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**Dated: 26.08.2020**

To

**All Officers of EPFO**  
**Head Office/Zonal Office's/Regional Office's**

**Subject: Implications of AI on the Indian Economy**

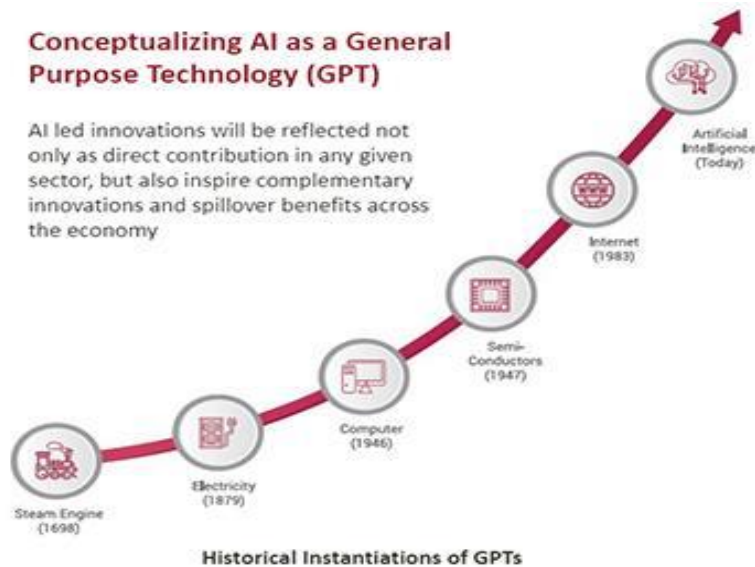
**Madam/Sir,**

NASSCOM, a not-for-profit industry association, is the apex body for the 180 billion dollar IT BPM industry in India, an industry that had made a phenomenal contribution to India's GDP, exports, employment, infrastructure and global visibility. In India, this industry provides the highest employment in the private sector.

Established in 1988 and ever since, NASSCOM's relentless pursuit has been to constantly support the IT BPM industry, in the latter's continued journey towards seeking trust and respect from varied stakeholders, even as it reorients itself time and again to remain innovative, without ever losing its humane and friendly touch.

NASSCOM is focused on building the architecture integral to the development of the IT BPM sector through policy advocacy, and help in setting up the strategic direction for the sector to unleash its potential and dominate newer frontiers.

NASSCOM has issued a publication on **"Implications of AI on the Indian Economy"**.



## **Key Findings:**

### **1. AI as a General-Purpose Technology**

AI's ability to lend itself to diverse range of applications across a range of sectors, resembles that of GPT

The economic impact of AI led innovations are not only reflected as direct contribution to sectors but also as indirect effects on productivity that GPTs trigger

### **2. Key Results from the Econometric Estimation**

The report results find a positive and significant relation between AI using firms and total factor productivity growth

The estimate suggests that a unit increase in AI intensity will increase TFP growth by 0.05%

On average, a unit increase in AI intensity by AI-using firms can return \$67.25 Billion or 2.5% of GDP to the Indian economy in the near term

### **3. Micro Evidence from Case Studies**

The report uses a capabilities framework as a guide to understand the causes that underline success or failure of India's ecosystem in conducting AI-based innovation

Capabilities of firms developing AI applications in India

- Investment Capabilities
- Production Capabilities
- Linkage Capabilities

Impact of AI on firms adopting AI based solutions

- Economic Implications for business adopting AI
- Social Implications of AI Applications
- Implications on labour market

### **4. Policy recommendations**

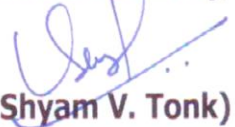
Government has an active role to play in creating institutions and enabling an AI ecosystem, while also encouraging private players to innovate and thrive

Action-oriented policy recommendations are critical for the implementation of a large-scale AI program

As can be seen from the key findings above, the publication by NASSCOM on "Implications of AI on the Indian Economy" is of immense importance for an Organisation like EPFO which is embracing technology for providing seamless services to our esteemed stakeholders. Accordingly, the publication on "Implications of AI on the Indian Economy" issued by NASSCOM is attached below for the benefit of EPFO.

**(This issues with the approval of Competent Authority)**

Yours faithfully,



**(Shyam V. Tonk)**

**Regional P.F. Commissioner-I (Training)**

# IMPLICATIONS OF AI ON THE INDIAN ECONOMY

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NASSCOM®



Google | July, 2020

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# | Foreword

India is on the cusp of tremendous opportunity for both economic progress and improvement in the general well-being of our people. By all measurable indicators of economic growth and human development, the current decade – the twenty-twenties will be India's.

India has, over the last several years, diligently built digital highways to bring equitable access of technology across the country. The emergence of transformative new technologies will enable India to build on top of these existing infrastructure and leverage technology for equitable social growth.

Artificial Intelligence, more specifically Machine Learning, holds both tremendous promise for India, from a technology capability perspective, as well as new exponential way of addressing some of the biggest challenges we face as a country and a society. India's strength lies in its large technology skilled workforce and the diversity of both use cases and data sources. Machine Learning enables intelligent combination of these complementary strengths to build data-driven large scale solutions, solutions that cater to India's unique needs and wants.

The Government of India has been working on developing a comprehensive AI ecosystem for the country. India's National Strategy for Artificial Intelligence envisages utilising this technology across three inter-connected layers: economic growth that is inclusive which positions India as the preferred playground for building world-class technology solutions.

This report has undertaken a comprehensive study of AI's potential and implication for India, and estimates that impact of AI on the economy in rather granular details. The results of the econometric study done at the firm level highlight the need for continued focus on building digital capabilities to fully utilise the power of AI / ML, both from efficiency and increase in capability perspective. Early and sustained investment in AI / ML, in both R&D and applications, is much required.

I look forward to examining the recommendations presented in this report in greater details and engaging with the authors to continue evolving India's AI journey.

**Amitabh Kant**  
CEO, NITI Aayog

# Acknowledgements

We are grateful to our sponsors Google and NASSCOM for giving us this opportunity to undertake a project that evaluates the growth potential and dynamics of a revolutionary technology, Artificial Intelligence, in the Indian ecosystem. We would like to thank their teams for their continuous support and guidance in helping shape the study to its current form. We are grateful to the team at Kreativ Street for designing the report and delivering its insights effectively and in style. We would like to thank Dr. Deb Kusum Das, Vatsala Shreeti and Raavi Agarwal for their extensive and formative support while working with challenging models and data.

In the present moment when Artificial Intelligence and its allied ecosystems in India are emerging, it is invaluable to gain insights on how various firms are creating and using AI. For such insights, we thank all the companies that offered their time and shared insights on current business practices. We are also grateful to stakeholders from academia, government and civil society for participating in consultations that formed our perspectives on the potential and challenges facing the AI ecosystem in India.

Finally, we are grateful to our team at ICRIER for their unending supply of wisdom, humour and coffee, and for giving us the hope that there are certain things in our lives that no AI can predict, automate or replace. *All errors are our own.*



# Executive Summary

India's Artificial Intelligence(AI) moment is truly here and now. At a time when a diverse range of applications based on AI are being developed, pushing its frontier further into uncharted realms of business and society, Indian policy makers are contemplating and charting its potential for growth and social transformation. Our study attempts to understand the impacts of AI in India and trace the pathways that help realise it.

AI's transformational potential stems from its ability to lend itself to a diverse range of applications across a range of sectors. One can witness AI-based applications in manufacturing, transforming quality control, production lines, and supply chain management, and in services creating personalized product offerings and high-quality customer engagement. AI applications are also common in sectors such as agriculture that had taken a back seat in technological innovations in the post-industrial world. AI also demonstrates the potential to address developmental challenges by responding to societies' immediate demands for healthcare, education and expanding access to finance and banking.

The consequences of AI diffusion stem from AI's pervasiveness in society, its ability to trigger innovation, and its tendency to transform and evolve. These are typical characteristics of a class of technologies that can be found across history, the emergence and diffusion of which have enabled the wealth of nations. These are called General Purpose Technologies (GPT). Technologies such as steam engines, electricity, computers, semi-conductors, and more recently the internet, can all be considered as belonging to the GPT class of technologies. Our study is based on the understanding that the implications of AI can be best understood by viewing AI as a GPT.

Historically, the economic impacts of GPTs have not been immediate but follow after its diffusion in the economy over time, i.e. once scale is achieved. There are two reasons that explain this phenomenon: firstly, in early phases of technology diffusion, an economy diverts part of its resources from productive activities to costly activities aimed at enabling the GPT. For instance, organisations adopting computers must also invest in training employees or hire computer scientists, re-arrange production activities or organisational structures to accommodate computer driven work-flows, all of which are costly. Secondly, it is only after the GPT is diffused and widely used in the economy that the statistics measuring GDP start counting and fully measuring the GPT.

Empirical research on GPTs such as AI, including ours, throws up the challenge of measurement. Early estimates on the economic impact of AI should be interpreted with the caveat that data on AI's adoption is not fully available or not adequately reflected in the data used to compute economic growth, at least not yet. Measuring the economic impact of AI is also difficult because of the magnitude of indirect effects on productivity that GPTs trigger. It is therefore common that studies on GPTs, while attempting to estimate their economic impacts, also engage in in-depth case studies and historical analysis of its impacts.

In the absence of a direct measure of AI at the firm level, we extend the idea from other studies to use investment in software, databases and computer machinery as a proxy of AI. Although software and databases may not accurately measure the impacts of AI, it is perhaps the best proxy given the commonality of infrastructure and capabilities involved in the use and adoption of AI. AI algorithms are essentially software trained to analyse and predict data patterns with the aid of computer hardware, optimised for such use. This measure of AI also provides the potential of ICT using firms to adopt AI in the future.

We estimate our model using a panel data set of 1553 firms (including manufacturing and services) over the period 2007-08 to 2016-17. We use a fixed effects multivariate panel-data regression for the estimation of the model. We identify firm specific determinants of total factor productivity (TFP) growth of which AI as an efficiency enhancing GPT is one of the explanatory variables.

#### **Box ES.1. Key Results from the Econometric Estimation**

The results find a positive and significant relation between AI using firms and total factor productivity growth. In fact, given that the firm is an AI using firm, total factor productivity growth increases with increase in AI intensity. The estimate suggests that a unit increase in AI intensity will increase the TFP growth by 0.05%.

The growth co-efficient suggests that on average a unit increase in AI intensity, measured as the ratio of AI to total sales, can return USD 67.25 billion or 2.5% of GDP to the Indian economy in the immediate term.

The business as usual growth in AI investments is unlikely to increase current levels of AI intensity. In order to trigger a positive growth shock, AI intensities should be sharply increased. For example, the investment of Rs. 7000 crore approved by the Ministry of Finance towards an Artificial Intelligence program could increase AI investments at rates higher than the business as usual rates. This increase in investment will lead to an approximate 1.3 times increase in AI intensity, translating into spillover benefits of USD 85.77 billion for the Indian economy (3.2% of GDP).

While the econometric estimation provides adequate evidence for policy to support its wider adoption, we derive actionable measures based on an evaluation of firm capabilities, both for firms developing and using AI. We engaged in in-depth interviews with thirteen AI companies in India, most of them still young and small-scale. The companies are currently developing applications for ten different sectors including law enforcement, healthcare, banking and finance, agriculture and manufacturing. In terms of the AI used, we find machine learning and its subsets, deep learning, deep neural networks, convolutional neural networks, among others, featuring prominently across organisations building and providing AI-based services. Natural Language Processing, Speech Recognition, and Computer Vision are other AI-based technologies that also feature across several use cases.

We use the capability theory framework to illustrate how AI firms in India are currently building skills, organising and utilising research and resources needed to run and test AI applications. We also explore the capability of AI firms in India to form networks that finance and market their products and services, that links the firm to the economy at large, and enables the diffusion of AI across the economy. We observe that at the root of all benefits stemming from AI-based applications is AI's ability to predict across a range of tasks. Examples of AI innovations across sectors find its positive impact on organisational efficiency that manifests in reduced time and costs, for various business processes, and enhanced quality control. There are also several interesting applications of AI in the social sector that impact a range of development and governance outcomes such as law enforcement, improvements in health and education, utilisation of natural resources, etc. Going by the nature of private and public interest in AI and the kinds of AI-based applications being developed, India is carving out a niche in the global ecosystem, deploying AI applications that focus on the social sector.

The rise of AI however, comes with several statutory warnings. Firstly, recent advances in AI have raised concerns around the use of complex AI systems that are applied without revealing details of the data used to train the model or the algorithm design that forms the basis of predictions. Such applications run the risk of leading to unfair and /or incorrect decisions if they are used in contexts for which they were not designed. Without careful upfront design and safety precautions, some AI systems may also be prone to error or breakdown when introduced to minor perturbations in data, representing situations that are beyond the scope of their training. Ongoing monitoring and fail-safe designs are therefore vital, especially in safety-critical systems such as self-driving cars, and military applications. Secondly, since AI by nature is labour substituting, immediate consequences of AI, take the form of inequality between labour and capital, and inequality within labor, i.e. between tasks with high and low skill content, raising contentious public policy concerns. However, the form this takes and the impact on human employment will depend on the manner in which organisations deploy AI tools and training.

These concerns raise questions on the role of the government and the nature of government policy that would enable the sustainable growth of the AI ecosystem in India. In our view, the government has an active role to play in creating institutions and providing public goods that enable an AI ecosystem, while also encouraging private actors to innovate and thrive.

The policy recommendations following from our analysis have been categorized into five broad themes. These themes include several actionable recommendations that are individually important to the implementation of a large-scale AI program and are summarized in BoxES.2 below:

### Box ES.2. Policy Recommendations

**Identifying a Nodal Agency Within the Government for Development and Diffusion of AI**, the design and workings of which will be critical to push wide-scale AI adoption in India

- Identify a nodal agency for coordinating all AI related activities in India.
- Nudge government departments to develop capabilities to adapt to AI-based governance mechanisms.
- Prioritise resources to build pockets of excellence for sectors that have already demonstrated positive economic and social impacts from AI.
- Offer government handholding to socially relevant applications.

**Building Collaborative Frameworks for Engagement between Governments, Industry and Academia** to foster growth and promote innovative localised solutions.

- Governments at the state and national level can directly foster growth among startups by inviting public-private partnerships and promoting innovative localized solutions.
- Cross-country collaborations catalyse the transfer and adoption of frontier technologies. Building on existing technologies can help promote AI-related capabilities in India, especially the hardware sector in which India is lagging behind.

**Building an All Encompassing Data Strategy** to improve state capacity to provide AI-compatible publicly available data and encourage unbiased, reliable, safe and inclusive data sharing practices

- Evaluate alternate data sharing models. Laws and regulations that encourage unbiased, reliable, safe, open and inclusive data sharing must be formulated for integration and dissemination of data.
- Examine the integration of public data that currently exists in silos and ensure compatibility for different uses.
- Enhance capacity of existing statistical agencies to collect and process publicly available data for AI use.
- Evolve data.gov.in to become a national resource for Artificial Intelligence. Develop a generalised meta-data standard for data.gov.in to enable integration of resources including but not limited to data, tools, literature, etc.

**Addressing India's Skill Gap in AI** to help build directly adaptable skills for the industry and facilitate recruitment of AI specialists

- Focused collaborations at the sector level, engaging students with corporates, can help build directly adaptable skills for the industry.
- Revise the education curriculum, especially for technology institutes, to necessarily include a program on AI
- AI training should go beyond technology curricula to include social sciences, that contribute to the process of constructing the algorithm and conducting an algorithmic impact assessment.
- Explore a market place for skilled AI professionals to meet the immediate skill gap that AI startups currently face.
- Facilitate recruitment of technology specialists from other countries.

**Addressing Governance Challenges in AI** to promote AI safety standards and guard against impacts of biased outcomes

- Algorithmic Impact Assessments to be adopted by ethics councils proposed to be set up at least at all Government funded research centres building AI for public use cases.
- Researchers from the public, private, and academic sectors should work together to outline basic workflows and standards of documentation for specific application contexts which would be sufficient to show due diligence in carrying out safety checks.
- Explore ways for India to enhance its participation in the AI standardisation process.
- Involve other specialists along with scientists in the process of AI design and application to check biases and their discriminatory impacts.

# 1. Introduction

“The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are undistinguishable from it”

Mark Weiser,  
1991, “The Computer for the 21st Century

Stanley Kubrick (1968) imagined the year of 2001 with mankind establishing civilization orbiting the Earth and probing the outer space using a ‘Heuristically Programmed Algorithmic Computer (HAL)’, which controls a space station and interacts with its astronauts. While reality fell short of a HAL in 2001, computing technologies and mathematical optimization led to massive progress of Artificial Intelligence (AI), enough to demand attention from nation states to further its advancements towards organizing and enhancing economic and social welfare. India is among several countries in the world that recently announced its national strategy for AI, #AIFORALL (2018)<sup>1</sup>, and constituted a task force<sup>2</sup> to identify relevant applications of AI in India including challenges faced or likely to be faced in the adoption of AI-based systems. By some measure, India is also seeing research in AI, with one study ranking India highly with respect to the number of ‘citable documents’, on AI, i.e. the number of research publications in peer-reviewed journals in the field of AI<sup>3</sup>. Not new to this story is the realm of the private sector that is currently ‘betting big’ on AI in India. An indication of this is the increasing funding in AI startups, both in terms of the total funds raised as well as the rounds of funding. Based on one estimate, the Indian AI market for startups attracted USD 762.5 million in 2019<sup>4</sup>.

Governments’ interest in AI can be traced to its potential for socio-economic gains. A report by the International Telecommunications Union (ITU)<sup>5</sup> finds wide-ranging applications of AI tools in achieving the 17 Sustainable Development Goals (SDGs) across all relevant UN organizations. For example, the UN Global Pulse has deployed ‘Neural Network Architectures’, a form of AI, to detect shelter structures from satellite images, at times of multiple humanitarian crises in East Africa and the Middle East. The Indonesian Government deployed similar capabilities to develop a crisis analysis tool that enhances disaster management efforts<sup>6</sup>. The government and public institutions in India are also building AI-based applications to address challenging social problems. The State Government of Arunachal Pradesh for instance, is using satellite-based systems to monitor the status of infrastructure projects in untraversable regions<sup>7</sup>. Several police departments in the country have partnered with AI startups to tighten security in public spaces. Railway services in India have incorporated AI to handle catering and other customer service requests. NITI Aayog has endorsed AI applications in precision agriculture, early diagnosis of diabetic retinopathy and building a language processing platform for multiple Indian languages<sup>8</sup>. The Robert-Bosch Centre for Data Science and Artificial Intelligence at IIT Madras is focusing on societal impact through AI, specifically in areas such as education, healthcare and agriculture<sup>9</sup>. There are also several interesting cases of AI-based applications that demonstrate private capital’s interest in the development and deployment of AI technologies. Wadhvani AI<sup>10</sup> is working on applications to screen low birth-weight babies in rural homes, provide integrated pest management solutions to reduce crop loss in cotton farms and to estimate case load for TB patients at the district level. A Poland based AI company, Synerise, is targeting the Indian market with AI-based personal learning solutions for students<sup>11</sup>. The list of possibilities is endless.

<sup>1</sup> NITI Aayog, 2018, Discussion Paper: National Strategy For Artificial Intelligence, [http://niti.gov.in/writereaddata/files/document\\_publication/NationalStrategy-for-AI-Discussion-Paper.pdf](http://niti.gov.in/writereaddata/files/document_publication/NationalStrategy-for-AI-Discussion-Paper.pdf)

<sup>2</sup> <https://www.aitf.org.in/>

<sup>3</sup> <https://www.thehindu.com/sci-tech/science/india-ranks-third-in-research-on-artificial-intelligence/article26030596.ece>

<sup>4</sup> <https://analyticsindiamag.com/report-indian-ai-startup-funding-in-2019/>

<sup>5</sup> <https://www.itu.int/pub/S-GEN-UNACT-2018-1>

<sup>6</sup> <https://www.analyticsindiamag.com/how-universities-are-embracing-ai-to-reform-indias-socio-economic-issues/>

<sup>7</sup> Notes from the AI Frontier: Applying AI for Social Good, McKinsey & Company, December 2018.

<sup>8</sup> <https://www.mckinsey.com/~media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Applying%20artificial%20intelligence%20for%20social%20good/MGI-Applying-AI-for-social-good-Discussion-paper-Dec-2018.ashx>

<sup>9</sup> NITI Aayog, 2018, Discussion Paper: National Strategy For Artificial Intelligence, [http://niti.gov.in/writereaddata/files/document\\_publication/NationalStrategy-for-AI-Discussion-Paper.pdf](http://niti.gov.in/writereaddata/files/document_publication/NationalStrategy-for-AI-Discussion-Paper.pdf)

<sup>10</sup> International Telecommunications Union, 2018, “United Nations Activities on Artificial Intelligence (AI)”, ITU Report

<sup>11</sup> <https://eng.wadhwaniai.org/>

<sup>11</sup> <https://economictimes.indiatimes.com/industry/services/education/polands-artificial-intelligence-provider-eyes-indias-education-sector/articleshow/69048492.cms?from=mdr>

The enthusiasm of private and public sectors in AI and the nature of AI-based applications being developed, especially that focus on development issues, is carving out a niche for India in the global AI ecosystem.

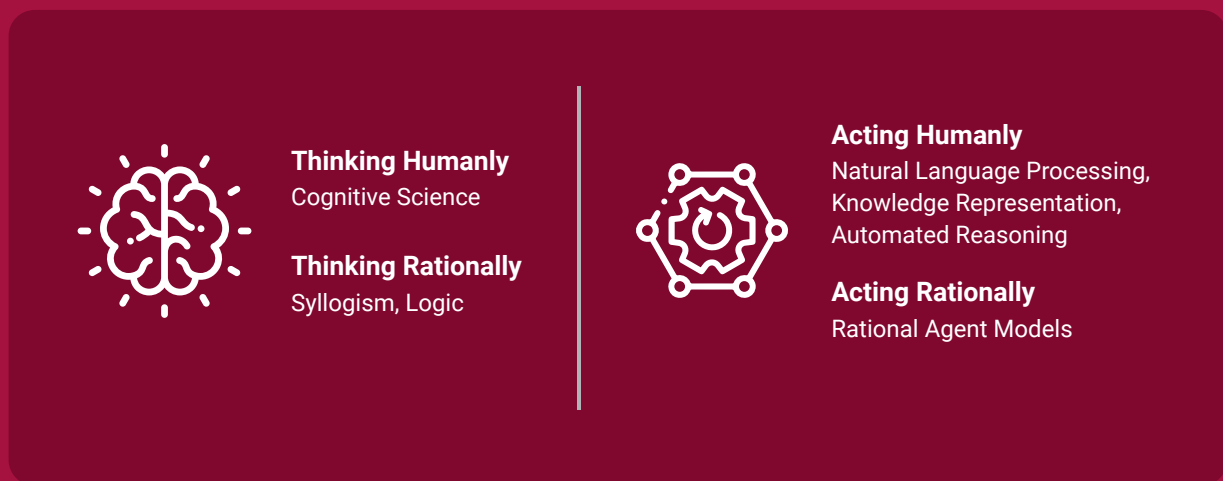
There is thus a palpable momentum in the Indian economy, both from the private sector as well as from the government to promote a flourishing AI-based ecosystem in the country, founded on the acknowledged potential of AI to trigger economic growth and social welfare. Establishing the magnitude of AI's impact on Indian economic growth and explaining the manner in which such growth is likely to be realised will further the Indian Government and economy's orientation towards this ecosystem. While there are several studies that attempt to explain how AI can drive growth, and some others that attempt to estimate and quantify the impact of AI on economic growth in advanced countries, there are almost none that attempt to estimate the impact of AI on productivity and economic growth in India. To the best of our knowledge this is the first study that comprehensively outlines the growth consequences of AI in India.

The rest of our report is organised as follows. Section 2 builds an understanding of AI and discusses the evolution of AI technologies over time. The section explores the versatility of AI through a range of its applications across different sectors, illustrating AI's role as a General-Purpose Technology (GPT). Section 3 of this report undertakes an exercise to estimate the implications of AI on the Indian industry using a well-established econometric model. Section 4 uses case studies of AI firms in India to identify capabilities that enable firms to innovate and adapt AI applications across different sectors of the economy. Section 5 concludes and offers policy recommendations based on the extensive data collected and analysed.

## 2. What is AI?

If AI is to be described in under one minute, the website of the Association for Advancement of Artificial Intelligence (AAAI) offers a useful solution. It defines AI as “the scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines.” If the reader has more than a minute to spend on the same question, a common starting point is Russell and Norvig’s (2009) textbook ‘Artificial Intelligence: A Modern Approach’.<sup>12</sup> As reproduced in Figure 2.1, the authors define AI across four broad dimensions – thinking humanly, acting humanly, thinking rationally and acting rationally.

Figure 2.1: A Framework for Understanding Artificial Intelligence



Source: Adapted from Russell and Norvig (2009)

Such expansive definitions of AI underscore the ambitious aims of the field. It comprises a vast array of subfields ranging from proving mathematical theorems to playing chess to diagnosing medical diseases, all of which are central to humanity and human intelligence. However, its aim is not merely to understand human intelligence. It is as if the field borrowed Marx’s quip<sup>13</sup>: *the aim of Artificial Intelligence is to not just understand intelligence, but to build it.*

<sup>12</sup> See: Russell, S., Norvig, P., 2010, Artificial Intelligence: A modern approach, Prentics Hall

<sup>13</sup> “Philosophers have hitherto only interpreted the world in various ways; the point is to change it.”, Marx, K., “Eleven theses on Feuerbach”.

## 2.1 Evolution of AI Technologies

The subject matter of Artificial Intelligence, as we know it<sup>14</sup>, has a history of more than 50 years starting with Turing's (1950) 'Computing Machinery and Intelligence'<sup>15</sup>, in which he asks, "*Can a machine imitate human intelligence?*" AI's evolution to the present has seen several winters and springs of research programs. While many consider AI to be a modern phenomenon, it in fact evolved in two phases, one occurring in the 1950s and 60s, and the second which began about two decades ago, in the 1990's. The period in between is referred to as the AI winter, a period of reduced interest in AI research marked by several episodes of failure. These include the failure in machine translation, abandonment of connectionism, and withdrawal of funding from several ambitious programs including DARPA and the Strategic Computing Initiative.

However, since the nineties, AI has made lengthy strides. The last couple of years have seen an explosion in AI activity especially in the area of self-driving cars, chatbots, digital assistants, etc. Alongside these innovations have been warnings of digital slavery. Several technology pioneers have warned against the dangers of AI and urged countries to prepare for its disruption to avoid potential risks. With adequate safeguards, the technology can generate impacts with minimum harm. A separate stream of related literature is being developed to focus on the transparent and responsible deployment of AI. Figure 2.2 highlights some key events in the evolution of AI since the 1950s.

Research<sup>16</sup> aimed at conducting an analysis of the evolution of AI across its many facets maps data from the International Joint Conference on AI organization (IJCAI) and the Association for the Advancement of AI (AAAI). Its analysis reveals that heuristic search and optimization and knowledge representation have declined during the period 1997 to 2017, while machine learning has increased through research in deep learning and reinforcement learning. The research further highlights how other categories have also shown spikes. For instance, cognitive modeling peaked in the 1990's, associated with the emergence of cognitive architectures such as ACT-R, EPIC, and SOAR. Multiagent systems peaked around 2010 when they were successfully applied to autonomous vehicles and gaming applications. Data mining, neural networks and probabilistic reasoning emerged in the 1980s and 1990s.

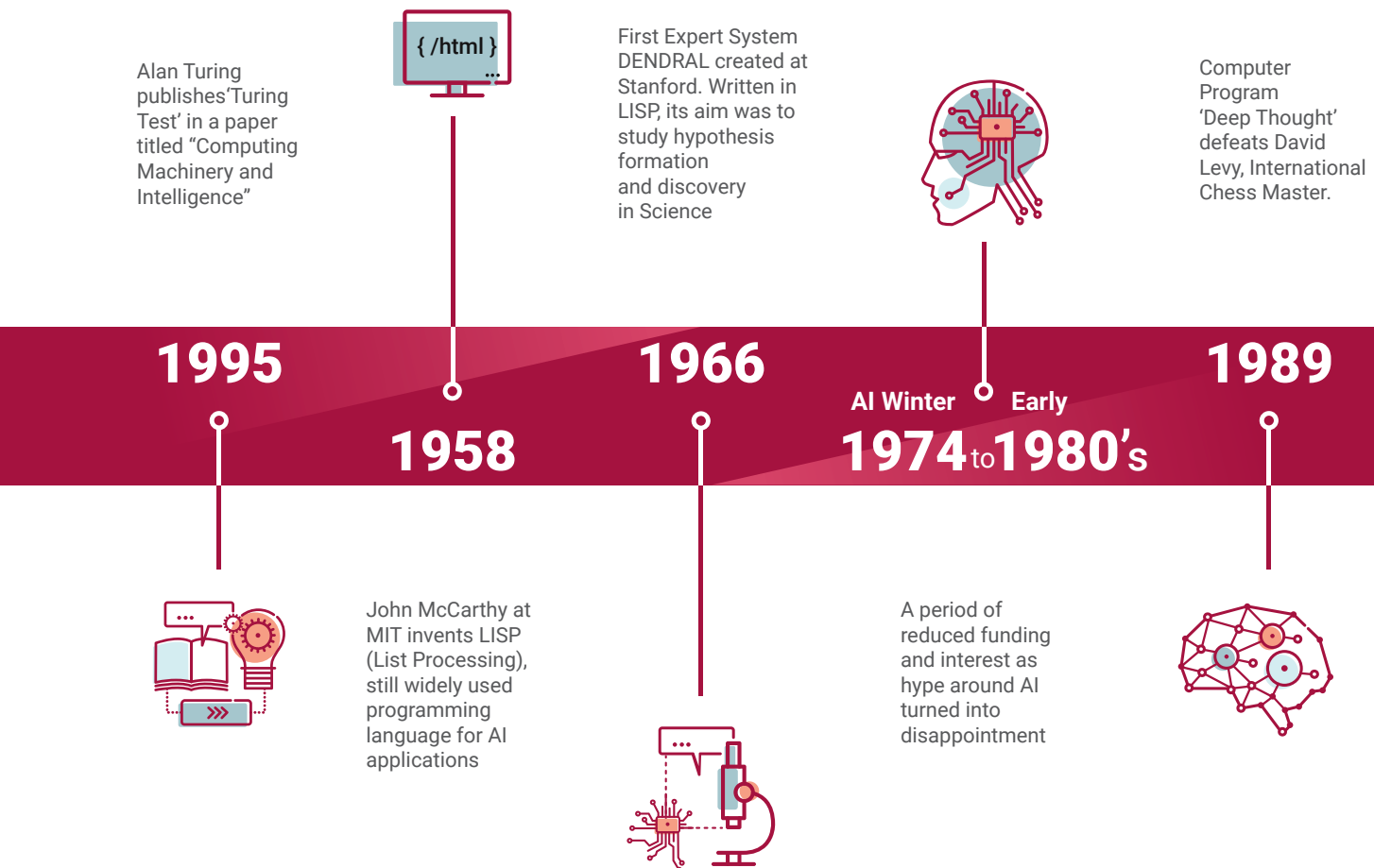
<sup>14</sup> Mayor (2018) provides a historical account of metaphors of artificial intelligence and technology going back to ancient Greece. See: Mayor, A., 2018, *Gods and Robots: Myths Machines and Ancient Dreams of Technology*, Princeton University Press

<sup>15</sup> Turing, A., 1950, *Computing Machinery and Intelligence*, *Mind*, 49: 433-460

<sup>16</sup> <https://www.ecnmag.com/blog/2018/04/infographic-journey-artificial-intelligence>, Access on 14.6.2019

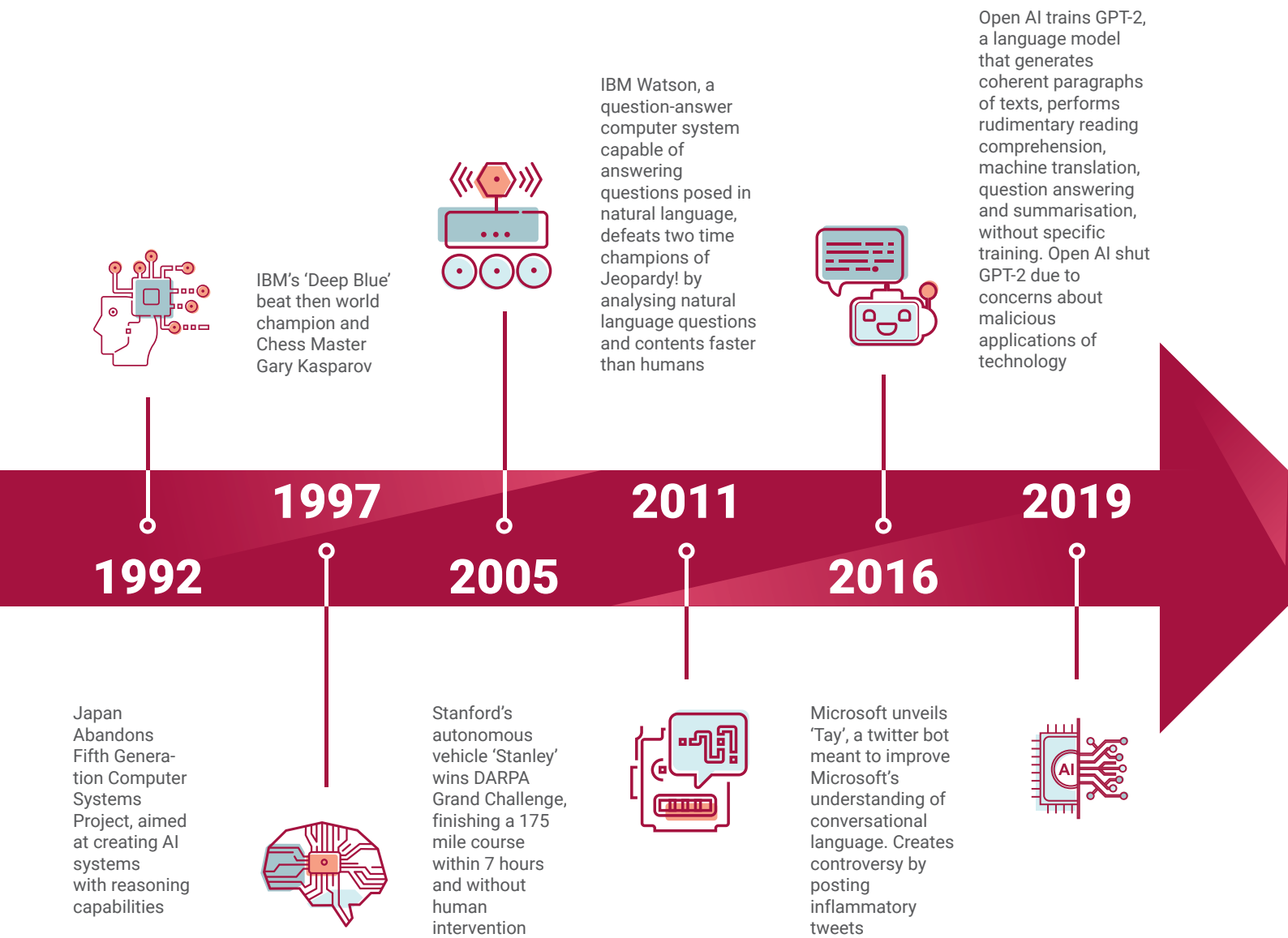


Figure 2.2: The Evolution of Artificial Intelligence



Source: Adapted from Digital Intelligence Today<sup>17</sup>

<sup>17</sup> Martinez-Plumed, F., Sheng Loe, B., Flach, P., O hEigeartaigh, S., Vold, K., Hernandez-Orallo, J., 2018, "The Facets of Artificial Intelligence: A Framework to Track the Evolution of AI", Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence (IJCAI-18).

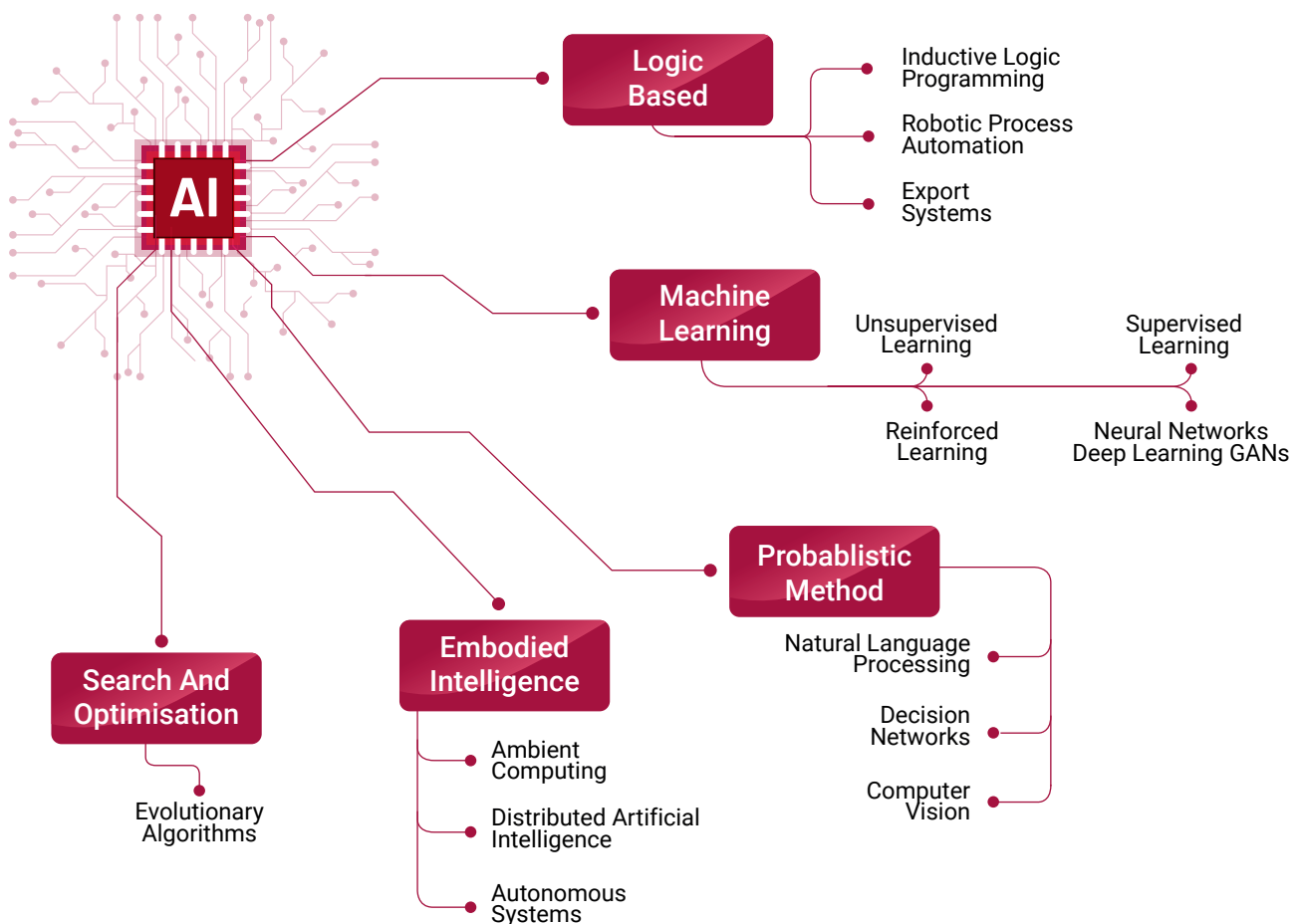


Source: Adapted from Digital Intelligence Today<sup>17</sup>

The dynamic nature of AI technologies makes it very difficult to arrive at a classification that captures all fundamental aspects of AI. Recent efforts to understand where machine intelligence is being used and how problems are being framed for AI to solve, was represented using an AI knowledge map. Figure 2.3 is adapted from the knowledge map that associates a technology solution to a problem domain and its proposed approach<sup>18</sup>.

The AI universe includes logic-based tools, knowledge-based tools, probabilistic methods, machine learning, embodied intelligence, search and optimization. Technologies mapped to these paradigms include robotic process automation, expert systems, computer vision, natural language processing, neural networks, affective computing, evolutionary algorithms, etc. In its current state of diffusion more than 80 percent of the current efforts in AI are driven by 20 percent of the technologies. The most widely adopted technologies are Machine Learning, Natural Language Processing and Computer Vision. The most recent research on AI focuses on lowering costs, improving general performance and addressing AI's potential risks. More specifically, research now includes work on 'Verification': the question of whether the system was built 'right'; 'Validity': the question of whether the right system was built; 'Security': the question of how to prevent intentional manipulation; and 'Control': the question of how to enable human control over an operating AI.

Figure 2.3: The AI Knowledge Map



Source: Adapted from Francesco Corea (2018)

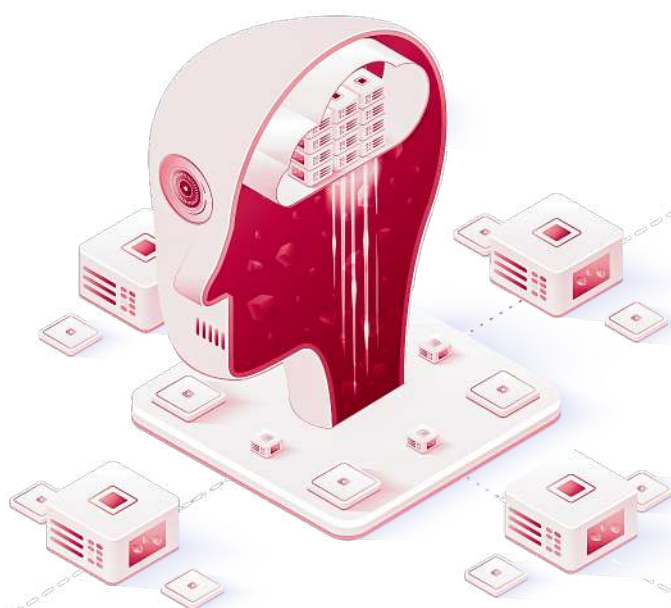
<sup>18</sup> AI Knowledge Map: How to Classify AI Technologies Available at [https://medium.com/@Francesco\\_AI/ai-knowledge-map-how-to-classify-ai-technologies-6c073b969020](https://medium.com/@Francesco_AI/ai-knowledge-map-how-to-classify-ai-technologies-6c073b969020)

### Box 2.1 Foundations of AI in India

AI research in India had its sporadic beginnings in the 1960s when Prof. H. N. Mahabala, upon returning from Massachusetts Institute of Technology (MIT), introduced a course in Artificial Intelligence at IIT Kanpur. It may be stated that Artificial Intelligence in India took off in the 1980s when the Indian Government, in association with the United Nations Development Programme (UNDP) launched the Knowledge Based Computing System (KBCS) program, as a part of Indian Fifth Generation Computer Systems (FGCS) research program to develop a state-of-the-art AI programming environment upon which R&D efforts could be carried out.

Institutes such as the Indian Institute of Science (IISc), IIT Madras, Indian Statistical Institute (ISI) Kolkata and the Tata Institute of Fundamental Research (TIFR) were set up as nodal agencies leading the front on developing critical aspects of AI in India. Between 1986 and 1995, such nodal centers received INR 15 million, with each center producing approximately 15 PhDs, and employing 20 to 35 full-time researchers. Several AI-based applications emerged from these efforts, including, IIT Madras' 'Eklavya', a knowledge-based program designed to support community health workers in dealing with symptoms of illness in toddlers, CDAC's 'Sarani', a flight scheduling expert system and IISc's Computer Vision based image processing facility.

India's R&D capabilities in AI has since been growing steadily. Between 2010 and 2016, national institutes of importance such as the IISc, IIT Bombay, IIT Delhi, IIT Madras, IIIT Hyderabad, IIT Kanpur, IIT Kharagpur and ISI Kolkata feature among the top universities/research institutes for AI in India. India ranks 10th globally in terms of number of PhDs in AI, and 13th in terms of presentations in top AI research conferences. However, there remain significant challenges in developing, adopting and using AI in India, as will be spelled out in the subsequent sections of this report. The discussion explains India's position behind current world leaders such as the US and China.



## 2.2 Adoption and Application of AI

A fascinating aspect of Artificial Intelligence is its lack of specificity; individuals, communities, industries and governments are all using and reaping the benefits of AI technologies and its fast-evolving capabilities. To get a sense of the pervasiveness of AI technologies, it is useful to see how different applications of AI are impacting businesses across sectors of economic activity. In the following subsections we illustrate the use of AI across some prominent industries in India. This is followed by a sketch of how governments and other social development initiatives are leveraging AI, and finally, how AI is slowly but surely penetrating our daily lives.

### 2.2.1 AI for Industry

The McKinsey Global Institute (2018)<sup>19</sup> report provides a useful starting point to gauge the diffusion of AI across sectors and businesses. The report's heat map shows AI being highly relevant to automotive, banking, consumer goods, healthcare, insurance, pharmaceuticals, retail, telecommunications, and transport and logistics sectors.

Fundamentally, any industrial vertical that is data-oriented is set to undergo AI-driven transformation<sup>19</sup>. AI's capacity for industrial transformation stems from its versatility. AI lends itself to a diverse range of operations in different industries such that industries can do things differently and better.

The automotive industry for instance deploys AI extensively across different operations. A central aspect of industrial engineering, i.e. quality control, is greatly enhanced by the predictive powers of AI. The automobile company Audi uses Computer Vision equipped cameras to detect tiny cracks in sheet metal hitherto invisible to the human eye.<sup>20</sup> AI machines can detect defects up to 90% more accurately than humans<sup>21</sup>. Banks are also recognising the potential of AI for a range of applications that are transforming consumer experience and the way in which they operate. For instance, using data from past payment patterns, AI can predict and prompt the user's preferred mode of payment. Such applications of AI that are personalising banking experience for users is also creating significant helping retain customers<sup>22</sup>. The healthcare sector is leveraging AI's predictive capabilities to detect, for instance, breast cancer at early stages using Machine Learning techniques<sup>23</sup>, and screen for diabetic retinopathy using Deep Neural Net based algorithms<sup>24</sup>. It is reported that AI has the ability to improve health outcomes by 30 to 40%, cosequently reducing healthcare costs by 50%<sup>25</sup>.

The ability of an economy to adopt AI depends on its structural composition and the technological maturity of different sectors. While opportunities exist in most sectors and across business functions, digitised firms are more likely to adopt AI than their peers which lack technology infrastructure including skilled manpower. The current levels of automation vary across sectors and types of firms in the Indian industry. Cost of new technology, lack of talent and the baggage of legacy infrastructure are some of the common deterrents. Table 2.1 provides examples of current applications of AI across different sectors in India and their impacts on process efficiency, cost and quality of products, welfare outcomes, etc.

<sup>19</sup> <https://www.information-age.com/industries-ai-impact-123475559/>

<sup>20</sup> <https://www.capgemini.com/wp-content/uploads/2019/03/Ai-in-automotive-research-report.pdf>

<sup>21</sup> <https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/building-smarter-cars>

<sup>22</sup> <https://www.livemint.com/AI/v0Nd6Xkv0nINDG4wQ2JOvK/Artificial-Intelligence-in-Indian-banking-Challenges-and-op.html>

<sup>23</sup> <https://www.niramai.com/technology/>

<sup>24</sup> <https://www.healthcareitnews.com/news/google-verily-using-ai-screen-diabetic-retinopathy-india>

<sup>25</sup> <https://www2.frost.com/news/press-releases/600-m-6-billion-artificial-intelligence-systems-poised-dramatic-market-expansion-healthcare/>

Table 2.1: Examples of AI Applications across Industries in India

Study	Application	Impact
 Agriculture	Image processing and Machine Learning enabled Crop and soil monitoring and predicting impact of weather on crop output	Efficiency in allocation of farm inputs such as pesticides; efficiency in crop cycle management
 Manufacture	Computer vision enabled Quality control monitoring, predictive analytics, Machine Learning enabled supply chain management	High defection detection rates in quality control; productivity and efficiency gains from automation
 Healthcare	Predictive analysis to detect early stage diseases; Deep Neural Nets to interpret medical scans, pathology slides, skin lesion, retinal image, endoscopy, etc.	Rapid and accurate image interpretation that is enhancing diagnosis, improving workflow for health systems and reducing physician's errors, enabling patients to process own data
 Banking	Natural Language Processing for conversational bots, Image recognition and Deep Learning based fraud detection applications	Enhanced and personalised customer experience, increased accuracy in detecting credit-card anomalies and money laundering, enhanced risk analysis and early detection of security breaches.
 Retail	Machine Learning powered personalised recommendations and inventory management, Natural Language Processing powered 'conversational' commerce, computer vision powered smart shopping	Enhanced and personalised customer experience, efficiency gains from accurate pricing and seamless shopping, efficiency in inventory management
 Education	Machine Learning powered learning diagnostics for students, Deep Learning based super-charged videos and learning platform	Personalised learning methods, enhanced assessment of students and learning outcomes, enhanced support outside classroom
 Legal Services	Natural Language Processing and Machine Learning based due diligence and compliance support, contract review and management, and legal prediction	Efficiency gains from reducing time to produce legal documents, reduction in time taken to conduct due diligence, assurance in legal compliance, enhanced legal recourse based on legal predictions
 Utilities	Machine Learning, Deep Learning, Artificial Neural Nets based smart grids, energy demand forecasting and management	Intelligent utilities (water, electricity, oil and gas) grid systems, enhanced efficiency in utility allocation and use, enhanced energy management
 Transport	Machine Learning, Deep Learning and Advanced Neural Net based driver assistance, semi-autonomous vehicle programs and traffic management systems	Efficiency through decreasing costs of labor, enhanced driver safety, efficient routing systems and decreasing incidence of traffic jams, second-order energy saving effects
 Tourism	AI powered robotics for hospitality services, Natural Language Processing based interface with guests, Machine learning driven data analytics	Enhanced personalisation of consumer experience, efficient and empathetic hospitality design
 Media	Image recognition, speech-to-text transcription, metadata tagging as drivers of content monetisation strategies, automated media operations, Machine Learning based content-demand forecasting and management	Enhanced personalisation of media consumption, cost saving for media houses from optimal content monetisation strategies and demand forecasting

Source: Compiled by Author from Secondary Sources and Stakeholder Interactions

## 2.2.2 AI for Governance and Social Development

National governments and international governance agencies around the world are deploying AI-based solutions for a wide range of issues that are central to public policy and welfare. The predictive powers of AI and its flexibility, lends AI solutions to a range of challenges facing society. Governments can reach the underserved and deliver more efficiently, by judiciously fusing AI into its operations. A task-based analysis<sup>26</sup> finds that AI can speed up governance tasks by 20 percent, freeing up to 96.7 million hours and consequently saving \$3.3 billion for governments.

Other concrete instances of AI's capabilities can be observed in the area of public utilities. For instance, Australia's public sector company, Melbourne Water which operates across the city of Melbourne, is using Machine Learning techniques to manage the differential rates at which its water pumps are running so as to maximize efficiency in its water distribution system<sup>27</sup>. In India, AI is demonstrating its potential to enhance law enforcement capabilities through Deep Learning based applications such as facial recognition systems, which are being used by law enforcement agencies to efficiently track missing children<sup>28</sup>. Delhi Police has partnered with ISRO to develop an analytical system called Crime Mapping Analytics and Predictive Systems (CAMPS) which helps them ensure internal security, also controlling crime. Similar programs are being adopted in other states such as Jharkhand and Karnataka<sup>29</sup>. Dubai police has signed an MoU with the Indian startup Staqu for its predictive policing solutions which were already piloted and adopted by states such as Rajasthan, Punjab and Uttarakhand. Defense Services in India use AI for intelligence, surveillance, etc, though several of these projects are still in the pilot or testing phase.

The International Telecommunications Union (ITU) published a report on the United Nations' activities on AI<sup>30</sup>, which compiles how different UN agencies are deploying solutions to achieve various Sustainable Development Goals (SDGs). For instance, the International Labor Organization (ILO) initiated a project that uses Big Data based AI algorithms to monitor incidence of child labor in Kyrgyzstan. The United Nations Children's Fund (UNICEF) is using AI to generate insights on the spread of an epidemic and Deep Learning methods to increase empathy for victims of natural disasters<sup>31</sup>. In India, we find innumerable AI applications focusing on developmental outcomes. A recent media report stated that 11% of AI startups in India were focused on the education sector. These include Toppr, Edu Gorilla, Embibe, etc<sup>32</sup>. Other critical areas of application include `securing lives of the disabled, healthcare, child nutrition, etc. IIT Kharagpur has developed a solution that filters fake news and alerts users during disasters. GnoSys, a smartphone application developed for the deaf and mute, uses natural language processing, neural networks, and computer vision to translate gestures and sign language into speech. The app is expected to change the life of an estimated 18 million people in India who are hearing impaired.

AI is claimed to have become critical to governance in the 21st century. In the era of Big Data, AI technologies such as sensors and Machine Learning, can provide real time insight on the efficacy of government regulations and lapses in regulatory oversight. The government in India has publicly acknowledged the role of AI in enforcing good governance and proper regulations in India<sup>33</sup>.

<sup>26</sup> <https://www2.deloitte.com/insights/us/en/focus/cognitive-technologies/artificial-intelligence-government.html>

<sup>27</sup> <https://www.melbournewater.com.au/what-we-are-doing/news/driving-efficiency-artificial-intelligence-and-machine-learning>

<sup>28</sup> <http://facetagr.com/>

<sup>29</sup> <https://www.analyticsindiamag.com/how-indian-police-is-tapping-into-data-analytics-to-prevent-crime/>

<sup>30</sup> International Telecommunications Union, 2018, United Nations Activities on Artificial Intelligence

<sup>31</sup> Ibid

<sup>32</sup> <https://www.thenewsminute.com/article/india-s-1st-disability-focused-accelerator-invites-applications-tech-startups-104058>

<sup>33</sup> <http://pib.nic.in/newsite/PrintRelease.aspx?relid=188684>



## 2.2.3 AI for Households/ Individuals

While literature and cinema have offered us an imagination of a futuristic society driven by AI and related applications<sup>34</sup>, a range of AI driven applications have now in reality come to permeate our digital and analog lives. AI driven transformations are slated to have become deep and fundamental<sup>35</sup>, in a manner that will greatly impact how humans relate to each other. Several pioneers and leaders have weighed on AI's impact on humans and they find that while AI increases human 'effectiveness', AI also threatens human autonomy, agency and capabilities<sup>36</sup>.

An ordinary day in the lives of most people today is filled with activities using AI applications, often without noticing. An AI powered Siri or Alexa may set an alarm, while monitoring sleep quality patterns<sup>37</sup> to enable one sleep better. As the Natural Language Processing (NLP) driven AI-assistant goes through one's schedule for the day, an autonomous self-driven car can aid in safely transporting people to a destination of their choice<sup>38</sup>. Children going to school will be monitored by Machine Learning and related techniques of AI that crunches data to aid in improving teaching and children's learning outcomes<sup>39</sup>. Individual retail and shopping experiences are transformed by AI driven product recommendation, used by online retailers such as Amazon. The shopping experience is itself transformed with computer vision- based technologies churning 'just walk out' stores that do not have check-out counters<sup>40</sup>. An individual has not yet reached half a day, but has already significantly interfaced with AI. In fact, the People + AI Research (PAIR) survey finds that several respondents in India were not aware that they were using AI in everyday apps<sup>41</sup>.

It is apparent by now that the applications of AI are wide-ranging and cut across various levels of society from households to governments. Their wide-ranging use cases naturally lead to their pervasiveness in society. As will be explained below, these features of AI lend credibility to the view that AI is a 'General Purpose Technology', which are a class of technologies that have, historically, powered economic growth and triggered deep transformations in societies.

## 2.3 AI as a General-Purpose Technology

Advances in AI are clearly among humanity's pivotal inventions. Andrew Ng (2015) stated emphatically<sup>42</sup>, "Just as electricity transformed almost everything a hundred years ago, today I actually have a hard time thinking of an industry that I don't think AI will transform in the next several years." This statement is also important for it (unwittingly) draws attention to a common conceptual framework: AI, like electricity, is a GPT<sup>43</sup>. Simplistically, GPTs are technologies that impact economic growth by fundamentally transforming both household living as well as ways in which firms conduct business. The three critical features characterizing GPTs are (i) pervasiveness, (ii) technical improvements and (iii) their role in enabling other innovations. One can think of electricity, or more recently, the Internet such GPTs<sup>44</sup>.

(See Figure 2.4). Conceptualising AI as a GPT implies, that AI led innovations will be reflected not only as direct contribution in any given sector, but also inspire complementary innovations and spillover benefits in other sectors of the economy.

<sup>34</sup> <https://www.technologyreview.com/s/609131/fiction-that-gets-ai-right/>

<sup>35</sup> <https://www.nytimes.com/2019/06/18/opinion/david-chalmers-virtual-reality.html>

<sup>36</sup> <https://www.pewinternet.org/2018/12/10/artificial-intelligence-and-the-future-of-humans/>

<sup>37</sup> <https://time.com/5494363/sleep-artificial-intelligence/>

<sup>38</sup> <https://www.wired.com/story/future-of-transportation-self-driving-cars-reality-check/>

<sup>39</sup> <https://www.mckinsey.com/featured-insights/artificial-intelligence/the-role-of-education-in-ai-and-vice-versa>

<sup>40</sup> <https://www.theguardian.com/business/2018/jan/21/amazons-first-automated-store-opens-to-public-on-monday>

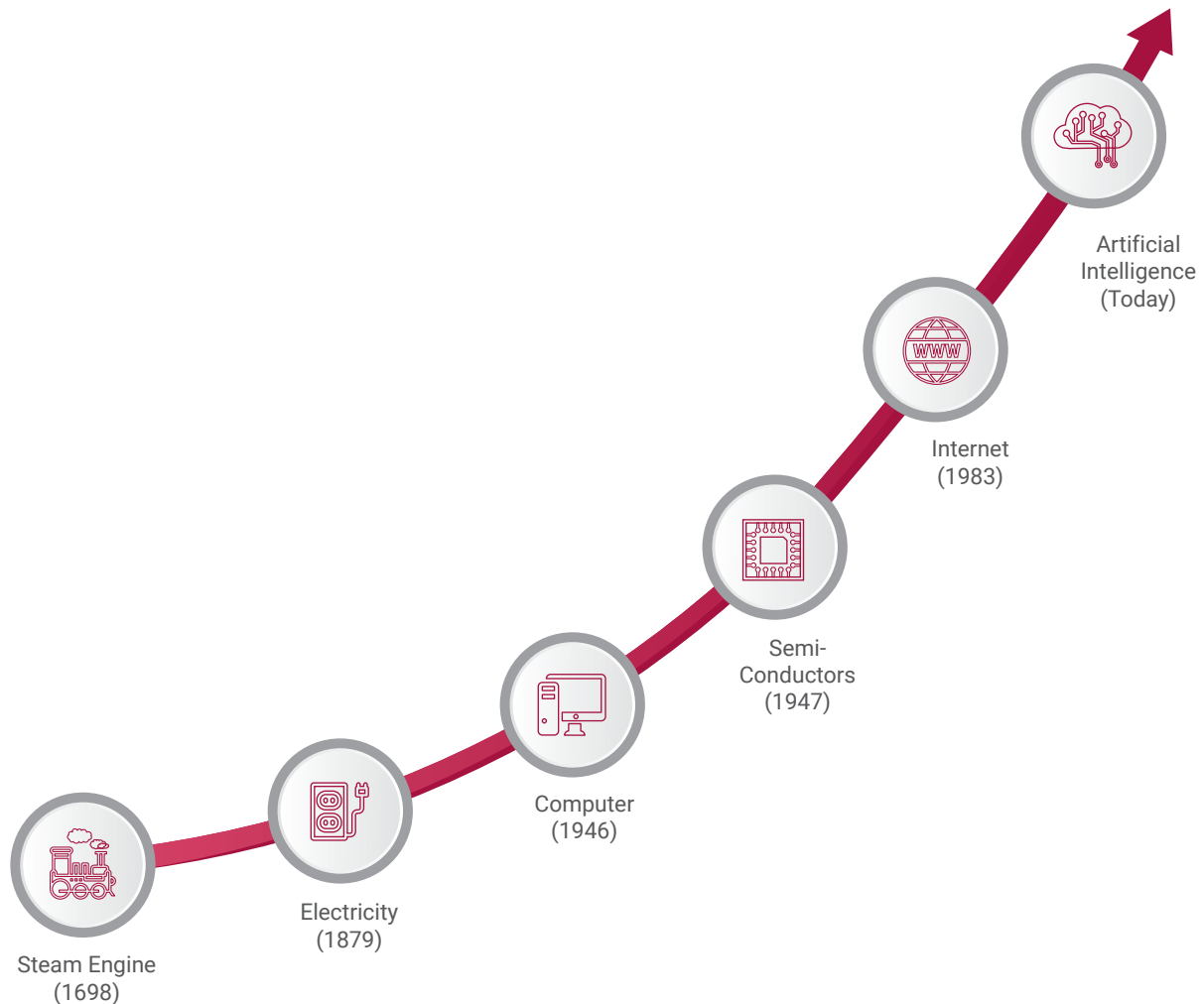
<sup>41</sup> <https://ai.google/research/teams/brain/pair>

<sup>42</sup> <https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity>

<sup>43</sup> Electricity and information technology are considered to be among the most important GPTs. See: Jovanovic, Boyan & Rousseau, Peter L., 2005. "General Purpose Technologies," Handbook of Economic Growth, in: Philippe Aghion & Steven Durlauf (ed.), Handbook of Economic Growth, edition 1, volume 1, chapter 18, pages 1181-1224 Elsevier

<sup>44</sup> Jovanovic, Boyan & Rousseau, Peter L., 2005. "General Purpose Technologies," Handbook of Economic Growth, in: Philippe Aghion & Steven Durlauf (ed.), Handbook of Economic Growth, edition 1, volume 1, chapter 18, pages 1181-1224 Elsevier

Figure 2.4: Historical Instantiations of GPTs



Source: Authors Compilation<sup>45</sup>

While there are no formal empirical tests that can detect General Purpose Technologies, it is possible to describe the extent to which AI matches up to three key features of GPTs<sup>46</sup>.

**Pervasiveness:** The pervasiveness of AI across various 'application sectors' is documented in the World Intellectual Property Organization's (WIPO) recent Technology Trends 2019: Artificial Intelligence Report<sup>47</sup>. AI applications also include social and behavioural sciences, military, agriculture, energy management, education, document management, publishing, etc. Deloitte recently published a report stating that while AI is getting better it is also becoming more pervasive<sup>48</sup>. From 79 million in 2018, the annual shipment of devices embedded with AI is likely to increase up to 1.2 billion in 2023.

<sup>45</sup> Icons used from <https://www.flaticon.com/home>

<sup>46</sup> Jovanovic, B., Rousseau, P.L., 2005, General Purpose Technologies, NBER Working paper no. 11093

<sup>47</sup> See: <https://www.wipo.int/publications/en/details.jsp?id=4386>

<sup>48</sup> <https://www2.deloitte.com/insights/us/en/focus/signals-for-strategists/pervasive-intelligence-smart-machines.html>

Technological improvements: The field of AI continues to undergo significant transformations, with not just improvements in its performance and applicability<sup>49</sup>- from the 'Turing Test' to Big Data driven Machine Learning techniques, but also rising and falling trends in various techniques. For instance, from 1997 to 2017, while research on heuristic search and optimization, cognitive modeling, knowledge representation has declined, research on game theory, Machine Learning and natural language processing has witnessed a consistent rise<sup>50</sup>. Using data on patent filings, WIPO finds that telecommunications, transportation, life and medical sciences, personal devices, computing and Human-Computer Interactions (HCI) are the top application fields.

Enabling Innovations: The diffusion of AI has enabled a wide range of activities that were hitherto unimagined. UN activities on AI report the use of Machine Learning techniques for environmental protection in Mongolia, disaster preparedness in Maldives, and the development of cloud-based geospatial solutions for enhanced management of natural resources. The proliferation of predictive algorithms and natural language processing has transformed business processes in the financial services sector. This includes fraud detection, processing insurance claims and customer interactions. AI's predictive capabilities are reducing costs and altering organisational structures. Networked turbines, intelligent power distribution and automated manufacturing are now realities made possible with the diffusion of AI technologies.

General Purpose Technologies have, in the past, unlocked the growth potential and played a significant role in explaining the wealth of nations<sup>51</sup>. Artificial Intelligence, as argued, demonstrates certain fundamental characteristics of General-Purpose Technologies, and thus to an extent validate the future promise of AI-driven economic growth. The comparison with critical features of GPTs in general, is an imperfect yardstick to test whether AI is a GPT or not and it is up to history to validate such claims, but such comparisons indicate that at the least, AI has the makings of a General-Purpose Technology. However, the transition towards an AI-based economic system is not a natural occurrence. Unlocking the potential of AI requires an understanding of the short-run possibilities and long-run dynamics of such growth, and equally importantly, the opportunities and challenges in the process of diffusing AI across societies in a manner that is welfare-enhancing.

In order to illustrate the growth impacts of AI in this report, we adopt the understanding of AI as a GPT. Doing so allows us to link AI with an existing understanding of GPTs and derive an understanding of its economic implications, while appreciating novel economic and regulatory challenges posed by AI.

<sup>49</sup> See: <https://www.em360tech.com/tech-news/tech-features/artificial-intelligence/>

<sup>50</sup> Martinez-Plumed, F., Loe, B.S., Flach, P., hEigeataigh, S.O., Vold, K., Hernandez-Orallo, J., 2018, The Facets of Artificial Intelligence: A Framework to Track the Evolution of AI, Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-2018

<sup>51</sup> Lipsey, R.G., Carlaw, K.I., Bekar, C.T., 2005, Economic Transformations: General Purpose Technologies and Long-Term Economic Growth, Oxford University Press

### 3.

# Estimating the Impact of AI on Indian Industry

The General-Purpose nature of AI means that its growth consequences will be wide-ranging, affecting various levels, from households and firms to the larger macro economy. The drivers of this growth are likely to emerge from productivity gains to businesses and increased consumer demand from customised products and services. Economists supporting the unconstrained and perpetual growth story<sup>52</sup>, argue that countries engage in research and development (R&D) to create productivity enhancing systems (such as AI) to perpetuate growth in instances of changing labour, capital and output trends. AI in turn makes the process of scientific discovery and R&D easier, which triggers further innovation and economic growth<sup>53</sup>.

The disruptive effects of AI, like other forms of automation and technological evolution have also been a topic of discussion in the literature. There is increasing worry that machines will replace almost everyone. A McKinsey report argues that 73 million jobs may be destroyed by automation by 2030 because of the rise of new technologies<sup>54</sup>. Contrary to the notions that AI (and AI driven automation) will lead to job losses, it is also argued that the relationship between AI driven automation and job losses depends on the level of demand in the sectors that are prone to automation in the economy<sup>55</sup>. Infact, AI driven automation increases firm productivity and reduces prices for firms in that sector. The demand triggered by such price reductions can result in higher employment. There is a similar argument for automation induced productivity to create demand for labour in non-automated tasks<sup>56</sup>. However, gains from automation induced productivity are larger than the increase in wages for labour, leading to higher inequality. A policy response to prepare for such risks are discussed in the final chapter of this report.

While there is a lack of systematic data on the use of AI, there have been attempts to present high-level findings on the impacts of AI using empirical methods. The research that exists is mostly derived from past technologies (such as factory robots) that capture only part of the economic reach of AI<sup>57</sup>. There are comparatively more studies on robots, as against AI, owing to their physical nature and the ability to track them over time and location<sup>58</sup>. In order for an economy to effectively absorb technologies, firm-level data often becomes necessary to develop a complete and thorough understanding of its impact on growth, productivity, labour and equality<sup>59</sup>.

Notwithstanding limitations of data, recent research attempts to measure the impact of AI using case studies or modeling AI through proxy variables. Table 3.1 summarises these estimates.

<sup>52</sup> Peretto, P.F., Seater, J.J., 2013, Factor-eliminating technical change, *Journal of Monetary Economics*, vol. 60

<sup>53</sup> Agarwal, A., McHale, J., Oettl, A., 2018, Finding Needles in Haystacks: Artificial Intelligence and Recombinant Growth, NBER Working Paper no. 24541

<sup>54</sup> McKinsey & Company: Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., Henke, N., Trench, M., 2017, "Artificial Intelligence: The Next Digital Frontier?", McKinsey Global Institute Discussion Paper

<sup>55</sup> James Bessen, 2018, "AI and Jobs: The Role of Demand", NBER Working Paper 24235

<sup>56</sup> Acemoglu, D., Restrepo, P., 2018, "Artificial Intelligence, Automation and Work", NBER Working Paper 24196

<sup>57</sup> Agarwal, A.K., Gans, J.S., Goldfarb, A., 2018, Economic Policy for Artificial Intelligence, NBER Working Paper no. 24690

<sup>58</sup> Saemans and Raj, 2018, "AI, Labour, Productivity and the Need for Firm-Level Data", NBER, Working Paper 24239

<sup>59</sup> Ibid

**Table 3.1 A Summary of Empirical Estimations on the Impact of AI**

Study	Objectives	Methodology	Findings
PWC (2018)	To demonstrate AI's full economic potential globally through channels of productivity and consumption enhancement	<p>Analyses the productivity impacts of AI by modelling the impact of software, databases, computer hardware and machinery on labour productivity</p> <p>Developed AI impact index to evaluate AI's impact on products across sectors, sub-sectors and product lines.</p> <p>Use the results as inputs in a computable general equilibrium model to estimate the net impact of AI on the economy until 2030</p>	AI led increase of 14%, equivalent to \$15.7 trillion in global GDP by 2030.
McKinsey Global Institute (2018)	To assess the practical applications and economic impacts of advanced AI techniques across industries and business functions.	Maps AI techniques to the type of problem they can solve using 400 case studies across 19 industries. The industries include aerospace, defence, travel and public sector organisations and addressing functions such as marketing, sales, supply chain management, product development and human resource management.	Artificial neural networks enable annual value creation of \$3.5 to \$5.8 trillion. In consumer facing services, marketing and sales benefit the most from application of AI techniques. In manufacturing, the greatest potential is in supply chain logistics and manufacturing.
Accenture (2018)	To estimate the impact of AI as a factor of production on major developed economies.	Models AI as a new factor of production, a capital-labour hybrid, and not just a driver of total factor productivity.	AI yields the highest economic benefits for the United States in absolute terms, implying a 4.6 percent growth rate by 2035, while Japan could more than triple its gross value-added growth during the same period.

Source: Compiled by Author

## 3.1 Challenges of measuring impact of GPTs including AI

It may be argued that the impact of AI, given its intangible features may not be routed through the role it plays as a 'factor of production'. The famous Ford Assembly Line provides an illustration<sup>60</sup>. The Ford Assembly line is an organizational structure that enabled efficient production. Its impact goes beyond 'factors of production'. This view is validated in empirical studies that attempt to capture the economic impacts of GPTs. A study estimating the relationship between broadband defined as a GPT, and firm level productivity, reasons that factors such as organizational processes and routines, product and process knowledge enhancement, administrative, managerial and financial coordination practices are all impacted by the GPT and that productivity is improved by acting on all these factors<sup>61</sup>.

Historically, the economic impacts of GPTs have not been immediate but follow after its diffusion in the economy, i.e. over a period of time. There are two reasons that explain this phenomenon. Firstly, in early phases of technology diffusion, an economy diverts part of its resources from productive activities to costly activities aimed at enabling the GPT. For instance, organizations adopting computers must also invest in training employees or hire computer scientists, re-arrange production activities or organizational structures to accommodate computer driven work-flows, all of which are costly economic activities. Secondly, it is only after the GPT is diffused and widely used in the economy that the statistics measuring GDP start counting and fully measuring the GPT. This study frames AI as a GPT, and since GPTs impact productivity that goes beyond labor and capital, TFP is an appropriate variable on which AI has an impact.

Empirical research on GPTs such as AI, including ours, means confronting the challenge of measurement. Estimates of the economic impact of AI are subject to the caveat that data on AI adoption is not available or adequately reflected in the data used to compute economic growth, at least not yet. Measuring the economic impact of AI is also difficult because of the magnitude of indirect effects on productivity that GPTs trigger. It is therefore common to engage in case studies and historical analysis of its impact to supplement the econometric estimates.

<sup>60</sup> David, P., 1990, The Dynamo and the Computer: An Historical Perspective on the modern productivity paradox, The American Economic Review, Vol. 80, No. 2.

<sup>61</sup> Majumdar, S.K., Carare, O., Chang, H., 2009, Broadband Adoption and firm productivity: evaluating the benefits of general purpose technology, Industrial and Corporate Change, Vol. 19, No. 3

## 3.2 Econometric Estimation

While there are no studies that uniquely focus on the growth impacts of AI in India, there are several that attempt to capture the sources of economic growth and the impact of technological change on Total Factor Productivity (TFP) at the national and sectoral levels. TFP is normally understood as a 'residual' term that can explain how factors other than capital and labour, such as investments in R&D, improvements in firm level capabilities and technologies, can trigger growth.

Research on TFP began with the seminal work of Tinbergen (1942)<sup>62</sup>; He calculated efficiency by generalising the Cobb- Douglas production function. With the help of an aggregate production function, Solow (1957)<sup>63</sup> constructed the famous eponymous residual index that explains the growth of output not explained by the growth rate of inputs. As the literature on TFP developed, several economists aimed to determine the drivers of TFP. Some popular studies on TFP include Griliches (1973)<sup>64</sup> who estimates the impact of R&D on TFP, and Coe and Helpman (1995)<sup>65</sup> who estimate cross-country growth spillovers from using R&D.

TFP as a concept has also been used to comment on productivity, economic growth and technical change across various sectors in India. For instance, economists use TFP as a measure to find that the productivity of industries such as cement and fertilizers rose due to technological change and industrial policy reform in the early 1990s<sup>66</sup>. On recent ICT led innovations, research finds a direct impact of ICT investment on the aggregate economy and manufacturing growth, and an indirect impact on TFP growth in the ICT sector as well as ICT using sectors<sup>67</sup>. Basant and Fikkert<sup>68</sup> using data on Indian firms from 1974-75 to 1981-82 find evidence of positive impacts of R&D, foreign technology purchase and international spillovers on productivity in Indian firms. Satpathy, Chatterjee and Mahakud<sup>69</sup> use panel data for 616 manufacturing firms over the period 1997-98 to 2012-13 to identify the determinants of TFP across 10 industries. We adapt their model to test the impact of AI on firm-level TFP in India.

The primary objective of our econometric specification is to identify firm-specific determinants of TFP growth, of which AI, as an efficiency enhancing GPT, is one of the explanatory variables. In the absence of a direct measure of AI at the firm-level, we extend the idea from other studies to use investment in software, databases and computer machinery as a proxy of AI. For the purpose of this study we do not include investments in electronics hardware that may also be considered as contributing to the AI ecosystem, since its functions may go much beyond AI related processes. Using software and databases may not accurately measure the impacts of AI, but it is perhaps the best proxy given the commonality of infrastructure and capabilities involved in the use and adoption of AI. AI algorithms are essentially software trained to analyse and predict data patterns with the aid of computer hardware, optimised for such use. This measure of AI also provides the potential of ICT using firms to adopt AI in the future.

We estimate the model using a panel data set of 1553 firms (including manufacturing and services) over the period 2007-08 to 2016-17. We use the Centre for Monitoring of the Indian Economy (CMIE) Prowess database. The panel is not uniform in the representation of firms across the 26 industry categories<sup>70</sup>. The largest representation is from trade, business services, manufacture of chemicals and chemical products, manufacture of metals and fabricated metal products and manufacture of transport equipment including automobile parts. The data includes only those companies that have non-zero investments in software over the period of analysis. AI intensity is measured as the ratio of investments in software to total sales. On average, AI intensity is higher for services as compared to manufacturing firms.

<sup>62</sup> Tinbergen, J., 1942, Zur Theorie der Langfristigen Wirtschaftsentwicklung, *Weltwirtschaftliches Archiv*, 55, 511-549

<sup>63</sup> Solow, R.M., Technical Change and the Aggregate Production Function, *Review of Economics and Statistics*, 39(3), 312-320

<sup>64</sup> Griliches, Z., 1973, Research Expenditures and Growth Accounting, in B.R. Williams, ed. *Science and Technology in Economic Growth*, New York, Macmillan

<sup>65</sup> Coe, D.T., Helpman, E., 1995, International R&D Spillovers, *European Economic Review* 39, 859-887

<sup>66</sup> Krishna, K.L., 2006, Some aspects of total factor productivity in Indian agriculture. In R.Radhakrishna, S.K. Rao, S.D. Mahendra, K. Subbarao (eds), *India in a globalizing world, essays in honour of C.H. Hanumantha Rao*, Academic Foundation. Krishna, K.L., 2007, What do we know about the sources of economic growth in India?, In A. Vaidyanathan & K. L. Krishna (eds), *Institutions and markets in India's development: Essays for K.N. Raj*. Oxford University Press.

<sup>67</sup> Erumban, A. and Das, D.K., 2016, Information and Communication Technology and Economic Growth in India, *Telecommunications Policy*, 40(5), 412-431

<sup>68</sup> Basant, R. and Fikkert, B., 1996, The Effects of R&D, Foreign Technology Purchase, and Domestic and International Spillovers on Productivity in Indian Firms, *The Review of Economics and Statistics*, Vol 78, Issue 2, 187-99

<sup>69</sup> Satpathy, L., Chatterjee, B. and Mahakud, J. 2017, Firm Characteristics and Total Factor Productivity: Evidence from Indian Manufacturing Firms, *The Journal of Applied Economic Research*, 11:1(2017):77-98

<sup>70</sup> Industry categories are based on RBI's KLEMS categorization of industry



For instance, the average AI intensity for firms in the financial services sector is 0.23 compared to .004 in manufacture of electrical and optical equipment. For certain companies in financial services, business services and trade, the AI intensity is over 1, indicating an investment which is higher than the sales in a given year. In our sample of firms, the AI intensity does not exceed over 1 for any firm in the manufacturing sector. These trends match evidence on deployment of technology and AI by firms across industry sectors. Several other studies highlight the early adoption of AI by firms in the financial and business services sector. A study by CIS in 2018<sup>71</sup> finds IT and services industry to have taken a leap in its day-to-day activities through the adoption of AI. Several IT services companies in India have developed AI platforms and virtual assistants for process management. AI solutions are also helping banks and credit lenders approve loans and assist the underwriting process. Within manufacturing, automobiles, electronics, and heavy electrical production units have also progressed in deploying AI, both in the process of manufacturing - including through smart factories, and the end product. (Please refer to Appendix I for a measure of AI intensity by industry category).

The other determinants of TFP growth that we test through our model include the size of the firm, disembodied technological intensity, advertisement intensity<sup>72</sup> and control variables for time and industry category. The data on Total Factor Productivity Growth (TFPG) has been extracted for 26 industry categories from the Reserve Bank of India's KLEMS Database<sup>73</sup>. The model specification and variable definitions are provided in Box 3.1.

Descriptive statistics are provided in Table 3.1

## Table 3.1 Descriptive statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
TFPG <sub>jt</sub>	.005	.037	-.098	.235
Size <sub>jt</sub> (Assetsotherthansoftware)	42572.4	197204.9	-158.6	6173340
DisembodiedTech <sub>jt</sub> (Royalty & Technical Fee Intensity)	.008	.117	0	8.23
Alinti <sub>jt</sub>	.029	1.05	-.0000003	110
ADVinti <sub>jt</sub>	.04	1.75	0	180

<sup>71</sup> AI and the Manufacturing and Services Industry in India, Centre for Internet & Society, 2018 Available at [https://cis-india.org/internet-governance/files/AIManufacturingandServices\\_Report\\_02.pdf](https://cis-india.org/internet-governance/files/AIManufacturingandServices_Report_02.pdf)

<sup>72</sup> Used in Eaton, J., Kortum, S., 1999, International Technology Diffusion: Theory and Measurement, International Economic Review, 40(3); Shih, H.Y., Chang, T.S., 2009, International diffusion of embodied and disembodied technology: a network analysis approach, Technology Forecasting and Social Change, 76(6)

<sup>73</sup> The values for 2016-17 have been extrapolated using the previous series. We use the KLEMS Database Manual (2017) for concordance of industry classifications based on NIC 2008 to the KLEMS categories to attach a KLEMS codes to each firm in the data set. The KLEMS category including firms on public administration and defense has been left out in this exercise for lack of data. However, there is some adoption of AI in public administration in India, especially within defence services and taxation departments

## Box 3.1: Definitions for Variables

$$TFPG_{ijt} = \alpha + \beta_1 Size_{ijt} + \beta_2 DisembodiedTech_{ijt} + \beta_3 Alint_{ijt} + \beta_4 Advint_{ijt} + \beta_5 Sector_j + \beta_6 Year_t + \varepsilon$$

TFPG<sub>ijt</sub> is the measure for total factor productivity in year t for KLEMS sector j..

$\beta_1 Size_{ijt}$  is the measure of firms size denoted by total other assets (net of software stock) for firm i belonging to sector j in the year t. Literature presents mixed results on the direction of relationship between firm size and total factor productivity growth.

$\beta_2 DisembodiedTech_{ijt}$  is the measure of technological intensity for firm i in Sector j in the year t. Disembodied technological intensity is calculated as the ratio of royalty and technical know-how to sales of the firm. We expect a positive sign for the coefficient as disembodied knowledge intensity, measured in terms of royalty and technical know-how as a ratio of sales

$\beta_3 Alint_{ijt}$  is measured as the ratio of software investments to total sales in a given year. This is our primary variable of interest and we hypothesize that  $\beta_3$  will be positive.

$\beta_4 ADVint_{ijt}$  is a measure of advertisement intensity for firm i in sector j at time t. Advertisement intensity is the ratio of expenditure on advertisement to sales. According to the literature, consumption of finances in advertisements can adversely impact the total factor productivity growth of a firm

$\beta_5$  and  $\beta_6$  are coefficients for the control variables - KLEMS sector and year respectively is the constant term,  $\varepsilon$  is the error term

We use a fixed effects multivariate panel-data regression for the estimation of the model<sup>74</sup>. The panel fixed effects eliminate any unobserved heterogeneity. The robustness checks using additional control variables help check for endogeneity driven by an omitted variable bias. The model estimates are therefore consistent. **The results find a positive and significant relation between AI intensity and total factor productivity growth. The estimate suggests that a unit increase in AI intensity will increase the TFP growth by 0.05%.** The coefficient for firm size is negative and significant. The coefficients for disembodied technological intensity and advertising Intensity are insignificant. The dummy variables for KLEMS categories are mostly significant as are the controls for time. (Please refer to Appendix 2 for the results of the model).

For easy interpretation of the econometric estimates, we use the outcomes of the TFP growth model to arrive at impacts on Gross Value Added (GVA). Output growth can be decomposed into the contribution of factor inputs and TFP growth<sup>75</sup>. We use this relation to estimate the contribution elasticity of TFP growth on GVA. The estimation is based on a simple regression with fixed effects using a panel data for 27 KLEMS categories over the period 2008 to 2017. The results of our model suggest that on average 50 percent increase in rate of growth of GVA can be attributed to TFP growth<sup>76</sup>. Through the two-step methodology (i) estimating the impact of AI on TFP growth and (ii) measuring the contribution elasticity of TFP growth on Gross Value Added we are able to arrive at an estimate of the impact of AI intensity on GDP<sup>77</sup>. We use the nominal GDP of 2017-18 as the base year for the estimation. **The growth co-efficient suggests that on average a unit increase in AI intensity by AI using firms in the economy can return USD 67.25 billion (2.5 % of GDP) to the Indian economy in the immediate term**<sup>78</sup>. However, the trends in AI intensity over the period 2008 to 2017 do not find any business as usual increase in AI intensity. These are also reflected in the current diffusion of AI in India. Achieving a critical threshold in diffusion through fresh investments in AI, can provide a positive shock to the sector that amplifies the growth effects. **For instance, the recently approved investment of Rs. 7000 crore by the Ministry of Finance for NITI Aayog's AI program**<sup>79</sup> **could increase AI investments at rates higher than the business as usual rates. This increase in investment will lead to an approximate 1.3 times increase in AI intensity, translating into spillover benefits of USD 85.77 billion (3.2 % of GDP) for the Indian economy.**

<sup>74</sup> We test the variables for presence of unit roots and apply cointegration tests to examine whether the series of variables have a stable, long run relationship. The test results suggest that the panels are cointegrated. We use the Im-Pearson-Shin and Fisher type test for unit roots. We use the Im-Pearson-Shin and Fisher type test for unit roots

<sup>75</sup> <https://m.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=&ID=785>

<sup>76</sup> We use robust standard errors to correct for heteroscedasticity. The scatter plot for predicted values and residuals finds no correlation ruling out any endogeneity.

<sup>77</sup> GDP = GVA + net taxes, we assume the elasticities estimated for GVA will also apply to GDP

<sup>78</sup> One-unit increase in AI leads to a 0.01 \* 0.5 increase in GVA. 0.005 \* USD 2690 Billion (nominal GDP for 2017-18)

<sup>79</sup> <https://www.moneycontrol.com/news/india/niti-aayog-gets-rs-7000-cr-for-artificial-intelligence-project-report-4419411.html>

Indian industries are far from the global AI frontier. For example, the International Federation of Robotics highlights India's low robot density (85 industrial robots per 10000 employees) in the automotive sector compared to that of China (505 per 10000 employees). While companies recognize the potential of AI, there are concerns related to cost and the ability for investments in AI to deliver good returns. Once AI becomes mainstream, its growth impacts are likely to become more noticeable in GDP. These estimates also hide the huge impacts that are being witnessed at the micro-level in sectors such as agriculture, education and healthcare. As these initiatives scale-up, the estimates at the macro-level are bound to multiply. Moreover, the policy initiatives nurturing AI are also recent. The recent spurt in AI investments in startups in 2017 and 2018 are only early signs of a future that is still to unfold. The analysis also suggests that certain sectors are more likely to adopt AI, for instance, the scale of adoption in financial services and retail trade is much higher than manufacturing in India. The changing structure of the economy and the ability of sectors to adapt to new technologies will also impact the potential of AI to generate economic value in the future.

Through this model we provide the first India estimate for AI on firm productivity and GDP in India. The results unambiguously establish a positive relation between AI adoption and economic growth, subject to caveats mentioned above. While the econometric estimation provides adequate evidence for policy to support its wider adoption, the actionable measures will be based on an evaluation of firm capabilities, both for firms developing and using AI. Such analysis can establish the transition of firms towards adoption of AI. In the next chapter we use the capability framework to demonstrate the AI potential of firms and their consequent growth impacts using examples of AI-based innovations across sectors.

## 4. Opening up the ‘black box’: Micro-Evidence from Case studies of AI companies in India

The unraveling of General-Purpose Technologies such as AI is a complex phenomenon that requires attention to the engineering of AI for specific applications, and its consequent impact on micro-level processes across types of organisations, including governments and civil society. Through case studies on AI, we can witness how the growth potential of AI, examined through econometric estimations in the previous sections, is actually being realised<sup>79</sup>. There are two parts to this story - the first concerning challenges and capabilities faced by organisations in developing applications for specific sectors, the second concerning the impacts experienced by firms that are adopting AI-based solutions.

The case studies vary by AI technologies being used to design applications across various sectors of the economy. (Please refer to Figure 4.1) We engaged in in-depth interviews with thirteen AI companies in India, most of them still young and small-scale, with the exception of Aspiring Minds established in 2008. The average number of employees vary between 11-50 across most firms. These firms are also well embedded within networks of venture capital and start-up capital that finance their operations. The companies are currently developing applications for ten different sectors including law enforcement, healthcare, banking and finance, traditional agriculture and manufacturing sectors. In terms of the AI used, we find Machine Learning and its subsets, deep learning, deep neural networks, convolutional neural networks among others, featuring prominently across organizations building and providing services. Natural Language Processing, Speech Recognition, and Computer Vision are other technologies that also feature across several use cases.

### 4.1 Insights from Case Studies

We use the capabilities framework as a guide to understand the causes that underlie the success or failure of India’s ecosystem in conducting AI-based innovation. The first part of the analysis captures capabilities that are being exercised or lacking among firms that develop applications. This is followed by an analysis of the impacts of AI on firms that have adopted AI-based solutions.

<sup>79</sup> Lipsey, R. G., Carlaw, K.I., Bekar, C.T., 2005, “Economic Transformations: General Purpose Technologies and Long Term Economic Growth”, Oxford University Press

Figure 4.1: Framework for Selection of Case Studies

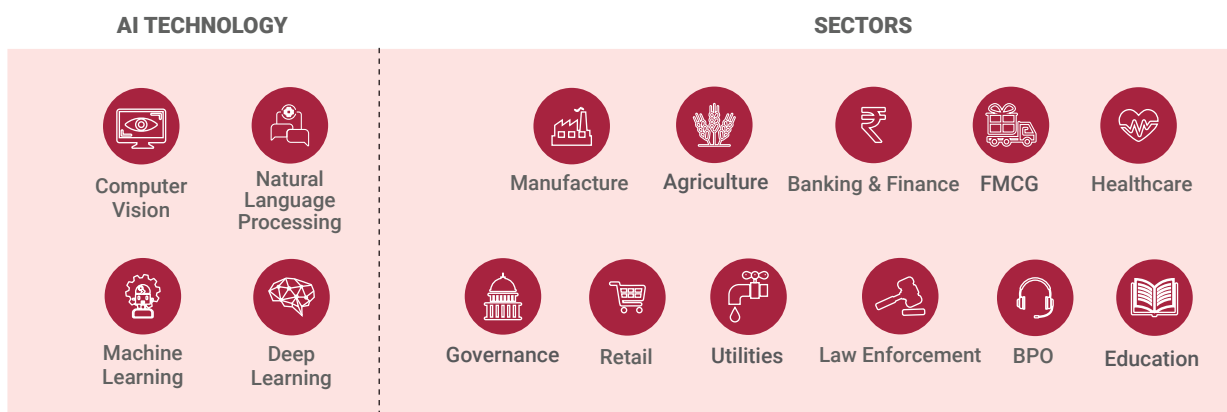
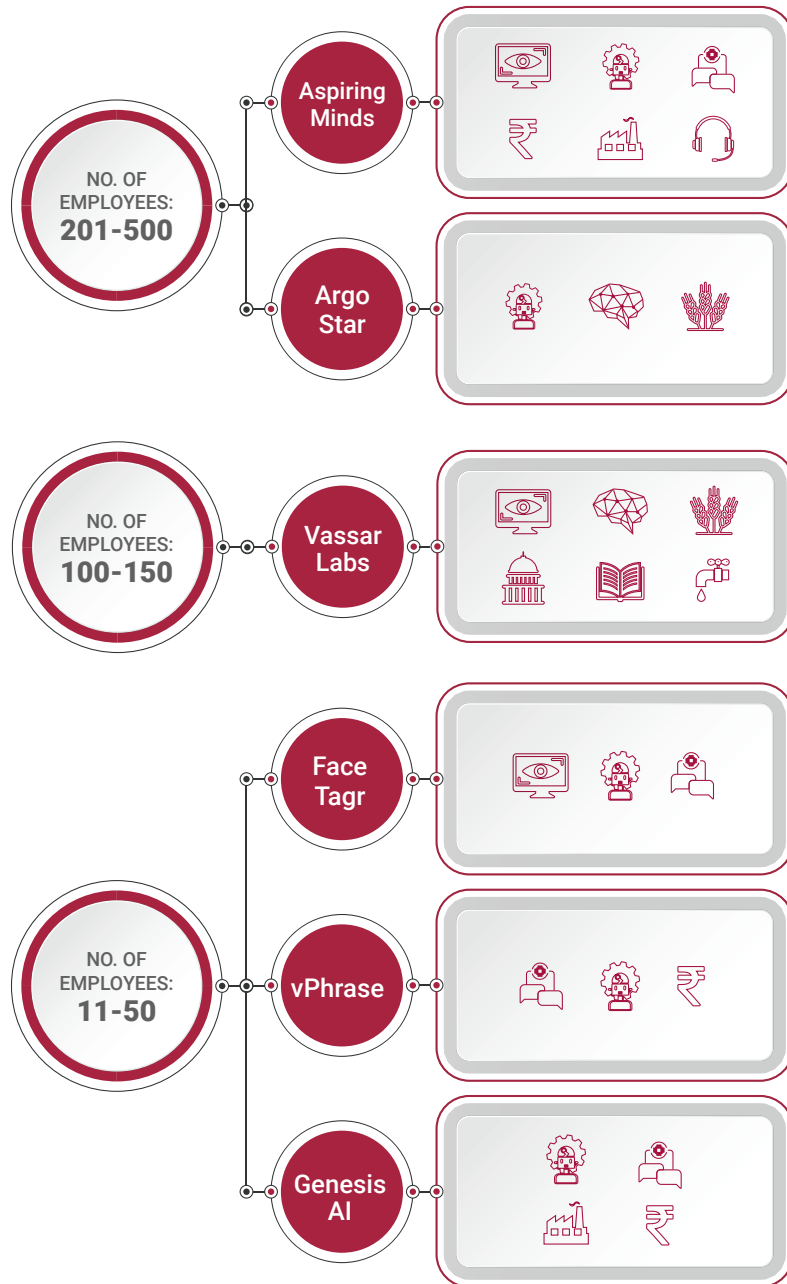
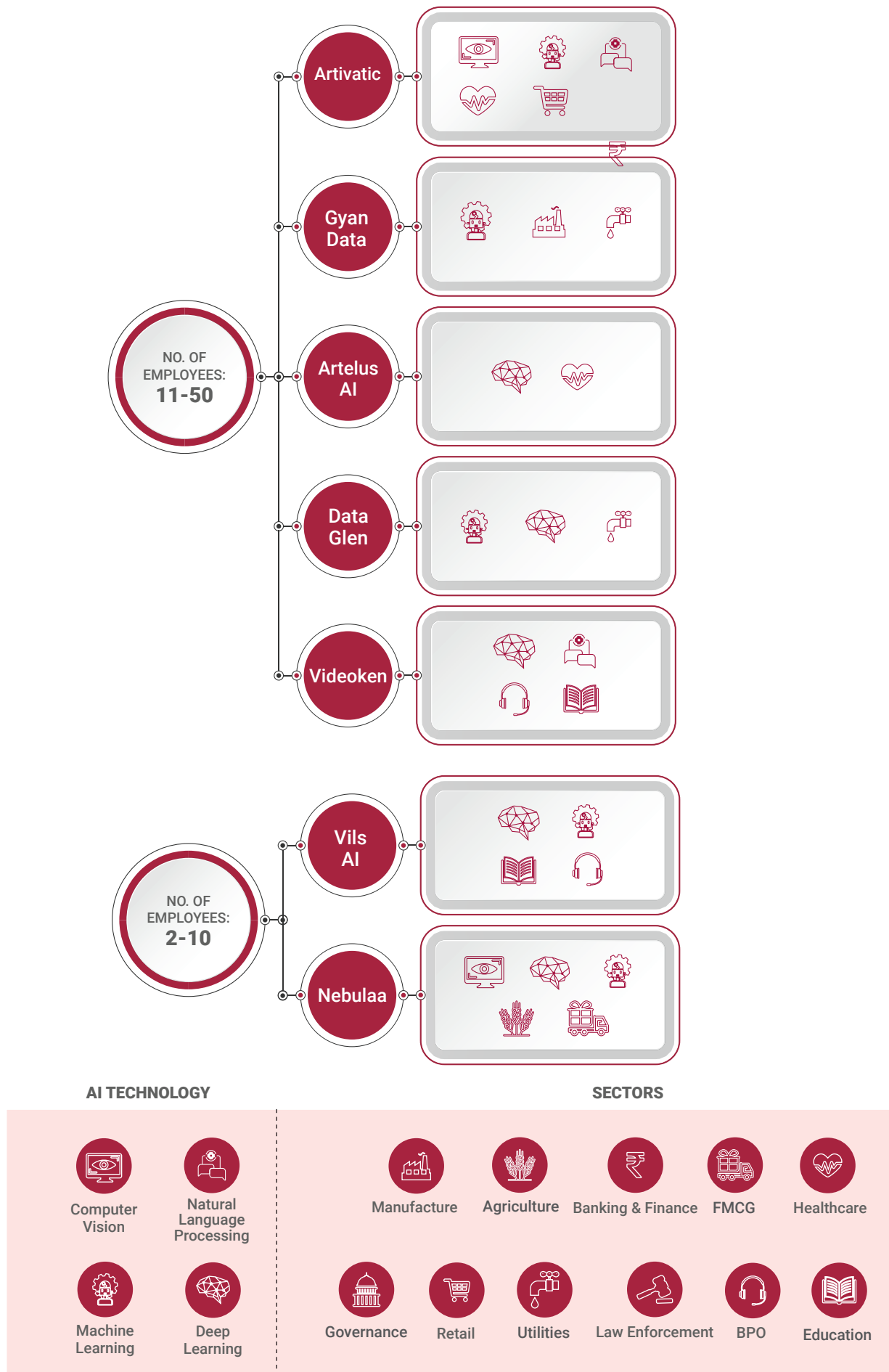


Figure 4.1: Framework for Selection of Case Studies



## 4.1.1 Capabilities of firms developing AI applications in India

The framework guiding the case study analysis is based on the ‘capability theory of the firm’<sup>80</sup>. The fundamental pursuit of this framework is to ask what it takes i.e., what are the requisite capabilities for an organisation to successfully perform the tasks of innovating and adopting (building) complex technologies such as AI. However, not all tasks directed towards innovation realise any outcome, and with some, costs of innovation may outweigh realisations of benefits, making such activities unviable and unattractive. Innovation is therefore subject to market failure. Yet, organisations work with different degrees of uncertainties to innovate. They deploy resources to innovate and build resilience to bear the costs of innovation. They are pro-active in designing and marketing products and enable themselves to connect to the economy at large. The capability theory is essentially an attempt to develop concepts that can help in understanding why organisations succeed or fail in innovating or adopting complex technologies such as AI.

There are three broad categories of capabilities<sup>81</sup>:

1. **Investment capabilities:** These constitute the skills needed to identify, prepare, obtain and design requisite technology. It also requires the firm to equip, staff and commission a new facility for the project.
2. **Production capabilities:** These constitute skills needed to perform tasks such as quality control, operation and maintenance, and other complex activities such as redesigning core technologies, research and innovation.
3. **Linkage capabilities:** These constitute skills that are required to transmit and receive information, skills and technology from suppliers, consultants, subcontractors, services firms, and technological institutions.

### Box 4.1 Growth Fables: Sources of India’s Software Capabilities

The story of the rise of India’s software industry is also a story of building capabilities to overcome deficiencies in India’s institutional structures and compete at the global level. Historical experience informs that building India’s competitive Software and IT sector constituted three important elements: 1. Employable talent pool; 2. Avenues to raise capital; 3. Mechanisms to build and validate reputation. The pre-liberalisation institutional landscape in India was deficient in well-functioning labour and capital markets that could provide an employable talent pool and avenues for companies to raise capital. Moreover, the business of software-based services relied on reputations of firms. Firms had to guarantee customers that their software-based offerings were of high quality. Absence of such mechanisms and institutions was a challenge for software-based companies in India.

The frontrunners of India’s Software and IT sector had different ideas. Tata Consultancy Services, one of India’s first software companies, made up for the absence of employable talent for software operations and management, by pooling in talent from its other businesses. Infosys tapped into foreign institutional structures such as NASDAQ, in the absence of adequate avenues for raising capital in India, and in the absence of institutions that guarantee quality control. Many Indian firms leveraged the Indian diaspora network in the U.S. through organisations such as TIE (The India US entrepreneur) and NASSCOM that strengthened their credibility, particularly in the Silicon Valley. Indian software firms diverted significant efforts towards getting certified, so much so that by 2001, half of the world’s software development centers with Carnegie Mellon University CMM Level-5 (its highest) rating were located in India and half of the top 400 firms (as rated by NASSCOM) acquired ISO 9000, SEI or other certifications by end of 2002.

We organise the synthesis of our case studies based on a chronology of events, touching upon how organisations that are engineering applications marshal the skills required to build AI, organise and utilise the research and resources needed to run and test applications, and form networks that finance and market their AI-based products and services in ways that links the firm to the economy at large and which enables the diffusion of AI across the economy.

<sup>80</sup> Pioneered by Edith Penrose in Penrose, E., 1959, *The Theory of the Growth of the Firm*, Oxford University Press

<sup>81</sup> Based on the work of Lall, S., 1992, *Technological Capabilities and Industrialization*, *World Development*, Vol. 20, no.2, pp. 165-186.



## Investment Capabilities

Investment capabilities as already explained are the skills needed to identify, prepare, obtain and design requisite technology. Investment capabilities determine the appropriate scale at which business operations can be feasibly conducted given the product, the choice of technology and the firm's understanding of how the technology operates.

Investment capabilities enable firms in the AI ecosystem to identify a problem for which a solution can be used to achieve a given scale of operations. This would include the extent to which the AI-based solution can be deployed (i.e. the scale of operations) and the choice of AI technology, be it Machine Learning, Natural Language Processing, Computer Vision, etc. or a combination of such technologies. Building investment capabilities requires that firms employ high-skilled researchers who can guide the designing of appropriate solutions. It further requires proficient managers who can organise requisite resources to commission such projects.

From our case study interviews, we find that hiring high-skilled researchers was a smooth process for some firms. For instance, the firm Artelus expressed no major concern in constituting a high-skilled research team that designed and improved their solution for detecting diabetic retinopathy. The firm Agrostar, which provides solutions for improving farm output and reduce crop-related risks, also expressed confidence in the research team they recruited. However, several other firms expressed a skill mismatch. The firm Aspiring Minds, which provides pre-employment assessment including products such as video analytics, stated that in response to a mismatch between requisite skills and skills on offer, the firm constituted an internal training mechanism to equip researchers to perform according to the requirements of the organisation.

Most of the companies constituting our case studies noted that the AI ecosystem in India requires a boost in high-skilled researchers and those with experience in the field of AI. Several companies also noted the need for a greater provision of graduate level courses in applied AI. They expressed concerns regarding educational institutions' inability to prepare graduates, particularly those trained in computer science and AI, for the demands of the industry.

The demand for skilled AI researchers can be conjectured to be related to the scale of operations of the firm, and consequently the user demand for AI solutions. Several firms from our case studies stated that they are currently constrained to scale up solutions, attributing to slow adoption of AI solutions by user groups. Crucially, these firms expressed uncertainty regarding how they might adapt to problems that may arise as a result of scaling up. In an expanding AI-based ecosystem, acquiring investment capabilities, will be crucial for such firms to survive, scale-up and thrive.

## Production Capabilities

Production capabilities can be understood to be the ability of a firm to perform tasks such as quality control, operations and maintenance, and other complex activities such as redesigning core technologies, organising research, and conducting innovation. For a firm supplying AI solutions, production capabilities can include four major activities: 1. Organising and generating data, 2. Training and improving AI algorithms, 3. Producing research on AI-based tools that are being developed by the firm and 4. Patentability of AI-based applications.

The major input for the production of AI solutions is data, which is used to ‘train’ the algorithm and improve its accuracy and performance. Several firms reported the challenge of collecting data, particularly those firms whose solutions rely on problems of the social sector and which depend on publicly available data. For instance, the firm FaceTagr, which uses AI-based facial recognition solutions to aid law enforcement agencies to reunite missing children, stated that its solutions rely heavily on publicly available data that is scant. In response to data scarcity, Vassar Labs, which provides last-mile decision support for governance structures and agriculture, reported deploying sensors and generating their own data to train their algorithms. Other firms, particularly those that are offering AI-based solutions to the private sector rely on data internal to the customer firms.

The emergence of data privacy and data protection regulations, most prominently the European General Data Protection Regulation (GDPR), may lead to additional costs and constraints in the production of data-intensive solutions. However, such laws are yet to come into force in India, and the firms in our case studies, with the exception of very few companies, were not yet mandated to comply with any data protection regulation. Through our case study interviews, we find that firms supplying solutions had no ambiguities as to who owns the data. AI firms using data internal to the user firms to train the algorithm, clearly belonged to the user firm. Some firms maintained the distinction between data and meta-data, where the latter related to personal information and remained confidential to protect privacy of individuals.

All the firms included in the case study analysis have a research team that is tasked to develop and improve offerings of the company. Several companies actively publish their research across peer-reviewed journals, while some firms have also been engaging with interdisciplinary research and publications that formed the basis of their algorithms. The patentability of AI applications is another strong indicator of a firm’s production capability. It signals the firm’s ability to develop, apply and improve a novel technology. All of the firms that feature in our case study filed patents either in the U.S., in India, or both<sup>82</sup>. However, not all firms were granted patents. For some firms such as Nebulaa, Artivatic Data Labs, and Facetagr, the patents filed are still pending, whereas, firms such as vPhrase Analytics solution, VideoKen, and DataGlen, have been granted several patents for their AI solutions.

## Linkage Capabilities

Linkage capabilities, as defined above, are the skills that are required to transmit and receive information, skills and technology from suppliers, consultants, subcontractors, services firms, and technological institutions. Firms supplying AI-based solutions in India network with research institutions, user industries, consumers and other well-established suppliers of AI technologies, among whom, various forms of interactions take place.

From our case studies, we find several firms benefitting from their association with prominent universities. Aspiring Minds board of advisors comprise of professors from Harvard, research scientists from MIT, and psychologists from Wesleyan University, observing and overseeing the firm’s operations and the development of its AI solutions. Closer to home, the firm Gyan Data, which provides Machine Learning solutions for manufacturing firms, continues to exchange research and recruit its employees from IIT Madras. Two of its founders are professors at IIT Madras, and one a professor at Columbia University.

<sup>82</sup> The location of customers (the service area of the firm) was a major determinant of whether the firm would file patents in India or abroad, or both.

Such university-industry linkages are crucial in fostering capabilities for firms to develop and deploy innovative applications. For instance, IIT-Bombay joined IBM's "AI Horizons Network", an international consortium of leading universities around the world, which included MIT, University of Michigan, University of Maryland among others, working with IBM to develop AI related capabilities. IIT-Bombay and its graduates are set to work with the consortium to develop commercial AI capabilities, such as Machine Learning and natural language processing based applications for financial services, retail and healthcare services.

There are other firms in our case studies list that have benefitted from linkages to other large technology companies that are invested in the AI ecosystems around the world. For instance, the firm VideoKen, which provides an AI-based video indexing platform, is led by a founder with strong ties to Xerox and IBM's research units. The firm DataGlen, led by a founder who was earlier a research scientist at IBM, collaborated with General Electric (GE) to publish two patents on its machine and deep learning applications for solar power generation, which are however, owned by GE. We also find large technology companies, such as Google, incubating AI startups in India. Google's 'Solve for India' for instance, provides mentorship and technology support for nascent AI applications and enables small-scale applications to be scaled up for wider industrial use.

An interesting aspect of many of the firms that feature in the case studies is their embeddedness within networks of strategic investors and venture capitalists. Several firms reported their sources of finance to be angel/strategic investors based overseas, and their role went much beyond finance. Firm reputation plays a significant role in the success of an application being developed and adopted widely. In order to assure the quality of an AI application, even before a contract for its adoption is signed, suppliers depend on their network of scientific advisors and prominent investors to signal reputation and assure users of its quality.

## 4.1.2 Applications and Implications of AI

The firms interviewed by us service both domestic and foreign clients, with applications ranging across sectors including civil society and governance. We observe that at the root of all benefits stemming from AI applications is its ability to predict<sup>83</sup> across a range of tasks. Greater predictive capabilities in turn translate into greater information and insight about any given task or process, which in different contexts translates into different impacts, as will be discussed below.

## Economic Implications for Businesses Adopting AI

The versatility of AI-based applications means that its economic impacts can be felt across both core and supporting functions in activities of production and organization.

We noticed that AI's capabilities have been leveraged to improve quality testing and control methods across a range of industries. For instance, Nebulaa uses data from various agricultural markets in India in a convolutional neural net based grain analyser for quick, accurate and cheap quality testing. Their current efforts have reduced the testing time of grains from 30 minutes to almost instantaneous results and lowered costs by 75 percent. They plan to expand their services to newer agricultural markets in India.

Firms using AI applications also reported reductions in turnaround time for a range of processes, and consequently, a reduction in costs. For instance, the application developed by vPhrase uses generational natural language processing to develop an application that creates a presentation of facts and data analytics with humanised narratives for several firms in the banking and financial services sector. This application has drastically reduced the time and cost in generating analytical and personalised reports for clients of such firms.

<sup>83</sup> Also persuasively argued by Agarwal, A., Gans, J., Goldfarb, A., 2018, "Prediction Machines", Harvard Business School Publication

We also noticed AI's ability to greatly enhance the efficiency of supporting functions within a variety of organisations. For example, the use of solutions for the human resources and recruitment function. Aspiring Minds developed an AI-powered pre-employment assessment and video interview analytics tool that leverages Machine Learning, Natural Language Processing and Computer Vision techniques to help employers screen potential employees more efficiently. User firms reported that large scale hiring processes that took 3 months was reduced to about a week. Onboarding processes have also likewise seen increase in efficiency through AI-based applications. The firm, VideoKen created an application that uses Deep Neural Nets and Natural Language Processing to index educational videos to enable users to personalize learning from videos online and improve learning outcomes. Its current customers include consultancy firms that are using onboarding videos to save time in inducting new employees.

## Social Implications of AI Applications

We observed AI's growing presence and applications in areas that are crucial for a better society. One instance of AI generating positive impacts on healthcare is demonstrated by the firm Artelus. Artelus developed an screening tool that checks for Diabetic Retinopathy, early onset of TB, lung and breast cancer, using deep learning techniques. Artelus's product captures and analyzes retinal images of patients within 15 seconds, and can detect an occurrence of Diabetic Retinopathy within 3 minutes, with 93% accuracy. Facetagr's AI-based application is another instance of AI's potential for increasing social welfare. Facetagr's solution uses deep learning based facial recognition application to assist law enforcement agencies in identifying missing children in Tamil Nadu. Reportedly, 4000 policemen in Tamil Nadu use Facetagr with a much higher rate of reuniting missing children.

We noticed several applications of AI that greatly improved use and regulation of critical natural resources such as groundwater and renewable energy. For instance, Vassar Labs is providing Deep Neural Net based application that predicts groundwater rich areas and the rate of groundwater depletion using data from sensors and satellite as inputs to local governments. Despite a weak monsoon, the application helped groundwater recharge increase by 2 meter in parts of Andhra Pradesh. Consequently, agricultural revenue increased by 40% for the government, against the same land and water use. DataGlen is another instance of a firm that developed an AI-based optimization program for decentralized and distributed solar grids using Machine Learning and Deep Learning techniques. They report 7-10% increase in solar power generation and greater quality in solar panel maintenance from units that have adopted their AI application.

## Implications on the Labour Market

The structural changes driven by technologies such as AI have both economic and social implications. The automation of tasks will result in labour displacement, which need reskilling/ upskilling for reappointment. The final consequences on the labour market depend on the structural constituents of an economy and the distribution of tasks that are likely to be automated. However, through our case studies we observe the potential of AI solutions to directly impact labor<sup>84</sup>. For instance, the firm vPhrase, which developed an AI-based application for presentation of data analytics and generating humanized narratives, noted that the user firms of their application, who belonged largely to the services sector, saw the potential to replace tasks of those involved in making and giving presentations. Similarly, the firm Genesis AI, which developed AI-based action-recommendation and document processing systems, stated that its user firms saw the potential for an increase not just in task automation, but also an increase in workforce intensity, i.e., an increase in the amount of output per worker. The firm Artivatic Data Labs stated that the user firms of its automated fraud detection, risk profiling, document verification applications changed the existing division of tasks among their workforce.

The existing AI applications do not have the potential to replace all tasks conducted by labor en masse, but only those tasks that are routine and non-cognitive. Moreover, some firms also noted that the productivity increases caused by the proliferation of AI-based applications, while potentially replacing tasks in the short run, may create more jobs in the medium to long-term. Additionally, the emergence of data annotation & labelling companies in India's city suburbs presents a huge opportunity for India's high-school graduates. Easily trainable tasks that improve the employability of India's emerging labour force.

<sup>84</sup> As a caveat, we note that since most of the AI-based application that feature in our case studies are small in scale, it remains in the dark whether these AI-based applications when scaled up have different impacts on the nature of work within organizations.

<sup>85</sup> Reference <https://factordaily.com/indian-data-labellers-powering-the-global-ai-race/>

As demonstrated in the previous section, there is significant evidence of the potential of AI to trigger economic growth and improve social outcomes. The growth potential of AI has been demonstrated in this section through firm-level impacts of AI-based applications across a range of sectors and tasks. Furthermore, to understand what it takes for India to develop a growth enhancing AI-based ecosystem, we evaluate firms in India that have developed AI applications. Such an exercise shows promise and informs creating an institutional environment that enables firms to foster critical capabilities to address challenges, scale up solutions and speed-up diffusion of AI across the economy.

## 5. Conclusions and Policy Recommendations

The analysis in this report establishes an unambiguous impact of AI on economic growth in India. Both the econometric estimation as well as the case study analysis finds AI applications spread across multiple sectors of the Indian economy. While diffusion is still limited, there is adequate evidence establishing AI-led increase in firm efficiencies. In a recent business survey conducted by IDC, while 77 percent respondents agreed that AI is an instrument to improve organisational efficiency, only one third among them had adopted AI. The study estimates these firms to increase their competitiveness by 2.3 times by 2021. Impacts in the future, the report suggests, are realisable on account of firms increasing their investments in research, developing in house capabilities of developers and data engineers, building data governance practices, etc.

The econometric exercise in this study examines the impact of AI on firm-level efficiency in India. AI is measured as investments in software, the closest approximation to AI at the firm level, in the absence of other direct measures on AI. We posit that AI determines firm-level total factor productivity (TFP), a residual variable that determines aspects of growth that are not determined by labour and capital. This setup directly follows from the argument that AI is a General-Purpose Technology and that it plays a much broader role than 'factors of production', affecting different aspects of a firm's organizational, administrative and financial coordination operations. Total Factor Productivity is, therefore, the most appropriate measure to capture the effects of AI on economic growth.

The results of the econometric framework show a significant and positive relation between firms that use AI and their TFP growth. Moreover, TFP growth is found to increase with increasing intensity of AI such that a unit increase in AI intensity will increase TFP growth by 0.05%. For easy interpretation of the econometric estimates, we use the outcomes of the TFP growth model to arrive at impacts on Gross Value Added (GVA). The estimation is based on a simple regression with fixed effects. The results of our model suggest that on average 50 percent increase in rate of growth of GVA can be attributed to TFP growth. The growth co-efficient suggests that on average a unit increase in AI intensity by AI using firms in the economy can return USD 67.25 billion to the Indian economy in the immediate term. However, trends over the period 2008 to 2017 do not find any significant increase in AI intensity. These are also reflected in the current diffusion of AI in India. Achieving a critical threshold in diffusion can provide a positive shock to the sector that amplifies the growth effects. The investments of Rs. 7000 crores approved by the government could increase growth in AI investments at a rate higher than the business as usual rate. This increase in investment will lead to an approximate 1.3 times increase in AI intensity, translating into spillover benefits of USD 85.77 billion for the Indian economy.

In order to explain these impacts, we studied 13 firms developing and testing AI technologies in India. We find these companies, largely small-scale start-ups, developing applications for services in law enforcement, healthcare, banking and finance, as well as for agriculture and manufacturing sectors. In terms of the prominent AI technologies, we find Machine Learning and its subsets, deep learning, deep neural networks, convolutional neural networks and the like to feature in most AI applications. Natural Language Processing, Speech Recognition, and Computer Vision are other AI technologies that feature across the case studies. Applications developed by these firms have meaningfully impacted the businesses that adopted them, as well as social outcomes in health, education, agriculture, law enforcement, etc. While these applications are visible across sectors, the impacts exist only in pockets, and are yet to become widespread. Several applications are still in the process of being developed and tested. Moreover, the high cost of new technologies and the inability of adopters to trust them also impact scalability.

There are, however, substantive issues that cautions against its unhindered deployment and development. For instance, recent advances in AI have raised concerns around the use of complex AI systems that are applied without revealing details of the data used to train the model or the algorithm design that forms the basis of predictions. Such applications run the risk of leading to unfair and /or incorrect decisions if they are used in contexts for which they were not designed..This phenomenon is problematic not only because it makes it harder to determine the trust worthiness of an AI system, but also for the possible unfair biases inherited by algorithms from human prejudices and those hidden in the training data<sup>87</sup>. There are several ways in which bias creeps into an algorithm even before the data for the algorithm is collected, and even through stages of building the algorithm such as when 'framing the problem', when collecting data and when preparing the data. Fixing algorithmic bias has also proven to be difficult. The effects of bias can only be known ex-post, and downstream. Moreover, algorithms may be constructed without accounting for the social context within which it may be applied, which may lead to unintended consequences on society.

AI systems may also be prone to error when introduced to minor perturbations in data, representing situations that are beyond the scope of training. For instance, Google's Inception-v3 classifier, correctly labelled canonical poses<sup>88</sup> of objects, but failed to recognize the same objects when these are in unusual poses. What this means essentially is that when placed in an environment different from a training environment, the AI frequently breaks down. This is not only a hindrance for generalising applications but is also a problem for the use of autonomous systems such as self-driving cars, and military applications. The problem of brittleness or breakdown is also closely related to the larger problem of AI safety, in which, as defined by Dafoe (2018)<sup>89</sup>, AI systems behave in unanticipated manner or are in risk of accidents.

Another contentious policy issue arising out of AI diffusion is that of inequality. Since AI by nature is labour substituting<sup>90</sup>, immediate consequences of AI, take the form of inequality between labour and capital, and inequality within labour, i.e. between tasks with high and low skill content. However, the form this takes and the impact on human employment will depend on the manner in which organisations deploy AI tools and training. If the economy manages to create as many different tasks as are being taken over by AI and automation, while simultaneously attending to the challenges of education, skill training and employability, the economy can stabilize the inequality arising out of AI. Research on skill content of tasks in India suggests that between 1983 and 2011, the task intensities of manual tasks has declined while the intensity of 'Non-routine Cognitive Analytical', and 'Non-routine Cognitive Interactive' tasks has increased, with changing technology being the driving force. A large spike in skill-based inequality is thus imminent in an AI-based ecosystem in India; policy must simultaneously address the challenge of education, skill training and employability, alongside boosting the diffusion of AI.

The government has already laid the groundwork for building an AI ecosystem in India through the appointment of a Task Force on Artificial Intelligence<sup>91</sup>. The report submitted by the Task Force and the National Strategy for Artificial Intelligence presented by NITI Aayog are the beginning of a national strategy for AI in India<sup>92</sup>. The report by NITI Aayog lays down a set of recommendations to address the biggest challenges and opportunities for India in the field of AI, including research, data democratisation, accelerating adoption and reskilling with privacy, security, ethics and intellectual property rights permeating as common denominators for the recommended initiatives. Apart from increasing the budget allocation for AI the reform package announced by the new Finance Minister in July 2019 spoke about plans to improve skills in the area of artificial intelligence, big data and robotics.

There are differences in how countries have approached policy making in AI. For instance, China and USA, the two nations leading AI development have polar opposite approaches to policy in AI. The AI ecosystem in the United States thrives despite the absence of a national policy and is largely driven by the private sector. On the other hand, in China, the government has handheld companies and institutions into building the AI ecosystem. This comparison differentiates between the role of the Government as an enabler and that of a developer/ adopter. In the context of India, we perceive the policy direction to be a combination of both.

The policy recommendations following from our analysis have been categorized into five broad themes. These themes include several actionable recommendations that are individually important to the implementation of a large-scale AI program. These approaches have already been set in motion by Government policies discussed above, but require a further boost.

<sup>87</sup> See: <https://www.technologyreview.com/s/612876/this-is-how-ai-bias-really-happens-and-why-its-so-hard-to-fix/>

<sup>88</sup> See: <https://www.aitrends.com/ai-insider/machine-learning-ultra-brittleness-and-object-orientation-poses-the-case-of-ai-self-driving-cars/>

<sup>89</sup> Dafoe, 2018, AI Governance Agenda

<sup>90</sup> Aghion, P., Jones, B.F., Jones, C.I., 2017, Artificial intelligence and Economic Growth, NBER Working paper no. 23928

<sup>91</sup> Report of Task Force on Artificial Intelligence; <https://www.aif.org.in/>

<sup>92</sup> Discussion Paper National Strategy for Artificial Intelligence [http://www.niti.gov.in/writereaddata/files/document\\_publication/NationalStrategy-for-AI-Discussion-Paper.pdf](http://www.niti.gov.in/writereaddata/files/document_publication/NationalStrategy-for-AI-Discussion-Paper.pdf)



# 1. Identifying a Nodal Agency Within the Government for Development and Diffusion of AI

The Task Force on Artificial Intelligence recommended an Inter-Ministerial National Artificial Intelligence Mission to act as **a nodal agency for coordinating all AI related activities in India**. However, there should be more clarity on the nature of this nodal agency and its relation to ministries and state governments. The design and workings of the nodal agency will be critical to push wide-scale AI adoption in India. The task force recommended a Rs 1,200 crore corpus for five years under the Budget for the national mission. A well-endowed fund will have the ability to invest in long term research and development projects that help build the scale for AI adoption in India.

The objective of Inclusive AI is also one that can be achieved through top-down policy making centered within a nodal agency that is accountable for its implementation. While market forces will drive adoption in certain sectors of the economy, **the socially relevant applications of AI may need government handholding**. Some of the important coordinating functions of this body could include collaborations focusing on capacity building, developing a framework for explainable AI in the form of algorithmic impact assessments and on general policy making, including issues such as patenting. Section 3(k) of the Patents Act, 1970 exempts algorithms from being patented which is claimed to disincentivise AI development in the country and exposes AI developers to intellectual property theft. A review of such overarching policies will also contribute to the ecosystem. Besides the explicit policy initiatives targeted at fostering an AI-based ecosystem, the agency could **nudge the Government departments to develop their own internal capabilities to adapt to the fast-changing AI-based governance mechanisms** in India.

Finally, our research suggests that certain sectors are ripe for AI applications in India. These include healthcare, agriculture, education, fintech, retail and select manufacturing industries. It might be useful for a National Strategy to prioritise resources and build **pockets of excellence for sectors that have already demonstrated the potential for positive economic and social impacts in India**.

# 2. Building Collaborative Frameworks for Engagement between Governments, Industry and Academia

Industry-University partnerships have been the usual norm for industrial nations to build on a growing pool of academic talent to enable industrial growth and technological change. India's industrialisation during the 1970s and 80s has also benefitted from similar linkages. It is unsurprising that the concentration of IT and Software industries in India is clustered around R&D labs and research institutions set up in Bangalore, which continue to benefit from such linkages. **Governments at the state and national level can directly foster growth among startups by inviting public-private partnerships and promoting innovative localised solutions**. There are already some examples of such collaborations within AI - Microsoft partnered with IIT Kharagpur to develop a search algorithm that could help users in identifying subjective information and trusted opinions<sup>93</sup>. Aiming to foster growth for India's nascent artificial intelligence (AI) and Machine Learning (ML) ecosystem, NITI Aayog and Google have also signed a statement of intent (Sol)<sup>94</sup> to work on a range of initiatives to help build the AI ecosystem across the country. Partnership with Google will unlock massive training initiatives, support start-ups and encourage AI research through PhD scholarships. Creating a conducive environment that promotes such linkages will contribute significantly towards enhancing India's AI-based ecosystem.

Collaborations should not be confined to domestic boundaries. **Cross-country collaborations catalyse the transfer and adoption of frontier technologies. Building on existing technologies can help promote AI-related capabilities in India, especially the hardware sector in which India is relentlessly lagging behind**. Japan has already established R&D Centres in India through companies like Panasonic, Toshiba and Hitachi<sup>95</sup>. India and South Korea<sup>96</sup> have also expressed intention to collaborate in the global AI market by building partnerships between Indian IT companies and Korean engineering and hardware companies. The MoU also intends to establish two additional India-Korea Joint Network Centers focusing on Cyber Physical System- Artificial Intelligence and Internet of Things in the agriculture, energy, water, transportation and the semiconductor sectors. Such partnerships can help India move towards and integrate with the global AI ecosystem.

<sup>93</sup> See: Lall (1980) for Sector-wise case studies

<sup>94</sup> Microsoft joins IIT Kharagpur for search algorithm study  
<https://www.bgr.in/news/microsoft-joins-iit-kharagpur-to-create-deeper-search-engine/>

<sup>95</sup> NITI Aayog and Google sign Sol to help grow AI ecosystem in India

<sup>96</sup> Japan and India to collaborate on Society 5.0 : HiroshigeSeko  
<https://medium.com/redact/japan-and-india-to-collaborate-on-society-5-0-hiroshige-seko-c9111bd520b0>

### 3. Building an All Encompassing Data Strategy

Justice Srikrishna's draft Personal Data Protection Bill 2018, set the ball rolling on a large debate that focused on broad issues related to the ownership, collection and use of data. Data is central to research and development of AI applications. Several countries have highlighted the importance of creating data policies and resilient open data infrastructure in their national AI policies. The Economic Survey 2019 also emphasises on the concept of data as a public good and encourages the use of administrative, institutional and transactional data available with the government to be used for improving service delivery and targeting of welfare schemes.

**The government must evaluate alternate data sharing models.** The government has already indicated an intention to build a national data and analytics platform in collaboration with private players. This idea needs further development with details on collaboration mechanisms, the collection infrastructure, use of statistical analysis, etc. **There is also a case for integration of public data that currently exists in silos and enabling its compatibility.** E-Estonia's principles of once-only, where an individual's data is collected once by an institution, eliminating data duplication and bureaucracy is a great example. The India government's DigiLocker initiative is an attempt in that direction. The Government needs to devote attention to **enhancing capacity of existing statistical agencies to collect and process AI-compatible publicly available data.** Some of this data can be shared with the private sector after due consideration. An immediate policy step may be to **evolve data.gov.in to become a national resource for Artificial Intelligence**, assimilating and indexing responsibly, anonymised public data. The government may also consider creating a sub-repository for aggregation of other data from public sources.

In order to integrate data from multiple sources, **the government must train individual departments to take responsibility.** The relevant departments and institutions include the Department of Science and Technology, Department of Biotechnology, Ministry of Health, Ministry of Human Resource Development, Ministry of Finance, Ministry of Agriculture, Ministry of Electronics and Information Technology, Niti Aayog, Ayushman Bharat, among several others. **Developing a generalised meta-data standard for data.gov.in will enable integration of resources including but not limited to data, tools, literature, etc.**

**Finally, laws and regulations that encourage unbiased, reliable, safe, open and inclusive data sharing must be formulated for integration and dissemination of data.** They should include data standards for access, usage, security and privacy.

### 4. Addressing India's Skill Gap in AI

As the nature of work changes with automation, millions of people may need to switch occupations and acquire new skills. This will impact the structure of India's existing labor force. While research has established that AI has the potential to create net new jobs, a lack of relevant skills might mean that a majority of the displaced workforce will continue to remain unemployed. Countries such as Australia and US have launched programs that actively seek to encourage the migration of skilled professionals in science, technology, engineering and mathematics (STEM). In India, IBM has announced significant collaborations to advance the skills and careers of more than 200,000 women students in Science, Technology, Engineering and Maths (STEM) fields. The collaborations began in March 2019 with the signing of agreements with three state governments – Karnataka, Telangana and Andhra Pradesh. India's most recent skill report<sup>97</sup> states that the country is likely to see an automation of 40% to 50% of its existing jobs. Sectors likely to witness this change first are financial services, manufacturing, transportation, shipping, etc. Specific profiles that are likely to get replaced include the role of data entry clerks, cashiers, financial analysts, telemarketers, customer-service executives, etc. **Focused collaborations at the sector level, engaging students with corporates, can help build directly adaptable skills for the industry.**

<sup>97</sup> <https://www.analyticsindiamag.com/india-south%E2%80%89korea-artificial-intelligence/>

**There is an absolute need to revise education curriculum, especially for technology institutes, to necessarily include a program on AI.** Currently, about 23 institutes in India offer B.Tech programs in AI. There remains tremendous potential to offer more wide-spread training in AI technology. Moreover, AI needs to be understood as being socially embedded, interacting and affecting individuals and communities in myriad ways. It is therefore **suggested that AI training go beyond technology curricula to include social sciences, to contribute to the process of constructing the algorithm and in conducting an algorithmic impact assessment.**

**A market place for skilled AI professionals is an innovative way to meet the immediate skill gap that AI startups currently face.** The NVIDIA-Bennett Research Lab for Artificial Intelligence currently trains 300 AI interns using an engagement mechanism with startups, academia and industry. Such market places are not only a platform to tap AI skill but also for exchange of ideas. AI Global a non-profit organization has developed a marketplace to accelerate enterprise adoption of responsible AI. It is an online collaboration hub that bring together professionals to accelerate best practices in practical and responsible application of AI. Similarly, Bonseyes, an open and expandable AI platform in Switzerland has developed an eco-system of collaboration among leading academic and industrial partners to provide access to advanced tools and services for AI products.

Finally, skill deficits can be met by launching programs **that facilitate recruitment of technology specialists from other countries.** A great example is the French Tech Visa launched in January 2017, a fast-track procedure targeted at inviting technology entrepreneurs and professionals into the country.

## 5. Addressing Governance Challenges in AI

There is increasing fear within civil society on how Artificial Intelligence can threaten human rights. Several countries including India have integrated provisions for ethical AI in their national strategies. Germany's Data Ethics Committee promotes the adoption of ethical and legal principles through the process of developing and applying AI. The Council of Europe<sup>98</sup> proposed a process of 'Algorithmic Impact Assessment'<sup>99</sup> to account for biases that knowingly or unknowingly creep into an algorithm. The national strategy for AI in India also recommends setting up of ethics councils at each research centre and calls for sector specific guidelines for privacy, security, and ethics. **The elements of an Algorithmic Impact Assessment may be adopted by such councils.** The key elements could include (i) impacts to be assessed on fairness and justice derived within the existing frameworks on human rights, Indian constitution and other democratic values (ii) redressal mechanisms for affected individuals and/or communities to challenge bias and seek compensation (iii) where feasible and necessary, agencies to disclose the results of impact assessment and solicit public comments.

It is also essential to take precautions against both accidental and deliberate misuse of AI with risks to safety. But this needs to be within reason, in proportion to the damage that could ensue and the viability of the preventative steps proposed, across technical, legal, economic, and cultural dimensions. There are many challenges to the safety and security of AI systems.

The challenge is how to foster good safety practices and provide assurance that systems are sufficiently reliable and secure so that companies and society can feel confident in their use. For ideas on how to do this we can look at analogies from elsewhere. For instance, **researchers from the public, private, and academic sectors should work together to outline basic workflows and standards of documentation for specific application contexts which would be sufficient to show due diligence in carrying out safety checks.** Such standards have the ability to influence the development and deployment of AI-based systems by mandating product specifications for explainability, robustness, and fail-safe design<sup>100</sup>. They also serve to signal and disseminate global best practices. Current work on developing AI-based global standards is in early stages<sup>101</sup>. There is a significant role for the Government in this aspect, as demonstrated by US and China who prioritise engagement in standardisation through IEEE and ISO/IEC. **The various ways in which the Indian government can effectively participate in standardisation processes for AI are** (i) It can build capacity for engagement in standard setting organizations by creating dedicated technical teams well versed in AI that engages in activities of Standard Setting Organizations (SSO) (ii) It can pursue development of parallel standards through the creation of consortia of relevant stakeholder groups that can be proposed and disseminated through international standard setting fora (iii) Standards can be used as tools to induce cultural change. This is because the criteria established and described within standards are not just enforceable rules, but also create expectations on what it means to adhere to a specific standard. Following enforceable standards will induce organisations to internalise routines and carry out practices that may inculcate a culture of responsibility and safety.

Finally, adopting a “Human in the loop” maybe necessary at one or more points in the decision-making process of an otherwise automated system. The challenge is in determining whether and where in the process people should play a role, and what precisely that role should entail, taking into account the purpose of the system and the wider context of its application. Ultimately, AI systems and humans have different strengths and weaknesses. Selecting the most prudent combination comes down to a holistic assessment of how best to ensure that an acceptable decision is made, given the circumstances. **Involving other specialists along with scientists in the process of AI design and application will also help check biases and their discriminatory impacts. Incase of application in the social sector or for citizen services a mechanism for audits and public accountability must be instituted.**

AI’s transformative impact on socio-economic growth is well acknowledged. However, such technologies and their likely transformations need nurturing to help them achieve true potential and avert adverse social consequences. India’s approach towards fostering a welfare enhancing AI-based ecosystem must therefore address not just the constraints hindering AI driven growth, but must also address and prepare for safeguarding against adversities that emanate from such growth to truly achieve an AI-driven transformation.

<sup>99</sup> <https://www.coe.int/en/web/portal/-/unboxing-artificial-intelligence-10-steps-to-protect-human-rights>

<sup>100</sup> A practical baseline is provided in Reisman (2018)

<sup>101</sup> Cihon (2019)

<sup>102</sup> Ibid

## **| Epilogue**

The analysis presented in this report was completed before Covid-19. If the pre-pandemic consensus was that AI was going to break trend and spike, the probability that it will happen post Covid-19 has shot up considerably. There will be many more applications and data, encouraging faster diffusion across the economy. Estimates in this study will accordingly need to be revisited in this light.

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### Appendix 1: Number of AI Firms and AI Intensity Across KLEMS categories

Industry	Klemscode	Number of Firms	Average AI Intensity	Maximum AI Intensity
Agriculture, Hunting, Forestry and Fishing	1	17	0.001	0.02
Mining and Quarrying	2	12	0.003	0.10
Food Products, Beverages and Tobacco	3	56	0.001	0.04
Textiles, Textile Products, Leather and Footwear	4	99	0.002	0.26
Wood and Products of wood	5	2	0.001	0.02
Pulp, Paper, Paper products, Printing and Publishing	6	33	0.003	0.08
Coke, Refined Petroleum Products and Nuclear fuel	7	14	0.000	0.00
Chemicals and Chemical Products	8	179	0.002	0.17
Rubber and Plastic Products	9	57	0.001	0.03
Other Non-Metallic Mineral Products	10	38	0.001	0.02
Basic Metals and Fabricated Metal Products	11	133	0.002	0.62
Machinery, nec.	12	95	0.002	0.03
Electrical and Optical Equipment	13	80	0.004	0.58
Transport Equipment	14	107	0.002	0.07
Manufacturing, nec; recycling	15	20	0.004	0.35
Electricity, Gas and Water Supply	16	31	0.001	0.01

Construction	17	89	0.004	0.96
Trade	18	133	0.031	23.00
Hotels and Restaurants	19	30	0.014	1.35
Transport and Storage	20	54	0.004	0.16
Post and Telecommunication	21	31	0.013	0.91
Financial Services	22	36	0.296	11.53
Business Service	23	153	0.159	110.00
Education	24	7	0.028	0.88
Health and Social Work	25	30	0.005	0.10
Other services	26	17	0.010	0.22

### Appendix 2: Results of the Estimation

Variable	Model 1	Model 2	Model 3
TFPG <sub>jt</sub>			
Size <sub>ijt</sub> (OtherAssets)		-.00000002 (-2.23)	-.00000002 (-2.22)
DisembodiedTech <sub>ijt</sub> (Royalty & Technical Fee Intensity)			-.0004 (-0.09)
Alint <sub>ijt</sub>	.0006 (2.97)	.0006 (2.96)	.0005 (2.34)
ADVint <sub>ijt</sub>			.0001 (1.57)
Year 2009	-.001 (-.74)	-.001 (-.72)	-.001 (-.72)
Year 2010	.006 (4.28)	.007 (4.45)	.007 (4.45)
Year 2011	.012 (9.3)	.012 (9.54)	.012 (9.53)
Year 2012	-.003 (-2.12)	-.003 (-1.88)	-.003 (-1.88)
Year 2013	-.003 (-2.32)	-.003 (-2.02)	-.003 (-2.02)
Year 2014	-.006 (-3.93)	-.006 (-3.63)	-.006 (-3.64)
Year 2015	.009 (6.13)	.01 (6.54)	.01 (6.54)
Year 2016	.018 (10.83)	.019 (11.41)	.019 (11.4)
Year 2017	.005 (3.43)	.006 (4.03)	.006 (4.02)

**Note:**

Values in parenthesis are t values denoting statistical significance. We use results of Model 3 for our estimates.

### Appendix 3: Summary of Case Studies

Name of the company	Year of Commencement	AI Tech	Sector Served	AI solution offered	Firm Size (employees)	Modes of Financing	Academia connections/ Research background/ Startup experience	Patents on AI	Data management practices (ownership & storage)	AI Impact on jobs	AI impact on efficiency	Perceived challenges of AI for India
Face tagr	2016	Facial recognition using deep learning	Law enforcement	High accuracy Facial Recognition to target reuniting missing children in Tamil Nadu	11- 50	Self-funded: Bootstrapping by running parallel overseas business	Founder studied Neural Networks and AI in the US	Pending, 4 filed patents in the US.	Data gathered from open data from Ministry of Welfare, social media, NGOs and missing children data; Stored in Indian cloud - based solution	No impact on jobs due to AI yet	4000 policemen in Tamil Nadu use Facetagr; reduced time in finding missing children; Higher rates of reuniting missing children	Projects for public procurement face funding constraints; No Indian standard for facial recognition
v Phrase Analytics Solution	2015	Machine Learning; Generational Natural Language Processing	Banking and Finance	Presentation of facts and data analytics with humanized narratives	11- 50	Venture Capital investors; support from start-up incubators (CIIE-IIM A)	Research links to Innovation academy, University of Dublin	Patent in India and US published	Client data used to train algorithms, but owned by client; Internally generated data on market research, financial data stored in overseas cloud	Future job-automation likely	Reduced time and costs in generating analytical and personalized reports	Paucity of fundamental and breakthrough research on AI; Educational institutions don't recognize AI as subject matter
Genesis AI	2013	Machine Learning; Natural Language Processing	Manufacturing Banking, and Finance	Vernacular Chatbot; prediction based action recommendation for decentralized tasks; document processing	11- 50	Self-funded	Research Scientist founder with PhD in AI	N/A	Data storage based on client requirement; US client data stored in U.S cloud.	Increase in job automation; increase in extant workforce intensity.	Turn around time for processing documents reduced from 1 day to 20 minutes	N/A

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Artivatic Data Labs	2016	Machine Learning; Computer Vision; Natural Language Processing;	Banking and Finance, Fintech, Healthcare, Retail	Insurance Fraud, Risk profiling, underwriting & claims, document verification, and onboarding	11- 50	Overseas (Singapore) investors; Startup accelerators	IIT Delhi, previously set up 2 startups	Pending	Data gathered from open source; client owns data. Overseas cloud storage	Changes in division of tasks	Significant reduction in turn-around time for verifying documents	Nascent environment in India, but future perception is positive
Aspiring Minds	2008	Machine Learning; Computer Vision; Natural Language Processing; Speech Recognition	Banking and Finance, BPO companies, manufacturing	AI-powered pre-employment assessment and video interview analytics	201-500	Overseas investors (Omidyar network; Ajit Khimji Group)	Research Scientists from multiple universities under board of advisors;	1 out of 12 patents granted.	Business to Customer data owned by the company; Business to Business data owned by clients	No impact on jobs due to AI yet; risk of lower level job displacement, but business growth might increase available jobs	Large scale hiring process times reduced from 3 months to one week	Indian Government's approach is still high-level and does not outline roadmaps to how AI centric developmental goals need to be achieved;

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Nebu laa	2016	Machine Learning; Deep Convolutional neural network for Image analysis	Agri-culture; FMCG	Auto-matic Grain Analyzer capable of quick grain quality testing, adapted to local infrastructure	2-10	Google 'Solve For India'	N/A	Pending	Data gathered and used from different agricultural markets across Indian states	No impact on jobs due to AI yet; Auto-mation in agri-culture not possible due to small land holdings	Turn around time reduced from 30 minutes to instant; average cost of analysis reduced from 800 rs to rs 200	N/A
Gyan Data	2011	Machine Learning	Manu-facturing	Custom made data based solutions for fault diagnosis and predictive maintenance	11-50	Startup incubator at IIT Madras; Incubator holds some equity	Research Scientist founders, strong ties to IIT Madras	None	Clients data used only to train algorithms but data is owned by client	No impact on jobs yet	15-20% savings when implemented on a production line. Reduction in defect rates in foundries from 5% to a near 0%	Shortage of fundamental research in AI in India; Greater need for Industry-Academia interaction.
Vassar Labs	2014	Machine Learning, Deep Neural Net	Governance, Agri-culture, Smart Cities, Utilities, Education	Last-mile decision support using real time data from sensors; Platform for Predictive Analytic Models.	100-150	Self-funded	Research Scientist founder; ties to IIT, MIT	None	Data gathered from satellite, sensors, publicly available data, not owned by the company.	No impact of on jobs due to AI yet	Ground water recharge increased by 2 meters across State (Andhra Pradesh) despite monsoon deficit; Revenue increase to government by 40% from agriculture, with same proportions of land and water use.	Scaling-up solutions in India is a challenge, with data availability as one of the key barriers. Consequently, reinvestment in solutions also a challenge.

Name of	Year of Commencement	AI Tech	Sector Served	AI solution offered	Firm Size (employees)	Modes of Financing	Academia connections/ Research background/ Startup experience	Patents on AI	Data management practices (ownership & storage)	AI Impact on jobs	AI impact on efficiency	Perceived challenges of AI for India
Video Ken	2017	Deep Neural Net, Natural Language Processing	Sector agnostic; Services, Consultancies	Video indexing platform targeting improved learning outcomes from online educational videos	11- 50	Seed-funding, Angel investors	Research Scientist founder; ties to IBM research, Xerox research	6 US patents issued	Data gathered from online video streaming platforms; Data not owned by the company; compliance with copyright laws and GDPR	No impact on jobs due to AI; job losses foreseeable	Ease of on-boarding; Internal technical training time reduced	India is constrained more by skill shortage than by the emergence of technologies.
Data Glen	2015	Machine Learning, Deep Learning techniques	Utilities (Electricity)	AI-based optimizing analysis for increasingly decentralized and distributed solar power grids	11- 50	Strategic investors	Research Scientist founders; ties with IBM research, MIT, IISc.	2 Patents, with General Electric (GE)	Data generated from solar inverters, weather monitors; data stored in cloud based solution; data owned by end customers	Skill augmentation due to AI; no impact on jobs due to AI	7-10% improvements in power generation from solar panels; optimal maintenance of solar panels	Shortage in available data sources, also stemming from lack of investments in data collecting sensors; Data sharing arrangements cannot be enforced top down by State; Lack of large government grants to Indian R&D in AI.
Agro star	2008	Machine Learning based techniques	Agriculture, m-commerce	Machine Learning based crop management advisory application	201-500	Venture Capital	In-house Agronomists	None	Primary data collected from field surveys, data generated from own m-commerce platform	None		

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Arte lus	2014	Deep Learning based techniques	Health-care	Image Processing based TB and Diabetic Retinopathy detection	11- 50	Angel funds, self-funding/ bootstrapping	None	Filed for 27 patents	X-ray based data made available by Stanford university, own data generated from applications, platform data from hospitals. Data stored in cloud servers located in India	Increases doctor's work intensity, augments doctor's skills	Greater than 90% accuracy in detecting Diabetic Retinopathy	Cut throat competition among AI-based firms in healthcare sector; lack of cooperation and data sharing activities
Vils		Machine Learning, Deep Learning based techniques	Services and Education	ML Powered Human Resource assistance, pre-employment assistance, and student outcome assessment and recommendation engines	2-10	Bootstrapping, venture capital	N/A	None	Data collected from user-firms, stored in cloud servers located in India	None		









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