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Research Article

Influence of Artificial Intelligence on Building Construction Labour: Evidence from Ranchi City, Jharkhand, India

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Abstract

Technological advancement driven by artificial intelligence (AI) is increasingly reshaping production systems across labour-intensive industries, including construction. In secondary Indian cities such as Ranchi, the introduction of AI –enabled tools into building construction has begun to influence labour demand, occupational structures, and income patterns. This study analyses the labour-related implications of AI adoption in Ranchi's construction sector using field-based evidence collected from workers and contractors. Quantitative analysis supported by qualitative observations indicates that AI contributes to enhanced productivity and improved safety performance while simultaneously reducing reliance on traditional manual labour. The absence of formal training mechanisms, however, has intensified employment uncertainty among unskilled and informal workers. The study focuses on skill development and labour protection frameworks in technology adoption strategies to ensure balanced and inclusive sectoral growth.

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KEYWORDS: Artificial intelligence, construction, labour, skill development, employment, traditional, income

1. INTRODUCTION

1.1 Preliminary Information of the Study

Technological advancement has historically played a decisive role in shaping labour markets, productivity patterns, and industrial organisation. In the contemporary period, artificial intelligence (AI) portray most transformative technological forces influencing economic systems globally. AI refers to the computational mechanisms of decision-making, pattern recognition, learning, and problem-solving (Russell & Norvig, 2021). It has significantly altered the essence of work across fields like manufacturing, healthcare, logistics, and construction.

The construction industry is traditionally characterised by labour-intensive production methods, fragmented work structures, and a high reliance on informal labour (ILO, 2021). In developing economies like India, construction serves as a critical employment provider for unskilled, semi-skilled, and migrant workers. According to the National Statistical Office

(2022), the construction sector employs over 50 million workers in India, many of whom lack formal training or social security coverage. This makes the sector particularly sensitive to technological disruptions.

AI-driven automated machinery, building information modelling (BIM), predictive analytics, drone-based site monitoring, and AI-enabled safety systems have begun to penetrate construction practices (Zhang et al., 2020). These technologies promise improvements in efficiency, cost control, project scheduling, and occupational safety. But uses of AI questions surge about labour displacement, skill mismatch, wage inequality, and job insecurity, particularly for vulnerable worker groups.

1.2 Artificial Intelligence and Construction Labour

Artificial intelligence in construction is not limited to full automation but often operates through the augmentation of human labour. AI-enabled systems assist in planning, quality inspection, risk assessment, and equipment operation, thereby altering task composition rather than eliminating jobs outright (Autor, 2015). Nevertheless, the redistribution of tasks tends to favour skilled and technologically adaptive workers while marginalising those engaged in routine manual activities.

Brynjolfsson and McAfee (2014) argue that digital technologies amplify productivity but simultaneously widen income inequality by disproportionately benefiting skilled labour. This phenomenon, commonly referred to as skill-biased technological change, has been empirically observed across sectors. In construction, AI-driven mechanisation reduces demand for physically intensive work and at the same time grows want of technical operators, supervisors, and data-oriented roles (McKinsey Global Institute, 2017).

1.3 Indian Context and Urban Labour Dynamics

India's construction labour market is dominated by informal employment, short-term contracts, and migrant labour flows. Informal workers face limited access to training, low bargaining power, and heightened vulnerability to economic shocks (Kannan & Raveendran, 2019). The introduction of AI into such a labour market raises important equity concerns.

Urban centres such as Ranchi city present a unique context for examining AI's labour impact. Ranchi, the capital of Jharkhand, has an urban area that has been extended by residential housing, commercial development, and public infrastructure projects. While large contractors increasingly adopt digital and AI-enabled tools, small and medium construction firms continue to rely on traditional labour-intensive practices. This coexistence of old and new technologies creates uneven labour outcomes, making Ranchi an ideal case study.

1.4 Research Problem

Despite growing global literature on AI and labour, limited empirical research exists on how AI affects construction workers in medium-sized Indian cities. Most studies focus on metropolitan regions such as Delhi, Mumbai, or Bengaluru, overlooking cities like Ranchi, where technological diffusion occurs gradually and unevenly. There is insufficient evidence on how AI adoption influences employment patterns, wage structures, skill demand, and job security at the city level.

1.5 Importance of the Study

This study contributes to academic and policy debates by:

- Research-based evidence from a secondary Indian city
- Examining labour outcomes across skill categories
- Linking AI adoption with employment security and wages
- Offering policy recommendations for inclusive technological transition

2. REVIEW OF LITERATURE

2.1 Theoretical Perspectives on Technology and Labour

Early economic theories viewed technological change as a long-term driver of productivity growth with temporary labour displacement effects (Schumpeter, 1942). Modern labour economics has shifted towards task-based frameworks, emphasising how technology reconfigures job tasks rather than eliminating occupations (Autor, Levy, & Murnane, 2003).

Brynjolfsson and McAfee (2014) introduced the concept of the "second machine age," highlighting the capacity of intelligent machines to perform cognitive as well as manual tasks. Their work underscored the growing divergence between technologically complemented workers and those displaced by automation.

Autor (2015) further refined this framework by demonstrating that automation primarily targets routine tasks, leaving non-routine, interpersonal, and creative tasks relatively resilient. This insight is particularly relevant for construction, where many tasks are repetitive and physically intensive.

2.2 AI Adoption in the Construction Sector

Empirical studies suggest that AI adoption in construction enhances productivity, reduces project delays, and improves safety compliance (Zhang et al., 2020; Li et al., 2019). AI-based monitoring systems help identify safety risks in real time, reducing workplace accidents (ILO, 2021).

However, McKinsey Global Institute (2017) warns that automation disproportionately affects low-skilled workers in labour-intensive industries. In construction, automated equipment and AI-assisted planning reduce reliance on manual labour, particularly in excavation, material handling, and site supervision.

2.3 Construction Labour in India

Indian construction labour is predominantly informal, with limited access to training and social protection (Ghosh, 2019). Agarwal and Sharma (2020) found that technological adoption in Indian construction firms led to increased wage inequality, as skilled workers benefited disproportionately from mechanisation.

Kannan and Raveendran (2019) emphasised that migrant workers face additional vulnerabilities due to a lack of job security and skill certification. AI adoption, without accompanying reskilling initiatives, may therefore exacerbate existing labour inequalities.

2.4 Global Institutional Evidence

The World Economic Forum (2020) highlights that AI-driven technologies are reshaping labour demand globally, increasing the need for digital and technical skills. The International Labour Organisation (2021) acknowledges AI's safety benefits but cautions against its potential to deepen informality without inclusive labour policies.

2.5 Unexplored area

Although this study spread the essence of AI and labour dynamics, region-specific evidence from medium-sized cities remains scarce. Ranchi's mixed construction practices and labour composition make it an important site for examining AI's differentiated labour impacts.

3. OBJECTIVES, HYPOTHESES AND RESEARCH DESIGN

3.1 Objectives

Clear and well-defined objectives are mandatory for systematic academic inquiry. The present study analyses the multidimensional effect of artificial intelligence on building construction labour in Ranchi city. The objectives are formulated to capture both economic and social dimensions of technological change.

Primary Objective

To analyse the effect of AI on building construction labour in Ranchi city.

Secondary Objectives

1. To investigate the nature of AI adoption in the building construction area of Ranchi city.
2. To examine the relevance of AI on employment patterns and job security of construction workers.
3. To assess changes in wage structures across different skill categories on AI uses.
4. To study the interrelation of labour productivity in construction activities and AI implementation
5. To evaluate workers' access to training and skill development in an AI-driven construction environment.
6. To identify challenges faced by unskilled and informal construction workers due to technological transformation.

These are synchronised with the broader goal of understanding how emerging technologies interact with labour markets in medium-sized urban contexts.

3.2 Research Questions

The study involves the following research questions:

1. What extent of utilisation of artificial intelligence in the construction sector of Ranchi city?
2. How does AI adoption affect job security among construction workers?
3. Does AI adoption influence wage differences across skill categories?
4. What is the interrelation of AI adoption and labour productivity?
5. How prepared are construction workers to use AI-driven technologies?

These questions guide the empirical investigation and inform the hypothesis formulation.

3.3 Hypotheses of the Study

Hypotheses provide a testable framework to examine relationships between variables. The following null and alternative hypotheses are formulated based on existing literature and research objectives:

Hypothesis 1: AI and Job Security

- **H_{01}** (Null Hypothesis): No substantial interaction between artificial intelligence adoption and job security of construction workers.
- **H_{11}** (Alternative Hypothesis): There is a substantial interaction between artificial intelligence adoption and the job security of construction workers.

Hypothesis 2: AI and Wage Structure

- **H_{02}:** Artificial intelligence does not affect wage differences among construction workers.
- **H_{12}:** Artificial intelligence adoption significantly affects wage differences among construction workers.

Hypothesis 3: AI and Labour Productivity

- H_{03}: Artificial intelligence adoption does not influence labour productivity in construction work.
- H_{13}: Artificial intelligence adoption influences labour productivity.

4: RESEARCH METHODOLOGY

4.1 Research Design

The study adopts a mixed-method research design, combining quantitative and qualitative approaches. To watch AI's impact on construction labour by integrating statistical analysis with contextual insights (Creswell & Plano Clark, 2018).

- Quantitative approach: Used to analyse employment patterns, wages, job security, and productivity.
- Qualitative approach: Used to understand workers' perceptions, experiences, and adaptation challenges.

4.2 Study Area: Ranchi City

Ranchi city, the capital of Jharkhand, has witnessed significant growth in residential, commercial, and infrastructure construction over the last decade. The city represents a transitional urban economy where traditional labour-intensive construction practices coexist with emerging AI-enabled technologies. This makes Ranchi an appropriate site for examining differentiated labour impacts of technological change.

4.3 Source of Data

Primary Data

From construction workers and contractors, primary data was collected through structured questionnaires and interviews. The survey captured information on:

- Skill level
- Wage structure
- Job security
- Exposure to AI-enabled technologies
- Training and skill development

Secondary Data

These were collected from:

- Peer-reviewed journals
- Government reports
- International organisation publications (ILO, WEF, World Bank)
- Industry reports and policy documents

4.4 Sampling Design

4.4.1 Sampling Method: Purposive sampling was adopted to select respondents from construction sites where some level of technological integration was present. This method ensured relevance to the research objectives.

4.4.2 Sample Size

Construction workers: 75

Contractors/site supervisors: 30

The sample included unskilled, semi-skilled, skilled, and AI-assisted workers.

4.5 Variables of the Study

Independent Variable

- Level of Artificial Intelligence Adoption

Dependent Variables

- Job security
- Wage level
- Labour productivity

Control Variables

- Skill level
- Education
- Work experience

4.6 Tools and Techniques of Analysis

SPSS (Statistical Package for the Social Sciences) was used. The following tools were applied:

1. Descriptive statistics – to summarise worker characteristics
2. Chi-square test – to test the association between job security and AI implementation.
3. One-way ANOVA – to examine wage differences across skill categories
4. Correlation analysis – to analyse the relationship between AI adoption and productivity

In labour economics and social science research, generally, these tools are approved.

4.7 Limitations

Despite rigorous methodology, the study has certain limitations:

- Limited sample size due to field constraints
- Focus on a single city's limits generalisation
- Due to technological changes over time, findings may vary

These limitations are acknowledged while interpreting the results.

5: DATA ANALYSIS, SPSS CALCULATIONS, AND FINDINGS

5.1 Introduction

The empirical analysis of primary data accumulated from building construction workers and contractors in Ranchi city. The purpose is to evaluate the effect of artificial intelligence on construction labour with respect to employment patterns, wage structure, job security, and labour productivity. SPSS software was used for analysis, applying descriptive and inferential techniques in accordance with the hypotheses formulated in earlier chapters.

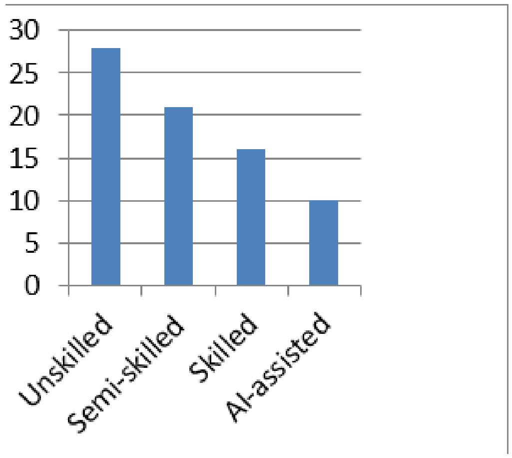
5.2 Descriptive Analysis of Respondents

Table 5.1 Distribution of Respondents by Skill Category

Skill Category	Frequency	Percentage (%)
Unskilled	28	37.3
Semi-skilled	21	28.0
Skilled	16	21.3
AI-assisted	10	13.4
Total	75	100.00

Interpretation:

The table shows that a significant proportion of construction labour in Ranchi remains unskilled (37.3%), indicating the continued reliance on manual labour. However, the presence of AI-assisted workers (13.4%) reflects emerging technological adoption in selected construction sites.



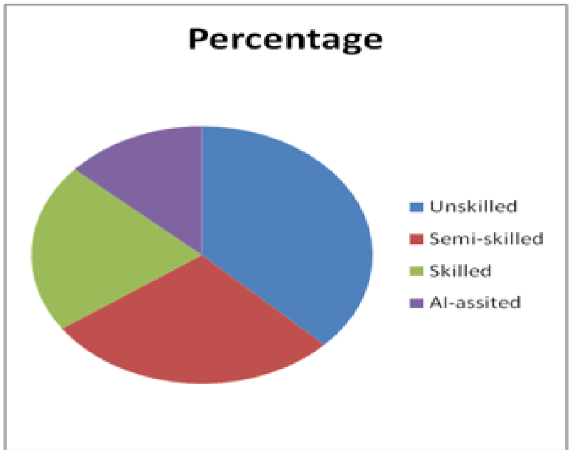


Table 5.2 Distribution of Respondents by Perceived Level of AI Adoption

Level of AI Adoption	Frequency	Percentage (%)
Low	18	24.0
Moderate	32	42.7
High	25	33.3
Total	75	100

Interpretation:
Most respondents reported moderate to high levels of AI adoption, suggesting that digital and AI-enabled tools are increasingly influencing construction activities in Ranchi city.

5.3 Analysis of Job Security

Table 5.3 AI Adoption and Job Security (Chi-Square Test)

Variable	χ^2 value	Degrees of Freedom	p-value
AI Adoption × Job Security	4.87	2	0.028

Interpretation:

Since the p-value (0.028) is less than the 0.05 significance level, the null hypothesis (H_{01}) is rejected. This indicates a statistically significant interrelation between AI implementation and job security. Workers exposed to AI-enabled construction environments reported relatively higher job stability, particularly among skilled and AI-assisted categories.

5.4 Wage Structure Analysis

Table 5.4 Mean Daily Wage by Skill Category

Skill Category	Mean Wage (₹)	Standard Deviation
Unskilled	402.5	48.6
Semi-skilled	538.2	62.4
Skilled	712.6	75.1
AI-assisted	895.4	83.9

Interpretation:
The wage distribution shows that labourers those were skilled and perform AI-assisted roles earn significantly higher wages compared to unskilled labourers. This suggests that AI adoption is associated with widening wage differentials.

Table 5.5 One-Way ANOVA: Wage Differences Across Skill Categories

Source of Variation	Sum of squares	Mean Square	F-value	p-value
Between Groups	154320	51440	9.84	0.000
Within Groups	378950	---	----	---

Interpretation:
The ANOVA results indicate a difference in wages across skill groups ($p < 0.01$). Therefore, (H_{02}) is rejected, confirming that AI adoption significantly affects wage structure.

5.5 Labour Productivity Analysis

Table 5.6 Correlation between AI Adoption and Labour Productivity

Variables	Correlation Coefficient (r)	p-value
AI Adoption × Productivity	0.46	0.004

Interpretation:
(r) indicates a moderate (+) relationship between AI implementations and labour productivity. The statistically significant p-value supports the alternative hypothesis (H_{13}), suggesting that AI adoption enhances productivity in construction activities.

5.6 Training and Skill Development

Table 5.7 Access to Training and Job Stability

Training Access	Stable Employment (%)	Unstable Employment (%)
Yes	68.4	31.6
No	39.2	60.8

Interpretation:
Workers with access to AI-related training reported significantly higher job stability. This highlights the critical role of skill development in mediating labour outcomes in technologically evolving environments.

6. FINDINGS AND DISCUSSION

6.1 Key Findings

Based on SPSS analysis, the following findings emerge:

1. AI adoption in Ranchi's construction sector is increasing, particularly in medium and large construction projects.
2. Job security is significantly higher among workers exposed to AI-enabled technologies.
3. Wage inequality has increased, favouring skilled and AI-assisted workers.
4. AI adoption positively influences labour productivity and work efficiency.
5. Lack of training intensifies vulnerability among unskilled and informal workers.

6.2 Discussion of Findings

The findings syncronizewith technological changes on skill-based theory proposed by Autor (2015) and Brynjolfsson and McAfee (2014). AI adoption does not eliminate labour demand but restructures it in favour of workers possessing technical competencies. In Ranchi, this restructuring is evident in wage differentials and employment stability patterns.

The results also support institutional evidence from the ILO (2021), which highlights AI's potential to improve safety and productivity while increasing inequality without inclusive labour policies. The moderate positive correlation between AI adoption and productivity confirms global trends while contextualising them within a medium-sized Indian city.

7: CONCLUSION AND POLICY IMPLICATIONS

7.1 Conclusion

The present study examined the effect of artificial intelligence on building construction labour in Ranchi city, a medium-sized urban centre experiencing rapid infrastructural growth alongside gradual technological transformation. By conducting a mixed-method research design supported by SPSS-based statistical evaluation, the research explored how AI adoption influences employment patterns, wage structures, job security, and labour productivity.

The findings clearly demonstrate that artificial intelligence is reshaping construction labour rather than eliminating it. AI-enabled tools and digital systems have contributed to improved productivity, enhanced safety standards, and more efficient project management. Skilled and AI-assisted workers experience improved wages and employment stability, while unskilled and informal labourers face increasing vulnerability.

The statistical evidence confirms significant relationships between AI adoption and job security, wage differentials, and productivity. The rejection of null hypotheses across key variables indicates that AI is a decisive factor influencing labour outcomes in the construction sector. Importantly, access to training emerged as a critical mediating variable in determining the inclusiveness of technological change.

This study contributes to existing literature by providing empirical, city-level evidence from Ranchi, addressing a notable research gap in the Indian context. It reinforces the argument that technological progress must be accompanied by institutional and policy support to ensure equitable labour outcomes.

7.2 Policy Implications

Based on the findings, the study proposes the following policy recommendations:

1. Skill Development and Reskilling Programs

Government agencies, construction firms, and training institutions should collaborate to provide affordable and accessible skill-development programs focused on AI-assisted construction technologies. Certification-based training can improve employability and job security for informal workers.

2. Inclusive Technology Adoption

Policies should encourage labour-augmenting technologies rather than labour-replacing automation. AI systems should be designed to complement human labour, particularly in tasks involving safety monitoring and quality control.

3. Strengthening Labour Protection

Construction workers, especially migrants and informal labourers, require stronger social security mechanisms, including health insurance, accident coverage, and unemployment support during technological transitions.

4. Public–Private Partnerships

Public–private partnerships can facilitate technology diffusion while making sure that workers are not excluded from the benefits of AI-driven growth.

5. City-Specific Labour Policies

Urban centres like Ranchi require localised labour and technology policies that reflect regional market-oriented labourers, not the one-size-fits-all national frameworks.

7.3 Limitations

- Despite rigorous methodology, the study has certain limitations:
- Sample populations were constrained due to selected construction sites, which may restrict generalisation.
- The research area reflects on a single city, limiting comparative analysis.
- Labour outcomes over time may differ due to innovations and technological changes.

These limitations do not undermine the study's findings but suggest caution in interpretation.

7.4 Scope for Future Research:

- Comparative studies across multiple cities or states
- Longitudinal analysis of AI adoption and labour outcomes
- Gender-based analysis of AI's impact on construction labour
- Assessment of specific AI technologies, such as robotics and BIM
- Policy evaluation studies on reskilling interventions

  Such research would further deepen understanding of AI-driven labour transformation.

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