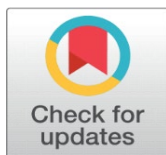


IMPACT OF AI ON LABOR PRODUCTIVITY IN THE MANUFACTURING SECTOR IN INDIA

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ABSTRACT

This research paper primarily analyses the relationship between labor productivity and Artificial intelligence in the Indian manufacturing sector. For this purpose, variables such as the amount of capital stock and expenditure on research and development were chosen as independent variables. Here the expenditure on R&D is considered as a proxy for investment in AI. Although Artificial Intelligence has been playing a vital role in output maximization, here the attempt is made to capture AI's impact on Labor productivity, The data of capital stock and labor productivity were taken from the RBI KLEMS database and the expenditure on research and development taken from NSTMIS, Department of Science & Technology. The data has been filtered for the research period from 1991 to 2022. The data was converted into log form for easier statistical interpretation. The measure of central tendency and correlation matrix were executed. For each variable stationery of the data has been worked out using the Augmented dickey fuller unit root test. It was observed that there were mixed differences. Hence the ARDL (Autoregressive Distributed log) model was chosen for accurate model building. The results of correlation analysis showed a strong relationship between capital stock and labour productivity at 0.92 percent. And the expenditure on R&D and Labour productivity had a strong correlation of 0.91 percent. That of capital stock and R&D had 0.95 percent. Tests for serial correlation and multicollinearity were executed. The short-run results of Auto Regressive Distributed Lag showed that the coefficient of past labor productivity has a positive impact on the current labour productivity at $P < 0.005$. Whereas in the long run, the research and development investment coefficient suggests the relationship with labor productivity is positive but only with a marginal significance because the P-value is a little above the benchmark. So, the result should be carefully inferred. By and large, the short-run dynamics show persistency in the labor productivity changes and a potential negative influence of the temporary increase in capital stock on the current variation in labor productivity.

Keywords: Labor Productivity, Artificial Intelligence, Labor, Productivity, Indian Manufacturing Sector, Short-Run, Capital Stock, Development, Statistical Interpretation, Distribution

1. INTRODUCTION

Artificial Intelligence has been a useful instrument in recent times. Any task can be made easy and time-saving by using AI's features. AI's applications in production, logistics, transportation, and service delivery have had a huge impact on society. This has sparked heated discussions regarding AI's present and potential consequences on society, which have led to important social and economic developments. (Makridakis, 2017). When compared to previous general-purpose technologies, artificial intelligence (AI) has a substantial impact on almost every sector and organization globally.

The integration of AI technology in the manufacturing sector has emerged as a pivotal development in recent years (Li et al, 2017). This integration has been driven by the rapid advancement of core technologies in the "Internet plus AI" era (Li et al, 2017). This transition is triggering a significant transformation in the models, methods, and ecosystems of the manufacturing industry, as well as in the development of AI itself (Li et al, 2017). Furthermore, the integration of AI technology with information communication, manufacturing processes, and related product technologies has led to the

emergence of new models, means, and forms of intelligent manufacturing (Li et al, 2017). These innovative methods can be identified by their use of smart sensors and controls, which allow manufacturers to increase their competitiveness using smart manufacturing techniques. (Li et al, 2017).

Numerous studies have been conducted on the factors that determine productivity in Indian manufacturing, such as state development spending, labour market flexibility, and trade liberalization (Mitra, 2008). When AI is introduced into the industry, these elements are likely to interact. Additionally, the impact of a flexible labour market has been examined in connection to labour productivity, employment, and real wages in Indian manufacturing (Bhattacharya, 2011; Bhattacharya, 2015). These relationships are projected to be affected by the adoption of AI, which could result in modifications to the labour market and the allocation of gains in productivity. Inequal wages within firms has increased due to innovation in the usage of AI, which suggests AI implications have a multifaceted impact on labour productivity including labour quality and quantity (Alderucci et al, 2019).

This study delves into filling the gap observed in prior research with a motive to conduct empirical evidence. Therefore, we have taken a unique element of labour market such as labour productivity, capital stock, and expenditure in research and development to determine the relationship between labour productivity and the application of Artificial intelligence in the manufacturing sector in Indian territories. The aggregate data of public and private industries' labour productivity and capital stock data are taken from the RBI KLEMS database from the year 2011 to 2022. The source of expenditure on research and development data is from the Ministry of Science and Technology annual report titled S&T indicator-research and development statistics. The empirical analysis employs uses of time series data estimated with the ARDL model (Autoregressive distributed lag differences), as it allows working with non-stationarity and time series data with mixed integration. Moreover, this model includes lags of both dependent and independent variables as regressors in the model. In the ARDL model the independent and dependent variables are related both at present and in the lagged values. While data analysis we found that there was a positive relationship between all the chosen variables in the study, Further the study also found that there is the strongest relationship between capital stock research and development expenditure and the labour productivity and amount of capital stock share a close relationship with each other, which indicates both variables mover together closely. The functional relationship between labor productivity and knowledge stock is positive. When the capital stock increases the labour productivity also increases and vice versa.

The later part of this paper is structured as follows. In the next section, an overview of the theoretical and empirical literature exploring the recent upsurge of artificial intelligence is listed. Here the previous studies and their analysis on the relationship between artificial intelligence and productivity have been presented. Proceeding ahead the empirical model based on autoregressive distributed lag is constructed.

Objectives:

1. To analyze the current state of AI through R&D expenditure in the Indian manufacturing industry.
2. To understand capital stock's influence on labor productivity in the manufacturing sector.
3. To measure the Impact of R & D expenditure on Labor Productivity in the manufacturing sector.

2. LITERATURE REVIEW

Using generative AI can assist in higher growth from 0.1 to 0.6 percent annually by the year 2040 based on the speed at which technology has been embraced. Based on the impact of AI-related innovation on firm growth, employment, and revenue, the organization that have been using AI-related inventions are progressing 25 percent faster in employment and 40 percent quicker in revenue growth. These outcomes demonstrate a favorable relationship between AI-related innovations and increases in revenue, employment, and firm size. (Alderucci et al, 2019).

Previous studies have identified a range of challenges and opportunities in adopting of AI in the manufacturing sector. Sharma (2021) highlights the challenges of poor data quality, lack of understanding of cognitive technologies, data privacy, integration problems, and expensive technologies in the public manufacturing sector of India. Nelson discusses the potential societal implications of AI in manufacturing, including its impact on the workforce, job upskilling and deskilling, cybersecurity vulnerability, and environmental consequences. Famili (1992) provides a comprehensive overview of AI applications in manufacturing, including machine learning in industrial planning and decision-making, and the use of AI in manufacturing integration. Ikumapayi (2022) emphasizes the potential of AI and ICT in sustainable manufacturing, particularly in the prediction, management, and advancement of industrial activities and processes.

A Study conducted by Dean Alderucci findings suggests that AI innovations are associated with higher employment, revenue per employee, and value-added per employee. However, AI innovation may accelerate skill-biased technological change and increase earnings inequality within firms. (Alderucci et al, 2019). Another study by Rizvi et al, 2021 revealed that AI applications can increase quality and productivity in India's manufacturing sector. With research and development, AI mitigates errors and maintains the supply chain by analysing outcomes and forecasting demands to support higher profits in intense competition. (Rizvi et al, 2021). However, this growth in profit margins cannot be achieved until major shifts in AI and the workforce are brought and ready to work together with the technology according to the study conducted in 2007 by A.Erumban, India's manufacturing sector is significantly less productive than that of the US, Germany, South Korea, Hungary, and Poland.

Data Source and Methodology

The data for this study has been fetched from the RBI- KLEMS (capital, labor, energy, materials, and service inputs for the years 1991 to 2022). The study also considered data from the Ministry of Science and Technology's annual statistical reports.

The final dataset covers almost every Indian manufacturing industry including private and public sectors industries from the year 1991 to 2022. All the manufacturing industries are considered in the study.

In the model has an endogenous variable labor productivity and two exogenous variables capital stock and expenditure on R&D. The labor productivity is taken as value added per person employed at constant prices 2011-12 in thousands of Rupees. The capital stock and expenditure on R&D are also considered at constant prices.

Specification of Econometric Model:

The study utilized the ARDL model to obtain unbiased long-run estimates derived from the relationship between endogenous and exogenous variables. The test for unit root has been conducted and ascertained that there is no variable integrated at first difference. The unit root test confirmed the variables integrated into different orders. Labor productivity is integrated at the level and capital stock and expenditure on R&D are integrated at first order. The result of the bound test showed that the variables are cointegrated. Hence short-run ARDL and Long-run error correction models are specified.

$$Y_t = \gamma_{0i} + \sum_{i=1}^p \delta_i Y_{t-i} + \sum_{i=0}^q \beta_i X_{t-i} + \epsilon_{it}$$

Where Y_t is a vector and the variable in (X_t) is allowed to be purely integrated at level or first order or cointegrated. δ_i and β_i are coefficients. γ_{0i} is the constant. $i=1, \dots, k$; p, q are optimal lag orders. ϵ_{it} is the vector of the error terms.

$$\begin{aligned} \Delta \ln LP_t &= a_{01} + b_{11} \Delta \ln LP_{t-i} + b_{21} \Delta \ln KS_{t-i} + b_{31} \Delta \ln RD_{t-i} + \sum_{l=1}^p a_{1i} \Delta \ln LP_{t-i} + \sum_{l=1}^q a_{2i} \Delta \ln KS_{t-i} + \sum_{l=1}^q a_{3i} \Delta \ln RD_{t-i} \\ &\quad + \epsilon_{1t} \\ \Delta \ln KS_t &= a_{01} + b_{12} \Delta \ln LP_{t-i} + b_{22} \Delta \ln KS_{t-i} + b_{32} \Delta \ln RD_{t-i} + \sum_{l=1}^p a_{1i} \Delta \ln KS_{t-i} + \sum_{l=1}^q a_{2i} \Delta \ln LP_{t-i} + \sum_{l=1}^q a_{3i} \Delta \ln RD_{t-i} + \epsilon_{2t} \\ \Delta \ln RD_t &= a_{01} + b_{13} \Delta \ln LP_{t-i} + b_{23} \Delta \ln KS_{t-i} + b_{33} \Delta \ln RD_{t-i} + \sum_{l=1}^p a_{1i} \Delta \ln RD_{t-i} + \sum_{l=1}^q a_{2i} \Delta \ln LP_{t-i} + \sum_{l=1}^q a_{3i} \Delta \ln KS_{t-i} + \epsilon_{3t} \end{aligned}$$

$\Delta \ln X_t$ Represents the change in the natural logarithm of the respective variable (LP, KS, RD) at time t . a_{01} : Constant term for the intercept. a_{1i}, a_{2i}, a_{3i} : Coefficients representing the lagged values of the variable X (LP, KS, RD). b_{1i}, b_{2i}, b_{3i} : Coefficients indicating the lagged values of the other variables (LP, KS, RD). ϵ_{3t} : shows the error term, capturing unobserved factors influencing the variable at time t . $\sum_{l=1}^p$ & $\sum_{l=1}^q$: Summations over the specified lag lengths.

The model captures the relationship between the current value of each variable and its lagged values, as well as the lagged values of the other two variables. Coefficients a_{1i}, a_{2i}, a_{3i} indicate the influence of the lagged values of the same

variable on the current change. Coefficients b_{1i} , b_{2i} , b_{3i} indicate the impact of the lagged values of other variables (LP, KS, RD) on the current change.

Descriptive Statistics:

Table-1 Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
LP	4.031	.144	3.801	4.292	3.801	4.292	.124	2.027
KS	6.76	.227	6.406	7.109	6.406	7.109	.02	1.645
RD	4.733	.439	3.68	5.123	3.68	5.123	-1.33	3.557

The table-1 reveals the measure of central tendency. The mean labour productivity of around 4.031 indicates the average production per unit of work, which is approximately 4.031. The labour productivity distribution has a slight rightward skewness, with a positive skewness of 0.124. Even if most of the observations are clustered around or slightly below the mean, this recommends that the distribution is skewed to the right by a few higher values. The positive kurtosis of 2.027 indicates that the labour productivity distribution appears to have larger tails and a sharper peak when compared to a normal distribution. This implies that the probability of extreme values both high and low occurring is larger than what a normal distribution would indicate.

The capital stock available for production is around 6.76 units on average, as shown by the mean capital stock of 6.76. The skewness of 0.02 suggests that observations have equal distributions around the mean, indicating a roughly symmetric capital stock distribution. Though not as much as labour productivity, the distribution does have a sharper peak and somewhat heavier tails than a normal distribution, according to the positive kurtosis of 1.645. This suggests that compared to a normal distribution, high values are less likely but still more common.

Based on the mean research and development expenditure of around 4.733 units, the average amount invested in research and development is approximately 4.733 units. The negative skewness of -1.33 suggests that there appears to be a leftward bias in the distribution of spending on research and development. This suggests that more observations have lower research and development spending in comparison to bigger ones. A strong positive kurtosis of 3.557 shows that the distribution seems to have very heavy tails and a high peak. It suggests that the probability of extreme values—high and low—occurring is far higher than it would be in a normal distribution, enhancing the probability of outliers or a significant variation in the amount of money allocated to research and development across observations.

Table-2 Matrix of correlations

Variables	(LP)	(KS)	(R&D)
LP	1.000		
KS	0.927	1.000	
R&D	0.917	0.951	1.000

From the table-2 respective variable's correlation is inferred. The correlation coefficient of roughly 0.927 between LP and KS suggests a strong positive linear relationship between labor productivity and capital stock. This suggests that enterprises with larger capital stocks typically have higher labor productivity, which might be generated by upgraded facilities, more advanced technology, or more effective manufacturing techniques. The correlation coefficient of nearly 0.917 between LP and RD indicates a strong positive linear relationship between labor productivity and research and development expenditure. This suggests that firms that invest more in research and development tend to achieve higher levels of labor productivity, possibly through innovation, process improvement, or product development. Capital stock and research and development spending have a very robust positive linear relationship, as shown by the correlation coefficient of roughly 0.951 between KS and RD. It could be concluded from this that organisations with larger capital stocks also tend to devote more funds to research and development initiatives, possibly to advance technological capabilities, creating new goods, or increasing operational effectiveness.

Table-3 Result of the ARDL (4,1,0) Regression

D.LP	Coeff.	Std.Err.	t	P>t	Interval]
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	[95%Conf					
ADJ						
LP						
L1.	-1.642	0.263	-6.250	0.000	-2.199	-1.085
Long Run						
KS	0.412	0.106	3.900	0.001	0.188	0.635
RD	0.095	0.047	2.010	0.062	-0.005	0.196
Short Run						
LP						
LD.	0.760	0.207	3.660	0.002	0.320	1.199
L2D.	0.944	0.205	4.610	0.000	0.510	1.379
L3D.	0.786	0.204	3.860	0.001	0.354	1.217
KS						
D1.	-3.907	1.633	-2.390	0.029	-7.370	-0.445
_cons	1.398	0.825	1.690	0.110	-0.351	3.147

Source: Author's Calculation

The coefficient of lagged labour productivity is -1.642, which means that a 1% increase in the lagged labour productivity (LP) leads to a 1.642% decrease in the current labor productivity. This suggests that a higher level of labour productivity in the past is associated with slower growth in labour productivity in the future. In simpler terms, higher labor productivity tends to slow down future growth in labor productivity. This could be due to factors like diminishing returns from existing technologies or reaching a saturation point in efficiency.

Whereas, the coefficient of capital stock (KS) is 0.412. For every unit increase in capital stock, labor productivity increases by 0.412%. In other words, increasing capital stock (e.g., investments in machinery and equipment) leads to an increase in labour productivity in the long run. Research and development (RD) coefficient is 0.095. A one-unit increase in research and development spending results in a 0.095% increase in labour productivity.

In the short run, labour productivity first lagged difference suggests that 0.760% increase in labor productivity is linked with a one-unit increase in the first leg of labour productivity. The second lagged difference of 0.944% increase in labour productivity is associated with a one-unit increase in the second lag of labour productivity. The third lagged difference 0.786% increase in labor productivity is connected with a one-unit increase in the third lag of labour productivity. These short-run dynamics capture how historical trends affect the present. A 3.907% decrease in capital stock leads to a decrease in labor productivity in the short run. This coefficient suggests how a recent change in capital stock affects the immediate change in labour productivity, likely showing how quickly new investments start to impact productivity.

Based on the R-squared (0.7457) and adjusted R-squared (0.6344) values, the ARDL model demonstrates a strong overall fit for explaining changes in labour productivity (D. LP). This suggests that a significant portion of the variation in D. LP can be captured by the model. Furthermore, the comparatively low Root Mean Squared Error (0.0328) shows that, on average, the model's predictions match the definite results.

3. CONCLUSION

The results reveal that there exists a strong relationship between capital stock and labour productivity to 0.92 per cent. And the expenditure on R&D and Labour productivity had a strong correlation of 0.91 percent. That of capital stock and R&D had 0.95 percent. Tests for serial correlation and multicollinearity were engaged. The short-run results of ARDL showed that the coefficient of past labor productivity has a positive impact on the current labour productivity at $P < 0.005$. Whereas in the long run, the research and development investment coefficient suggests the relationship with labor productivity is positive but only with a marginal significance because the P-value is a little above the benchmark. So, the result should be carefully inferred. By and large, the short-run dynamics show persistency in the labour productivity changes and a potential negative influence of a temporary increase in capital stock on the current variation in labour productivity.

CONFLICTS OF INTEREST

None.

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