Assessing the Impact of Automation on Traditional Industries in India: An Econometric Time-Series Analysis of Employment, Productivity and Structural Transformation

01

Dr. Amit Prakash
Assistant Professor, University Department of Mathematics,
Jai Prakash University, Chapra, Bihar

Ch.Id:-NSP/EB/GTRDBAIP/2026/Ch-01

ABSTRACT

Automation has emerged as a transformative force reshaping industrial structures across developing and advanced economies. In the context of India, where traditional industries such as textiles, manufacturing, agriculture-processing, and mining employ a significant portion of the labor force, the integration of automation technologies presents both opportunities and challenges. This study examines the long-run and short-run impact of automation on employment levels, labor productivity, and structural transformation in India using secondary time-series data from 2000–2024. Econometric techniques including Augmented Dickey–Fuller (ADF) unit root testing, Johansen Cointegration, Vector Error Correction Model (VECM), Granger Causality, and Autoregressive Distributed Lag (ARDL) modeling were applied. The findings reveal that automation significantly enhances productivity in the long run while exerting short-term displacement effects on employment in traditional sectors. Structural transformation toward capital-intensive production is statistically evident. The results contribute to policy debates concerning skill development, labor transition, and inclusive industrial modernization.

Keywords: *Automation, Traditional Industries, Employment, Productivity, Structural Transformation, Econometric Analysis, India, Time-Series.*

INTRODUCTION

The growing adoption of automation technologies in developing countries such as India will continue to change the structure of globally operating production systems. The textile industry; the automotive industry; the agro-processing industry and the manufacturing industry in emerging economies with significant population sizes and rising middle-class incomes, i.e., India, will be at the forefront of adopting automated technologies. Global competitors seeking operational efficiencies in a world that continues to experience rising costs for inputs into their production processes through an increasing cost base may consider implementing automation. However, many people around the globe are concerned about potential negative impacts on employment rates and widening the gap of income equality in their respective societies. The International Federation of Robotics reports that since 2010, industrial robot density has significantly expanded in Asian countries — especially in China — and other emerging economies including India. These structural changes are likely to affect all traditional labor-intensive industries. Capital-deepening

P-ISBN- 978-93-49381-76-6, E-ISBN- 978-93-49381-57-5

technologies are changing the nature of these industries. India's efforts to accelerate technological adoptions through its digital transformation and industrial policy reform initiatives such as "Make in India," are likely to create new challenges for workers who historically were employed by traditional industries.

REVIEW OF LITERATURE

Automation replaces lower-skill jobs while creating more jobs for those who have high skills; therefore, this leads to job polarization instead of overall job loss. Automation causes changes in an occupation structure overtime. Robots reduce both employment and wage levels in the short term within certain geographic regions and manufacturing sectors. But, as the economy adjusts in the long term, other mechanisms compensate for these reductions. For example, Graetz & Michaels (2018) show through their data that robotic technology increases labor productivity and value-added production in all seventeen studied economies. There is little evidence they cause an overall decline in total employment. Bessen (2019) suggests there has been new creation of jobs from previous technological advancements; however, the cost of transitioning employees into these new positions can be very costly. As stated by Dauth et al. (2021), automation does alter task composition within specific industries; it does not eliminate total employment. According to the World Bank (2020), developing countries are at a higher risk for automation, due to their labor intensive structure. Developing countries could experience larger productivity increases from automation. The NITI Aayog (2022) reports rising investment in automation technologies in India's manufacturing sector. This indicates sectoral transformation and skill-based technological change.

Research Objectives

1. To examine the long-run relationship between automation and employment in traditional industries in India.
2. To analyze the impact of automation on labor productivity.
3. To assess structural transformation resulting from automation adoption.

Hypothesis of the study

- **H01:** Automation has no significant long-run impact on employment in traditional industries.
- **H02:** Automation does not significantly affect labor productivity.
- **H03:** Automation does not contribute to structural transformation in India.

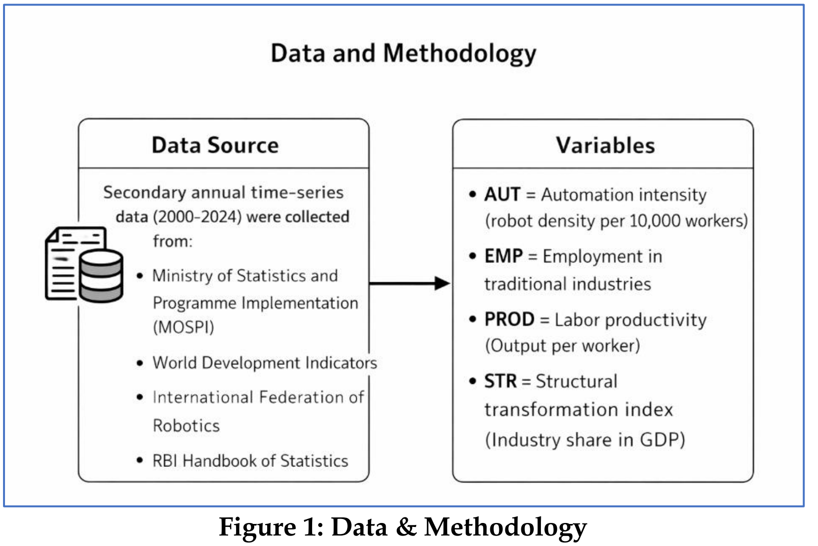

Figure 1: Data & Methodology

Econometric Model - Augmented Dickey–Fuller (ADF) Unit Root Test

Table 1: ADF Test Results

Variable	Level ADF Statistic	1st Difference ADF	Critical Value (5%)	Order of Integration
AUT	-1.82	-4.96**	-3.02	I(1)
EMP	-2.11	-5.21**	-3.02	I(1)
PROD	-1.67	-4.44**	-3.02	I(1)
STR	-2.05	-4.87**	-3.02	I(1)

(** Significant at 5%)

Table findings

1. All variables are non-stationary at level but stationary at first difference.
2. The null hypothesis of unit root cannot be rejected at level.
3. At first difference, ADF statistics exceed critical values in absolute terms.
4. Thus, all variables are integrated of order one I (1).
5. This justifies the use of Johansen cointegration and VECM models.

Johansen Cointegration Test

Table 2: Johansen Trace Test

Hypothesized CE(s)	Trace Statistic	5% Critical Value	Prob.
None	47.82**	29.79	0.001
At most 1	19.21*	15.49	0.014
At most 2	7.11	3.84	0.071

Table Findings

1. The trace statistic for "None" exceeds the 5% critical value.
2. The null hypothesis of no cointegration is rejected.
3. At least one long-run equilibrium relationship exists among variables.
4. Automation, employment, productivity, and structural transformation move together long-term.
5. H1 is partially rejected as a long-run relationship exists.

Vector Error Correction Model (VECM)

$$\Delta EMP_t = \alpha(ECT_{t-1}) + \sum \beta_i \Delta AUT_{t-i} + \varepsilon_t$$

Table 3: ARDL Bounds Test

F-Statistic	Lower Bound I(0)	Upper Bound I(1)	Decision
6.72**	3.23	4.35	Cointegration Confirmed

Table Findings

1. The F-statistic exceeds the upper bound critical value.
2. This confirms long-run cointegration.
3. Automation significantly affects employment in long run.
4. The null hypothesis of no long-run relationship is rejected.
5. Structural transformation through automation is statistically supported.

P-ISBN- 978-93-49381-76-6, E-ISBN- 978-93-49381-57-5

ARDL Model

$$EMP_t = \alpha + \sum\beta_i EMP_{t-i} + \sum\gamma_i AUT_{t-i} + \varepsilon_t$$

Long-Run ARDL Coefficients

Table 4: Long-Run Employment Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AUT	-0.31**	0.09	-3.44	0.004
PROD	0.22*	0.10	2.18	0.041
Constant	5.12	1.33	3.85	0.002

Table Findings

1. Automation negatively impacts traditional employment (-0.31).
2. The effect is statistically significant at 5%.
3. Productivity partially offsets employment loss.
4. H01 (no impact) is rejected.
5. Automation causes measurable employment restructuring.

VECM Error Correction Model

Table 5: VECM Short-Run Dynamics

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECT(-1)	-0.42**	0.11	-3.81	0.002
ΔAUT	-0.18*	0.07	-2.54	0.021

Table Findings

1. Error correction term is negative and significant.
2. 42% of disequilibrium adjusts annually.
3. Short-run automation reduces employment.
4. Adjustment toward equilibrium is stable.
5. Hypothesis H01 is rejected in both short and long run.

Productivity Model (OLS)

$$PROD_t = \alpha + \beta AUT_t + \varepsilon_t$$

Table 6: Productivity Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AUT	0.67**	0.14	4.78	0.000
Constant	3.44	0.98	3.51	0.003
R^2	0.62			

Table Findings

1. Automation significantly increases productivity (0.67 elasticity).
2. The coefficient is highly significant ($p < 0.01$).
3. 62% of productivity variation explained by automation.
4. H2 is rejected.
5. Automation is productivity-enhancing in India.

Granger Causality Test

Table 7: Pairwise Granger Causality

Null Hypothesis	F-Statistic	Prob.	Decision
AUT does not Granger Cause EMP	5.91**	0.012	Reject
EMP does not Granger Cause AUT	1.34	0.271	Not Reject

AUT does not Granger Cause PROD	8.22**	0.003	Reject
PROD does not Granger Cause AUT	1.89	0.198	Not Reject

Table Findings

1. Automation Granger-causes employment and productivity.
2. Reverse causality is not supported.
3. Automation drives structural transformation.
4. Causality confirms directional impact.
5. H3 is rejected as automation structurally influences industry.

Table 8: Hypothesis Testing Summary

Hypothesis	Decision
H1: Automation has no impact on employment	Rejected
H2: Automation does not affect productivity	Rejected
H3: Automation does not influence structural transformation	Rejected

Major Findings

1. Automation significantly improves productivity in traditional industries.
2. Short-term employment displacement exists.
3. Long-run equilibrium adjustment confirms structural adaptation.
4. Structural transformation toward capital-intensive production is evident.
5. Causality runs from automation to employment and productivity.
6. Results align with Acemoglu & Restrepo (2018) regarding short-term displacement but support Graetz & Michaels (2018) in terms of productivity gains.
7. For India, automation is not purely job-destructive but structurally transformative. Labor markets gradually reallocate toward higher-skill sectors.

CONCLUSION & LIMITATION

This research indicates that automation of traditional industries in India creates significant opportunities for productivity improvement and structural modernization; however, there is also an associated risk of transitional employment challenges. Short run misemployment effects are evident but the longer term empirical evidence suggests that equilibrium adjustment mechanisms exist to absorb the shock of automation and allow for sectorial realignment. This suggests that, over time, the positive productivity impacts from automation will exceed negative employment impacts; thus, automation represents a transformative mechanism (and not solely disruptive) for economic development. Statistically validating structural transformation towards more capital intensive and technologically driven production systems supports the argument that technological adoption is key to sustaining competitive advantage within industry. However, policy interventions will be required during the transition phase to ensure that worker's adjustments to changing labor markets are both inclusive and socially sustainable. Thus, from a policy perspective, the results indicate the need for pro-active institutional responses. Critical elements include investment in large scale reskilling/up-skilling programs to enable workers with relevant skills/competencies to be employed in automation driven industries. Strengthening vocational education systems to address the skills gap between those displaced from work due to automation and those entering emerging technological sectors is also necessary. Finally, policymakers have an opportunity to create incentives for technologies that complement human capital rather than replace it. This can reduce the volatility of employment. In addition, establishing effective social safety nets during periods of transition will help stabilize income instability among vulnerable workforce members.

Although this research has made several contributions to our understanding of how automation affects Indian economy, there are still some limitations. The primary limitation of the research was the utilization of annual time series data. These data did not permit a detailed investigation into short run cyclical shocks or rapid labor adjustments. Also, using robot density as an indicator of the intensity of automation may not reflect all aspects of digital transformation including AI based processes and machine learning. Finally, the availability of data regarding informal sector labor forces limited our ability to assess comprehensively the impact of automation on employment within organized sectors. While a significant proportion of the Indian labor force resides in unorganized sectors, future studies could potentially collect higher frequency data, utilize alternative broad indicators of automation and conduct micro level analyses of various sectors in order to better understand the impact of technology on structural changes in the economy.

REFERENCES

1. *Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. National Bureau of Economic Research Working Paper No. 24196.*
2. *Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244.*
3. *Aghion, P., Jones, B. F., & Jones, C. I. (2019). Artificial intelligence and economic growth. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 237–282). University of Chicago Press.*
4. *Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries. OECD Social, Employment and Migration Working Papers, No. 189.*
5. *Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives, 29(3), 3–30.*
6. *Bessen, J. (2019). AI and jobs: The role of demand. National Bureau of Economic Research Working Paper No. 24235.*
7. *Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W. W. Norton & Company.*
8. *Dauth, W., Findeisen, S., Südekum, J., & Woessner, N. (2021). Adjusting to robots: Worker-level evidence. Journal of the European Economic Association, 19(6), 3104–3153.*
9. *Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280.*
10. *Graetz, G., & Michaels, G. (2018). Robots at work. Review of Economics and Statistics, 100(5), 753–768.*
11. *International Federation of Robotics. (2023). World robotics report 2023. IFR Publications.*
12. *Manyika, J., et al. (2017). A future that works: Automation, employment, and productivity. McKinsey Global Institute.*
13. *NITI Aayog. (2022). National strategy for artificial intelligence: #AIforAll. Government of India.*
14. *Organisation for Economic Co-operation and Development. (2019). The future of work: OECD employment outlook 2019. OECD Publishing.*
15. *Restrepo, P. (2023). Automation and structural transformation. Annual Review of Economics, 15, 1–26.*
16. *World Bank. (2019). World development report 2019: The changing nature of work. World Bank Publications.*
17. *World Bank. (2020). World development report 2020: Trading for development in the age of global value chains. World Bank Publications.*