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Article

Artificial Intelligence, Structural Transformation, and the Rethinking of Labour-Intensive Growth in India

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Abstract: This study examines how artificial intelligence (AI) interacts with structural transformation to shape labour market outcomes in India, with particular focus on whether labour-intensive growth remains a viable strategy for inclusive development. India's demographic advantage demands large-scale productive employment, yet traditional pathways through manufacturing-led industrialisation are being disrupted by AI and automation technologies that affect both routine and cognitive tasks across sectors. Using a descriptive-analytical method, this paper draws on secondary data from the Periodic Labour Force Survey (PLFS), the India Employment Report (2024), World Bank indicators, OECD (Organization for Economic Co-operation and Development) publications, and IMF (International Monetary Fund) research to examine sectoral employment trends, AI adoption patterns, and workforce exposure across skill levels and regions. The findings reveal that India's structural transformation remains incomplete: employment growth is concentrated in low-productivity construction and informal services rather than in manufacturing. AI adoption follows a highly uneven trajectory, confined largely to formal, urban, high-skill environments, while the majority of workers remain in low-exposure, low-complementarity occupations that are bypassed by technological productivity gains. This creates a form of technological dualism that reinforces existing labour market segmentation. The study concludes that while labour-intensive growth retains developmental relevance, its viability depends on the simultaneous pursuit of technological upgrading, broad-based skill development, and supportive institutional frameworks. India's challenge lies not in choosing between employment and technology, but in redesigning its growth strategy so that both reinforce each other.

Keywords: Artificial Intelligence; Structural Transformation; Labour-Intensive Growth; Employment; India; Technological Change; Informal Economy

1. Introduction

Artificial intelligence technology functions as the primary force driving current economic change. Unlike earlier mechanisation, the present wave of AI now affects cognitive functions, professional tasks, and service work, extending its reach into every sector of the economy. This creates a fundamental challenge for development economics: societies that depend on large-scale job creation must identify solutions when technology begins to alter existing human work patterns.

The scholarly discourse on AI and labour markets has generated a rich body of empirical and theoretical work. Acemoglu and Restrepo [1] establish that automation displaces workers from specific tasks while simultaneously creating new functions, with the net employment outcome depending on the balance between these forces. Autor [2] demonstrates that technological change transforms task requirements rather than eliminating work entirely [3], though his analysis is weighted toward advanced economies. More recently, Cazzaniga et al. [4] show that AI's effects are asymmetric, favouring high-skill workers and technologically advanced firms. At the country level, the World Bank [5] documents rising AI-related job postings across developing nations including India, though the distribution is geographically and sectorally concentrated. The International Labour Organisation (ILO) [6] cautions that technological progress in developing countries intersects with weak social protection systems and pervasive informal employment, producing outcomes that differ substantially from high-income contexts.

The Indian situation requires special attention. The economy shows ongoing GDP (Gross domestic product) growth, an expanding service sector, and increasing digital participation, yet employment outcomes remain deeply uneven. A substantial proportion of workers remain in informal positions that lack productivity or stability. India possesses a demographic advantage through its large young workforce, but this advantage requires the creation of jobs that are both sufficiently numerous and economically secure.

Developing economies have historically relied on labour-intensive growth as their primary engine of structural transformation. Workers moved from low-productivity agriculture into manufacturing and services capable of absorbing large numbers of workers. AI complicates this pathway by delivering productivity gains that reduce worker requirements in certain tasks while concentrating benefits among skilled employees and technologically advanced firms.

Despite a growing body of research on AI and employment, a critical gap persists in the literature. Studies examining AI's labour market effects—such as Acemoglu and Restrepo [1] and Autor [2]—focus predominantly on advanced economies with formal, well-regulated labour markets. Empirical research on innovation and technological change in developing countries, including ILO [6] and World Bank [5] reports, documents AI adoption trends but does not directly examine whether labour-intensive growth remains a viable development strategy under conditions of increasing AI penetration. No prior study has explicitly linked AI-driven technological change to the viability of labour-intensive growth as a development pathway in a large emerging economy such as India. This paper addresses that gap. It investigates how AI applications interact with India's labour market—characterised by informality, uneven sectoral employment, and significant skill heterogeneity—to determine whether labour-intensive growth remains viable. The study demonstrates that such growth retains value but requires complementary strategies: technological adaptation, skill development, and appropriate policy frameworks [7].

The paper is structured as follows: Section 2 presents the conceptual framework; Section 3 reviews the literature; Section 4 states the research objective and hypotheses; Section 5 describes the methodology; Section 6 analyzes the data; Sections 7 and 8 discuss policy implications and limitations; Section 9 concludes.

2. Conceptual Framework: Structural Transformation, Labour-Intensive Growth, and Technological Change

Structural transformation describes the reallocation of workers and productive activity from agriculture toward manufacturing and modern services. Development economics considers this process central because genuine development emerges through productivity enhancement, improved employment quality, and more equitable income distribution [8]. Classical theory, exemplified by Lewis's dual-sector model, explained this transition as the absorption of surplus agricultural labour into modern industrial employment [9]. Later scholarship showed that transformation requires not only sectoral reallocation but also organisational changes and improved working conditions.

Labour-intensive growth has historically been the key mechanism within this process. Textiles, construction, and basic manufacturing employed large numbers of workers while achieving incremental productivity improvements that did not immediately require advanced skills. This pathway remains particularly relevant for India, where employment generation on a large scale is a developmental imperative.

AI presents a new challenge to this model. Unlike previous waves of mechanisation, AI-driven productivity improvements affect both routine processes and cognitive work tasks. Critically, whether AI substitutes for or complements human labour depends on the skill profile of the workforce, the sectoral composition of employment, and the strength of institutional frameworks. India's dual economic structure—characterised by a productive formal sector and a vast informal labour market—means that AI may raise productivity in formal environments while leaving the majority of workers behind, creating barriers to labour-intensive development.

Two theoretical models underpin the analytical framework of this paper. The first is Lewis's dual-sector model [9], which predicts that development proceeds through the transfer of surplus labour from low-productivity agriculture to high-productivity modern sectors. This model implies that labour-intensive growth is the natural engine of structural transformation in labour-abundant economies: wages remain low while the modern sector expands, allowing firms to absorb workers at scale. The second is Acemoglu and Restrepo's task-based framework [1], which distinguishes between the displacement effect of automation—in which machines replace workers in specific tasks—and the reinstatement effect—in which new tasks are created that restore labour demand [10]. Their model predicts that net employment effects depend on which force dominates [11]. In advanced economies, reinstatement has historically kept pace with displacement. In developing economies with weak institutional capacity, concentrated AI adoption, and a large informal sector, reinstatement may lag displacement significantly—threatening the viability of the labour-intensive pathway Lewis described. Together, these two frameworks generate the central analytical tension of this paper: AI disrupts the Lewis mechanism before the reinstatement predicted by Acemoglu and Restrepo has time to take effect, creating a structural trap for labour-abundant emerging economies such as India.

The framework adopted in this paper treats AI not as a uniform disruptive force but as a context-dependent technological change whose developmental implications must be assessed at the intersection of structural conditions, institutional capacity, and policy design. Labour-intensive growth is defined here as the capacity of an economy to absorb a large number of workers in productive employment through sectors that do not immediately require advanced skills at entry. AI penetration refers to the extent to which AI technologies are deployed in firms' production processes, measured through job postings, task-level exposure indices, and firm-level adoption surveys. Automation risk in emerging economies is understood as the conditional probability of task displacement, modulated by institutional preparedness, informality, and complementarity between AI and existing workforce skills.

3. Literature Review

The literature relevant to this paper is organised into four interconnected themes: labour-intensive growth and structural transformation; AI and labour-market change; the uneven exposure of developing economies to AI; and India-specific studies on employment transition. Together, these strands demonstrate that understanding AI's role in India requires more than technological analysis—it demands a comprehensive developmental perspective.

3.1. Labour-Intensive Growth and Structural Transformation

The concept of labour-intensive growth originates from classical development economics. Lewis [9] proposed that development occurs through the transfer of surplus workers from traditional low-productivity sectors to modern high-productivity sectors, generating development when large numbers of workers secure productive employment. Later scholars demonstrated that the smooth transition Lewis anticipated is not automatic.

Recent research shows that structural transformation does not proceed as continuously or completely as traditional frameworks assumed. Productivity improvements remain confined to particular sectors, leaving many workers in informal or low-productivity employment—explaining how nations including India achieve output growth without commensurate employment improvement.

Rodrik [12] deepens this critique through the concept of premature deindustrialisation: developing nations reach their manufacturing employment peak at an earlier and lower income level than historical precedents suggest. Rodrik [12] extends this argument, linking development strategy directly to employment outcomes and showing that policy choices, institutional factors, and industrial strategies shape labour market results in ways that earlier frameworks overlooked.

Empirical evidence from India supports these concerns. The India Employment Report (2024) [13] shows non-agricultural employment growth concentrated in construction and low-productivity services rather than manufacturing. Extensive informal work and rising educated unemployment confirm incomplete structural transformation [14]. The existing literature has limitations: it analyses sectoral change without adequately assessing job quality, and treats movement away from agriculture as progress even when destination jobs remain informal and insecure.

3.2. Artificial Intelligence and Labour-Market Change

Acemoglu and Restrepo [1] provide a foundational framework distinguishing displacement effects—where automation removes workers from specific tasks—from reinstatement effects—where new functions are created. Net employment outcomes depend on the relative strength of these two forces. The assumption that new tasks automatically emerge at the same pace as automation is not guaranteed in developing country contexts.

Acemoglu and Restrepo [15] further demonstrate using US labour market data that each additional robot per thousand workers significantly reduced employment in affected commuting zones, highlighting the real displacement potential of automation even in high-income markets with robust social safety nets, and suggesting potentially larger risks in less protected labour markets.

Autor [2] shows that automation primarily affects routine activities while technology supports non-routine cognitive and interpersonal tasks. This task-based framework is influential, though its applicability to informal sectors in developing countries is contested. Cazzaniga et al. [4] describe AI as producing asymmetric benefits: high-skill workers and technologically advanced firms capture most productivity gains, challenging earlier assumptions that technological progress would raise incomes broadly.

Huang [16] demonstrates that AI's labour market impact varies substantially across regions and sectors. Green et al. [17] show that AI increases demand for analytical and adaptive skills. The OECD [18] documents that firms typically respond to AI adoption through workforce restructuring and upskilling rather than mass hiring—depressing the extensive margin of employment even while raising the intensive margin. The principal limitation of this strand is its heavy reliance on data from formal sectors in advanced economies, underestimating how informality and institutional weaknesses mediate technological change in developing countries.

3.3. Developing Economies and Uneven Exposure to AI

The World Bank [5] documents rising AI-related labour demand across developing nations, but emphasises that digital technology adoption does not translate into universal productivity gains. AI adoption follows concentrated patterns, with specific industries and geographic areas experiencing far higher deployment rates. Demombynes et al. [19] provide evidence that workers in developing regions face lower exposure to AI-automated processes. Reduced exposure does not confer protection: workers in low-exposure occupations tend to perform tasks that contribute little to productivity growth, leaving them structurally marginalised rather than shielded.

The ILO [6] reinforces this point, noting that technological progress in developing countries intersects with weak social protection and pervasive informality. For India, the central question is not simply the level of AI exposure but whether technological change can support, rather than undermine, inclusive structural transformation.

3.4. India-Specific Labour-Market Realities and AI Transition

The Indian labour market exhibits deep structural constraints: widespread informality, pervasive underemployment, a manufacturing deficit relative to the economy's development stage, and extensive skill mismatch. The India Employment Report 2024 [13] demonstrates that employment challenges extend beyond unemployment to encompass job quality and labour underutilisation.

The ILO–Tandem Research study [20] reinforces that technology's impact depends on institutional preparedness and sectoral conditions. The ICRIER (Indian Council for Research on International Economic Relations) [21] report maps AI exposure and complementarity across Indian workers, finding that the majority fall into a low-exposure, low-complementarity category. This reveals a paradox: these workers are protected from immediate automation displacement but also excluded from the productivity gains AI delivers—marginalisation through exclusion rather than substitution. World Bank evidence on AI job postings [22] confirms employer demand for AI-related skills is concentrated in formal urban sectors requiring advanced qualifications, confirming selective and uneven AI diffusion.

3.5. Literature Gap

The existing literature provides useful but fragmented insights. Research on AI and employment typically treats technological change as an independent variable without situating it within the broader development challenge of sustaining labour-intensive growth. Conversely, structural transformation literature rarely incorporates the mediating role of AI.

This paper addresses this gap by explicitly linking AI-driven technological change with the viability of labour-intensive growth in India. The study investigates AI's impact on the factors that determine employment-driven economic development: sectoral labour absorption, workforce skill composition, and firm-level labour demand adjustment. The challenge is not merely technological disruption but a potential structural realignment of development pathways with significant implications for policy design in labour-abundant economies.

4. Research Objective and Hypotheses

This study pursues a single, clearly defined research objective: to examine whether labour-intensive growth remains a viable development strategy for India in an environment of increasing AI adoption, and to identify the conditions under which such growth can be sustained.

This objective encompasses the assessment of structural employment patterns, the uneven diffusion of AI across sectors, skill groups and regions, and the implications for development policy. From this objective, four testable hypotheses are derived:

H1. *Labour-intensive growth as a standalone development strategy is weakening in India due to structural constraints and changing sectoral employment patterns.*

H2. *The effects of artificial intelligence on employment in India are uneven across sectors, skill levels, and regions.*

H3. *Labour-intensive growth remains viable only when supported by technological adaptation, skill development, and appropriate institutional frameworks.*

H4. *The diffusion of AI is contributing to technological dualism within India's labour market, reinforcing divides between formal and informal sectors.*

The hypotheses provide the analytical structure through which the research objective is assessed, using sectoral employment data, AI exposure indicators, and firm-level evidence.

5. Methodology

The research employs a descriptive-analytical design, drawing on secondary data and synthesising existing literature to assess how AI-related technological change affects India's ability to pursue labour-intensive development strategies. A triangulation approach is adopted because AI data in developing countries remains fragmented and evolving. This study does not claim to employ comparative trend analysis or qualitative causal inference; the method is explicitly descriptive-analytical, identifying patterns across multiple independent data sources and interpreting them through a coherent theoretical framework.

The primary data sources are: (i) the Periodic Labour Force Survey (PLFS), which provides sectoral employment statistics, workforce composition, and job quality indicators; (ii) the India Employment Report 2024 [13], jointly produced by the ILO and the Institute for Human Development (IHD); (iii) World Development Indicators [23] for cross-country structural comparisons; (iv) IMF [4,17,24], OECD [18,19], World Bank [5,20,23,25], and ICRIER [21] reports, which provide evidence on AI adoption in the workplace, AI-related job postings, skill requirements, and firm-level responses to automation.

The analytical approach combines two methods. First, a comparative assessment examines sectoral growth rates, employment distributions, and AI exposure patterns to identify structural imbalances and emerging dualism. Second, an interpretive synthesis connects these empirical patterns to the four hypotheses and to the broader theoretical literature on structural transformation.

The methodology has acknowledged limitations. The research relies exclusively on secondary data. Evidence on AI in India is skewed toward formal sector environments. AI-related indicators such as job postings and exposure measures provide proxies rather than direct measurements. These limitations are recognised but do not diminish the consistency of patterns identified across multiple independent sources.

6. Data Interpretation and Analytical Discussion

This section evaluates India's development prospects by examining sectoral employment data, AI exposure indicators, and firm-level evidence. The analysis tests all four hypotheses.

6.1. Structural Employment Patterns and Labour Absorption

India's structural transformation remains incomplete and uneven. The India Employment Report (2024) [13], drawing on PLFS data, shows that employment growth is not concentrated in manufacturing-led industrialisation. **Table 1** demonstrates that manufacturing employment grew at only 3.00% per annum during 2019–2022, while construction grew at 6.37%—more than twice the manufacturing rate. Between 2012 and 2019, manufacturing employment actually declined by 0.33%. Construction is characterised by informal labour, low productivity, and limited upward mobility, confirming that aggregate employment growth masks weak quality of job creation. Services show high volatility (10.80% to 1.09%), while agriculture's reversal to 8.93% growth likely reflects distress-driven re-entry rather than genuine productivity improvement. These patterns support H1 and establish the conditional nature of H3.

Table 1. Compound Growth Rate of Employment across Sectors in India (2000–2022).

Compound Rate of Growth	2000–2012	2012–2019	2019–2022
Population (aged 15+)	2.39	2.07	1.15
Labour Force (aged 15+)	1.54	0.56	4.62
Workforce (aged 15+)	1.55	0.01	5.29
Agriculture	−0.39	−2.55	8.93
Manufacturing	2.89	−0.33	3.00
Construction	9.15	2.18	6.37
Services	−0.67	10.80	1.09
Total Non-Agriculture	3.86	2.09	2.61

Source: ILO and IHD (2024), India Employment Report [13].

6.2. AI Expansion and Cross-Country Comparison

The expansion of AI-related labour demand in India is evident from international comparisons. **Table 2** summarises World Bank data [22] showing that India experienced a rapid increase in AI job vacancies after 2016, eventually surpassing several advanced economies in the share of online job postings mentioning AI skills. However, this growth is confined to the formal and skilled segments. The high aggregate AI job-posting growth coexists with highly restricted labour market access, because firms deploy AI selectively in advanced operational contexts. This supports H2.

Table 2. AI Share of Online Job Postings by Country—Approximate Growth Trend (2012–2019).

Country	AI Share ~2012 (%)	AI Share ~2016 (%)	AI Share ~2019 (%)	Trend
India	~0.1	~0.4	~1.0+	Rapid rise; surpassed US/UK
USA	~0.2	~0.4	~0.8	Steady growth
UK	~0.1	~0.3	~0.6	Moderate growth
Australia	~0.1	~0.3	~0.5	Moderate growth
Canada	~0.1	~0.2	~0.4	Slow growth

Source: World Bank (2024) [22]; approximate values derived from the original source data.

6.3. Spatial Concentration of AI Demand

AI adoption in India is geographically concentrated. **Table 3** shows city-wise distribution of AI job postings [22], confirming that Bengaluru, Hyderabad, and Mumbai dominate AI-related job demand while smaller cities contribute marginally. The 'Other cities' category accounts for the largest share of total job postings but a much smaller share of AI-specific posts, indicating high concentration and low spatial diffusion. AI-driven opportunities are effectively limited to a small number of urban, high-skill clusters. This reinforces H2.

Table 3. City-Wise Distribution of AI Job Postings vs. Total Job Postings in India (2010–2019).

City	Share of All Job Posts (%)	Share of AI Job Posts (%)	AI Concentration Relative to Total
Bengaluru	~12	~38	High—3× above average
Mumbai	~11	~14	Above average
Hyderabad	~9	~12	Above average
Pune	~7	~8	Near average
Gurgaon	~6	~7	Near average
Chennai	~6	~7	Near average
Delhi	~8	~6	Below average
Noida	~4	~3	Below average
Kolkata	~4	~2	Low
Ahmedabad	~3	~1	Low
Other cities	~30	~2	Very low—under-represented

Source: World Bank (2024) [22]; approximate values derived from the original source data.

6.4. Workforce Exposure and Structural Segmentation

AI exposure across Indian workers is highly uneven. **Table 4** presents ICRIER data [21] showing that 70.34% of workers fall into the low-exposure, low-complementarity category (G1), meaning they neither face significant automation risk nor benefit from AI-driven productivity improvements. Only approximately 11–12% of workers occupy high-exposure categories (G3 and G4 combined). This pattern reveals that the majority of the workforce is not engaged in AI-complementary activities — not because they are shielded from disruption, but because they remain structurally confined to low-productivity occupations outside the frontier of AI adoption. Low exposure thus signals structural marginalisation, not security. This supports H2 and H4.

Table 4. Distribution of Indian Workers by AI Exposure and Complementarity.

Group	AI Exposure	Complementarity	Share of Workers (%)	Interpretation
G1	Low	Low	70.34	Structurally marginalised; no AI risk or benefit
G2	Low	High	5.32/5.77	Some complementarity but low exposure
G3	High	Low	2.11/5.42	Displacement risk without complementarity gains
G4	High	High	5.77/5.28	Full AI integration — productive and at risk

Source: ICRIER (2026) [21]; values from the original source data.

6.5. Firm Behaviour and Labour Demand Adjustment

Firm-level evidence further constrains the scope for labour-intensive employment expansion. **Table 5** presents OECD data [18] showing that firms in finance and manufacturing prioritise retraining or upskilling existing workers (64–71%) over hiring new workers (35–48%), with attrition and redundancies remaining relatively low (14–17%). AI adoption primarily affects the intensive margin—skill and task composition of existing workers—rather than the extensive margin of employment creation. Firms restructure internally rather than hiring broadly, reducing the contribution of AI adoption to large-scale job creation. This supports H3 and is consistent with H4.

Table 5. Firm Response to AI Adoption—Retraining, Hiring, and Workforce Adjustment.

Firm Response	Finance Sector (%)	Manufacturing Sector (%)
Retraining or upskilling internal workers	64%	71%
Buying services from external companies	53%	53%
Hiring new workers	35%	48%
Attrition or redundancies	17%	14%

Source: OECD (2023) [18].

6.6. Synthesis of Findings

The cumulative evidence demonstrates consistent patterns across all four hypotheses. India's structural transformation is incomplete and has shifted toward low-productivity informal sectors rather than manufacturing (H1 confirmed). AI adoption produces uneven effects across sectors, skill groups, regions, and firm types (H2 confirmed). Labour-intensive growth retains developmental relevance but only under conditions of technological adaptation, skill development, and institutional support (H3 confirmed). The combination of formal-sector AI adoption and informal-sector stagnation is creating technological dualism that risks permanently bifurcating India's labour market (H4 confirmed).

India's central development challenge is thus not simply that technology displaces workers, but that productivity-enhancing technological change is concentrated among a small formal, urban, high-skill minority, while the majority of the workforce remains trapped in low-productivity informality—neither threatened by automation nor benefiting from it.

7. Policy Implications

The findings establish several priority directions for India's development strategy. First, labour-intensive growth must continue as a policy objective, but through hybrid approaches that combine employment creation with technological integration. Sectors such as construction and labour-intensive manufacturing should be modernised through technology diffusion rather than simply protected.

Second, skill development and reskilling are central. As AI increases demand for analytical, digital, and adaptive capabilities, India must invest in broad-based human capital formation spanning higher education, vocational training, and continuous learning that enables workers to move between tasks and sectors.

Third, labour-intensive sectors must be strengthened through productivity enhancement rather than protection. This requires support for micro, small, and medium enterprises (MSMEs), improved technology access, and the development of accessible digital tools that workers in low-skilled environments can adopt.

Fourth, policy must address technological and spatial inequality. The concentration of AI adoption in urban high-skill clusters deepens regional disparities. Digital infrastructure expansion and targeted technology diffusion to smaller cities and rural areas are necessary to broaden access to productivity gains.

Fifth, institutional frameworks governing the labour market must evolve to accommodate technological change. Strengthened social protection, improved working conditions, and transitional support for displaced workers are essential complements to industrial and skills policy. The overarching challenge is to align AI adoption with employment-creation goals through coordinated industrial policy, skills strategy, and labour market governance.

8. Limitations of the Study

This study relies on secondary data, constrained by the availability and quality of existing datasets. AI-related evidence on India is skewed toward formal sector environments, limiting generalisability to the informal majority of the labour market. AI exposure measures, including job postings and task-based indicators, are proxies for technological change rather than direct measurements of AI's employment impact. The rapidly evolving nature of AI technology means that current findings may require updating as new data become available. These limitations are acknowledged, but they do not undermine the analytical framework or the robustness of patterns identified consistently across multiple independent data sources.

9. Conclusions

This paper examined whether labour-intensive growth remains a viable development strategy for India in an era of accelerating AI adoption. The analysis demonstrates that India's structural transformation is incomplete: employment growth is concentrated in low-productivity construction and informal services rather than manufacturing. AI adoption is highly uneven, confined to formal urban environments and high-skill workers, while the majority of workers remain excluded from both the risks and the benefits of technological change. The result is a form of technological dualism that reinforces pre-existing labour market segmentation.

The evidence confirms that labour-intensive growth retains developmental significance but cannot function as a standalone strategy in the current technological environment. Its viability depends on the simultaneous pursuit of technological upgrading, broad skill development, and institutional reform. India's challenge is to redesign its growth strategy so that technology and employment reinforce rather than substitute for each other.

The future of development in India lies not in choosing between technology and employment, but in structuring growth to align both—ensuring that AI diffusion extends productivity gains beyond formal sector enclaves and into the broader economy that the majority of India's workers inhabit.

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Institutional Review Board Statement

This research does not involve human or animal subjects, pathology reports, or any form of primary data collection from individuals. The study is based entirely on publicly available secondary data and published reports. Therefore, no ethics approval was required.

Informed Consent Statement

Not applicable.

Data Availability Statement

This study relies exclusively on publicly available secondary data sources, including the Periodic Labour Force Survey (PLFS), the India Employment Report 2024 (ILO & IHD), World Development Indicators (World Bank), OECD publications, IMF research, and the ICRIER AI exposure report (2026). All primary sources are fully cited within the manuscript. No proprietary or restricted datasets were used.

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Conflicts of Interest

The author declares no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the author used AI assistance solely for language refinement and proofreading support. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs were critically reviewed and edited by the author. The author takes full responsibility for the integrity and accuracy of the work.

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