AI-generated code snippets from public domains are used, can introduce security vulnerabilities into production systems.

The Issue of Bias

AI models are trained on vast datasets of human-generated text and data, which invariably contain societal biases. The critical risk is that an AI model may not only replicate but also amplify these biases at scale. At an organisational level, there may be inherent biases in AI implementation prioritisation, usage of data, and decision-making around AI.

To counteract this, several mechanisms are essential:

- Diligent Selection: Careful curation of training data and selection of models appropriate for the task.
- Diverse Teams: Ensuring a balanced and diverse team is involved in the development, validation, and monitoring processes.
- Robust Governance: Establishing a strong AI Governance Mechanism, as detailed below.
- Continuous Monitoring: Implementing continuous, real-time monitoring of the AI system's outputs to detect and correct bias as it emerges.

Data Security and Data Privacy

It is imperative for businesses to ensure that AI deployment does not result in data leakage or security breaches, or that data privacy is compromised. Beyond in-house data security and privacy measures, organisations should conduct due diligence on the AI tool supply chain: Who built the model? And who could potentially gain access to the organisation’s data via the model? While often linked, security and privacy have distinct mandates in the context of AI.

- Security: Protects the system and its data, through maintaining confidentiality (only authorised access), integrity (data is not tampered with), and availability (the system is accessible to authorised users).
- Privacy: Protects the rights of individuals whose data is being used. It involves providing clear notice that data is being collected, securing informed consent for its usage, and ensuring transparency in how that data is processed.

AI Governance

AI Governance provides the essential framework of processes, controls, and accountability structures required to oversee the responsible deployment of AI. Governance is vital for mitigating reputational, legal, and operational risks and building stakeholder trust.

Key components of a robust governance structure include:

- Ethical Policies: Developing clear guidelines that align AI use with company values and societal norms, explicitly forbidding biased, discriminatory, or harmful outcomes.
- Transparency and Explainability: Mandating clear documentation of the AI model's decision-making logic for internal stakeholders and, where required, regulators.
- Data Governance: Enforcing strict procedures to ensure data quality, privacy, and compliance with prevailing laws.
- Risk Management: Continuously monitoring AI outputs for errors, drift, or unintended behaviour, reinforcing the 'Human-in-the-Loop' concept.
- Accountability: Establishing clear roles, responsibilities, and escalation channels, often through an AI Ethics Board or a dedicated AI Officer.

Navigating the Evolving Regulatory Landscape

While the global regulatory environment for AI is still maturing, India has already established several key legal and policy frameworks that practitioners must navigate as discussed in section 2. For businesses in India, navigating this regulatory landscape demands a proactive stance. Staying abreast of evolving regulations in India and other geographies relevant to their business, whilst building an AI strategy that is responsible and likely to sustain through regulatory changes as more regulatory and policy frameworks are implemented.

6. Barriers and Challenges

While GenAI presents a transformative opportunity for Indian businesses, the path from initial excitement to scalable, responsible implementation is fraught with significant practical challenges. For practitioners aiming to champion AI adoption, navigating these barriers is critical.

1. Data-Related Deficiencies

The adage "garbage in, garbage out" is amplified with GenAI. The performance of these models is fundamentally dependent on the quality, volume, and relevance of the data they are trained on. Many Indian enterprises, even large ones, struggle with foundational data issues:

- **Poor Data Quality:** Data is often incomplete, inconsistent, or inaccurate, stored in fragmented legacy systems.
- **Inaccessibility:** Critical data remains locked in departmental silos, making it difficult to create the unified, comprehensive datasets required for effective utilisation with AI models.
- **Lack of Standardisation:** The absence of common data formats and definitions across the organisation hinders data aggregation and preparation.

As one interviewee noted, “Data quality is the primary criteria whenever we want GenAI models to learn.” (Interviewee 1). This data challenge is compounded by a widespread lack of documented internal processes. GenAI cannot deliver value in a vacuum; it must be integrated into existing business workflows. When these workflows are informal or poorly documented, it becomes nearly impossible to identify the right integration points or measure the technology's impact.

2. Infrastructure Gaps and Costs

GenAI is computationally intensive and expensive. This presents a significant barrier, particularly for the small and medium-sized enterprises that form the backbone of the Indian economy. Primary challenges include:

- **High Infrastructure Cost:** The requisite infrastructure, particularly high-performance GPUs and specialised cloud computing instances, comes at a premium. Many companies find the cost of building on-premise capabilities prohibitive, while reliance on cloud providers creates significant operational expenditure. As one interviewee said, “if you are going to implement everything yourself in-house, it's going to be significantly higher cost than just getting OpenAI and that API case.” (Interviewee 25)
- **Poor Quality of Existing Infrastructure:** Legacy IT systems within many Indian companies were not designed for the demands of large-scale AI and cannot support the throughput, storage, and processing speeds required.
- **Robustness comes at a cost:** Increased accuracy often comes with higher associated infrastructure costs. There is therefore a trade-off, whether 70% or 90% accuracy is acceptable for the given use case, and balancing the associated infrastructure costs since higher accuracy is achieved with higher parameter models which in turn require infrastructure with higher GPUs. Training small models for domain specific work is an alternative but these come with their own requirements for initial training.

3. Talent Shortage and Skills Gaps

India faces a talent shortage in key areas. There is a high demand but low supply of:

- Data Scientists and AI Engineers: Technical experts who can build, fine-tune, and maintain complex AI models. An interviewee found the limited AI talent frustrating as he said, “I have reviewed around 20 CVs in the last week because we have two positions in our company at the moment. Out of these 20 CVs, we selected only one CV. But all these 19 CVs have the title AI engineer.” (Interviewee 14)

- Domain Translators**:** Individuals who possess both business acumen and technical AI literacy, enabling them to "translate" business problems into AI use cases and communicate AI capabilities back to leadership.

4. Organisational Culture, AI Literacy and Resistance to Change

The lack of AI literacy is intertwined with a resistant organisational culture can hinder effective deployment and uptake of AI tools. An interviewee said, “we see a lot of resistance from people using the solution. Even at the time of deployment, we feel that there is a lot of resistance in terms of giving the right accesses, giving the right infrastructure or help because they feel it as a threat and they perceive it as a threat” (Interviewee 30). The resistance to change is often rooted in fears of job displacement and losing control. Without top-down strategic alignment and a commitment to upskilling, AI initiatives can stall against human inertia.

5. Cost and ROI Uncertainty

It is difficult to quantify return on investment from AI deployment, and therefore also difficult to justify initial investment. While the costs are high and immediate, whether through licensing proprietary, high-capability models or investing in in-house development; the returns, are frequently unclear and long-term. An interviewee said, “costs quickly add up right as you are using it”, meaning that the pay-per-use fees for proprietary GenAI models escalate quickly with usage. It can be hard to identify whether ROI is coming from AI deployment or process changes, and more broadly what the return is if any.

6. Regulatory Ambiguity

The legal framework for AI, data privacy, and intellectual property is still evolving, creating uncertainty, regulatory ambiguity and compliance risks for businesses. One interviewee said, “The policy game is still playing catch-up to what is happening in the outside world. And it is happening at such a rapid pace that policy and regulations are always two, three steps behind” (Interviewee 19).

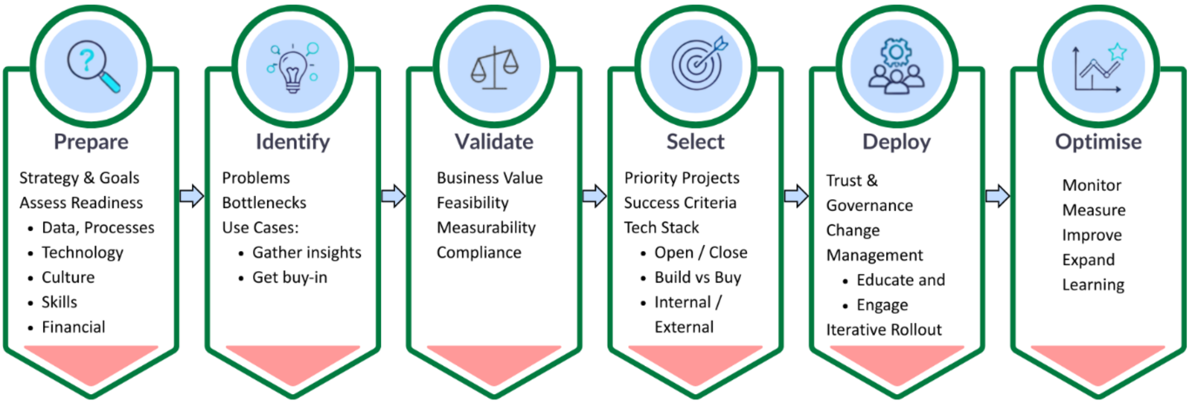
7. Trust, and Explainability of AI Models

Many advanced AI models function as black boxes, making it difficult to understand how they arrive at a particular decision. This lack of transparency is unacceptable in high-stakes environments like finance, healthcare, and legal services.

7. Framework: AI Implementation Journey

In this section we offer a hands-on guide to walk you through the implementation of GenAI solutions in a company from preparation to ideation, validation, selection, deployment and maintenance. This detailed framework draws on insights from existing literature together with interviews we undertook as well as the executive education training and consulting we have provided over the past year. We also draw on established business process improvement and change management principles to ground the framework.

Figure 3: AI Implementation Framework



Source: Author's own

1. Prepare

The first step is to gain clarity on the strategy and goals that the business has, and to assess internal readiness by reviewing organisational data and processes, technology, organisational culture, skills and finances.

Senior leadership must identify strategic and business focused imperatives for GenAI implementation: whether the primary objective is to, for example, drive revenue through improved sales forecasting, decrease operational costs via automated processing, or enhance efficiency by streamlining repetitive workflows. Businesses need to assess the organisational infrastructure and capabilities to understand the level of readiness. These include: quantity, quality and availability of data; clear processes and workflows; technological compatibility with modern cloud-based architectures; organisational culture open to change and AI implementation and availability of internal champions to lead the transition; sufficient skill levels and willingness to upskill for AI and financial capability to invest in AI.

The preparation phase culminates in a clear, quantifiable objective that aligns AI deployment with the overarching corporate strategy, ensuring the project remains focused on delivering tangible commercial value, and an understanding of available infrastructure and capabilities to drive projects.

2. Identify

Step two involves identifying possible problems and bottlenecks by gathering insights from across the business. The result should be a list of potential AI use cases as well as cross-organisational buy-in for implementation.

This stage demands an inclusive, cross-functional approach where leadership gathers insights from across departments, functions and levels to pinpoint problems and bottlenecks that can be solved or reduced through AI. By hosting structured problem-finding workshops across organisational levels, executives can surface use cases that may not have been immediately obvious to senior leaders. This is also a chance to gain buy-in from employees to give them a sense of ownership of the process and reduce fear of change – a common challenge in AI implementation.

The objective is to generate a comprehensive list of potential use cases or projects, ensuring that initiatives are grounded in the operational realities of the organisation, and have the necessary buy-in from stakeholders across the hierarchy.

3. Validate

The third step involves assessing the business value that each shortlisted AI project would bring against the technical and regulatory feasibility.

To validate the potential projects, it is essential to evaluate each proposal using measurable criteria, typically by scoring the potential impact on profitability and customer experience against the ease of implementation. This assessment must consider the availability of high-quality data, the maturity of existing technology, and the complexity of the regulatory landscape governing the specific application. By mapping these projects onto a quadrant of business value vs level of complexity, the organisation can distinguish between 1) 'low-hanging fruit'- projects that offer returns with manageable risk; 2) low feasibility and low value projects not worth considering; 3) high-complexity initiatives that require excessive resources; 4) high-impact, high-feasibility initiatives that allow the business to secure early wins and demonstrate the efficacy of AI without overextending resources.

The outcome of this phase should be a clear understanding of the complexity and feasibility of each proposed project.

4. Select

In the fourth step, leadership should choose a pilot project and define its success criteria; and decide on the tech stack and the mode of deployment such as through internal resources, off-the shelf or via external consultants.

In the selection phase the business must narrow the focus to a pilot project, resisting the temptation to pursue multiple disparate initiatives simultaneously. This prioritisation requires defining success criteria that are specific, measurable, and achievable within a three-to-six-month window, ensuring the project is safe enough to serve as a test case without risking core business continuity. Crucial to this step is the determination of the tech stack and the 'build versus buy' decision: Should you leverage existing software-as-a-service (SaaS) tools or integrate AI features within current platforms or build bespoke projects from scratch. Executives must decide whether to utilise internal talent or seek external consultants to manage the implementation, ultimately selecting a pilot that provides a clear 'before and after' metric to validate the investment and serve as a blueprint for future scaling.

At the end of this phase, the company should be ready with an AI implementation plan including the technology, the timeline and internal teams as well as external partners.

5. Deploy

The deployment step shifts the focus from strategic planning to the complexities of change management and operational governance as the pilot project is rolled out in an iterative manner.

Successful execution depends on CXO level internal champion, a dedicated project lead, and clear sign-off mechanisms, to manage the technical rollout. Ideally, subject matter experts who understand the nuances of the daily workflows that are being transformed should be on hand. It is vital to address employee apprehensions by framing AI as a tool for human augmentation rather than replacement, emphasising its role in removing mundane tasks to allow for higher-value work, and offering opportunities to upskill. The implementation should follow a phased approach, beginning with a proof of concept to test the tool against real-world data before committing to a full-scale rollout.

By prioritising education, engagement, and iterative testing, leadership can ensure that the technology is seamlessly integrated into the organisational fabric while minimising disruption to ongoing operations, while also ensuring that employees become accustomed to work with AI.

6. Optimise

The final step is to optimise and scale deployment by monitoring performance, measuring the success of the AI solution, and continuously learn and improve.

AI systems are dynamic and require ongoing supervision to ensure sustained performance and ethical alignment. Once the pilot is live, leadership must monitor the pre-defined metrics to quantify the return on investment and communicate these successes to build momentum across the company. Maintenance and optimisation involves a proactive approach to governance, where human oversight is utilised to detect model drift and reduced AI accuracy over time, and to mitigate any potential algorithmic biases that could lead to unwelcome outcomes. As the organisation gains confidence, the focus shifts toward upskilling the workforce and scaling and expanding AI solutions.

By establishing a continuous feedback loop and a robust governance structure, senior leaders can ensure the AI infrastructure remains resilient, transparent, and high-performing.

8. Implications for Policy, Practice and Academia

The successful and inclusive adoption of GenAI across India requires coordinated efforts from government, industry, academia, and individual businesses to address foundational challenges related to infrastructure, talent, data quality, and regulatory clarity. The following recommendations are designed to foster an environment enabling GenAI literacy, skilling and responsible deployment.

8.1. For Government and Policymakers

Government initiatives are crucial in shaping a responsible and sovereign AI ecosystem in India. Policymakers should focus on addressing the high costs of infrastructure and mitigating regulatory ambiguity to enable businesses to make the most of AI opportunities.

Launch MSME-Specific AI Adoption and Subsidy Programmes: Given that MSMEs form the backbone of the Indian economy, the government should introduce targeted schemes to make AI accessible to smaller enterprises. This could involve the creation of an AI Cloud infrastructure specifically for MSMEs, providing them with affordable access to high-performance computing resources and pre-trained models. Additionally, credit-linked subsidy schemes or digital transformation grants should be rolled out to help small businesses offset the high initial costs of hardware and software integration. By setting up regional AI advisory hubs, the government can provide hands-on consultancy to help traditional industries digitise their operations.

Incentivise AI Skilling, Upskilling, and Talent Retention: To address the growing talent gap, the government must collaborate with educational institutions and industry bodies to overhaul the national curriculum with a focus on data science and machine learning. Incentives such as tax breaks for companies investing in employee upskilling and the introduction of 'AI Fellowships' can help cultivate deep-tech expertise. Furthermore, to prevent brain drain, policy makers should consider offering grants and R&D credits to researchers and engineers who choose to build their startups or conduct high-impact research within the country. Strengthening the National Programme on AI to include vocational training for the existing workforce will ensure a more inclusive transition to an AI-driven economy.

Establish Clear Ethical Frameworks and Regulatory Guardrails: Policy makers must move beyond high-level principles to provide actionable regulatory clarity regarding responsible AI. This involves drafting sector-specific guidelines that address concerns around algorithmic bias, data privacy, and transparency, particularly in sensitive areas like healthcare and finance. By creating regulatory sandboxes, the government can allow firms to test innovative AI solutions in a controlled environment under regulatory supervision. This approach ensures that innovation is not stifled by over-regulation, while simultaneously building public trust through a clear legal framework that defines accountability for AI-driven decisions.

Promote India-Centric R&D to Solve Local Business Challenges: The government should prioritise funding for R&D initiatives that focus on solving problems unique to the Indian context, such as processing low-resource Indian languages or optimising supply chains in fragmented markets. Public procurement policies should be modified to give preference to indigenous AI startups, providing them with the necessary domestic market scale. By establishing 'National Centres of Excellence' dedicated to Indian-specific AI applications, the government can encourage the development of solutions that are not just globally competitive but also locally relevant. This includes supporting the creation of large-scale, anonymised public data sets that Indian startups can leverage to train models tailored for the domestic demographic and business landscape.

8.2. For Industry Bodies and Ecosystem Stakeholders

Industry bodies are positioned to facilitate collaboration, knowledge transfer, and risk mitigation across the ecosystem.

Establish AI Implementation Networks and Case Repositories: Industry associations should take the lead in creating a pan-India digital repository that documents successful AI use cases across various business functions. This platform should serve as a knowledge hub where companies, particularly MSMEs, can study how their peers have integrated AI to improve operational efficiency or customer experience. By facilitating peer-to-peer learning through regular webinars and networking mixers, associations can reduce the 'fear of the unknown' and provide a roadmap for digital transformation that is grounded in local market realities.

Foster Synergies between Academia, Startups, and Large Enterprises: To bridge the gap between theoretical research and commercial application, associations must create structured platforms for tripartite collaboration. This involves facilitating 'lab-to-market' initiatives where large firms provide the data and scale, startups provide the agile innovation, and academic institutions contribute deep-tech expertise. Industry bodies can organise sectoral hackathons and 'demo days' to help large enterprises identify homegrown AI startups that can solve specific legacy problems, thereby strengthening the domestic deep-tech ecosystem.

Develop Standardised AI Readiness Toolkits and Benchmarks: There is a pressing need for a common framework to help Indian businesses assess their digital maturity. Industry associations should develop bespoke toolkits that include self-assessment modules, data quality checklists, and ROI calculators. By introducing an 'AI Readiness Index' specific to sectors like manufacturing, retail, or BFSI, associations can help member firms benchmark their progress against domestic and international standards. This will provide a clear baseline for companies to understand whether they have the necessary infrastructure and talent before making significant capital investments.

Identify Sector-Specific Bottlenecks and Lead Policy Advocacy: Associations should conduct regular surveys and roundtables to identify the unique pain points member firms face during AI adoption, such as high computing costs, lack of specialised talent, or data silos. Once these challenges are documented, the associations must act as a unified voice to liaise with government bodies like NITI Aayog and the Ministry of Electronics and Information Technology (MeitY). This advocacy should aim to influence policy decisions regarding digital infrastructure subsidies, R&D tax incentives, and the creation of sector-specific data sandboxes.

Drive Responsible AI Governance and Sectoral Ethical Frameworks: While global AI ethics are important, industry bodies must work to contextualise 'Responsible AI' for the Indian landscape, considering factors like linguistic diversity and data privacy. Associations should develop voluntary codes of conduct and governance frameworks that address algorithmic bias and transparency. By providing sensitisation workshops on ethical AI deployment, they can help industries build consumer trust and ensure that AI systems are inclusive and fair. This proactive self-regulation will also prepare member firms for future legislative requirements.

8.3. For Research, Education, and Skilling

Addressing the talent shortage is paramount for ensuring widespread and effective GenAI implementation. The current landscape is built on rich, preliminary qualitative insights; future research must provide quantitative and longitudinal evidence to guide strategic investment.

Educate for Future Skills and Support Indigenous Tool Development: Academia should shift its focus towards producing specialised talent equipped with the advanced technical skills required to build and maintain AI systems from the ground up. Curricula must prioritise high-demand areas such as the development of indigenous tools, frameworks for Indian languages, and explainability mechanisms for Responsible AI. Mandatory modules on ethical AI usage, data governance principles, and prompt engineering should be integrated into non-technical streams such as Finance, HR, and Law. This multidisciplinary approach ensures that the future workforce can leverage AI as a sophisticated operational tool regardless of their specialisation. By embedding these skills into the foundation of higher education, institutions can produce graduates who are not just users of technology but informed critics capable of navigating the socio-technical challenges of the digital age.

Facilitate Lifelong Skilling and Workforce Transition: To manage the transition of the existing workforce into an AI-first world, the skilling ecosystem must provide robust opportunities for reskilling outside of traditional academic settings. Government and industry bodies should collaborate to create stackable micro-credentials and apprentice schemes that allow working professionals to upgrade their skills as AI roles evolve. These programmes should focus on human-agent collaboration, enabling factory workers or administrative staff to transition into roles such as AI technicians or supervisors. By fostering a culture of lifelong learning, the ecosystem can mitigate job dislocation and ensure that the workforce remains fit for the evolving demands of the global economy.

Conduct Detailed Sectoral Studies on AI Adoption and Barrier Mitigation: Researchers must move beyond broad national trends to conduct deep-dive, longitudinal studies of AI adoption across specific sectors like manufacturing, healthcare, and retail. These studies should focus on how businesses are practically mitigating barriers such as data privacy concerns, high computing costs, and the navigation of Intellectual Property (IP) rights in highly regulated environments. Providing evidence-based insights into how Indian firms are overcoming these hurdles will help create a practical roadmap for others. This research is essential for developing a nuanced understanding of the local 'AI puzzle' and informing more effective policy and business strategies.

Research on AI Ethics and Governance for MSMEs: Given the resource constraints of the MSME sector, researchers should focus on developing affordable and scalable governance frameworks that align with the latest national guidelines. This includes studying the impact of algorithmic bias and data security within small-scale manufacturing and service units. Research should aim to simplify 'compliance-by-design' for MSMEs, ensuring that ethical safeguards do not become a financial or administrative burden.

Foster Student Innovation and Pathways to Market Commercialisation: Universities should actively encourage students to solve real-world problems faced by Indian businesses and provide structured pathways to bring these solutions to the market. By leveraging existing infrastructure such as Atal Incubation Centres and Technology Business Incubators (TBIs), academic institutions can help student-led startups move through various Technology Readiness Levels. Creating dedicated 'AI Clinics' where students provide consultancy to local businesses can serve as a powerful experiential learning tool. This bridge between the classroom and the marketplace will ensure that academic innovation translates into tangible economic value and helps build a domestic ecosystem of AI-first companies.

9. Conclusion

The journey of GenAI in India has rapidly shifted from futuristic speculation to a foundational business imperative. As this white paper has detailed, for Indian organisations, the adoption of AI is no longer a choice but a strategic necessity to sharpen their competitive edge and avoid obsolescence. In a global economy defined by digital acceleration, the cost of inaction is no longer just lagging behind, it is the risk of becoming irrelevant.

While India boasts a high degree of workforce exposure to basic AI usage, the landscape remains uneven. The transition from ad-hoc experimentation to advanced, value-driven implementation is stalled by persistent structural gaps. To realise the full potential of GenAI, businesses must move beyond the "low-hanging fruit" of basic automation. The primary stumbling blocks, including fragmented data silos and poor data quality, reinforce the hard reality of "*garbage in, garbage out*." Furthermore, the talent shortage is no longer just a technical bottleneck; it is a strategic one. India urgently requires domain translators who can bridge he intersection of complex business problems and technical AI solutions.

To move forward, a dual approach is essential combining proactive policy with business readiness.

From a policy perspective, the focus must remain on strengthening Sovereign AI infrastructure and establishing adaptive regulatory sandboxes. This will provide the legal clarity and technical backbone necessary for high-stakes sectors to innovate. Likewise, working together with innovation and entrepreneurship ecosystems to build out enabling and nimble pathways to translate new AI technology into products and services and entrepreneurial endeavours that serve Indian businesses is necessary.

From a business perspective, organisations should pivot from ad-hoc experimentation to strategically think through Responsible AI implementation. This involves data readiness, investing in continuous upskilling, and ensuring a "Human-in-the-Loop" model where "Delegate, but Validate" is at the core. This ensures that efficiency never comes at the cost of ethics or accuracy.

Ultimately, AI offers India a unique trajectory for inclusive growth. If adopted thoughtfully, GenAI is not merely a tool for operational efficiency but a catalyst for societal transformation. By prioritising multilingual capabilities and democratising access for Tier 2 and Tier 3 cities, India can ensure that the benefits of the AI revolution are not confined to English-speaking urban centres but are shared across the entire digital economy. The transition to this AI-driven future will require patience, investment, and rigorous governance, but the path toward a *Viksit Bharat* is now inextricably linked to our ability to harness this technology responsibly.

References

Accenture opens genAI studio in Bengaluru. (2023). *The Economic Times.* Retrieved from https://economictimes.indiatimes.com/tech/technology/accenture-opens-genai-studio-in-bengaluru/articleshow/106091204.cms?from=mdr

Accenture. (2025). *AI: A declaration of autonomy*. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Tech-Vision-2025.pdf

Access Partnership FICCI. (2023). *The economic impact of Generative AI: The future of work in India*. Access Partnership. https://accesspartnership.com/wp-content/uploads/2023/06/The-Economic-Impact-of-Generative-AI-The-Future-of-Work-in-the-India.pdf

Anthropic. (2025). *Expanding our global operations to India with our second Asia Pacific office.* Retrieved from https://www.anthropic.com/news/expanding-global-operations-to-india

Boston Consulting Group. (2025a). *Unlocking impact from AI: Driving sustainable cost advantage with AI*. https://media-publications.bcg.com/BCG-Executive-Perspectives-Driving-Sustainable-Cost-Adv-with-AI-EP15-20May2025.pdf

Boston Consulting Group. (2025b). *The GenAI adoption conundrum*. Retrieved from https://www.bcg.com/publications/2025/india-the-genai-adoption-conundrum

Boston Consulting Group. (2025c). *India's AI Leap: BCG Perspective on Emerging Challengers*. Retrieved from https://www.rivista.ai/wp-content/uploads/2025/06/India-AI-Leap-BCG-Perspective.pdf

Capgemini. (2025). *Harnessing the value of AI: Unlocking scalable advantage*. www.capgemini.com/wp-content/uploads/2025/09/Final-Web-version-Report-Gen-AI-in-Organizations.pdf

Capgemini. (2025). *Rise of agentic AI: How trust is the key to human-AI collaboration*. https://www.capgemini.com/insights/research-library/ai-agents/

Confederation of Indian Industry. (2024). *Transforming Manufacturing with Generative AI.* Retrieved from https://cii.in/PublicationDetail.aspx?enc=8g1URkVJ2QKIw+3Ej409ELmZCStUd5YjUSvSdkE8E8jkZnBikzAJRNaN+kdG/Rb1VD57IiFEYoCJclpKCoFE46qWI/sXcDnuHXOhTzGsH+9FJt1uM6fCeT0fCboWJKZXjBosRemnkQm3NEQf7dKsa7505zweVgbOxxdlaoFmJdGAVwEskiFOjshM66FXs8a5

Deloitte. (2025, March). *Deloitte unveils Global AI Simulation Centre of Excellence in Bengaluru to drive real-time insights and innovation at scale.* Retrieved from https://www.deloitte.com/in/en/about/press-room/deloitte-unveils-global-ai-simulation-centre-of-excellence.html

Digital Personal Data Protection Act. (2023). *Digital Personal Data Protection Act, 2023.* Retrieved from https://www.dpdpa.in/

Doval, P. (2025). Google to spend $15 billion in India to build largest AI hub outside the US. *The Times of India.* Retrieved from https://timesofindia.indiatimes.com/business/india-business/google-to-spend-15-billion-in-india-to-build-largest-ai-hub-outside-the-us/articleshow/124557620.cms

Ernst & Young. (2024). *Global Capability Center (GCC) Pulse Survey 2024*. https://www.ey.com/content/dam/ey-unified-site/ey-com/en-in/newsroom/2024/11/ey-gcc-pulse-survey-2024.pdf

Ernst & Young. (2025). *How much productivity can GenAI unlock in India? The AIdea of India: 2025*. https://www.ey.com/content/dam/ey-unified-site/ey-com/en-in/services/ai/aidea/2025/01/ey-the-aidea-of-india-2025-how-much-productivity-can-genai-unlock-in-india.pdf

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, *63*(11), 139–144. https://doi.org/10.1145/3422622

Google Cloud. (2025). *AI business trends: 2025*. https://services.google.com/fh/files/misc/google_cloud_ai_trends.pdf
Jain, N., Madhumay, Sharma, D. (2024). *India's Generative AI Startup Landscape 2024*. NASSCOM. https://nasscom.in/knowledge-center/publications/indias-generative-ai-startup-landscape-2024-0
Microsoft, and LinkedIn. (2024). *2024 Work Trend Index Annual Report*. Microsoft. Retrieved from https://news.microsoft.com/annual-wti-2024/
Microsoft. (2025). *2025: The year the Frontier Firm is born*. www.microsoft.com/en-us/worklab/work-trend-index/2025-the-year-the-frontier-firm-is-born
Ministry of Electronics and Information Technology. (2025). *India's AI revolution - A Roadmap to Viksit Bharat.* PIB research unit. Retrieved from https://www.scribd.com/document/882397576/Doc-202536513901
Ministry of Electronics and Information Technology. (2025b). *10 Cutting-Edge Indian Startups Selected for Prestigious AI Accelerator Programme in Paris.* Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=2132377
Ministry of Electronics and Information Technology. (2025c). *India Commits to Safe and Trusted AI with New EoI initiative.* Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=2065579
Ministry of Electronics and Information Technology. (2025d). *India's Common Compute Capacity Crosses 34,000 GPUs - 3 More Startups to Develop and Deploy Indian Foundation Models.* Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=2132817
Ministry of Electronics and Information Technology. (n.d.). *IndiaAI Mission.* Retrieved from https://indiaai.gov.in/
Ministry of Electronics and Information Technology; Ministry of Information and Broadcasting. (2023). *Information Technology (Intermediary Guidelines and Digital Media Ethics Code) Rules, 2021*. Retrieved from https://www.meity.gov.in/static/uploads/2024/02/Information-Technology-Intermediary-Guidelines-and-Digital-Media-Ethics-Code-Rules-2021-updated-06.04.2023-.pdf
Nandi, A., Ajaykumar, S., Basrur, A., & Tripathi, P. (2025). *AI for India - Identifying Future Directions.* Observer Research Foundation. https://www.orfonline.org/public/uploads/posts/pdf/20250823104541.pdf
NASSCOM. (2022). *The NASSCOM AI Adoption Index*. https://www.nasscom.in/knowledge-center/publications/nasscom-ai-adoption-index
NASSCOM. (2024). *Generative AI Tracker - Tech Industry Activity in Q2FY2025*. https://nasscom.in/knowledge-center/publications/generative-ai-tracker-tech-industry-activity-q2fy2025
NASSCOM. (2025a). *India Generative AI Startup Landscape 2025 - Mapping the Momentum*. https://nasscom.in/knowledge-center/publications/india-generative-ai-startup-landscape-2025-mapping-momentum
NASSCOM. (2025b). *Generative AI in ER&D: A Game Changer for Product Innovation and R&D Efficiency.* Retrieved from https://nasscom.in/knowledge-center/publications/generative-ai-erd-game-changer-product-innovation-and-rd-efficiency
NITI Aayog. (2025a). *AI for Viksit Bharat: The opportunity for accelerated economic growth*. https://niti.gov.in/sites/default/files/2025-09/AI-for-Viksit-Bharat-the-opportunity-for-accelerated-economic-growth.pdf
NITI Aayog. (2025b). *Roadmap On AI for Inclusive Societal Development*. https://niti.gov.in/sites/default/files/2025-10/Roadmap_On_AI_for_Inclusive_Societal_Development.pdf
Parliament of India. (n.d.). *India Code*. Retrieved from https://www.indiacode.nic.in/

Press Information Bureau. (2025a). *Transforming India with AI: Over ₹10,300 crore investment & 38,000 GPUs powering inclusive innovation.* Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=2178092

PwC. (2025). *How boards can effectively oversee AI to drive value and responsible use*. https://www.pwc.com/us/en/services/governance-insights-center/library/board-oversight-ai.html

Ramani, S., Guan, L., & Roussiere, P. (2025). *The front-runners' guide to scaling AI: Lessons from industry leaders*. Accenture. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-Front-Runners-Guide-Scaling-AI-2025-POV.pdf

Singla, A., Sukharevsky, A., Yee, L., Chui, M., & Hall, B. (2025). *The state of AI: How organizations are rewiring to capture value*. QuantumBlack AI by McKinsey. https://www.mckinsey.com/~/media/mckinsey/business%20functions/quantumblack/our%20insights/the%20state%20of%20ai/2025/the-state-of-ai-how-organizations-are-rewiring-to-capture-value_final.pdf

Telecom Regulatory Authority of India. (2025). *[Current statistics on internet subscribers]*. Retrieved from https://www.trai.gov.in/

Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., & others. (2023). *Llama: Open and efficient foundation language models*. arXiv preprint arXiv:2302.13971.

Trilegal. (2025). *Approach paper on regulation of Gen AI in India*. trilegal.com/approach-on-regulation-of-genai-india/

United Nations Global Compact & Accenture. (2025). *Gen AI for the Global Goals: The private sector's guide to accelerating sustainable development with technology*. https://www.accenture.com/content/dam/accenture/final/accenture-com/document-3/Accenture-UNGC-GenAI-Global-Goals-Report.pdf

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., Polosukhin, I. (2017). Attention is all you need. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, R. Garnett (Eds.), *Advances in neural information processing systems* (Vol. 30). Curran Associates, Inc.

World Economic Forum (WEF). (2025). *Transforming small businesses: An AI playbook for India's SMEs*. Retrieved from https://reports.weforum.org/docs/WEF_Transforming_Small_Businesses_2025.pdf

Zimmermann, A., Casey, D., Bansal, A., Jump, A., Santoro, J., Cozza, R., Miclaus, R., Hare, J., Chitkara, V., Goodness, E., Velosa, A., Harwood, R., Valdes, R., Johnson, B., Brocklehurst, G., Verma, A., & Coshow, T. (2025). *Emerging Tech Impact Radar: Generative AI*. Gartner.

Appendices

Appendix 1: Interviewee Description

Interviewee	Description
Interviewee 1	Founder of an Aggregator startup that implements an AI feature
Interviewee 2	Strategy and SaaS Consultant at a Fintech startup
Interviewee 3	Product Manager at Sport-Tech startup
Interviewee 4	Managing Director at a Tech company
Interviewee 5	QA Head and Senior Manager at a Financial Wellness company
Interviewee 6	Founder and Director at a Tech Enabled Mental Wellness startup
Interviewee 7	Founder of an AI powered Event Experience startup
Interviewee 8	CTO at a Customer Experience Elevation startup
Interviewee 9	Corporate Innovation Manager at a startup incubator
Interviewee 10	Product Lead at a Recruitment Platform
Interviewee 11	Senior Manager at a Public-Private Partnership Sanitation Accelerator
Interviewee 12	Founder and CEO at an Agri-Tech startup
Interviewee 13	Founder and CEO at an Agentic AI startup
Interviewee 14	Founder of a Fintech SaaS startup
Interviewee 15	Head of Growth at an AI-driven Marketing Automation Platform
Interviewee 16	Founder and CEO at an AI-based Talent Acquisition startup
Interviewee 17	Founder and Principle Consultant at an IT consultancy
Interviewee 18	Senior Vice President at a Research Incubator
Interviewee 19	Government Civil Servant advising on AI policy
Interviewee 20	Applications engineer at a huge Info-Tech corporate
Interviewee 21	Co-founder at a Sustainable Gaming startup
Interviewee 22	Co-founder and CTO at an AI-based HR Tech startup
Interviewee 23	Co-Founder and CTO at an IT services and Consulting company
Interviewee 24	Product Lead at a Consumer Services company
Interviewee 25	Founder of an AI-based IT services startup
Interviewee 26	Senior Key Expert on AI at a huge Tech enterprise
Interviewee 27	PhD in AI based computational musicology and Project Manager at an IT Services company
Interviewee 28	Associate VP at an IT Services company
Interviewee 29	Associate VP focusing on software delivery at an IT Services company
Interviewee 30	Co-founder at an AI-based Computer Vision startup

Appendix 2: List of Figures, Boxes and Tables

Figure 1: AI to GenAI – A Timeline……………………………………………………………………………………………..6
Figure 2: GenAI Infrastructure Taxonomy…………………………………………………………………………………….8
Box 1: Sections Relevant to AI…………………………………………………………………………………………………….9
Table 1: IndiaAI Mission Pillars…………………………………………………………………………………………………..10
Table 2: Contributors to India's Sovereign AI Vision……………………………………………………………………..11
Table 3: Solutions and Impact by Functional Task: Marketing and Content Creation………………………..19
Table 4: Solutions and Impact by Functional Task: Administration and Support Function………………..20
Table 5: Solutions and Impact by Functional Task: Business Operations……………………………………………..20
Table 6: Solutions and Impact by Functional Task: Human Resources………………………………………………21
Table 7: Solutions and Impact by Functional Task: Sales and CRM……………………………………………………21
Table 8: Solutions and Impact by Functional Task: Data Analysis for Decision-Making & Forecasting………22
Table 9: Solutions and Impact by Functional Task: Physical Operations……………………………………………22
Figure 3: AI Implementation Framework……………………………………………………………………………………30

Appendix 3: IndiaAI Mission Pillars (Additional Information)

Pillar	Objective [IndiaAI Pillars]	Key Actions & Quantifiable Status (As of July 2025)
IndiaAI Compute Capacity	Democratises access to high-end, scalable AI computing infrastructure for startups, academia, and researchers.	Aims to establish a compute infrastructure of 10,000 or more GPUs via Public-Private Partnerships. 38,000 GPUs already provisioned at a subsidised rate of ₹65 per hour. (Press Information Bureau [PIB], 2025)
IndiaAI Innovation Centre	Focuses on developing and deploying indigenous Large Multimodal Models and domain-specific foundational models	Focuses on models tailored for critical Indian sectors. Four startups (including Sarvam AI and Soket AI) were selected in the first phase for foundational model development (PIB, 2025).
AIKosh (Dataset Platform)	Streamlines access to high-quality, non-personal datasets for research and innovation.	A unified data platform that hosts over 3,000 datasets and 243 AI models across 20 sectors, helping developers focus on solutions instead of data collection (PIB, 2025).
IndiaAI Application Development Initiative	Develops, scales, and promotes impactful AI solutions for India-specific challenges.	Focuses on critical areas like healthcare, agriculture, governance, climate change, and assistive learning technologies. Thirty applications have been approved (PIB, 2025).
IndiaAI FutureSkills	Builds a skilled AI workforce by enhancing educational programs and attracting top talent.	Aims to support 500 PhD fellows, 5,000 postgraduates, and 8,000 undergraduates. It also involves setting up Data and AI Labs in Tier 2 and Tier 3 cities (27 labs identified) (PIB, 2025).
IndiaAI Startup Financing	Provides risk capital and financial support to accelerate deep-tech AI startups.	Launched the IndiaAI Startups Global programme to help Indian startups (e.g., 10 selected startups) expand into international markets (MeitY, 2025b).
Safe & Trusted AI	Ensures responsible AI adoption by establishing strong governance and ethical guardrails.	Focuses on developing indigenous tools, frameworks, and self-assessment checklists for Responsible AI. Eight projects were selected in the first round focusing on bias mitigation, privacy-preserving ML, and explainability (MeitY, 2025c).

Disclaimer:
This document is authored by Dr. Lina Sonne Vyas and Vrushank Arur for informational purposes only. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Indian Institute of Technology Bombay (IITB). Any mistakes or omissions are the author's own. This white paper may not be construed as a legal document or endorsement.

Contact us:
Email: office.dsse@iitb.ac.in
Website: www.dsse.iitb.ac.in
Phone: +91 22-25765381

Citation:
Vyas, Lina Sonne, and Vrushank Arur. 2026. *GenAI for Business: Insights from India*. White paper. Mumbai: Desai Sethi School of Entrepreneurship, Indian Institute of Technology - Bombay.