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The Asymmetric Impact of Generative Artificial Intelligence Adoption on Wage Inequality: Evidence from Emerging vs. Developed Economies

Dr. NANDRU GOPI
Asst. Professor of Economics
SR & BGNR Government Arts and Science College (Autonomous), Khammam, Telangana State
Email: naruna081@gmail.com

Abstract: *This paper investigates the macroeconomic and microeconomic structural shifts driven by the rapid commercialization and adoption of Generative Artificial Intelligence (GenAI). Utilizing a comparative analytical framework spanning developed economies (e.g., United States, OECD nations) and emerging economies (e.g., India, Brazil, South Africa), we examine how the deployment of Large Language Models (LLMs) and advanced diffusion frameworks creates an asymmetric impact on labour markets. While historical automation targeted routine manual and cognitive tasks, GenAI uniquely targets high-skilled, non-routine cognitive domains. However, our findings suggest that rather than acting as a great equalizer, GenAI introduction polarizes labour structures unevenly across differing levels of economic development. Developed economies encounter immediate labour re-allocation and wage compression at the lower-middle tiers of cognitive work, balanced by immense capital-deepening among high-tier technical roles. Conversely, emerging markets encounter premature de-intellectualization, labour platform mechanics traps, and a worsening digital-divide wage gap caused by an elastic labour supply and missing safety nets. This study highlights these asymmetric dynamics and develops structured policy solutions spanning algorithmic taxation, dynamic skill architecture, and global platform standard harmonizations.*

Keywords: *Generative AI, Wage Inequality, Labour Economics, Digital Divide, Emerging Economies, Platform Mechanics.I*

1. INTRODUCTION

The global economic architecture is undergoing a foundational paradigm shift catalyzed by Digital Economics. At the heart of this disruption is the lightning-fast integration of Generative Artificial Intelligence (GenAI). Unlike previous waves of industrial automation—which primarily replaced routine physical labour or basic computational workflows—GenAI systems possess advanced semantic reasoning, synthetic code generation, and multi-modal creative capacities. Consequently, this technology directly intersects with high-skilled, non-routine cognitive tasks. Early market expectations hypothesized that GenAI might serve as a democratizing force, elevating the capabilities of less-skilled knowledge workers and shrinking wage gaps. However, early macroeconomic data reveals a highly segmented reality.

The core research problem addressed in this paper is the **asymmetric transformation of labour markets and the polarization of wage structures between developed and emerging economies**. Developed nations possess mature digital infrastructure, flexible institutional frameworks, and capital abundance. This environment allows them to quickly capture the productivity gains of GenAI, even as they weather significant labour displacement. Emerging market economies, by contrast, navigate these shifts under distinct structural constraints: high rates of economic informality, significant deficits in digital literacy, sovereign balance sheets constrained by fiscal limitations, and heavy reliance on business process outsourcing (BPO) and entry-level cognitive service exports. This paper provides a comprehensive comparative analysis to assess whether GenAI adoption expands or contracts the wealth gap between highly-skilled and low-skilled workers across these two distinct economic systems. By evaluating productivity trajectories, platform mechanics, and institutional buffers, we outline systemic solutions designed to prevent global labour market balkanization.

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                          [GenAI Commercial Deployment]
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├──> Developed Economies: Capital Deepening ──> High-Skill Wage Premium Grows
|                                            └──> Displaced Middle-Tier Retrains
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  └──> Emerging Economies: BPO Attrition   ──> Low-Skill Wage Compression
              └──> Platform Exploitation & Data Labour Traps
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The scope of this investigation covers the macroeconomic divergence between advanced and industrialising states. Over the last two decades, the global distribution of labour relied on a stable international division of cognitive work. Developed nations focused on capital-intensive research, development, intellectual property creation, and top-tier corporate strategy. Emerging market economies capitalised on demographic dividends and expanded higher education to absorb operational workloads, back-office computation, programming support, and call-centre management. This structural equilibrium is collapsing because the marginal cost of deploying an automated generative instance to execute code or draft corporate reports is near zero. Consequently, the fiscal returns on labour-export models are dropping sharply.

This paper breaks down these shifts into five interconnected themes. First, we outline the theoretical breakdown of traditional labour economics when confronted with semantic, self-generative capital. Second, we assess the microeconomic levelling effects observed within localised operations against the macroeconomic polarisation observed across international borders. Third, we formalise the production mechanics using a nested Constant Elasticity of Substitution (CES) model to show how wage volatility links directly to algorithmic compute capital. Fourth, we provide case-by-case evidence of industrial attrition, examining the degradation of outsourcing sectors alongside the expansion of low-tier digital gig-work. Finally, we establish an integrated policy matrix spanning cross-border fiscal adjustments, algorithmic asset tracking, and open-source sovereignty models designed to insulate labour from tech-driven shocks.

2. Literature Review & Theoretical Framework

2.1 The Evolution of Automation and Skill-Biased Technological Change (SBTC)

For decades, the dominant model for interpreting technology-driven wage variance has been Skill-Biased Technological Change (SBTC), popularised by Acemoglu and Autor (2011). This framework posits that new technologies complement highly educated workers while substituting for less-educated counterparts, driving up the skill premium. This model later evolved into the Task-Based Approach to Labour Markets, which distinguishes between routine and non-routine assignments. Traditional automation hollowed out middle-skill routine cognitive and manual tasks, such as bookkeeping, data entry, and assembly line operations, producing a polarised, U-shaped wage distribution across OECD nations.

The task-based model successfully explained the labour shifts of the late 20th and early 21st centuries. In those periods, computing systems operated on strict, explicit rules. Software could execute instructions reliably only if the inputs and logical rules were completely standardised. As a result, workers whose primary responsibilities could be codified into algorithmic steps faced intense wage competition and eventual displacement from corporate hardware. Meanwhile, workers performing abstract, non-routine tasks—such as advanced engineering, clinical diagnosis, strategic leadership, and creative production—saw their productivity rise as computing power reduced data-retrieval times and streamlined administrative overhead. This dynamic expanded the economic premium on high-level cognitive abilities and higher education, reinforcing structural inequality.

2.2 The Generative AI Paradigm Shift

GenAI breaks from the historical SBTC trajectory. Recent foundational studies indicate that Large Language Models (LLMs) disproportionately expose high-skilled, credentialed professions—including software engineers, legal analysts, financial planners, and technical writers—to automation or augmentation (Eloundou et al., 2023). Crucially, empirical evaluations show that GenAI exhibits a skill-levelling effect at the micro-level. Less experienced or lower-performing workers see larger performance boosts than highly proficient experts when utilising AI assistants (Brynjolfsson, Li, & Raymond, 2023). This micro-level levelling suggests that within an organisation, the technology can reduce productivity variance and compress internal wage gaps.

This shift happens because LLMs operate on probabilistic semantic patterns rather than rigid, pre-programmed rules. By predicting linguistic, visual, or mathematical structures based on vast, multi-modal datasets, these models perform contextual reasoning, translation, synthesis, and creative generation. As a result, tasks that previously required years of specialised training, such as software debugging, contract analysis, or graphic design, can now be executed via natural language inputs. Early field experiments by Brynjolfsson et al. (2023) [4] confirmed that tech-assisted entry-level customer support representatives closed the performance gap with seasoned supervisors rapidly. This pattern implies that the traditional return on specialised skill investments is shifting, which could alter how wages align with educational credentials.

2.3 The Global Digital Divide and Capital Flight

While micro-level experiments show localised levelling effects, translating these dynamics into broad macroeconomic wage equality remains problematic. The institutional and global dimensions of digital economics are highly unequal. As explored by Brynjolfsson and McAfee (2014), digital platforms operate under potent network effects and "winner-take-all" dynamics. Because the intellectual property, model architecture, and compute infrastructure powering GenAI are concentrated within a handful of multinational firms based in developed tech hubs, the resulting monopoly rents flow away from emerging markets. This creates a dual-layered labour dynamic: high-skilled supervisors in developed economies capture massive productivity premiums, while low-skilled workers in emerging markets are relegated to highly elastic, low-wage data annotation and content moderation roles within digital platform ecosystems (Korinek & Stiglitz, 2021).

This concentration of digital assets creates an unequal landscape for international competition. When an enterprise in an emerging market adopts an AI API developed by a foreign monopoly, a portion of its operating revenue is transferred out of the domestic economy as licensing fees. This process drains capital from the local ecosystem, limiting the country's ability to reinvest in public infrastructure or human capital. Additionally, the data generated by local users feeds back into foreign platforms, training their central models and reinforcing their competitive advantage. This self-reinforcing loop makes it difficult for developing nations to build independent digital sectors, threatening to lock them into downstream, consumer-tier dependencies where they cannot capture the structural returns of automation.

2.4 Macroeconomic Exposure and Structural Traps

The vulnerability of emerging economies is further deepened by the threat of "premature de-intellectualisation." Historically, developing nations transitioned workers from low-productivity agriculture to manufacturing, and subsequently to services, including export-oriented IT hubs (Muro, Maxim, & Whiton, 2019). GenAI risks disrupting this development path by automating entry-level service roles before these economies can build advanced industrial or R&D sectors. When foreign firms choose automated software over offshore service teams, the traditional mechanism for transferring technical knowledge across borders breaks down.

Furthermore, as Autor, Mindell, and Reynolds (2022) [2] note, institutional buffers dictate how smoothly a labour market handles automation shocks. Developed economies can utilise structured safety nets, professional retraining funds, and intellectual property revenue to ease labour transitions. Emerging economies, by contrast, frequently contend with high informality and limited fiscal room, leaving displaced workers with few choices outside the low-wage informal sector. Consequently, the macroeconomic impact of GenAI risks widening the economic divide between developed and developing nations, turning an internal skill-levelling tool into a global driver of wealth polarisation.

3. Methodology & Analytical Model

To evaluate these asymmetric dynamics, this paper builds a conceptual comparative framework analysing two representative archetypes across the international landscape.

3.1 Country Archetypes Comparison

Structural Feature	Developed Economy Archetype (e.g., US, Germany)	Emerging Economy Archetype (e.g., India, Brazil)
Labour Supply Elasticity	Inelastic (Ageing demographics, skilled labour scarcity)	Highly Elastic (Youth bulges, vast informal pools)

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Dominant Service Sector	High-value R&D, strategic management, IP-heavy	Business Process Outsourcing (BPO), IT support, data entry
Digital Capital Stock	High concentration of cloud compute & proprietary LLMs	High reliance on imported APIs & consumer-tier software
Social Safety Net	Robust (Unemployment insurance, universal basic services)	Fragmented or entirely absent formal safety nets
Tax Base Composition	Highly reliant on corporate and personal income taxes	Heavily reliant on indirect taxes, tariffs, and informal trade
Infrastructure Readiness	Ubiquitous 5G, continuous power grids, high device access	Intermittent power grids, localized connectivity, hardware deficits

3.2 Production Function Specification

We model the aggregate production function (Y) through a nested Constant Elasticity of Substitution (CES) structure to illustrate how algorithmic capital alters labour margins across different stages of economic development:

$$Y=\left[\alpha K_{A}^{\rho }+\beta L_{H}^{\rho }+\gamma (L_{L}^{\sigma }+AI^{\sigma })^{\frac{\rho }{\sigma }}\right]^{\frac{1}{\rho }}$$

Where:

- ✓ K_{A} represents specialised AI compute capital (including server farms, GPUs, and specialised tensor processing arrays).
- ✓ L_{H} is high-skilled cognitive labour, capable of structural system design, complex prompt optimisation, and strategic oversight.
- ✓ L_{L} is low-skilled cognitive labour, responsible for routine operations, basic script compliance, data entry, and basic verification.
- ✓ AI is the effective labour-substituting volume of deployed generative agents and automated software instances.
- ✓ ρ dictates the elasticity of substitution between top-tier inputs and the broader operational layer ($\epsilon_\rho = 1 / (1 - \rho)$).
- ✓ σ dictates the internal elasticity of substitution between manual human workers and automated software instances within the lower operational layer ($\epsilon_\sigma = 1 / (1 - \sigma)$).

3.3 Elasticity Parameters and Wage Equations

In tasks involving routine cognitive work, the substitution elasticity between automated instances and entry-level human labour approaches infinity ($\sigma \rightarrow 1$). Conversely, top-tier compute capital (K_{A}) and high-skilled labour (L_{H}) serve as strong complements, meaning their structural elasticity of substitution is extremely low or negative.

To determine the wage rates for high-skilled labour (W_{H}) and low-skilled labour (W_{L}), we calculate the marginal product of each labour pool by taking the partial derivatives of the aggregate production function:

$$W_{H}=\frac{\partial Y}{\partial L_{H}}=\beta L_{H}^{\rho -1}\cdot Y^{1-\rho }\cdot \left[\alpha K_{A}^{\rho }+\beta L_{H}^{\rho }+\gamma (L_{L}^{\sigma }+AI^{\sigma })^{\frac{\rho }{\sigma }}\right]^{\frac{1}{\rho }-1}$$

$$W_{L}=\frac{\partial Y}{\partial L_{L}}=\gamma L_{L}^{\sigma -1}(L_{L}^{\sigma }+AI^{\sigma })^{\frac{\rho }{\sigma }-1}\cdot Y^{1-\rho }\cdot \left[\alpha K_{A}^{\rho }+\beta L_{H}^{\rho }+\gamma (L_{L}^{\sigma }+AI^{\sigma })^{\frac{\rho }{\sigma }}\right]^{\frac{1}{\rho }-1}$$

By isolating the skill premium ($\omega = W_H / W_L$), we can evaluate the structural drivers of internal wage polarisation:

$$\omega =\frac{\beta }{\gamma }\left(\frac{L_{H}}{L_{L}}\right)^{\rho -1}\left(1+\left(\frac{AI}{L_{L}}\right)^{\sigma }\right)^{1-\frac{\rho }{\sigma }}$$

This formulation reveals a critical macroeconomic insight: when software substitution (AI) increases, the impact on the skill premium depends heavily on the ratio of automated instances to human labour (AI / L_L) and the baseline elasticity metrics (ρ and σ).

In developed economies, where the supply of high-skilled labour (L_{H}) is relatively scarce and infrastructure capital (K_{A}) is abundant, the skill premium rises because high-tier workers directly manage and optimise automated networks. In emerging markets, an oversupply of low-skilled cognitive labour (L_{L}) facing direct substitution from automated software (AI) suppresses the denominator, driving up wage inequality despite lower concentrations of domestic technological infrastructure.

4. Empirical Discussion: The Asymmetric Impact

4.1 Developed Economies: The Capital-Deepening and Task-Reallocation Phase

Advanced economies adopt GenAI through intensive capital deepening. Because wage floors are high, labour unions add structural friction, and high-skilled labour is scarce, businesses have strong financial incentives to integrate GenAI systems directly into enterprise operations.

4.1.1 The High-Skill Wage Premium

High-skilled workers who successfully incorporate GenAI into their workflows see their marginal productivity rise significantly. For example, a senior software engineer using automated programming tools can focus on architecture and design rather than syntax debugging, allowing them to manage complex systems in less time.

Similarly, a financial analyst utilising automated tools to run real-time risk simulations can handle larger client volumes and focus on high-value strategy. This dynamic increases their marginal economic value to the enterprise, allowing them to capture higher compensation and driving up the upper-tail wage premium within advanced labour markets.

4.1.2 The Middle-Skill Displacement Cushion

Workers in middle-tier administrative, paralegal, and basic copywriting positions face real displacement as automation scales. However, because advanced economies possess substantial capital buffers, dynamic consumer demand, and robust service sectors, this displaced labour can often be reallocated into high-touch human interaction roles, such as strategic account management, collabourative education, clinical care coordination, and advisory services.

While frictional unemployment rises during these transitions, systemic institutional support—including unemployment insurance, corporate retraining programs, and government-subsidized certification pathways—helps cushion the shock, reducing the risk of long-term poverty traps for displaced workers.

4.2 Emerging Economies: The BPO Attrition and Platform Exploitation Trap

In emerging economies, the labour market dynamics unfold under very different parameters, which can lead to severe wage compression and structural polarization.

4.2.1 The Decoupling of Export Services (BPO Attrition)

For decades, emerging markets like India, the Philippines, and Poland leveraged lower domestic labour costs to anchor global service supply chains, covering customer support, software maintenance, and medical transcription. GenAI directly automates many of these workflows at a lower marginal cost.

As Western corporations deploy localized conversational agents and automated programming interfaces, international demand for entry-level, offshore white-collar labour faces sharp drops. The resulting labour oversupply within emerging domestic markets forces wages down across the local white-collar spectrum, as displaced workers compete for a shrinking pool of traditional service roles.

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4.2.2 The Rise of Platform Mechanics and the Data Proletariat

While high-value AI design and model development remain concentrated in developed tech hubs, the backend pipeline relies on low-paid manual labour for data annotation, reinforcement learning from human feedback (RLHF), and content moderation. This has fueled a sprawling gig-platform economy across regions like Sub-Saharan Africa and South Asia.

On these global platforms, workers face piece-rate compensation models with minimal bargaining power, missing benefits, and zero upward wage mobility. This creates an uneven international division of labour: developed economies own the high-yield intellectual capital, while emerging economies provide the highly elastic, low-cost data labour required to maintain those systems.

4.2.3 Worsening Domestic Wealth Disparity

The small, highly educated elite within emerging markets—those with advanced technical degrees and access to international venture capital—can leverage GenAI to scale local fintech, logistics, and consumer applications, capturing significant wealth.

Meanwhile, the broader labour force is often cut off from these gains due to systemic gaps in hardware access, unstable electrical grids, and language barriers, since many foundation models are optimized for major western languages. This dynamic drives an internal wealth gap that can outpace the polarization seen in developed nations, as the local tech elite detaches from the economic realities of the broader domestic workforce.

5. Strategic Solutions and Policy Frameworks

To prevent GenAI from locking in global labour inequality, we outline four concrete, actionable interventions designed for international implementation.

5.1 Algorithmic Automation Tax and Re-Investment Funds

To offset the rapid decline of corporate tax bases as labour income shifts to automated systems, countries should evaluate a targeted tax on algorithmic automation. This mechanism targets corporate windfalls generated by replacing large segments of white-collar labour with proprietary automated agents.

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The revenue generated from this tax should flow into dedicated **Sovereign Human Capital Development Funds**. These funds would provide direct funding for technical retraining programs, helping displaced service workers transition into specialised domestic roles like clean energy installation, public healthcare coordination, and physical infrastructure modernisation. By taxing the automated substitution of labour, governments can convert technological displacement into a sustainable revenue source for human capital development.

5.2 Dynamic Skill Architecture and AI Literacy Infrastructure

Traditional university degrees operate on multi-year cycles that cannot keep pace with the iterative shifts of generative software. Educational systems need to transition to a continuous, dynamic training model.

1. **AI Skill Vouchers:** Governments should issue digital training vouchers directly to citizens, allowing them to purchase modular, industry-verified micro-certifications in human-AI collaboration, prompt optimisation, and data governance.

2. **Infrastructure Investments:** Emerging nations must actively bridge the foundational digital divide by subsidising high-speed fibre connectivity, scaling edge computing infrastructure, and ensuring public schools have affordable access to open-source foundation models. This approach ensures that entering workers possess the baseline technical capabilities required to work alongside AI tools rather than being replaced by them.

5.3 Global Platform Standard Harmonisation

To prevent cross-border exploitation within digital gig platforms, an international regulatory framework is required. Under the guidance of organisations like the International Labour Organisation (ILO), member states should establish basic labour baselines for distributed digital workers. This framework must require international technology firms to implement transparent algorithmic pay minimums, provide mental health support for content moderators dealing with sensitive material, and establish clear mechanisms for dispute resolution.

By standardising digital platform labour regulations globally, countries can prevent an international "race to the bottom" where multinational firms exploit gaps in domestic labour protections to arbitrage data labour costs.

5.4 Sovereign Open-Source Model Repositories

Emerging economies must actively avoid absolute dependence on closed-source, foreign cloud architectures. By building and supporting localised open-source model repositories trained on regional languages, cultural frameworks, and domestic economic data, governments can foster independent technological ecosystems. This infrastructure empowers local small businesses and tech entrepreneurs to build tailored software solutions without paying costly licensing fees to foreign corporate monopolies. Developed collectively through regional alliances, these open-source frameworks allow emerging markets to maintain digital sovereignty, retain domestic data assets, and capture a larger share of automation-driven productivity gains.

6. Implementation Matrix & Policy Roadmap

The table below outlines a structured timeline and distribution of institutional responsibilities to transform these strategic concepts into measurable policy outcomes:

Policy Initiative	Primary Institutional Owners	Short-Term Focus (1-2 Years)	Medium-Term Focus (3-5 Years)	Long-Term Target (5+ Years)
Algorithmic Automation Tax	Ministries of Finance, Central Banks, Internal Revenue Authorities	Establish audit metrics for automated agents and register cloud-compute assets.	Roll out automated windfall taxes on enterprises that replace labour at high margins.	Integrate automated asset revenues directly into national social security networks.
Dynamic Skill Architecture	Departments of Education, National Skill Development Corps	Launch public AI literacy voucher systems and distribute digital skill credits.	Transition higher education into modular, short-cycle micro-credentials.	Achieve continuous, lifelong skill re-alignments across the domestic labour force.
Global Platform Harmonisation	International Labour Organisation (ILO), Trade Unions, Ministries of Labour	Mandate transparent algorithmic pay baselines and verify data on worker compensation.	Enforce cross-border dispute resolution systems for platform contractors.	Standardise international legal protections for all distributed digital labour.
Sovereign Open-Source Models	National Research Councils, Telecomm Authorities, Tech Consortia	Allocate state funding for regional language data collection and model design.	Deploy subsidised, open-source localised LLM access for small businesses.	Eliminate dependence on closed-source, foreign proprietary software monopolies.

7. Conclusion

Generative Artificial Intelligence is redefining the relationship between technology, productivity, and labour distribution. Our analysis demonstrates that if left to unregulated market forces, GenAI deployment is highly likely to drive asymmetric wage inequality, both within and between nations. While developed economies possess the institutional resilience and capital depth to reallocate displaced workers, emerging markets face immediate risks from service export erosion, digital platform dependency, and worsening internal wealth gaps.

Mitigating this technological polarisation requires shifting from reactive interventions to proactive structural policies. By instituting algorithmic tax frameworks, building dynamic lifelong learning systems, harmonising global platform labour standards, and investing in sovereign open-source digital infrastructure, the global community can decouple technological progress from economic inequality. The goal of digital economics should be a balanced framework where automation boosts human capability across all levels of development, rather than concentrating wealth among a select few.

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