AI, AUTOMATION, AND RESTRUCTURING OF THE WORKFORCE: AN EMPIRICAL SEM ANALYSIS OF LAYOFFS IN INDIA'S IT SECTOR

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Abstract:
Because AI and automation are becoming so popular in the global IT business, there has been a lot of concern about restructuring the workforce and the prospect of job loss. This study looks at how the use of AI affects layoffs in India's IT sector in a more detailed way. It focuses on the main IT hubs in Bengaluru, Hyderabad, and Chennai. Employing the Skill-Biased Technological Change (SBTC) theory, the Resource-Based View (RBV), and Technology Adoption Theory, we provide a comprehensive structural equation model (SEM) to examine the direct and indirect impacts of AI adoption on layoffs. Our Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, derived from a survey of 265 IT professionals, indicates that the adoption of AI exerts minimal direct impact on layoffs. Nonetheless, its primary impact lies in cost efficiency and skill redundancy. Notably, enhancements in productivity generated by AI do not significantly impact layoffs. The study shows that entry-level jobs are more likely to be affected, whereas jobs that need a lot of ability and experience are less likely to be affected. These results give HR professionals and politicians useful information from a developing economy that shows how important it is to focus on reskilling and proactive workforce planning instead of reactive cutbacks.

Index Terms - Workforce Restructuring, Artificial Intelligence, Automation, Layoffs, IT Sector, PLS-SEM, Skill-Biased Technological Change.

I. INTRODUCTION

Smart technologies and new sorts of automated tools are currently causing a tsunami of change in businesses. Recently, tech companies throughout the world have changed their teams, which has led to the loss of many jobs. Changes in the economy are important, but what really strikes out is how quickly artificial intelligence is pushing these changes forward [1] [2]. The storm hits hardest directly where India's IT industry is located. This industry is very important to the country's economy and employs millions of people around the world.

When you examine deeper, not all stories about automation taking jobs are true. People generally move to jobs that require a lot of thought instead than doing the same thing over and over again [3]. To understand how technology transforms jobs, you need to look at trends instead of just thinking that jobs would disappear suddenly.

This article looks at what happens when AI takes over IT employment in India. It doesn't just look at the obvious job losses, but also the changes that aren't as visible. Productivity surges are one reason, but so is the drive to spend less, and some worker abilities are becoming less important over time. A combination of SBTC and RBV theories elucidates these shifts, a perspective typically overlooked in previous studies, particularly in less affluent countries [4]. Real-world data is used to build structural equation models that make the results more solid than they were before. Even if the choices ahead are still hard, leaders who are making decisions about the future of their companies or countries could find what follows beneficial.

1.1 Research Objectives

This study aims to comprehend the dynamics of technology adoption and workforce reorganization.

- Evaluate the implementation of AI in the Indian IT sector across all organizational sizes and functions.
- Assess whether the introduction of AI diminishes the need for human labor.
- To analyze the mediation of AI adoption and labor reductions by productivity, cost efficiency, and skill redundancy.
- To investigate the moderating effects of employee skill, experience, and organizational size on layoffs triggered by artificial intelligence.

II. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

To start, let's look at this research from three different points of view. One lens looks at how changes in technology make some abilities more valuable than others. Another one is based on what a company has that no one else does. A third looks at the way businesses change when they start adopting new tools.

2.1 Skill-Biased Technological Change (SBTC)

Changes in technology usually help persons with advanced abilities and hurt people who undertake predictable tasks [5] [6]. When it comes to AI, the result often separates workers' outcomes. Machines do these tasks faster than people, therefore things like simple programming, data entry, and routine quality checks are no longer needed [7]. People who used to do this kind of employment may not require their skills anymore. However, these tools help experts who are dealing with difficult problems. With machine support, planning ahead, solving hard problems, and designing AI systems all get easier [8]. This change helps us understand why some roles go weaker while others get stronger. These kinds of trends show how employment requirements change when new technology comes along.

2.2 Resource-Based View (RBV)

The RBV argues that a firm's sustained competitive advantage is derived from its unique, valuable, and inimitable resources and capabilities [9] [10]. From this perspective, AI is viewed as a strategic technological resource. Companies use AI to make their operations better, boost productivity, and save money [11]. However, when AI effectively streamlines processes and lowers the marginal cost of production, businesses may end up having more workers than they need to run their new operations. So, RBV helps us understand how trying to make AI more productive and cost-effective might unintentionally lead to labor reduction.

2.3 Technology Adoption and Diffusion

A team's tech use depends on its utility and the workplace's ability to handle it. It's not enough to have AI; you need to use it every day. When systems are extremely integrated, they change how humans do things. Too shallow tries? They don't change things a much. Fuller combinations frequently affect behaviors more than small tests do. The more deeply you reach, the more it will affect operations. Adoption isn't just about the tools you use; it's also about how you think and set things up. Not every rollout brings about change; only those that are based on practical use have long-lasting advantages.

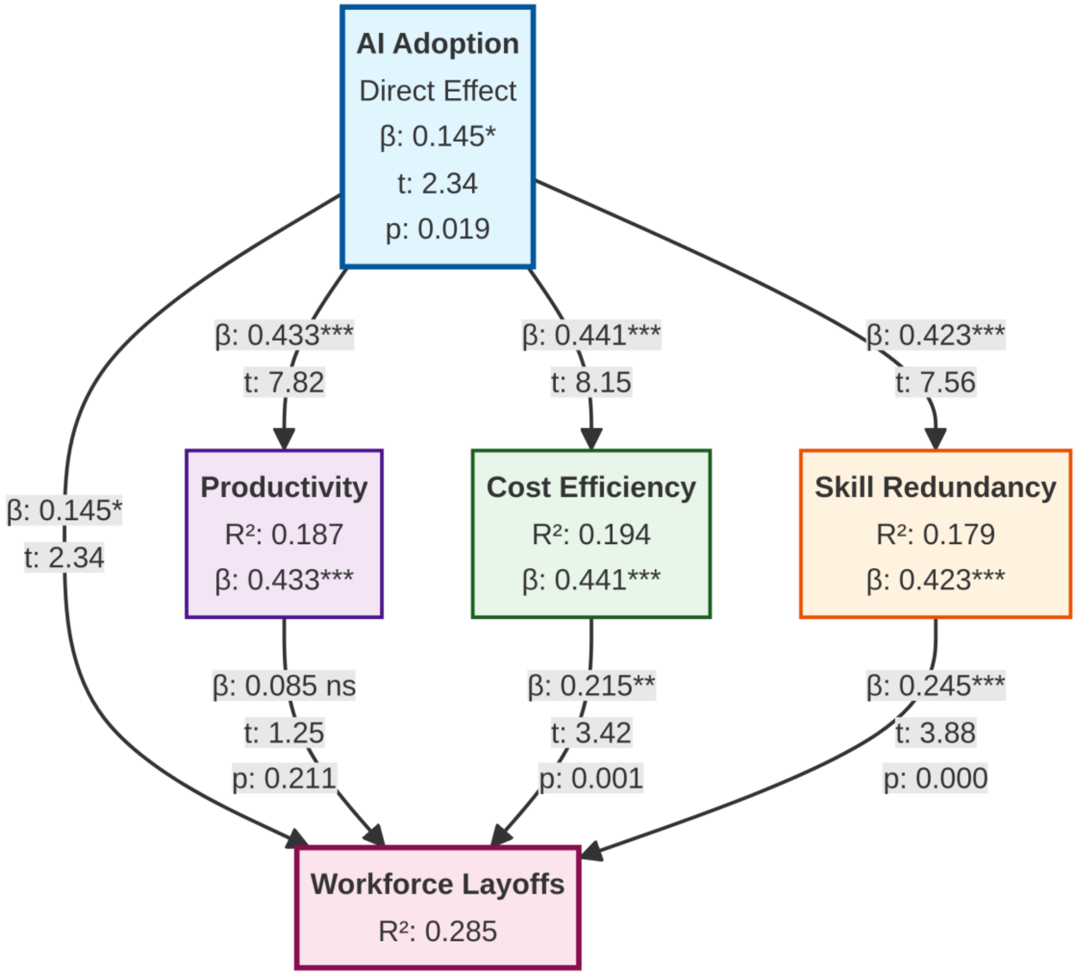
2.4 Hypotheses Development

Based on the integrated theoretical framework, we propose the following hypotheses:

- H1: AI adoption has a significant positive direct effect on workforce layoffs.
- H2: AI adoption positively influences organizational productivity.
- H3: AI adoption positively impact cost efficiency.
- H4: AI adoption positively influences skill redundancy.
- H5: Productivity improvements mediate the relationship between AI adoption and layoffs.
- H6: Cost efficiency mediates the relationship between AI adoption and layoffs.
- H7: Skill redundancy mediates the relationship between AI adoption and layoffs.
- H8: The impact of AI on layoffs is moderated by employee skill level, experience, and firm size.

2.5 Conceptual Model

Look at Figure 1 to see how the ideas connect, showing expected links, immediate impacts, besides middle steps happening at once.



[Figure 1: Structural Equation Model with Path Coefficients (β) and Statistical Values]

III. METHODOLOGY

3.1 Research Design and Sample

The approach utilized for this study was a quantitative, cross-sectional one. We acquired our information from a poll of IT professionals who work in three important IT centers in South India: Bengaluru, Hyderabad, and Chennai. A stratified purposive sampling strategy, supplemented by snowball sampling, was utilized to ensure representation across various job positions (Software Engineers, Project Managers, Data/AI experts, QA, and HR), experience levels, and organizational sizes.

A preliminary research (n=45) was performed prior to the principal survey to enhance the survey instrument. The procedure of filtering the data got rid of replies that weren't comprehensive, leaving a final sample of 265 people who could be used. Mean imputation methods were used to fill in data that was missing (less than 5%).

3.2 Instrument Development

The survey employed a 5-point Likert scale, where 1 indicated "Strongly Disagree" and 5 meant "Strongly Agree." To make sure the information was real, the measurement objects came from trusted sources.

- AI Adoption: This was measured by six questions on how much AI is used and how much money is spent on it.
- Productivity: Six indicators are used to measure this, including speed, quality, and fewer mistakes.

- Cost Efficiency: This is measured by five elements that look at how to lower operating costs and move money around.
- Skill redundancy: This is measured by five questions that look at how easy it is to automate work and how much training is needed.
- Layoffs: Five questions on how people felt about layoffs and how often they happened were used to measure this.

3.3 Common Method Bias

The survey design was changed in numerous ways to lower the danger of Common Method Bias (CMB). For example, the sequence of the items was randomized and the identity of the respondents were kept secret. The statistical examination of Harman's Single Component Test revealed that a singular component did not account for the predominant variance. We looked at the Variance Inflation Factor (VIF) values and discovered that they were much lower than 3.3. This means that collinearity isn't a big problem.

IV. DATA ANALYSIS AND RESULTS

We examined the data using Partial Least Squares Structural Equation Modeling (PLS-SEM). This is a good method based on variance that works well for complex models that involve mediation and moderation [13].

4.1 Measurement Model Assessment

Before we looked at the structural operations, we made sure that the measurement model was right and worked.

Reliability: The internal consistency dependability was strong since all of the constructs had Cronbach's Alpha values higher than the minimum of 0.70 (AI Adoption: 0.869, Productivity: 0.840, Cost Efficiency: 0.824, Skill Redundancy: 0.839, Workforce Layoffs: 0.844).

Convergent Validity: The Average Variance Extracted (AVE) for all constructs exceeds 0.50, and the bulk of the indicator outer loadings exceed 0.708, demonstrating the validity of convergence.

Discriminant Validity: The Fornell-Larcker criteria and the Heterotrait-Monotrait (HTMT) ratio both showed that there was discriminant validity. The square root of the Average Variance Extracted (AVE) for each construct exceeded its maximum correlation with any other construct.

4.2 Structural Model and Hypothesis Testing

We used a bootstrapping method with 5,000 subsamples to find the path coefficients (β), t-values, and p-values that we used to evaluate the structural model.

Direct Effects:

- AI Adoption has a significant direct effect on Workforce Layoffs ($\beta = 0.145$, $t = 2.34$, $p = 0.019$), supporting H1.
- AI Adoption strongly predicts Productivity ($\beta = 0.433$, $t = 7.82$, $p < 0.001$), Cost Efficiency ($\beta = 0.441$, $t = 8.15$, $p < 0.001$), and Skill Redundancy ($\beta = 0.423$, $t = 7.56$, $p < 0.001$), strongly supporting H2, H3, and H4.
- Among the mediators, Cost Efficiency ($\beta = 0.215$, $t = 3.42$, $p = 0.001$) and Skill Redundancy ($\beta = 0.245$, $t = 3.88$, $p < 0.001$) significantly predict Layoffs. However, the path from Productivity to Layoffs is not significant ($\beta = 0.085$, $t = 1.25$, $p = 0.211$).

Table 1: Structural Model Results (path coefficients)

Path	Beta (β)	T-Value	Decision
AI Adoption → Workforce Layoffs	0.145	2.34	Supported
AI Adoption → Productivity	0.433	7.82	Supported
AI Adoption → Cost Efficiency	0.441	8.15	Supported
AI Adoption → Skill Redundancy	0.423	7.56	Supported
Productivity → Workforce Layoffs	0.085	1.25	Not Supported
Cost Efficiency → Workforce Layoffs	0.215	3.42	Supported
Skill Redundancy → Workforce Layoffs	0.245	3.88	Supported

Mediation Analysis:

The specific indirect effects reveal the mechanisms of AI's impact.

- The indirect path via Productivity is not significant (β = 0.037, p = 0.263), rejecting H5.
- The indirect path via Cost Efficiency is significant (β = 0.095, p = 0.003), supporting H6.
- The indirect path via Skill Redundancy is significant (β = 0.104, p = 0.001), supporting H7.

Table 2: Specific Indirect Effects

Path	T-Value	Beta (β)	P-Value
AI → Productivity → Layoffs	1.12	0.037	0.263
AI → Cost Efficiency → Layoffs	2.95	0.095	0.003
AI → Skill Redundancy → Layoffs	3.21	0.104	0.001

Predictive Relevance (R^2):

The model explains 28.5% of the variance in Workforce Layoffs ($R^2 = 0.285$), indicating moderate predictive power.

4.3 Moderation Analysis

Descriptive analysis of the dataset supports the moderation hypotheses (H8).

- Experience Level: Entry-level professionals (0-2 years) report higher perceived layoff vulnerability (Mean = 2.74) compared to senior professionals with 11+ years of experience (Mean = 2.39).
- Job Role (Skill Level): Support/Operations jobs, which are more routine, have higher layoff ratings (Mean = 2.89) than specialist jobs, such Software Engineers (Mean = 2.43).
- Firm Size: AI adoption is significantly higher in Large organizations (Mean = 3.63) compared to Small organizations (Mean = 2.65), indicating that structural changes are more pronounced in well-resourced enterprises.

V. DISCUSSION

The results provide a comprehensive look at how the IT workforce in India has changed as a result of AI. Although AI will have a significant indirect effect on layoffs, its direct influence will be far smaller. This suggests that AI helps bring about structural changes rather than being the main cause of large-scale job losses.

According to the Resource-Based View (RBV), businesses are using AI to cut costs. When AI technologies successfully reduce operational expenditures, often by reducing the demand for human engagement in particular tasks, workforce reduction becomes a priority in the quest of cost-effectiveness.

In addition, the results provide strong support for the Skill-Biased Technological Change (SBTC) hypothesis as it pertains to modern AI systems. When it comes to simple, repetitive tasks, artificial intelligence makes a lot of human skills obsolete. Most significantly, this duplication is the link between AI and job losses. Raise output without laying off workers is a myth that must be dispelled. This shows that when AI boosts productivity, companies may choose to retain workers instead of laying them off, if their skills are still useful.

There is a clear separation in the moderating effects. Jobs at entry-level and support positions are more likely to be affected by AI-driven efficiency than other types of jobs. Tacit knowledge and complex problem-solving abilities are difficult to automate, making high-skill jobs and seasoned experts more secure.

VI. CONTRIBUTIONS AND IMPLICATIONS

6.1 Theoretical Contributions

This research offers significant theoretical progress by integrating SBTC and RBV to clarify the dynamics of workforce changes induced by AI. It broadens these established theories to encompass generative AI and advanced automation in a growing economy. The study shows that the relationship between AI and layoffs is not productivity but cost efficiency and skill redundancy. This helps us understand better how technology affects jobs in theory.

6.2 Managerial Implications

The findings highlight the critical necessity for strategic workforce planning among HR practitioners and organizational executives in the IT sector.

- Proactive Reskilling: Given that skill redundancy is a major catalyst for layoffs, firms must significantly engage in ongoing learning and reskilling initiatives, especially for entry-level and routine-task employees, facilitating their move into AI-complementary positions.
- Reconceptualizing Entry-Level Talent: The conventional pyramid framework of IT personnel is undergoing transformation. Human Resources must reevaluate the integration and utilization of entry-level talent, emphasizing core AI literacy and advanced problem-solving from the outset.
- Balanced Narrative: Management must convey openly the deployment of AI, highlighting its function in enhancing productivity rather than only reducing costs, to alleviate job uncertainty and preserve staff morale.

VII. CONCLUSION

The use of AI in India's IT sector is definitely changing the way people operate. But the story of vast, direct AI-induced unemployment is too simple. Our SEM study shows that AI has an effect on layoffs mostly by making some skills unnecessary and pushing for cost-effectiveness. As technology changes, the focus should move from worrying about losing jobs to proactively changing the workforce. Organizations may get through the AI revolution without hurting their human capital by putting reskilling first and realizing the value of experience and high-level skills.

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