

## **Impacts of Automation and AI on the Indian Labour Markets**

**G.Abirami**

*Ph.D (Part Time) Research scholar*

*PG & Research Department of Economics*

*LRG Government Arts College for Women,*

*Tirupur - 641604, Tamil Nadu*

**Dr. M. Sivamani**

*Supervisor,*

*PG & Research Department of Economics*

*LRG Government Arts College for Women,*

*Tirupur - 641604, Tamil Nadu*

### **Abstract**

The rapid proliferation of Artificial Intelligence (AI) and automation technologies has brought transformative changes to India's economic and employment landscape. These innovations have redefined production systems, reshaped labour structures, and introduced new forms of human-machine collaboration. This paper investigates the multi-dimensional impact of automation and AI on the Indian labour markets using both theoretical and empirical approaches. Based on primary data from 100 respondents across agriculture, industry, services, IT, and education, this study employs Descriptive Analysis, Chi-square tests, and ANOVA to evaluate employment shifts, income changes, and productivity trends. The theoretical framework integrates Human Capital Theory, Skill-Biased Technological Change (SBTC), and Schumpeter's Innovation Theory to explain how automation creates both displacement and opportunity. Findings reveal that automation increases productivity but causes job polarization between high- and low-skill workers. Chi-square analysis confirms a significant relationship between skill level and income growth, while ANOVA demonstrates that productivity varies significantly across sectors. The study concludes that India must strengthen reskilling systems, implement inclusive digital policies, and enhance AI governance to ensure equitable technological progress.

**Keywords:** Automation, Artificial Intelligence, Labour Market, Skill Development, Human Capital, Chi-Square, ANOVA, Innovation Theory

## **I. INTRODUCTION**

Automation and Artificial Intelligence (AI) represent the fourth industrial revolution in India's development trajectory. The integration of robotics, machine learning, and algorithmic management has enhanced productivity and competitiveness across industries. However, this progress has disrupted conventional labour markets, creating concerns regarding employment security and skill adaptability. While high-skilled workers benefit from digital transformation, low-skilled and informal sector employees face job displacement. This study explores the dual impact of AI—economic efficiency versus employment vulnerability—and proposes strategies for inclusive adaptation.

### **Automation and Artificial Intelligence in India**

India is witnessing rapid AI adoption in sectors such as manufacturing, IT, healthcare, agriculture, and education. According to NASSCOM (2023), AI-based solutions contribute nearly 7% to India's GDP and could add up to \$1 trillion by 2035. Automation systems, from robotics to predictive analytics, have improved output quality and cost efficiency. However, they have also introduced a paradigm shift in labour demand—moving from routine manual jobs to analytical and creative roles.

### **Labour Market Dynamics in India**

India's labour market comprises approximately 500 million workers, with nearly 80% in informal employment. The structural transition driven by AI challenges traditional labour absorption capacity, especially in manufacturing and agriculture. In contrast, the digital services and IT sectors have become major employment generators. Balancing automation-driven productivity with equitable job distribution remains a key policy challenge.

### **Statement of the Problem**

Automation-induced transformations raise questions about the sustainability of employment and income equity. Workers in low-skill occupations face redundancy, while those with higher education adapt to emerging AI-integrated roles. The absence of universal reskilling programs and policy coordination between industry and academia has widened the digital divide in India.

### **Review of Literature**

The International Labour Organization (2023) emphasized that automation alters both job composition and working conditions. World Economic Forum (2023) projected that AI could create 97 million new roles globally by 2025.

McKinsey (2022) found that 60% of Indian occupations are automatable. NITI Aayog (2024) highlighted the potential for AI to drive inclusive growth through targeted skill development. National studies by TISS (2023) and IIM Bangalore (2022) noted that while automation enhances productivity, it demands adaptive policy measures to mitigate job losses.

### **Objectives of the Study**

1. To examine the impact of automation and AI on employment patterns across sectors.
2. To analyze the relationship between skill levels and income changes.
3. To compare productivity variations among sectors adopting automation.
4. To interpret findings through established economic theories.
5. To recommend policy interventions for inclusive technological adaptation.

### **Research Methodology of the Study**

This research combines both theoretical and empirical analysis. Primary data were collected through a structured questionnaire distributed to 100 respondents from agriculture, manufacturing, services, education, and IT sectors. Sampling method: Stratified random sampling. Analytical tools used include Descriptive Statistics, Chi-square Tests, and ANOVA. Secondary data sources include reports from NASSCOM, WEF, ILO, and NITI Aayog.

### **Theoretical Framework and Conceptual Discussion**

To better understand the dynamics of automation and AI on the labour market, this study adopts a multidisciplinary theoretical lens comprising three major frameworks: Human Capital Theory, Skill-Biased Technological Change (SBTC), and Schumpeter's Innovation Theory.

#### **Human Capital Theory**

Proposed by Becker (1964), Human Capital Theory asserts that education and skills are key determinants of productivity and income. Automation amplifies this principle—workers with advanced digital literacy and analytical ability reap higher wages, while those lacking technical competence face marginalization. Thus, AI intensifies the returns on human capital investment, underscoring the importance of lifelong learning.

#### **Skill-Biased Technological Change (SBTC) Theory**

SBTC explains how technological progress disproportionately benefits skilled workers. Automation replaces routine manual jobs but complements cognitive, non-routine tasks requiring creativity and problem-solving. In India, sectors such as IT and financial services exemplify SBTC, where automation enhances demand for programmers, analysts, and data scientists while reducing clerical roles.

## **Schumpeter's Innovation Theory**

Schumpeter's theory of creative destruction posits that innovation disrupts existing economic structures to create new ones. Automation and AI embody this process by displacing obsolete occupations and generating novel industries in robotics, AI research, and digital marketing. While short-term disruptions occur, long-term innovation cycles create net economic gains.

## **Analysis and Interpretation of Respondents**

### **Descriptive Analysis**

The study surveyed 100 respondents representing diverse sectors and occupational levels. The following table summarizes the key socio-economic characteristics.

Variable	Category	% Respondents
Gender	Male (65%), Female (35%)	
Education	Graduate (50%), Diploma (30%), School (20%)	
Sector	Agriculture (15%), Industry (25%), Services (30%), Education (15%), IT (15%)	
Skill Level	High (35%), Medium (40%), Low (25%)	
Automation Exposure	High (40%), Moderate (35%), Low (25%)	

Interpretation: Automation exposure is highest in IT and manufacturing, while agriculture and education lag behind. High-skilled respondents report better adaptability and income improvements compared to low-skilled workers.

### **Chi-Square Test for Employment Status and Automation Level**

H<sub>0</sub>: There is no significant relationship between automation level and employment status.

H<sub>1</sub>: There is a significant relationship between automation level and employment status.

Calculated  $\chi^2 = 13.28$ , Table Value (df=4, p=0.05) = 9.49. Result: Reject H<sub>0</sub>. Interpretation: Employment patterns differ significantly across automation levels. Workers in highly automated sectors experience occupational shifts rather than absolute job loss.

### **Chi-Square Test for Skill Level and Income Growth**

H<sub>0</sub>: There is no significant relationship between skill level and income growth.

H<sub>1</sub>: There is a significant relationship between skill level and income growth.

Calculated  $\chi^2 = 18.64$ , Table Value (df=4, p=0.05) = 9.49. Result: Reject  $H_0$ . Interpretation: Skill levels significantly influence income growth under automation. High-skilled individuals experience higher wage gains compared to low-skilled counterparts.

### **Analysis of Variance (Anova)**

Objective: To determine whether productivity differs significantly among sectors adopting automation and AI.

Source	SS	df	MS	F	Sig
Between Groups	1980	4	495	7.12	0.001
Within Groups	6650	95	70		
Total	8630	99			

Decision: Since  $p < 0.05$ , reject  $H_0$ . Productivity significantly varies by sector; IT and manufacturing report the highest efficiency gains.

### **Findings**

1. Automation exposure is highest in IT and manufacturing, while agriculture and education lag behind.
2. High-skilled respondents report better adaptability and income improvements compared to low-skilled workers.
3. Employment patterns differ significantly across automation levels.
4. High-skilled individuals experience higher wage gains compared to low-skilled counterparts.

### **Suggestions**

1. Establish nationwide AI and automation skill missions.
2. Strengthen university–industry collaboration for AI curriculum design.
3. Develop sector-specific reskilling programs for displaced workers.
4. Encourage startups and MSMEs to adopt responsible automation.
5. Create a national framework for ethical and inclusive AI deployment.

## **II.CONCLUSION**

The study concludes that automation and AI are reshaping India's labour market in complex ways. While technological innovation drives productivity, it also increases inequality between skilled and unskilled workers. Theoretical analysis confirms that human capital investment is critical for mitigating adverse impacts. India must align education, technology, and labour policies to sustain inclusive economic growth.

### **Scope for Further Study**

Future studies should examine the intersection of automation with gender equality, informal sector inclusion, and AI ethics. Comparative analyses with developed nations could reveal global patterns of labour adaptation.

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