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Potential Impact of Artificial Intelligence on the Indian Economy

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Abstract

From a technology capability perspective, artificial intelligence (AI) holds tremendous promise for India, to address some of the biggest challenges we face as a country. The adoption of AI across different sectors of the economy is found to have delivered positive returns by reducing risk, time and capital expended. It has enabled a range of innovation across different application sectors leading to massive economic and social benefits. This paper attempts to provide estimates for the impact of AI on total factor productivity (TFP) of Indian firms. We use an econometric specification that helps identify firm-specific determinants of TFP growth, of which AI, as an efficiency enhancing GPT, is one of the explanatory variables. We estimate the model using a panel data set of 311 firms, both manufacturing and services, listed on India's Bombay Stock Exchange for the period 2010 to 2020. While the econometric estimation provides adequate evidence for policy to support its wider adoption, the actionable measures is only possible by evaluating firm capabilities, both for firms developing and using AI. In the paper we discuss and illustrate examples of open government data, that increase the opportunity for rapid localised AI-led innovation.

JEL Classification: O3, D24, O14, C5

Potential Impact of Artificial Intelligence on the Indian Economy

Mansi Kedia and Richa Sekhani[1]

1. Introduction

Living life to the tap of a screen or on the click of button was not something ordinary people had ever imagined. Yet, Artificial Intelligence (AI) today, shadows our day-to-day activities. AI applications spawn sectors of economic activity, governance and human interactions. From simple applications such as automatic generation of financial statements and tele-assistance for customer care to sophisticated applications such as medical diagnosis and self-driving cars, are all facilitated by AI (Smith, 2019). Even creative arts, a field known for human craftsmanship, has seen a proliferation of AI applications (Ghose, 2016). The Covid-19 pandemic, brought to fore, public good uses of AI, including its application in health, education, agriculture, transportation, law enforcement and judicial decision-making.

The omnipresence of AI makes it challenging to confine its application- reach into a single definition. Accordingly, there are several definitions and impressions of what constitutes AI. For instance, the website of the Association for Advancement of Artificial Intelligence (AAAI) defines AI as "the scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines.[2]" Russell and Norvig's (2009) textbook titled "Artificial Intelligence: A Modern Approach" defines AI across four broad dimensions – thinking humanly, acting humanly, thinking rationally and acting rationally. A true artificially-intelligent system is understood to be one that can learn on its own, and can improve on past iterations, getting smarter and more aware, allowing it to enhance its capabilities and its knowledge (Adam, 2017).

The universe of AI comprises of logic-based tools, knowledge-based tools, probabilistic methods, machine learning, embodied intelligence, search and optimisation. Technology mapped to these paradigms include robotic process, automation, expert systems, machine learning, natural language processing, computer vision, speech etc. These technology forms vary in terms of processing capacity, the type of data used and more fundamentally the problem at hand (Taddy, 2018). While data fuels AI applications, algorithms are the engines. The technology categorisation along with the typically associated AI applications are illustrated in *Figure 1* below.

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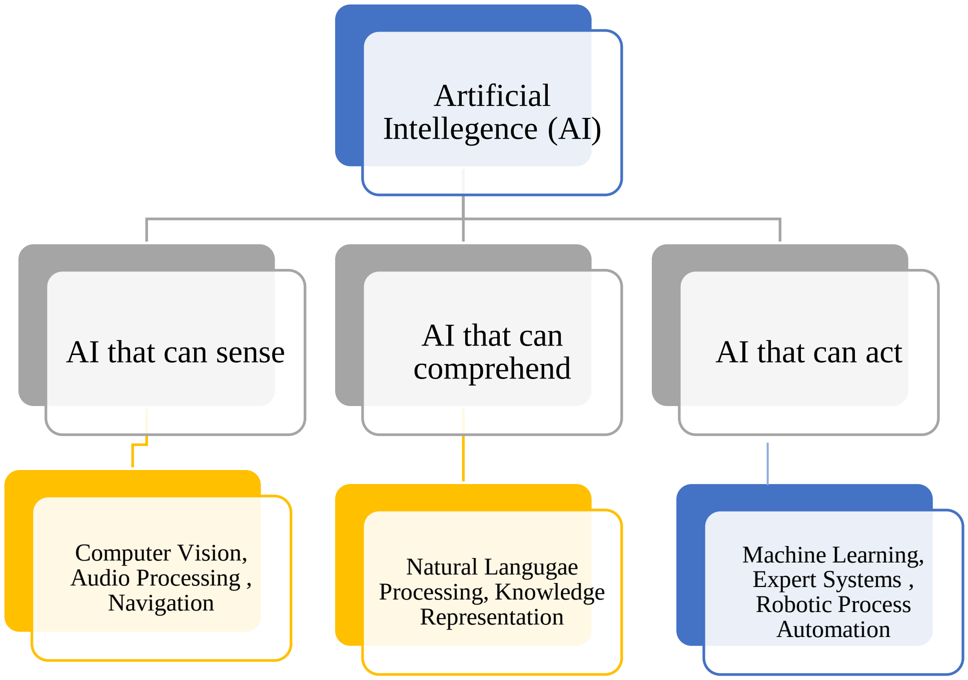
[2] https://www.aaai.org/

Figure 1: Emerging Artificial Intelligence (AI) technologies



The concept of computer vision has been successfully applied to facial recognition. For example, Facebook uses the technology for tagging friends in photos and Snapchat uses it to recognize a person's face when applying filters.	Email applications automatically prompt when you try to send an email without the attachment that you referenced in the text of the email. This is an application of Natural Language Processing.	Uber uses Machine Learning (ML) to determine price surge during peak hours by estimating rider demand. Paypal also uses ML for fraud risk assessment that helps distinguish between legitimate and illegitimate transactions.

Source: Compiled by authors

The last couple of years have seen an explosion in AI activity. The adoption of AI across different business processes is found to have delivered positive returns by reducing risk, time and capital expended. It has catalysed technical improvements and enabled a range of innovation across different application sectors (Bresnahan et.al, 1995). While these impacts were not immediately visible, investments in intangible capital including organisational changes, re-skilling and training, have made AI enabled growth quite evident(Brynjolfsson et.al, 2017). At the country level, flurries of national policies on Artificial Intelligence (AI) have recognised the economic and social benefits of its application[3].

[3] National strategies implemented by countries includes Japan, Canada, America, Russia, China, France, German etc.

This paper builds on research from a report published by ICRIER in 2020 (Kathuria et.al, 2020), to provide estimates for the impact of AI on the total factor productivity (TFP) of Indian firms. We find that adoption of technology by Indian industry is largely concentrated within the top 10 percentile, firms that have a capacity to invest in both technology and skilled personnel. More specifically, current AI adoption in India is driven by large global technology conglomerates, select startups and Global Capability Centres (GCCs) located in India (Mehta et.al, 2020). Given the low-levels of digitization across the small and medium sized firms, the ICRIER report using data of almost 1500 Indian firms, presented relatively low impacts of AI on TFP, albeit positive. This report extracts from the older data set, a group of firms that belong to the top 500 firms listed in India's Bombay Stock Exchange to demonstrate the potential of AI adoption in the Indian industry.

With this background, section 2 will provide a snapshot of various AI applications and their adoption. Section 3 will provide an estimate of AI on the Indian industry using a panel data regression of over 300 publicly listed firms belonging to the manufacturing and services sector in India. Section 4 will present case studies to explore the public good applications of AI technology in India and their potential for monetization. In highlighting the case studies, we will emphasize on the importance of data sharing. Section 5 concludes.

2. Adoption and Application of AI

The use of artificial intelligence is benefitting individuals, communities, industries and governments. AI applications that influence the daily lives of people and households include Siri, Cortana and Bixby, examples of virtual personal assistants, that learn continuously about a user through daily engagement and provide personalised help on a number of tasks. Video Games are another example where the use of AI has revolutionised gaming experience for users. The game Middle Earth: Shadow of Mordor,[4]launched in 2014, is designed to memorize patterns and characters, to help the user while playing the game. The shopping experience has also transformed with computer vision- based technologies churning 'just walk out' stores that do not have check-out counters (Reuters, 2018). These experiences are however common place only for the privileged sections of the society in India; for several others the opportunity to access these services are still a distant dream. Moreover, as users are becoming more and more dependent on technology for personal experiences, new behavioural and psychological concerns are being reported that need to be acknowledged and dealt with separately (Bartneck et.al, 2021).

AI for Governance and Social Good

Applications falling in the category of *AI for Good* address a variety of developmental objectives including applications to diagnose cancer patients, support navigation for the blind, aid disaster relief efforts, etc. Though wide ranging, these applications are mostly small scale. Several pilot

[4] https://boardgamegeek.com/boardgame/144845/games-middle-earth

initiatives illustrate how the new and unexpected applications of AI can improve human lives. For instance, the UN global pulse deployed 'Neural Network Architectures', a form of AI, to detect shelter structures from satellite images at the time of multiple humanitarian crises in East Africa and the Middle East. The Indonesian Government deployed similar capabilities to develop a crisis analysis tool to enhance disaster management efforts. *Precision Agriculture for Development (PAD)* uses AI to provide personalised, low-cost, information through interactive voice response; *Educate Girls* uses machine learning techniques to target out-of- school girls; and the *Center for Effective Global Action* uses big data and machine learning methods to reduce gender gap in access to credit. GnoSys,[5] 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. The report titled "Artificial Intelligence and Life in 2030", provides several other such examples.[6]

Another important initiative in this area is Google DeepMind, working in partnership with clinicians, researchers and patients to solve real-world healthcare problems. The technology combines machine learning and systems neuroscience to build powerful general-purpose learning algorithms into neural networks that mimic the human brain (King, 2019). DeepMind and several other organisations have used deep learning to predict the structure of proteins associated with SARS-CoV-2, the virus that causes COVID-19 (OECD, 2020).

AI for Industry

AI is at the centre of the ecosystem around *Industry 4.0*[7], optimizing the computerization of industry during the third technology revolution. The McKinsey Global Institute (2018)[8] report provides a useful starting point to gauge the diffusion of AI across sectors and businesses. The report shows AI being highly relevant to automotive, banking, consumer goods, healthcare, insurance, pharmaceuticals, retail, telecommunications, transport and logistics sectors.

Retail and e-commerce are one of the sectors where AI is deployed extensively. AI applications enhance consumer experiences with the use chatbots, powered by AI programs to respond to consumer queries. Banks are also demonstrating an appetite for AI. They use a range of

5 https://gnosystech.com/

6 Artificial Intelligence and Life in 2030, Stanford University. September 2016. https://ai100.stanford.edu/sites/g/files/sbiybj9861/f/ai100report10032016fnl_singles.pdf

7 Industry 4.0 refers to a new phase in the Industrial Revolution that focuses heavily on interconnectivity, automation, machine learning, and real-time data. Industry 4.0, which encompasses IIoT and smart manufacturing, marries physical production and operations with smart digital technology, machine learning, and big data to create a more holistic and better-connected ecosystem for companies that focus on manufacturing and supply chain management. While every company and organization operating today is different, they all face a common challenge—the need for connectedness and access to real-time insights across processes, partners, products, and people.

8 https://www.niramai.com/technology/

applications to enhance consumer experience and increase the efficiency of their operations. For instance, using data from past payment patterns, AI applications can predict and prompt the user to their preferred mode of payment. In a completely different environment, AI based driver assistants are bringing massive changes to navigation and road safety. AI assistant can check blind zones, measure the exact distance to objects, and prevent road accidents.

Appen's 2020 State of AI and ML Report, on a cross-section of industries from around the world, found that 41 percent companies had adopted an AI strategy during the pandemic. Organisations invested in Ai driven automation to expedite remote working, enhance user and decrease costs. In fact, 75 percent organisations cited AI as critical to their success in 2020 (Appen, 2021), and many were already benefiting from its adoption. In India, the IDC Maturity Benchmark for Artificial Intelligence found that almost 25 percent organisations surveyed were in the *AI practitioner* stage, i.e., those beginning to align their AI strategy to that of the enterprise, while only 8.4 percent were in late stages of maturity (IDC, 2021).

The widespread application of AI has growth consequences leading to productivity gains in businesses and industries as well as increased consumer demand from customized products and services. The ability of an economy to adopt AI depends on its structural composition and the technological maturity of different industry 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 section below provides an provides an estimate for the potential impact of AI on Indian industry using an understanding of AI as a general-purpose technology.

3. Estimating the Potential Impact of AI

For several decades now, growth economists have used technical changes to explain economic growth at the macro level (Abramovitz, 1956, Solow, 1957) and profits and market shares of firms at the micro level (Acemoglu, 2000). The Schumpetarian creative destruction explained the positive impact of new technologies and new industries on growth; bridging the gap between macro and micro economics (Schumpeter 1942). Technology is defined as the use of scientific knowledge for practical purposes or applications, whether in industry or in our everyday lives[9]. Technology can be of various types – mechanical, electronic, industrial, communications, medical, etc. The growth literature focuses on General Purpose Technologies (GPTs), a set of core technologies that have substantial and pervasive societal and economic effects. Some of the commonly cited “generic”, or “general purpose” technologies are electricity, steam engines, semi-conductors and more recently information and communication technologies (ICT), which are all proven to have far reaching consequences on productivity gains. With the potential of profound impacts on the Indian economy AI is also considered by several economists as a GPT. Angrew Ng in 2015 stated “Just as electricity transformed almost everything a hundred years ago, today I

[9] https://study.com/academy/lesson/what-is-technology-definition-types.html

actually have a hard time thinking of an industry that I don't think AI will transform in the next several years." While AI led innovation would have direct impacts on any given sector, it also has the capacity to inspire complementary innovations and spillover benefits in other sectors of the economy. AI applications demonstrate key characteristics of GPTs – pervasiveness, technological improvement and the ability to spawn innovation.

- *Pervasiveness*: A technology is classified as a GPT when the share of new capital associated with it, reaches a critical level and adoption is widespread across industries Cummins and Violante (2002, p. 245). As per a report by Gartner (2019), the number of businesses using AI has grown by 270 percent in the last four years. In a recent survey conducted by Congilytica[10], over 40% respondents stated that they will implement AI in one or more identified patterns by 2025 and almost 90% responded that they will have some sort of in-progress AI implementation within the next 2 years.

- *Technological Improvement:* Bresnahan and Trajtenberg suggest that the efficiency of the GPTs improve over time. In the case of AI, from the 'Turing Test' to data driven machine learning techniques, there has been several seasons of technological advancements that AI has witnessed. 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[11]

- *Ability of the GPT to spawn innovation*: All GPTs support innovation. The adoption of AI has catalysed technical improvements and enabled a range of innovation across different application sectors (Bresnahan et.al, 1995). For instance, machine learning has improved the performance of labelling content on photos. With the decline in error rates from one per 30 frames to one per 30 million frames, self-driving cars have become a reality (Brynjolfsson et.al, 2017).

Just as other GPTs, AI demonstrating the fundamental characteristics of a GPT, holds the promise of unlocking growth potential and play a significant role in explaining the wealth of nations (Lipsey et.al, 2005). However, not every study measuring the economic implications of AI (very few in number), model AI as a GPT. For instance, a study by Accenture (2018), treats AI as a new factor of production and not a driver of total factor productivity. However, one may argue 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. 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

[10] The survey is conducted for 1500 decision makers in multiple industries and regions
[11] https://em360tech.com/tech-news/tech-features/artificial-intelligence/

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. Some of the commonly cited studies on the economic impacts are summarised in Table 1 below.

While AI's impact on gross domestic product (GDP) and productivity are striking, research has also established the destructive effect of AI on jobs and employment. A report by McKinsey Global Institute suggested that intelligent agents and robots could eliminate as much as 30 percent of the world's human labour by 2030. As per the study, **a**utomation would displace between 400 and 800 million jobs by 2030, requiring as many as 375 million people to switch job categories entirely. Similarly, a PWC study titled "How will automation impact jobs?" stated that 30 percent of the existing jobs could be automatable by mid 2030s. The financial services sector was noted to be vulnerable to automation in the short term, while transport was likely to get impacted in the longer run (PWC,2018). An optimistic line of reasoning suggests that the countervailing effects are expected to become stronger and fully compensate the initial decline in labour with a reorganisation of businesses. According to the World Economic Forum report titled "The Future of Jobs", machines and algorithms in the workplace are expected to create 133 million new roles, and displace 75 million jobs by 2022. Similar findings from the report by Bloomberg stated that "more than 120 million workers globally would need retraining in the next three years due to AI impact on jobs" (Bloomberg, 2019). While these predictions do highlight the unemployment risks associated with AI, it is also argued that the relationship between AI driven automation and job losses will depend on the level of demand in the sector prone to automation (Saemans et.al, 2018). While the focus of the paper is not on employment, the relationship between AI and jobs is one to explore for sustained economic growth, especially for economies like India where the challenge of unemployment poses serious threat to national well-being.

Table 1: Research Measuring the Impact of AI on Productivity and Growth

Study (Year)	Objectives	Methodology	Findings
PWC (2018)	To demonstrate AI's full economic potential globally through channels of productivity and consumption enhancement	Analyses the productivity impacts of AI by modeling the impact of software, databases, computer hardware and machinery on labor productivity Developed AI impact index to evaluate AI's impact on products across sectors, sub-sectors and product lines. Use the results as inputs in a computable general equilibrium model to estimate the net impact of AI on the economy until 2030	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, defense, travel and public sector organizations 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 (2016)			AI can double annual economic growth in gross value added (GVA) terms for the set of 12 developed economies (that contribute 50 percent to the total world GDP). US, Japan, Germany, Austria, Sweden and the Netherlands are some of the countries that stand to gain the most.
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-labor 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 authors from various report

3.1 Measuring the Impact of AI on Total Factor Productivity

We measure the economic impact of AI, based on the understanding that AI can be best viewed 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. In the case of AI as well, economists have been puzzled by the 'productivity paradox'. This paradox, a gap between the expectations of the economic effects and the effects that appear in data, are therefore not new. Solow's famous 1987 quip read – *You can see the computer age everywhere but in the productivity statistics*.

Empirical research on GPTs such as AI, also 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 not therefore uncommon that studies on GPTs, while attempting to estimate their economic impacts, also engage in in-depth case studies and historical analysis of its impacts.

The model adopted in this paper, following our previous research (ICRIER 2020), measures the impact of AI on total factor productivity. The concept of total factor productivity (TFP) has played a critical role in the discussion on empirical growth. It is an implicit part of the circular income flow model that measures output per unit input. Also referred to as "multi-factor productivity", under certain assumptions, it can be thought of as the level of technology or knowledge. The research on TFP goes at least as far as Tinbergen (1942) who calculated the efficiency by generalizing the Cobb-Douglas production function. With the help of an aggregate production function, Solow (1957) including various other economists, tried measuring the contribution of production factors and technology on economic growth. Various lines of research found strong evidence of TFP growth being an important source of overall growth (Easterly and Levine, 2001; Bosworth and Collins, 2003). As the literature on TFP evolved, various scholars measured the impact of research and development (Grilliches, 1973) and technology on TFP (Romer,1990; Aghion and Howitt,1998). The concept rests on models of endogenous technological change that explain growth.

Research focused on economic growth in India, have found ICT led innovations and investments to positively impact aggregate economic growth including the growth of manufacturing and various sectors using ICT (Erumban et.al, 2016). Using data on Indian firms from 1974-75 to 1981-82, Basant and Fikkert found evidence of the positive impact of R&D and foreign technology on firm productivity. Similarly, Satpathy, Chhaterjee and Makhakud used a panel data for 616 manufacturing firms, over the period 1997-98 to 2012-13, to identify the determinants of TFP across 10 industries. Our previous study adopted their model to test the impact of AI on firm TFP in India. The model estimates suggested a small but significant impact of AI on firm productivity. This paper uses a data sub-set, a group of firms that belong to the top 500 firms listed on India's Bombay Stock Exchange to demonstrate the potential of AI adoption in the Indian industry. The firms listed in the exchange exhibit a degree of homogeneity in terms of scale, capabilities and technological adoption. We use this paper to compare the results of AI adoption among relatively well-capitalised and technologically advanced companies, to that in a wider set of firms belonging to the manufacturing and services sectors in India. Accordingly, the data set is sized down from 1553 firms to 311 firms over the period 2010 to 2020. AI is defined as investment in software, databases and computer machinery. It has been common practice in the existing literature to use this as proxy for AI. We do not include investments in electronics hardware that may also be considered as contributing to the AI ecosystem, since its functions go much beyond AI related processes. We understand that 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 use an econometric specification that helps identify firm-specific determinants of TFP growth, of which AI, as an efficiency enhancing GPT, is one of the explanatory variables. Box 1 provides the definition of variables used the for the estimation. We estimate the model using a panel data set of 311 firms, both manufacturing and services, listed on India's Bombay Stock Exchange for the period 2010 to 2020. We use the Centre for Monitoring of the Indian Economy (CMIE)'s Prowess database. The companies represent 26 industry categories as defined by the Reserve Bank of India's KLEMS categorisation[12]. The data includes only those companies that have non-zero investments in software over the period of analysis, i.e. those that represent some investment in AI. The data set is skewed towards manufacturing firms, representing almost two-thirds of the sample. The average AI intensity, measured as the ratio of AI investments to sales, is .002 for the manufacturing sector and .06 for the services sector. Sectors such as financial services exhibit very high AI intensities. 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[13] 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. (Please refer to **Appendix 1** for a measure of AI intensity by industry category). It is good

[12] The KLEMS catgeorisation consists of 27 industry categories of which one is public administration and defense which we dropped from the analysis. Also, the data set does not reflect any company from the education services industry. https://rbi.org.in/Scripts/KLEMS.aspx

[13] 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

to note here that the AI applications adopted by industry are still simple machine learning algorithms and not complex technologies which are

Box 1: Definitions for Variables

$$TFPGijt = \alpha + \beta 1Sizeijt + \beta 2ResearchDevijt + B3DisembodiedTechijt + \beta 4AIintijt + \beta 5ADVijt + \beta 6Sectorj + \beta 7Yeart + \varepsilon$$

TFPGjt is the measure for total factor productivity growth in year t for KLEMS sector j.

β1Size$_{ijt}$ is the measure of firm 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.

β2ResearchDev$_{ijt}$ is the measure of expenditure on research for firm i in Sector j in the year t. We expect a positive sign for the coefficient of expenditure on Research Development. Economists have argued that research and development (R&D) activities help to foster innovations, which in turn affect the TFP of a company.

β3DisembodiedTech$_{ijt}$ 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

β4 AIint$_{ijt}$ 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 β4 will be positive.

β5 ADV$_{ijt}$ is a measure of the advertising expenditure intensity for firm i in sector j at time t. Advertising expenditure intensity is the ratio of advertising expenditure to sales. According to the literature, consumption of finances in advertising can adversely impact the total factor productivity growth of a firm

β6 and β7 are coefficients for the control variables - KLEMS sector and year respectively

α is the constant term, ε is the error term.

presently expensive and consequently rare.

The other determinants of TFP growth that we test through our model include the size of the firm, disembodied technological intensity, advertisement intensity, research and development expenditure[14] 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

[14] 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)

of India's KLEMS Database. The model does not capture the impact of another variable that impacts TFP growth. Literature emphasizes on the role of embodied technology, the measure of capital goods. The descriptive statistics are provided in Table 2 below.

Table 2: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
$TFPG_{jt}$	.005	.038	-.2342664	.1243626
$Size_{ijt}$ (Assetsotherthansoftware)	10.5424	1.539	2.292535	16.08969
$DisembodiedTech_{ijt}$ (Royalty & Technical Fee Intensity)	.0107927	.0791108	0	2.587102
$ResearchDev_{ijt}$	.0072265	.0188522	0	.1975282
$AIint_{ijt}$	.0150862	.1830252	0	5.162214
$ADVint_{ijt}$	.0256993	.2449323	0	10.875

We use a fixed effects multivariate panel-data regression for the estimation of the model[15]. 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. We also use robust standard errors to address heteroskedasticity in the model. The model estimates are therefore consistent[16]. ***The results find a positive 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 0.3%.*** This coefficient is significantly higher than the 0.05 percent estimated using the larger set of manufacturing and services companies and demonstrates the adoption of AI by bigger and well- capitalized firms. It also highlights the potential for firms in the Indian industry to gain from AI adoption.

The coefficient for research and development is positive and significant, aligned to findings in the literature. Firm size, determined by assets (net of software) and disembodied technological intensity are insignificant. The coefficient for advertising expenditure picks up the correct sign, but is 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).*

Indian industries are from the frontier where AI has percolated across and within sectors. 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, as is the case with most GPTs. These estimates also

15 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

16 We also test the residuals from the estimation for presence of unit roots and find the estimates to be consistent

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. The analysis also suggests that AI adoption is going to be non-linear across sectors. The changing structure of the economy and the ability of firms to adapt to new technologies such as AI will determine future growth in the economy.

Through this model we establish an unambiguous positive relation between AI adoption and economic growth. Though the estimates are best treated as an order of magnitude. For the impacts to be understood in greater granularity, a better measure of AI at the firm-level would be necessary. 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 section we discuss and illustrate examples of other growth centres where availability of data and deployment of AI can lead to significant economic benefits. These applications directed towards governance and development have carved out a niche for India in the area of *AIforGood.*

4. Data, AI and Economic Potential

Even though AI technologies have existed for several decades, it's the explosion of data, the raw material for AI, that has allowed it to advance at incredible speed. IDC predicts that world data will collectively grow to 175 Zettabytes by 2025.[17] About a third of the data in the digital universe (more than 13,000 exabytes) has the potential to be used as *Big Data* if it is tagged and analyzed (Gantz.J et.al, 2012). Given, its importance, data has been declared as the world's most valuable resource, beating oil in the process (Humby, 2006).

Economists have popularly pitched for data to be treated as a public good. The public good argument is based on non-rival and non-excludable principles, advocating its equitable use for the public at large. The lack of open access to quality data prevents it from being put to the best possible use. It also enables the formation of monopolies that tie people and enterprises into proprietary formats. To address this issue, countries have highlighted the importance of creating resilient open data infrastructure in their national policies. Governments have a fundamental role in setting up these institutions where data is made available as a public good. The International Open Data Charter (ODC)[18] was launched with an understanding that good data was essential in achieving the sustainable development goals (SDGs). The Open Data Barometer defines open data as data which is available online, open-licensed, machine readable, available in bulk and free of charge[19]. More than 50 percent countries covered in the barometer had an open data initiative in place. However, the latest report identifies some worrying trends which include a majority of data

[17] https://www.seagate.com/in/en/our-story/
[18] https://opendatacharter.net/
[19] https://opendatabarometer.org/leadersedition/report/#executive-summary

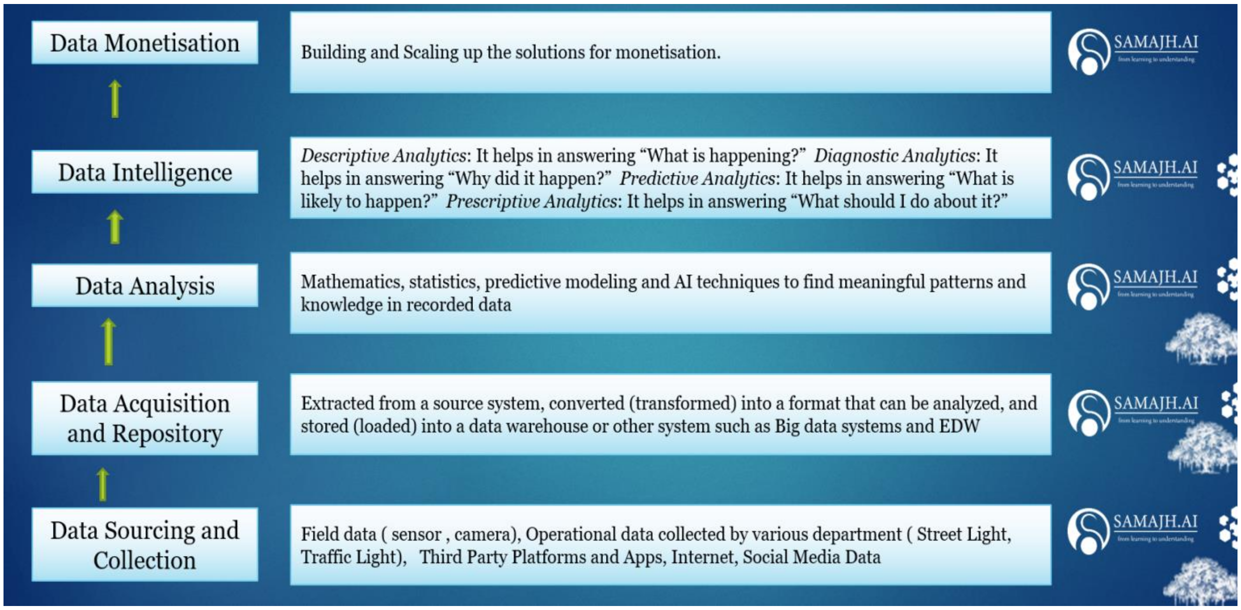
sets remaining closed to the public even in countries such as UK and USA which are open data leaders.

With the launch of *data.gov.in* in October 2012, India also embarked upon its journey of Open Government Data (OGD). As a part of the OGD movement, India has agreed to provide public access to government-owned data (along with its usage information) in machine-readable formats at no additional cost. However, India is yet to adopt the Open Data Charter. Also, the quality and range of data available on this platform can be significantly improved to feed into large scale AI applications that have proven to improve governance and generate revenue for governments in several other countries. For instance, Transport for London (TfL) releases a lot of data in an open format for developers to use, free of charge. The latest information suggests that more than 600 apps were being powered using TfL's open data feeds that supported the growth of London's tech economy to the value of £14 million annually in gross value added and over 700 jobs (National Infrastructure Commission Report). According to a report on the Economic Impact of Open Data by the European Data Portal, the open data market size for EU is likely to be in the range of €199.5 – €334.2 billion, generating between 1.12 and 1.97 million jobs (European Data Portal, 2020).

The government in India is also sitting on a similar gold mine. Like most other countries it is the largest owner of all forms of data. Some of the case studies we present in the sub-sections below highlight the potential of government data, *hitherto* unutilized, to generate revenue for the government and add value to the Indian economy. This will address the post-covid fiscal strain as well as the unemployment challenge, the country is currently facing. In some positive news, the government is not only making its data available but finding institutions to collect data and build data foundations which will become the backbone of India's AI economy.

The three initiatives illustrated below are India Urban Data Exchange (IUDX), Samajh.AI and AI Hub. In *Figure 2* below we map the progress of these initiatives to the stages in the life-cycle of data. Open government data impacts the stages of data sourcing and collection as well as data acquisition and repository. Since these costs can otherwise be very high, OGD can fast track innovation, by making this available free of charge. Samajh.AI uses a combination of available government data as well as sources its own through the installation of cameras and has successfully monetized applications developed on the basis of this data. IUDX and AI Hub are working towards building data sets. While IUDX pulls in data from different governing bodies in a city to a centralized command and control system that are able to present some analytics to improve the efficiency of public services, AI Hub is investing in data collection from private sources as well as through its own devices and systems and is still at the sourcing and acquisition stage. Each of these initiatives highlight the role that open government data can actually play in creating applications for improved governance that can also become a ready source for government revenue.

Figure 2: Life-Cycle of Data



Source: https://online.hbs.edu/blog/post/data-life-cycle

4.1 Samajh .AI

This AI start-up uses computer vision and image processing technologies on publicly available data to improve regulatory compliance for the transportation sector. The company developed an automated number plate recognition (ANPR) software that has the ability to read vehicle registration on number plates at the entry as well as exit points of a toll plaza. The wait-time at toll booths where the application was deployed, was completely eliminated, from the 7-10 mins spent earlier at each toll booth. Moreover, data collected from these installed cameras on vehicle frequency, type and classification of vehicles, number of vehicles, etc. are now shared with concerned authorities that carry out repair and maintenance of road networks. The company also created an AI – driven port audit system. With the help of cameras, the system accurately detected the number of containers being shipped out on a daily basis, that was grossly underreported. This helped government revenue from each port to increase by almost 50 percent. A third AI application was developed to improve vehicular compliance to speed limits. The company reported that using human monitoring, only 1-2 percent of actual violators were being fined. The computer vision-based AI application increased the number of violations that the authorities were able to detect and fine, increasing government revenue and improving traffic discipline.

4.2 India Urban Data Exchange (IUDX)

IUDX is an open-source software platform that is designed to facilitate secure and authenticated exchange of data amongst various city platforms and third party applications within a city. The platform intends to provide full control to data owners with a built-in accounting mechanism, forming the foundations of a data marketplace. IUDX envisages the use of this data to help citizens and the community benefit from innovative and cheaper applications and services (IUDX, 2018). The cities themselves can benefit from the reduction in development cost and faster development. Currently, there are ten cities under the IUDX umbrella - Agartala, Bengaluru, Bhopal, Bhubaneswar, Chennai, Faridabad, Pune, Surat, Vadodara, and Varanasi, each working on multiple use cases.[20] There are 52 datasets across these cities and the exchange is actively engaged with industry partners in developing and implementing different use cases[21][22].

In the bus occupancy use case, IUDX sources data from the Intelligent Transit Management System, Surat Money Open Loop Smart Card, QR code-based ticketing, and Google's bus-related real time data. All this data is used to derive the actual time of bus arrival and the numbers of passengers on board in real time, helping citizens plan their travel. A recent report by the Ministry of Housing and Urban Affairs said that lakhs of commuters in Surat Smart City are now using a mobile app of IUDX that provides actual time of bus arrival and real time occupancy of seats (Urban Update, 2021). The platform has minimized waiting time for users and also enhanced commuter experience by enabling seat selection. It helps the city administration analyse 7935 daily trips and optimally schedule 840 buses. According to industry representatives, every percentage increase in ridership due to certainties in estimated time of arrival and occupancy data is expected to add 2.85 crore to revenue per year. Further, the fleet optimization based on occupancy data, if implemented, can reduce the operational expenses by 15 percent. This pilot in Surat exhibits promise for data-driven smart mobility in other cities of India.

4.3 I-Hub

[20] https://catalogue.iudx.org.in/

[21] Of all the solutions developed so far, only one of the solutions uses AI. Video file systems stored from CCTV cameras has been installed in Agartala city to aid monitoring of city traffic, transportation and surveillance application.

[22] The data that are available includes physical location of air quality/environment monitoring sensors and air quality levels, flood sensors, weather stations, physical location of Yulu bike docking stations, bike hiring stations, and smart streetlights, road audit information, public transit bus information (bus stops, routes), public transit real time information, individual junction locations, signal cycle time, permitted modes of transport, e-*challans* generated for traffic violations, water distribution network information (discharge, pressure, flow, turbidity and chlorine levels, pH readings), real time position of solid waste management (SWM) vehicles, SWM vehicle mileage, fuel disbursement of SWM vehicles, safety scores from My Safetipin App, physical location of places of interest, revenue collected from property tax by municipal corporations, and civic issues reported by citizens

I-Hub is the Technology Incubation Hub (TIH) at IIIT Hyderabad, funded by the Union Department of Science and Technology (DST) that focuses on building a data foundation. AI Hub aims to harness the volume and variety of data available in India, that will become a valuable resource for AI developers and researchers all over the world. Some of the focus areas for the technology hub are mobility, healthcare, smart buildings, systems and other India specific research initiatives. So far, AI hub has started the process of data collection and curation for the healthcare and mobility sector. A few applications of research in mobility include driver assistance systems, road/ infrastructure mapping, road safety and resource optimization. The applications for the healthcare industry include diagnosis, prescription, success rate prediction etc.

Each of these initiatives while in nascent stages, reflect the immense potential of high-quality organised data.

5. Concluding Remarks

AI like any other general-purpose technology impacts entire economic systems. Its pervasiveness, innovational complementarities and dynamism has the potential to radically alter productivity gains for businesses with spillover benefits on the entire economy. This paper finds an unambiguous impact of AI on productivity of Indian firms. It also establishes adoption by relatively big firms in India and the potential impact AI can have on the industry as a whole. The econometric estimation finds a positive and significant relation between AI intensity and total factor productivity growth. More precisely, a unit increase in AI intensity by Indian firms can lead to a 0.3% increase in TFP growth, on average. However, the long-term impact of AI on the Indian economy will depend on the quantum of investment in AI research, developing local capabilities of data engineers and building data sets and related governance practices.

The paper also focuses on the lack of open access to quality data, which is a gold mine for AI-led innovation. There are several examples that demonstrate the role of public data in lowering consumer bills, improving governance and overall access to public services. Three case studies discussed in the paper highlight some of the current efforts of the Indian government and the private sector to carry forward the open government data initiative. While establishing the potential of this data, it also highlights the need to massively enhance the quality and range of open data sets. Strong public private partnerships and collaborations between government, industry and academia will be important to harness the value of data for innovative localised solutions. Finally, policy towards AI must also be accompanied with governance frameworks that enable its responsible use. Several governments recognize the risk of unethical data use and *Black Box AI.* Laws and regulations that encourage unbiased, reliable, open and inclusive data sharing will catalyse India's journey towards it AI potential.

Appendix

Appendix 1: AI Intensity by Industry

Industry Category	Count	AI Intensity
Agriculture, Hunting, Forestry and Fishing	2	0.001
Mining and Quarrying	4	0.001
Food Products, Beverages and Tobacco	15	0.001
Textiles, Textile Products, Leather and Footwear	10	0.002
Wood and Products of wood	1	0.0007
Pulp, Paper, Paper Products, Printing and Publishing	2	0.001
Coke, Refined Petroleum Products and Nuclear fuel	6	0.0002
Chemicals and Chemical Products	50	0.002
Rubber and Plastic Products	13	0.0007
Other Non-Metallic Mineral Products	17	0.001
Basic Metals and Fabricated Metal Products	29	0.002
Machinery, nec.	22	0.009
Electrical and Optical Equipment	12	0.001
Transport Equipment	19	0.003
Manufacturing, nec; recycling	3	0.002
Electricity, Gas and Water Supply	8	0.001
Construction	17	0.001
Trade	19	0.002
Hotels and Restaurants	5	0.147
Transport and Storage	14	0.004
Post and Telecommunication	6	0.014
Financial Services	8	0.372
Business Service	20	0.01
Education		
Health and Social Work	5	0.01
Other services	4	0.004

Appendix 2: Results of the Model

Variable	Model 2
$TFPG_{jt}$	
$Size_{ijt}$ (OtherAssets)	.0000451 (0.23)
$ReserchDev_{ijt}$	.0477826 (2.54)
$AIint_{ijt}$	.0031666 (3.11)
ADV_{ijt}	-.000005 (-0.00)
DisemboTechijt	-0049929 (-1.60)
Year 2011	.0014588 (0.39)
Year 2012	-.0010476 (-0.23)
Year 2013	-.0073341 (-2.06)
Year 2014	.0073085 (2.21)
Year 2015	.0100479 (2.74)
Year 2016	.0346011 (9.03)
Year 2017	.0156557 (3.97)
Year 2018	.0094536 (2.56)
Year 2019	.0199733 (4.39)
Year 2020	.0249982 (5.07)
Klemscode 2	-.0082209 (-12.47)
Klemscode 3	-.0120848 (-50.47)
Klemscode 4	- .0004005 (-1.46)
Klemscode 5	-.0065987 (-25.96)
Klemscode 6	-.0123599 (-48.30)
Klemscode 7	-.0067995 (-8.53)
Klemscode 8	-.020058 (-57.61)
Klemscode 9	.0149 (54.97)
Klemscode 10	.0150763 (48.27)
Klemscode 11	-.0138474 (-35.89)
Klemscode 12	-.0150808 (-66.94)
Klemscode 13	-.0079316 (-20.66)
Klemscode 14	-.0089074 (-27.96)
Klemscode 15	.0012462 (4.58)
Klemscode 16	-.0192401 (-26.35)
Klemscode 17	-.0241117 (-63.00)
Klemscode 18	-.0447181 (-170.16)
Klemscode 19	-.0118461 (-20.13)
Klemscode 20	-.0187929 (-51.34)
Klemscode 21	-.0381433 (-86.27)
Klemscode 22	-.0021425 (-2.97)
Klemscode 23	-.0036062 (-15.07)
Klemscode 25	-.0128771 (-46.03)
Klemscode 26	-.00762 (-24.94)

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