

How can mathematical modeling and economic theory be used to predict and manage the impact of generative AI on labor market dynamics in emerging economies?

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Abstract

Generative Artificial Intelligence (AI) is transforming the operations of economies, i.e., the way labor markets develop. While advanced economies already incorporate these changes, developing economies have a more complicated scenario. On the downside, they are vulnerable—thanks to their absence of infrastructure, high informality, and shortage of skills. On the upside, they have a special opportunity to bypass conventional development phases if they are able to accomplish the AI changes. This essay discusses the ways mathematical modeling and economic theory can aid in predicting and managing the effects of generative AI on labor market forces in developing economies.

Theoretical models of skill-biased and routine-biased technological change and Schumpeter's creative destruction capture how AI may substitute, rebuild, or complement human labor. Mathematical models of Computable General Equilibrium (CGE) models, Dynamic Stochastic General Equilibrium (DSGE) models, agent-based simulations, and task-level exposure analyses allow policymakers to estimate sectoral impacts, identify at-risk worker groups, and capture the effect of alternative policy choices.

The paper assesses AI adoption heterogeneity across industries and income groups and how such heterogeneity threatens to exacerbate global inequality. It also discusses policy interventions—like upskilling initiatives, worker protection, inclusive AI regulation, and public-private partnerships—that can ensure AI adoption is more inclusive. Based on international data sets, empirical analysis, and case studies from India and Nigeria, the essay plots a feasible course of action.

Finally, the article contends that the fate of developing economies with generative AI is not predetermined. With proper data, vision, and concerted policy effort, they can create a future where AI enhances human work, directs fair growth, and reduces—instead of expanding—the global development gap.

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I. Introduction

Generative Artificial Intelligence (AI), a rapidly expanding branch of machine learning, is now one of the century's most transformative technologies. Unlike the majority of AI applications, which are specifically designed to spot patterns or label data, generative AI models such as ChatGPT, DALL·E, and others have the ability to create entirely new content — from text and images to code and music. Already, this is revolutionizing creative industries, powering service automation, and enabling new forms of work. High-income economies already begun to adapt to these changes, but emerging economies — with emerging infrastructure, fast-growing labor markets, and a higher percentage of informal work — pose a unique set of challenges and opportunities.

It is crucial that we know the impact of generative AI on the working world of developing economies. These economies are heavily reliant on industries that are susceptible to automation, such as manufacturing, agriculture, and BPO. Although these economies will also benefit from "leapfrogging" technologies, these can also bypass traditional development paths. But unless they are forecast and addressed by prudent policy interventions, generative AI can further aggravate marginalization, displace vulnerable workers, and hamper inclusive growth initiatives.

This is where mathematical modeling and economic theory come in. These provide a formal structure for evaluating and predicting the effects of changes like generative AI on employment, productivity, and wages. Models such as Dynamic Stochastic General Equilibrium (DSGE) or Computable General Equilibrium (CGE) allow economists to simulate the consequences of different policy choices and predict in what sectors job losses or gains will occur. Meanwhile, economic theories such as Schumpeter's creative destruction or skill-biased technological change allow for a theoretical structure to explain determinants of labor market change, providing a conceptual framework within which one can place model results.

The emergence of generative AI, represented by the spread of large language models, represents a deeper change than preceding waves of automation. Technology has historically aimed at automating routine, manual,

and physical work. Conversely, generative AI capabilities encompass advanced cognitive functions such as analysis of data, content generation, and strategic problem-solving. This has created a distinct phenomenon whereby high-level, white-collar jobs, previously presumed to be proof against automation, are some of the most vulnerable. Although in higher-income economies, the analyses suggest a considerable proportion of jobs, about 60%, may be affected, they are not evenly spread across the world. In low-income and emerging economies, a reduced initial exposure of 40% and 26% was noted. However, this reduced exposure is not an indication of resilience; it tends to result from a more intense concentration of jobs in manual and agricultural industries and absence of the digital infrastructure necessary for extensive AI implementation. This asymmetry may induce a "winner-takes-all" phenomenon, potentially reducing the labor-cost lead of developing countries and exacerbating global imbalances, as some authors have warned.

This research is prompted by the deep puzzle of ignorance and complexity about the effect of generative AI on labor market trends in emerging economies. The extant literature, though expanding, is predominantly descriptive or concerned with the unique economic institutions of developed countries. It is typically based on fixed measures of employment exposure that do not capture the dynamic interactions of a host of variables, such as rates of technological diffusion, human capital formation, and institutional adaptability. For policymakers in developing economies, this analysis gap means a wide policy vacuum. Lacking a credible mechanism for anticipating the long-run consequences of generative AI, they must respond to, not anticipate, technological shocks. The issues are multi-dimensional, including the requirement to modernize digital infrastructure, the transformation of educational systems, and the creation of social safety nets that can be responsive to high-velocity technological change. A robust, predictive framework is therefore absolutely essential to bridge speculation and offer a basis for evidence-driven policy.

My motivation for studying this topic lies in the desire to use strict quantitative techniques for tackling urgent societal issues. The combination of fast-paced technological change and complex socio-economic systems offers an optimal intellectual landscape for investigation. Through creating and implementing mathematical models to solve this issue, I aim to help provide a better understanding of the forces that will define the global economy, and offer practical insights that will assist in making the rewards of this new era of technology accessible to all.

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II. Conceptual Basis

a. What is Generative AI

Generative AI is artificial intelligence software that can create new content instead of interpreting or analyzing existing information. They use enormous data sets and advanced machine learning to create human-sounding text, graphics, music, or even software code. Famous examples are ChatGPT, which can write essays or answer intricate questions in natural language, and image models like DALL·E. Generative AI is different from traditional automation software based on pre-coded rules in the sense that it can create new outputs based on intricate inputs, and that makes it especially effective in knowledge work, customer service, design, and content creation.

While generative AI holds the promise to make us more productive and creative, its ability to replicate work hitherto thought to be the exclusive preserve of human beings is at once marvelous and frightening. Of concern are not only who will lose their jobs, but how fast and unevenly these changes will happen, especially in countries that are still reeling from previous stages of technological adoption.

b. Emerging Economy Labor Market Dynamics

Younger, larger labor forces in developing economies, rapidly expanding digital connectivity, and mixed formal and informal work are typical. These conditions determine the way labor markets respond to technological change. The majority of the emerging economies have a high proportion of workers in routine and low-skilled jobs such as agriculture, manufacturing, and elementary services. These jobs are very vulnerable to automation, including generative AI, which can do repetitive communication, data entry, or even simple design.

At the same time, these economies are likely to have weaker social protection systems, restricted access to tertiary education, and lower investments in frontier technologies. This makes the potential disruption from

generative AI harder to handle. But it also presents unique opportunities: emerging markets are not bound by existing systems and can skip ahead to new AI-based industries if the appropriate investments are made.

Demographic trends count too. India, Nigeria, and the Philippines are all experiencing youth bulges in their populations, which could be a source of competitive strength for the world's digital economy — if youth workers are equipped with the appropriate skills. Without coordinated policy, AI has the potential to displace young workers before they are established in the labor market, increasing unemployment and inequality (Tony Blair Institute for Global Change, 2023).

c. Economic Theories Relating to Labor and Technology Introduction

There are a range of economic models that can be used to explain in which ways generative AI could impact employment, wages, and economic structure. Perhaps most often referred to is the Skill-Biased Technological Change (SBTC) model. This posits that technological change creates more demand for higher-skilled labor and less opportunity for lower-skilled employment. Generative AI, with the ability to automate both routine manual tasks and cognitive tasks, may even do so for middle-skilled work, driving labor markets towards polarization.

Routine-biased technological change is another central idea, which explains how technology substitutes rule-based and repetitive work — physical (such as factory work) or cognitive (such as mundane bookkeeping). Generative AI can speed it up by automating complex but routine work across sectors.

The theory of creative destruction, originally described by economist Joseph Schumpeter, also comes into play. It accounts for how innovation tends to drive out current industries to pave the way for new ones. In the case of AI, it implies that some jobs will be destroyed, but others will be formed — but the journey can be bumpy, particularly where institutions are poor or infrastructure is underdeveloped.

These theories are useful lenses but must be calibrated to the emerging economy reality. Where education is uneven and informality prevails, the impact of AI might not be the same in developed economies.

d. Mathematical Modeling in Labor Economics Overview

To connect theory and real-world savvy, economists apply mathematical models. Models simulate the effect on jobs, productivity, wages, and income distribution of technology, policy, or market shifts.

Arguably the most widely used instrument is the Computable General Equilibrium (CGE) model. It captures interdependencies between sectors, companies, and families within an economy and subjects system impacts to shocks — i.e., an unusually rapid rate of AI adoption — to simulation. CGE models are particularly well-suited to capture how generative AI might affect various sectors at once and to test policy interventions like tax credits or training subsidies (Bughin et al., 2018).

The second is the Dynamic Stochastic General Equilibrium (DSGE) model, which allows for uncertainty and time. These models are useful for examining how labor markets react in the short, medium, and long run. They can account for variables such as consumer choice, firms' investment, and government expenditure as well as provide an extremely accurate employment forecast.

Agent-based models are also picking up steam. These model individual behavior (e.g., employees changing jobs, firms embracing technology) to study how macro trends emerge. In countries with informal economies or segmented markets, agent-based models may better capture realities than ideal-market models.

In addition, input-output models can model the impact of a change in one industry (e.g., automation of call centers) on related industries (e.g., telecommunications or retail). They give an indirect job loss or gain estimate and are useful when estimating the net effect of generative AI.

While these models are valid, they are extremely assumption and data quality-sensitive, and assumptions drawn from those of developed economies — that can limit accuracy. For the majority of emerging economies, there is little or no credible labor market data, especially for informal work. Models consequently need to make assumptions or use proxies based on those of developed economies — that can limit accuracy. With local knowledge combined, however, these models are helpful to policymakers who must balance employment and innovation (IEDC, 2023).

Briefly, the impact of generative AI on emerging markets' labor markets requires theory and empirical work. Economic theory describes mechanisms of change, and mathematical modeling allows one to forecast predictions and evaluate policy choices. Both are the foundation for the remainder of this essay, which will outline how generative AI-driven labor transformations can be predicted through modeling, sector-specific risks can be managed, and responsive policy can be informed.

III. Modeling the Effect of Generative AI: Tools and Techniques

In assessing the potential of generative AI to reshape labor markets in developing nations, mathematical modeling—ranging from macroeconomic simulation to task-level analysis—takes precedence. The following are basic model types and their uses:

a. Macro-Economic Models: CGE and DSG

Computable General Equilibrium (CGE) models follow sectoral interactions among households, firms, and industries. They can forecast employment, wage, and output changes by simulating adoption shocks like the sudden deployment of generative AI in industries. CGE models are particularly useful for cross-sector ripple effect analysis and policy simulation like training subsidies or sectoral tax credits (Bughin et al., 2018).

Dynamic Stochastic General Equilibrium (DSGE) models include uncertainty and time horizons. They are most useful in investigating how labor markets rebalance over several years as a result of productivity gains, investment changes, or consumption shifts.

These models are particularly valuable to developing countries because they enable policymakers to weigh various possible scenarios—e.g., rapid AI deployment or phased implementation—and estimate inequality versus growth trade-offs.

b. Task- and Firm-Level Models: System Dynamics & Agent-Based Modeling

System dynamics models give a macro-perspective of feedback loops—i.e., the way in which AI automation affects demand, incomes, and hence aggregate consumption. System-dynamics modeling suggests that a recessionary spiral can occur if AI capital accelerates human labour too rapidly unless new job creation is able to offset displacement (Li et al, 2025).

Agent-based models track the behavior of individual agents—workers, firms, institutions—to trace how the collective outcome arises from micro-decisions. They are particularly powerful where there are large informal sectors or large heterogeneity in the skill of workers.

c. Task-Exposure Models and Empirical Impact Estimation

Sophisticated approaches have developed occupation-level automation vs augmentation exposure indices. For instance, a synthetic difference-in-differences estimation found that after the introduction of generative AI, occupations in high-automation exposure groups fell by ~17 %, whereas augmentation-prone occupations rose by ~22 % in listings and needed skill sets similarly updated (Chen et al, 2024).

These precise models assist in capturing the manner in which generative AI impacts labor demand—not just in direct job loss but through changes in wage structures, task composition, and new jobs.

d. Emerging Market Modeling Problems

A significant concern is data limitations: there are informal economies, restricted occupation data, and no real-time labor data, which complicate parameterization of models. Patterns of diffusion differ: AI diffuses quickly to urban technology sectors but lags in rural or informal labor markets.

Global models have to be adapted: too many indices and parameters (e.g. from US/EU labor studies) are not easily translatable to low- or middle-income contexts (Andersson Lipcsey, 2024).

IV. Sectoral and Skill-Level Impacts

To understand how labor markets will be affected by generative AI, one must see beyond national means to specific industry and job categories. Diverse industries, activities, and skill levels will experience AI adoption differently—ranging from total takeover by AI to partial augmentation by AI. In the developing economies, where industry structures are just as diverse from those of high-income countries, these impacts can be just as disrupting and transformative.

a. Sectors Most at Risk

The most vulnerable areas in the emerging economies are repetitive and routine tasks. Industry, agriculture, and customer services—areas with millions of workers—already see the beginning of automation driven by AI.

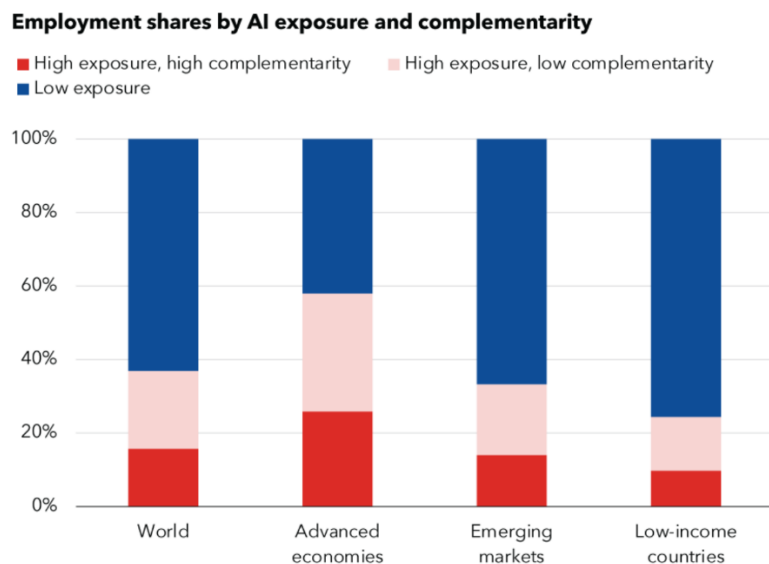
For example, business process outsourcing (BPO), a significant employer in India and the Philippines, is highly exposed. Generative AI platforms can now manage customer service calls, process insurance claims, and produce written work—functions that were previously performed by call center and administrative staff. The International Economic Development Council claims that such technologies can actually substitute services jobs that rely on standardized communication and documentation (IEDC, 2023).

In agriculture, AI may not necessarily replace farm labor in the short term but can have an influence on upstream and downstream industries—supply chain management and food processing—using intelligent automation, predictive analysis, and inventory management. These changes in the long term may reduce the need for low-skilled workers while increasing demand for technology-driven agricultural services.

Manufacturing is also under threat. Low-skilled assembly-line jobs in poor countries can be replaced with AI-based robots, particularly in export-oriented industries such as textiles or electronics. Automation will,

however, also be more gradual in this case than in high-income economies due to higher upfront costs and relative labor value (Bughin et al., 2018).

IMF's study examines the potential impact of AI on the global labor market. Many studies have predicted the likelihood that jobs might be replaced by AI, but in many cases AI is likely to complement human work. Most jobs are exposed to AI in advanced economies, with smaller shares in emerging markets and low income countries. The following graph highlights the same:



Source: International Labour Organization (ILO) and IMF staff calculations
Note: Share of employment within each country group is calculated as the working-age-population-weighted average.

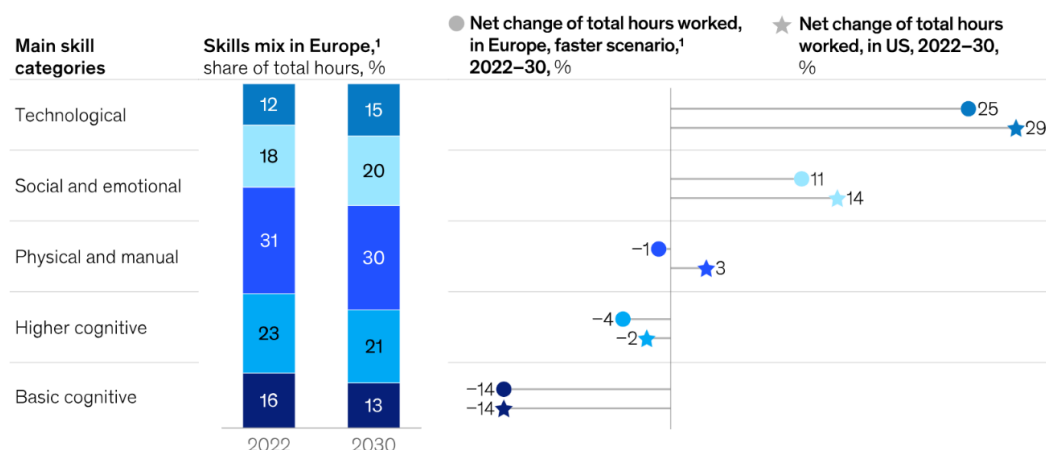
IMF

Source: ILO, IMF 2024

“In advanced economies, about 60 percent of jobs may be impacted by AI. Roughly half the exposed jobs may benefit from AI integration, enhancing productivity. For the other half, AI applications may execute key tasks currently performed by humans, which could lower labor demand, leading to lower wages and reduced hiring. In the most extreme cases, some of these jobs may disappear. In emerging markets and low-income countries, by contrast, AI exposure is expected to be 40 percent and 26 percent, respectively” (Georgieva, 2024).

These findings suggest emerging market and developing economies face fewer immediate disruptions from AI. At the same time, many of the emerging and developing countries don't have the infrastructure or skilled workforces to harness the benefits of AI, raising the risk that over time the technology could worsen inequality among nations. It implies that advanced economies face greater risks from AI—but also more opportunities to leverage its benefits—compared with emerging market and developing economies.

The following chart shows how automation and AI will accelerate the shift in skills that the workforce needs (US and Europe):



Source: McKinsey and Company, 2024

b. New Roles and New Skills Demand

While there are certain jobs that will be replaced by generative AI, others will be enhanced and new ones created. Those requiring technical proficiency in combination with human ability—such as AI model trainers, content editors, customer experience designers, and healthcare technologists—are set to grow.

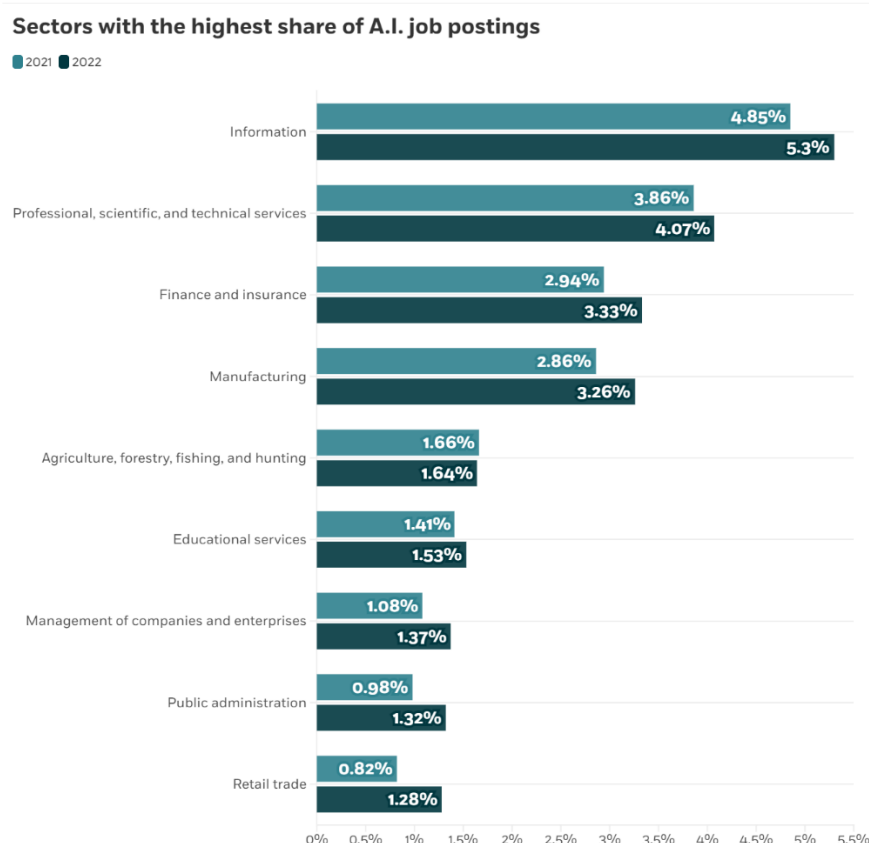
The Tony Blair Institute highlights that AI-capable, flexible, and soft-skilled work is becoming increasingly valuable. They encompass work where AI technologies are used to complement productivity rather than replace human discretionary judgment—like teaching, nursing, or small business management (Tony Blair Institute, 2023). Significantly, such work often requires hybrid skills that are currently under-prioritized in most emerging-market education systems.

Second, AI is reshaping skill sets in existing jobs. For example, marketing experts can now use AI tools to create campaign roadmaps, but will have to become specialists in strategy, data analysis, and ethical oversight. This transformation highlights the need for continuous upskilling and not one-time career shift.

Sectoral spread of AI job postings shows that generative AI has uneven take-up across industries. The following figure shows the most common cluster of AI job postings for 2021 and 2022 was under Information, followed by Professional, Scientific, and Technical Services, Finance, and Manufacturing. However, retailing, education, and public administration had relatively much lower percentages (Artificial Intelligence Index Report, 2023).

This development has two consequences. First, regions of established data concentration and digital infrastructure are inducing the adoption of AI, which serves to heighten sectoral divides. Second, regions of traditionally lower exposure—i.e., agriculture or retail—should anticipate experiencing delayed but disruptive change when lower-order models and applications are made more widely available.

The Chicago Booth Review further states that this differential diffusion will not necessarily render the labor market effect of AI immediate and pervasive, but rather localized and staged—upending certain professions and areas but leaving others relatively unaffected (Acemoglu & Restrepo, 2023). This provides room for social protection and reskilling programs to develop, if governments proceed.



Source: Artificial Intelligence Index Report 2023

c. Case Examples

In India, there is the early application of AI in technology outsourcing and services, leading to retraining labor in prompt engineering, AI support, and data labeling. Without the funding of training facilities by the government, rural workers and small companies will not benefit from it.

In Nigeria alone, more than 80% of employment is in the informal sector (Medium, 2024). AI will not replace informal workers directly, but it can disrupt sectors like mobile banking or logistics services if local players cannot compete with platform-based players. A VoxDev (2024) study revealed that generative AI has been raising productivity levels among skilled workers but increasing the wage differentials for low-skilled low-income workers in Bangladesh and Kenya. Such a trend suggests that if generative AI is left without reskilling and inclusive policy, it will increase income inequality in emerging economies (VoxDev, 2024).

V. Policy Responses and Management Strategies

Though generative AI presents undeniable dangers to the labor markets of emerging economies, there exist policies that can reverse disruption and harness AI for inclusive growth. The most effective policy interventions typically blend skill upgradation, institutional change, and investment in AI-appropriate sectors. Economic modeling and labor projection guide these policies by looking at where the most effective interventions are needed and most likely to achieve.

a. Competency Training and Continuing Learning

The optimum widely proposed response to the employment effect of generative AI is investing in skill development and continuous learning. The majority of workers in emerging economies may not be substituted in the near term, but their roles will shift rapidly. To prepare them to change, there must be upskilling programs with a focus on digital literacy, critical thinking, and AI-based processes.

Private sectors and governments need to work together to design modular, scalable training. For example, public-private training centers, vocational training attached to AI hardware, and online microcredentials can efficiently close the skills gaps. The Tony Blair Institute also highlights that industry-relevant short-term training, particularly for youth and women, can greatly enhance resilience to automation (Tony Blair Institute, 2023).

First and foremost, training programs cannot be reserved only for "tech" experts. With AI technologies going ubiquitous across all sectors, even agricultural, commercial, or public administration work will need basic AI literacy and data competence.

b. Constructing Labour Market Institutions and Social Protection

To reduce labor displacement, more robust labor institutions and safety nets are required. Unemployment insurance, official job-matching services, and labor protections are absent or feeble in most emerging economies. These deficiencies make AI-induced job loss particularly disastrous for the vulnerable.

They are used by governments to simulate the social and budgetary impacts of different support programs, such as wage subsidies, conditional cash transfers, or compensation for the loss of employment. These allow governments to make safety nets cost-effective and also well-targeted.

A few policy analysts have even suggested testing Universal Basic Income (UBI) in regions that are most at risk of being automated. As polarizing as UBI, it would act as a buffer for such transitioning populations—particularly in rural or informal economies where formalization of employment is not possible (IEDC, 2023).

c. AI-Driven Industrial Policy and Economic Diversification

Besides protecting existing jobs, policymakers ought to steer AI adoption into industries that can generate new ones. The emerging economies have a strategic benefit of integrating AI with clean energy, logistics, education, and healthcare—where AI can enhance, but not replace, labor-intensive services.

This requires a more sophisticated industrial policy, which aligns incentives, infrastructure, and R&D expenditure with national development long-term goals. Governments may also encourage AI-responsible entrepreneurship by offering tax credits, grants, or innovation sandboxes to AI-applying start-ups that tackle local issues.

According to the McKinsey Global Institute, economies that proactively seek AI adoption—through research spending, open data, and labor market policy—are likely to experience positive employment and productivity growth (Bughin et al., 2018).

d. Leveraging Public-Private Partnerships

Public-private partnership is at the heart of all aspects of addressing the labor effects of AI. The private sector owns most AI technology and infrastructure, and the government sets the enabling environment via education policy and regulation.

Effective partnerships may be:

- Government-industry collaborative reskilling programs that were co-funded
- Arrangements for sharing information to improve labor market prediction
- Innovation clusters or AI incubators with focus on addressing region-specific issues

The creation of national AI task forces or advisory boards with representation from labor unions, academia, industry, and government can offer a cross-sector coordination mechanism.

VI. International Cooperation and Global Governance

The change in the labor market caused by generative AI does not remain within national borders. Exclusion, exploitation, and uncontrolled technology spillover are real risks to the development of emerging economies. Hence, international cooperation and global good governance are required to make generative AI a tool of inclusive development and not a tool for increasing inequality.

a. Global Coordination towards AI Ethics and Standards

Maybe the biggest challenge of AI regulation is the lack of global standards for safe, ethical, and inclusive deployment that are universally accepted. Most AI technologies deployed in the emerging economies are produced in the Global North, with limited local adaptation to prevailing labor conditions or cultural practices. This can result in algorithmic bias, job loss, or abuse of technology.

To reverse this trend, global institutions such as the OECD, UNESCO, and World Bank have started to demand global AI governance standards that put a high value on fairness, transparency, and human rights. Such standards need to be broadened to encompass labor market effects—such as preventing AI systems from perpetuating discriminatory labor market hiring or wage compression.

Newer economies need to be accorded more voice in the formulation of these frameworks. Currently, many low-income countries have no voice internationally in AI policymaking, as such platforms are dominated by the great technology powers. The creation of regional blocs or coalitions, such as through the African Union or ASEAN, may accord them more bargaining power.

b. Cross-Border Support for Skills and Infrastructure

Another area of collaboration is international investment in AI digital infrastructure and human capital. The majority of the emerging economies are confronted with a double challenge: neither availability of AI technology nor human capital readiness to adapt to it. Cross-border development cooperation can be the bridge.

This entails investment in AI-training education programs such as coding schools, AI education in schools, and technical training of teachers. Development banks and multilateral institutions also need to invest in enhancing broadband penetration, cloud computing infrastructure, and local language AI models—especially in underdeveloped regions.

As the Tony Blair Institute states, countries that build robust partnership among local authorities, global tech companies, and global NGOs will be most likely to benefit from AI innovation without suffering its risks (Tony Blair Institute, 2023).

c. Avoiding "AI Colonialism" and Data Exploitation

Another issue on the cards is the risk of "AI colonialism" whereby developing economies become sources of data and sources of low-cost labor (e.g., to label data) without receiving much benefit from AI technologies. This is in imitation of historical patterns of resource extraction and unbalanced trade relations.

To prevent this, global regulation must include balanced data policies that are respectful of sovereignty, privacy, and value-sharing at the national level. Countries must be helped to build their own regulatory capacity to handle AI firms with operations in the country. Local innovation systems—i.e., AI start-ups, and research institutions—must be encouraged to prevent excessive reliance on technology imports (VoxDev, 2024).

While doing so, countries should adopt open data and knowledge-sharing partnerships that encourage inter-cooperation in AI research, particularly in mitigating global challenges like climate change, health care, or disaster relief.

d. Role of Multilateral Institutions

Governments, trade unions, and labor organizations are also at the core of facilitating knowledge exchange and policy coordination. They can also assist the emerging economies in establishing labor market monitoring systems and AI-readiness indices through which they can track and forecast future manpower requirements. For example, Bughin et al. (2018) observe that harmonized global policy and knowledge sharing are essential to making AI benefits more levelled, especially since job loss and productivity growth are not experienced evenly everywhere.

VII. Future Directions and Recommendations

The advent of generative AI is ushering profound changes to the labor markets of the world. Although young economies have specific weaknesses—e.g., poor infrastructure, informal work, and poorly developed social safety nets—there is also promise of seizing the strategic deployment of AI technology. Policymakers should

introduce foresight-driven approaches based on data, modeling, and regional circumstances to ensure generative AI becomes a force for collective expansion and not for widening inequality.

This section offers necessary guidance to governments, international partners, and institutions within emerging economies regarding how they can better manage the labor market transformation brought about by generative AI.

a. Enhance Data Gathering and Labor Market Monitoring

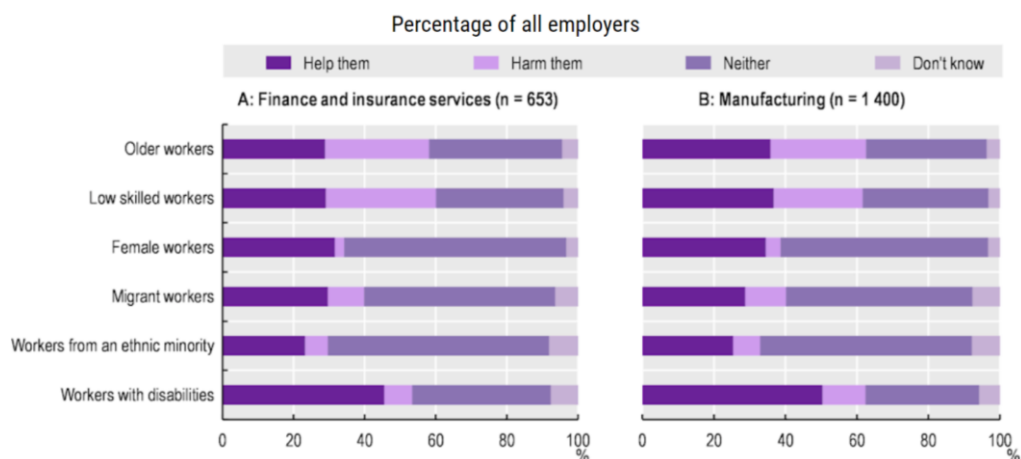
Improvement in labor market statistics systems is the most basic and first recommendation. Most of the developing economies suffer from poor, patchy, or incomplete labor statistics—particularly in the informal economy. This undermines evidence-based policy making and weakens mathematical modeling.

Governments should invest in:

- Real-time labor market information systems
- AI exposure indices specific to local professions
- Electronic job and skills mapping software
- Surveys that include informal, rural, and gender-disaggregated information

Better data enables better modeling of sectoral risk and the potential impact of AI technologies. AI technologies like task-level exposure mapping, which are already utilized in OECD economies, must be localized and applied. The World Bank and other international bodies can provide technical support to incorporate such tools in country planning systems (Bughin et al., 2018).

AI is not only dangerous to labor markets but also a chance to rectify long-standing imbalances—if offered the correct policies. The following figure reveals that employers in finance and manufacturing both have negative and positive attitudes toward the effect of AI on disadvantaged groups of workers. While almost half of the employers who were interviewed are of the view that AI can assist disabled workers, the majority view AI as likely to hurt low-skilled workers (and older workers, particularly in manufacturing), Lane et al. (2023).



Source: OECD Survey, 2023

These mindsets reveal the urgency for intervention. For instance, if low-skilled and older workers are most likely to be replaced, governments must invest in low-cost reskilling and digital upskilling focused on addressing their needs. Moreover, although employers believe that women would benefit from AI, women in their own workforce are less confident that AI will enhance the quality of their work, reflecting a gender perception gap between women and employers that must be closed through workplace inclusivity strategies.

AI policy-making should therefore not just protect jobs, but also ensure inclusiveness through fair access to new employment opportunities, training, and technology across various demographic categories.

b. Stress Equitable Development of Digital Infrastructure

Digital infrastructure access—broadband, device, cloud—is the basis for the adoption of generative AI. Without it, the potential for AI to boost productivity and jobs is out of reach for hundreds of millions of workers and entrepreneurs in developing economies.

Most rural or low-income communities do not have accessible internet, sufficient computing, or even basic digital hardware. To close these gaps, public investment and public-private partnerships are needed. Governments can focus on:

- Rural broadband rollouts
- Subsidy internet for poverty-level families

- Artificial Intelligence computing centers or cloud facilities for SMEs
- Native language corpus and AI model support

Equity must be prioritized in plans for infrastructure development. Otherwise, AI will widen existing digital divides and exclude vulnerable groups—especially women, the disabled, and those living in rural areas—from new job opportunities (Tony Blair Institute, 2023).

c. Design Flexible, Modular, and Inclusive Training Systems

Education and training systems need to shift away from fixed, degree-based systems to modular, flexible, and lifelong learning systems. The work environment is evolving too rapidly for traditional systems to catch up.

Recommendations are:

- Offering micro-credentials and short courses emphasizing in-demand AI-adjacent skills
- Integrating AI literacy across school and university curriculums
- Develop publicly sponsored upskilling programs for career middle-class workers
- Enabling women and vulnerable groups through adaptive, accessible training models

Notably, skill policies have to be synchronized with the outcomes of economic modeling. For example, if CGE models indicate high exposure to AI in manufacturing but new employment in logistics and health tech, training programs have to anticipate and facilitate the transitions (IEDC, 2023).

To achieve this role, governments need to establish national skills councils that include employers, educators, and researchers as well. These councils can review training priorities from time to time based on data and market indicators.

d. Foster Local AI Innovation and Entrepreneurship

Not only must emerging economies implement AI created elsewhere, but also build the ability to innovate with AI themselves. This means:

- Funding regional AI research centers
- Incubating technology startups and SMEs creating context-specific AI products
- Encouraging universities to engage with industry in AI innovation
- Creating regulatory frameworks to enable moral AI testing

Incentives such as grants, AI innovation hubs, and procurement processes can trigger local innovation in domains such as public administration, health, education, and agriculture. Frugal innovation, which is low-cost, resource-saving AI system development, can also enable broader diffusion in the regions and income groups.

As VoxDev (2024) highlights, countries that allow bottom-up experimentation with AI will be better placed to construct employment advantages while reducing undue reliance on foreign technologies and platforms.

e. Embrace Inclusive AI Policy and Governance Frameworks

Effective AI regulation must go beyond data privacy or cybersecurity—it must go as far as the labor market level. That includes developing national AI policies that deal specifically with:

- Workers' rights in an AI economy
- Role of AI in job displacement and reskilling
- Ethical standards for automated recruitment, tracking, and assignment

Policymakers have to ensure that AI use does not perpetuate exclusion or inequality. For instance, automated selection systems applied in recruitment or keeping track of productivity have to be governed to prevent discrimination against specific groups.

They also need to set up consultative institutions—the civil society groups, industry associations, and labor unions—to collectively craft AI policy. This creates legitimacy and public confidence in tech transformations (Tony Blair Institute, 2023).

f. Harness Regional and International Partnerships

Few of the emerging economies can make AI transitions independently. Cross-border cooperation is necessary to exchange knowledge, share resources, and harmonize standards.

Governments should:

- Create or become members of local groups for AI skill building and research
- Work towards greater representation on global AI governance platforms
- Access global education and infrastructure funding
- Collaborate on open-source AI platforms and open data to reduce the cost and increase participation

Development partners including the World Bank, UNDP, and African Development Bank can help countries in the establishment of AI-readiness frameworks and technical capacity building.

As Bughin et al. (2018) state, nations that collaborate on AI strategy and best practice stand a better chance of benefiting economically and inclusively, while those that isolate stand to be left behind economically and technologically.

g. Stimulate Job Creation in AI-Supporting Industries

Not all industries will be losing jobs. Some will be gaining jobs, particularly those where AI will boost productivity but not by sacrificing jobs. They are:

- Healthcare: Diagnosis using AI, record-keeping, telemedicine
- Transport and logistics: route planning and warehouse management
- Education: Personalized learning tools, AI-based learning
- Building and energy: smart infrastructure, project modeling

Policy should positively incentivize investment and employment in such AI-enabling sectors. Labour market modeling can direct subsidies, workforce planning, and incentives into the most employment-generating sectors. Generative AI offers emerging economies an opportunity to leapfrog—provided they get the policies right. By enhancing data systems, broadening access, investing in skills, and influencing innovation, governments can create a world where AI complements human work rather than replaces it. The answer lies in strategic foresight: using economic theory and modeling to not only predict the impact, but to direct it towards equity, sustainability, and shared prosperity.

VIII. Conclusion

The rise of generative AI is one of the most important 21st-century technology revolutions, with profound impacts on labor markets, productivity, and economic systems. In the developing world—where most people have vast informal sectors, youth bulges, and weak digital infrastructures—the stakes are especially enormous. While AI holds the promise of unleashing development, bypassing industrial phases, and producing new forms of employment, it also contains real dangers: job displacement via automation, skills mismatch, increased inequality, and foreign technology dependence.

This essay has explored how economic theory and mathematical modeling can also provide important guidance on how to manage those difficult transitions. From task-oriented job displacement modeling to computable general equilibrium (CGE) models for macroeconomic impact simulation, these tools provide governments in emerging economies with a rich toolset with which to predict AI's impacts and construct policy interventions that are effective, evidence-based, and resilient.

a. Summary of Main Findings

We began with the fundamental premises that frame the influence of generative AI on labor markets. Generative AI affects not only repetitive manual labor, but also cognitive, creative, and professional work—writing, designing, coding, and teaching. The broad range of effects thus amplifies the extent of labor transformation across both low-skilled and high-skilled labor. In emerging economies, the effect is superimposed on already existing vulnerabilities like informality, education deficits, and low digital penetration.

Theory in economics helps differentiate such concerns by distinguishing substitution effects (AI replacing human labor) from complementarity effects (AI complementing human productivity). Task-based frameworks illustrate that the impact of AI depends on a job's task structure and not the job itself. It can mechanize a teacher's lesson plans, for instance, but classroom engagement remains human-oriented. Attending to this nuance is crucial while crafting adaptive workforce strategies.

Then came mathematical models, namely CGE models, labor demand-supply projections, and occupational exposure scales, that were identified as suitable for simulating the impact of AI on employment, wages, productivity, and poverty. The models allow governments to conduct scenario analysis that allows them to experiment with the impact of different policy options before they are finalized. In developing economies where resources are limited, such forward planning is not a luxury—it is a matter of survival.

b. Strategic Implications for Policymakers

The middle sections of the essay outline certain ways of implementing these observations in the management of labor transitions. Some main priorities were spelled out:

- The development of skills must be prioritized in national AI agendas. Rather than upskilling high-tech experts only, inclusive, scalable, and modular upskilling must be prioritized for the whole workforce. AI literacy must be integrated into formal education and adult training settings (Tony Blair Institute, 2023).
- Institutions of the labor market—ranging from unemployment benefits to job-matching sites—must be expanded and digitized. The majority of informal workers in developing economies lack or have minimal basic protections and are thus highly vulnerable to being displaced by technology. Wage subsidies, portable benefits, and conditional income support must be tried and tested in economic frameworks for their impact.

- Encouragement of AI adoption should be promoted by policy directed at both productivity-enhancing and employment-absorbing industries. The industries include health care, agriculture, logistics, education, and public services. Governments should replicate and target investment and incentives in industries most likely to create net employment (Bughin et al., 2018).
- Regional innovation systems have to be developed to promote indigenous production of AI tools and services. Far from being passive consumers of foreign technology, developing economies need to invest in locally grown AI startups, research centers, and applications specific to local issues. VoxDev (2024) finds that nations that invest in local AI innovation are better protected from economic shocks from the global economy.
- Global governance structures must be equitable and inclusive. International policymaking with AI today is controlled by high-income economies. In order to be effective and fair, global structures must include the interests of the Global South—like equitable data practice, workers' rights, and digital sovereignty.

c. Challenges and Considerations

With the potential of these strategies, there are several challenges:

1. The data limitations in most low-income countries prevent the accurate modeling of the impacts of AI. Off-the-books employment, informal employment, and farm employment are typically not measured well in official statistics. The gap will be bridged through indigenous reform complemented by international support.
2. Political will and institutional capacity are missing. Sectors, levels of government, and ministries need to coordinate for effective AI transition management. Fragmented policies or responsive governance are typical problems in most countries. Long-term institutions that will guide digital transitions need to be built.
3. Social and ethical risks of AI—i.e., surveillance, algorithmic discrimination, and job deskilling—must be addressed alongside economic imperatives. If employees are left feeling dehumanized or exploited by AI, adoption will be thwarted. Human-centered design, worker advocacy, and rights-based governance are core to long-term adoption.
4. Imbalances within the global economy can become more profound if emerging economies remain behind in infrastructure and access to AI. Lacking coordinated global investment in digital public goods, development disparities can widen even if productivity rises across the globe.

These challenges underscore the need for adaptive governance—policymaking that is iterative, participatory, and responsive to feedback in real-time.

d. The Path Forward: A Balanced Approach

In the future, the goal cannot be to oppose adoption of AI, or to take on its adoption wholesale. Instead, policymakers in emerging economies must tread a middle course—using the techniques of mathematical modeling and economic theory to guide forward-looking, inclusive, and evolutionary approaches.

Some proposals for the next decade are:

- Establish National AI-Labor Observatories that publish exposure indices, sector outlooks, and policy dashboards at regular intervals. They can be linked with the technical support of development agencies and universities.
- Establish AI Workforce Transformation Plans at national and regional levels, updated every 2–3 years, based on modeling data and stakeholder engagement.
- Integrate AI literacy into national secondary school and higher level curricula, not as a technical competency but as a civic competency—such as media literacy or environmental literacy.
- Host AI innovation challenges for addressing public-sector issues—e.g., how to leverage AI to improve tax revenue collection, agricultural extension services, or small business credit access.
- Form regional AI alliances to share research, experience, and policy lessons, especially in Africa, South Asia, and Latin America. This could enable joint bargaining and shared infrastructure.

e. Final Reflection

Ultimately, the impact of generative AI on the labor markets of emerging economies is not predetermined. It will be in the balance, depending on choices made today—by governments, workers, firms, and international institutions. With smart, evidence-based, and inclusive policies, AI can be a tool of spreading opportunity, rather than replacing it.

Mathematical modelling and economic theory give us the vision to be able to foresee problems before they are in place, and to create wise, situational solutions. The question is not whether AI will re-make the future of work—but whether we are prepared to design that future in ways that are just, equitable, and sustainable.

IX. Limitations of the Analysis

While analysis for the purpose of this essay has highlighted potential and danger of generative AI for emerging economies, prevailing limitations remain.

a.Challenges of Data and Measurement

Comprehensive, current labor market statistics are not common for most emerging markets, particularly the informal sector. This makes it difficult to parameterize macro models like CGE and DSGE, which need exact data. Assumptions of high-income economies adopted as proxies may distort inferences. What's worse, measuring the "exposure" of jobs to AI is intrinsically problematic: the job will by necessity contain both substitution (automation of repetitive jobs) and augmentation (productivity increase by means of IA). The statistics at hand do not tend to reflect these subtleties, and displacement might thus be overpredicted and augmentation underpredicted.

b.Limitations of Model and Theory.

By definition, mathematical models are abstractions. CGE and DSGE models tend to assume rationality and efficient markets, a situation that could prevail less in economies characterized by informality, weak institutions, and restricted worker mobility. Likewise, theoretical models such as Skill-Biased Technological Change were formulated in the tradition of preceding automatization and do not necessarily reveal how generative AI destroys not just routine but also higher-skilled white-collar occupations.

c.External and Unexpected Forces.

Finally, AI's future is shaped by forces that act outside models: political will to establish policies, institutional capability to deliver social protection, and the global regulatory environment. Geopolitics, global norms, and crossborder data flows will all remake AI adoption and models cannot forecast. Final Reflection. The future of emerging economies in the era of generative AI is not set in stone. The technology is global, but its impact is profoundly local and varied. A multi-dimensional response—based on hard data, good economics, and flexible modelling—is the optimal way forward. With imagination and strategic policy-making, generative AI needs to be used not to exacerbate the development divide, but to bridge it, making it an engine of inclusive growth, not of polarization.

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