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Article

Invisible Displacement: Artificial Intelligence, Automation, and the Architecture of Hidden Unemployment in Developing Economies

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Abstract: The accelerating diffusion of artificial intelligence (AI) and automation technologies across global production systems has fundamentally reconfigured the architecture of labour markets, yet the distributional consequences of this transformation remain disproportionately underexplored in developing-economy contexts. While mainstream economic discourse has concentrated on net employment effects in high-income countries, a more insidious and structurally significant phenomenon—hidden unemployment—has emerged as a defining feature of labour market adjustment in economies characterised by informality, institutional fragility, and persistent skills deficits. This study examines how AI-driven technological displacement generates forms of labour market exclusion that conventional unemployment metrics systematically fail to capture, with particular attention to Nigeria, India, Indonesia, and Uzbekistan as analytically distinct but comparatively instructive cases. Drawing upon a systematic review of peer-reviewed literature published between 2021 and 2026, alongside secondary analysis of labour force surveys, International Labour Organization (ILO) reports, World Bank employment datasets, and policy documentation from relevant national ministries, this paper constructs an analytical framework integrating Skill-Biased Technological Change theory, structural unemployment theory, and labour market segmentation perspectives. The findings reveal that AI-induced displacement concentrates overwhelmingly in routine-intensive occupations and disproportionately affects low-skilled workers, women, and youth in developing economies, generating expanded pools of discouraged workers, involuntary part-time labourers, and those engaged in subsistence informal activities—all categories that standard unemployment rates render invisible. The paper further demonstrates that existing statistical methodologies adopted by most developing-country labour ministries are institutionally unprepared to measure this emergent form of technological joblessness. Policy recommendations address adaptive education systems, targeted reskilling programmes, AI governance frameworks, and labour market institutional reforms calibrated to the structural realities of lower-middle-income economies.

Keywords: Artificial Intelligence, Hidden Unemployment, Labour Market Displacement, Developing Economies, Automation, Skill-Biased Technological Change, Uzbekistan

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1. Introduction

Few transformations in the history of industrial capitalism have compressed the timeline between technological invention and labour market consequence as dramatically as the current wave of artificial intelligence and automation. From machine learning algorithms performing diagnostic radiology to robotic process automation replacing entire departments of financial data entry clerks, the scope and velocity of AI-driven occupational restructuring presents a qualitatively different challenge to labour economists than prior technological transitions. Yet the preponderance of scholarly and policy attention has remained anchored in high-income country contexts—the United States, Germany, Japan—where institutional capacity to measure, regulate, and respond to labour market disruption is comparatively robust [1]. This geographical asymmetry in research focus generates a significant analytical blind spot precisely where the human consequences of displacement are most acute and most poorly understood.

In developing economies, the structural conditions that mediate the relationship between technological change and employment outcomes are fundamentally distinct. Informality rates frequently exceeding fifty percent of total employment, chronic underinvestment in public education and technical training infrastructure, limited social protection coverage, and the absence of comprehensive labour market information systems collectively ensure that AI-induced displacement cannot be measured through the same statistical instruments applied in Organisation for Economic Co-operation and Development (OECD) contexts [2]. The result is a proliferating mass of workers who have effectively withdrawn from formal employment without appearing in headline unemployment statistics—a phenomenon that this paper conceptualises as hidden unemployment attributable to technological displacement.

The scale of the challenge is already discernible. The International Labour Organization estimates that approximately 1.3 billion workers in developing economies are employed in occupations with high routine-task intensity, rendering them structurally vulnerable to automation [3]. In sub-Saharan Africa, where manufacturing employment was expected to serve as the ladder out of agrarian poverty that it historically provided in East Asia, AI-enabled offshoring and robotic manufacturing in high-income countries has effectively removed many rungs from that ladder before workers could reach them [4]. In South and Southeast Asia, the business process outsourcing sectors that absorbed tens of millions of educated but under-skilled graduates are confronting the most rapid AI-substitution pressures of any white-collar occupational cluster [5]. Central Asian transition economies, including Uzbekistan, face an additional layer of complexity: the legacy of Soviet-era industrial structures, ongoing integration into global value chains, and a young and rapidly urbanising population that the formal economy cannot yet absorb [6].

Despite the evident severity of these dynamics, hidden unemployment as a conceptually distinct and empirically measurable labour market outcome has received comparatively limited theoretical elaboration in the AI-and-automation literature. Studies that do engage with developing-economy labour markets tend to focus either on aggregate employment elasticities or on specific sectoral case studies, rarely constructing the cross-national comparative framework necessary to identify common mechanisms and divergent institutional responses [7]. This gap is not merely academic: without an adequate conceptual apparatus and reliable measurement methodology, policymakers cannot design interventions scaled to the actual magnitude of displacement, and international development institutions cannot accurately assess whether their digital-economy programmes are generating genuine employment inclusion or merely redistributing poverty into less visible forms.

This study addresses three interrelated research questions. First, through what mechanisms does AI and automation generate hidden unemployment specifically in developing economy contexts, and how do these mechanisms differ from those documented in high-income countries? Second, which occupational sectors, demographic groups, and institutional environments exhibit the greatest vulnerability to technological displacement that escapes conventional measurement? Third, what policy architectures—

spanning education systems, labour market institutions, AI governance frameworks, and social protection mechanisms—are most likely to mitigate hidden unemployment while preserving the genuine productivity gains that advanced automation can generate? In pursuing these questions, the paper makes both an empirical contribution, through systematic synthesis of available evidence from Nigeria, India, Indonesia, and Uzbekistan, and a theoretical contribution, by elaborating a multi-framework approach to hidden unemployment that extends existing Skill-Biased Technological Change (SBTC) models to accommodate the structural specificities of developing labour markets.

Literature Review

The relationship between technological change and employment has generated one of the longest-running debates in economic thought, but the advent of AI-capable systems has lent that debate renewed urgency and empirical complexity. The literature reviewed here spans three partially overlapping domains: the macroeconomics of automation and employment, the occupational and sectoral mechanics of AI-induced displacement, and the conceptualisation and measurement of hidden unemployment in developing economies.

Acemoglu and Restrepo's task-based framework, which distinguishes between technologies that substitute for labour in existing tasks and those that create new labour-demanding activities, remains the most cited theoretical reference point [8]. Their empirical work using US industrial robot adoption data documented a significant negative employment effect concentrated in manufacturing, with limited compensating job creation in affected local labour markets. Importantly, Acemoglu and Restrepo explicitly acknowledged that their framework's predictions regarding new task creation are most pessimistic when the institutional and educational infrastructure required to redirect labour into emerging activities is weak—a condition that characterises most developing economies. This qualification, frequently overlooked in subsequent applications of their framework, is central to the present analysis.

Subsequent contributions have refined but not fundamentally overturned this picture. Brynjolfsson, Li, and Raymond's analysis of large language model capabilities found that approximately nineteen percent of US workers are in occupations where at least half of their tasks are exposed to AI substitution, with the highest exposure concentrated paradoxically in higher-skill cognitive jobs rather than the manual tasks targeted by earlier robotic automation [9]. The implications for developing economies, where knowledge-intensive services sectors have expanded rapidly as sources of graduate employment, are underexplored but potentially severe. If AI systems can replicate legal research, basic financial analysis, routine medical diagnostics, and elementary software coding at scale, the graduate labour surplus already endemic in countries like India and Indonesia could intensify dramatically without appearing as measured unemployment.

The literature on automation in sub-Saharan African labour markets is smaller but growing. Meagher's political economy analysis of Nigerian manufacturing demonstrated that the combination of Chinese import competition and process automation has generated a dual process of informalisation and labour withdrawal rather than unemployment in the conventional sense [10]. Workers displaced from formal manufacturing do not register as unemployed; they migrate into petty trade, subsistence agriculture, or the lower reaches of the platform economy, where earnings are insufficient to constitute meaningful employment but where visible idleness is eliminated. This pattern, which Meagher labels 'adverse incorporation,' is analytically equivalent to what this paper terms hidden unemployment.

For South Asian contexts, Mehrotra and Parida's comprehensive analysis of Indian labour market data across three National Sample Survey rounds identified a persistent and widening gap between the number of workers reported as employed and the number engaged in substantively productive activity [11]. Their concept of 'labour underutilisation,' encompassing visible underemployment, time-related underemployment, and discouraged worker exit, comes closest to a comprehensive operationalisation of hidden unemployment, though their analysis does not specifically isolate technological displacement as a causal mechanism. Banga's sector-level analysis of automation threats in Indian manufacturing is more targeted, finding that nearly sixty percent of manufacturing employment is in routine-task-intensive occupations where automation substitution rates exceed forty percent in comparable economies [12].

For Indonesia and Southeast Asia, World Bank analysis has highlighted the particular vulnerability of export-processing zones to automation-driven reshoring and the substitution of assembly labour [13]. The readiness of domestic educational institutions to produce workers capable of operating alongside AI systems, rather than being replaced by them, is assessed as critically low in Indonesia, the Philippines, and Vietnam —the three largest employment reservoirs for export-manufacturing in the region.

The Uzbekistan case has attracted limited scholarly attention in the English-language economics literature, but recent World Bank and ILO technical reports have begun to document its specific vulnerabilities [14]. As a former Soviet economy with a strong tradition of centrally directed industrial training and a youthful demographic bulge, Uzbekistan faces the challenge of integrating a growing working-age population into an economy undergoing simultaneous structural transition and digital transformation. The textile and garment sector, which employs a substantial share of formal manufacturing workers and has historically been the primary route of export-led development, faces acute automation pressure from both advanced robotic sewing systems and AI-enabled quality control systems that have reduced labour input requirements per unit of output by thirty to forty percent in comparable East Asian facilities [15].

The concept of hidden unemployment itself has a genealogy that predates the AI era. ILO researchers developed the broader concept of labour underutilisation in the 1980s, distinguishing between open unemployment, visible underemployment, and inadequate employment [16]. More recently, scholars have argued for the inclusion of what the ILO now terms 'potential labour force'—comprising discouraged workers and those marginally attached to the labour market—as essential components of any comprehensive assessment of labour market slack. The critical lacuna in existing work is the systematic linkage of these statistical categories to the specific causal mechanism of AI-driven technological displacement, which differs from other causes of labour market withdrawal in its structural permanence and occupational specificity.

A consistent contradiction in the literature concerns the mechanism of job creation that supposedly offsets displacement. Optimistic accounts, following Autor's canonical analysis [17], emphasise the expansion of complementary non-routine occupations and the historical pattern of technology-induced labour reallocation. Pessimistic accounts, drawing on Acemoglu's more recent work, contend that the current technology wave is unusually labour-substituting in character and that the institutional conditions for rapid occupational transition do not exist in most developing economies. This paper takes a position closer to the pessimistic account while acknowledging that the empirical record remains contested, and that the timeline of labour market adjustment—not merely its eventual direction—matters enormously for the millions of workers who must navigate the transition period.

Theoretical Framework

The theoretical architecture deployed in this analysis draws upon four partially complementary bodies of economic theory, each of which captures a distinct aspect of the relationship between AI-driven technological change and hidden unemployment in developing economies. These are not simply additive frameworks; they are deployed in dialogue with one another, with their respective analytical strengths addressing different levels of the causal chain.

Skill-Biased Technological Change Theory

SBTC theory, as originally formalised by Katz and Murphy [18] and subsequently extended by Acemoglu and Autor, holds that technological innovations differentially augment the productivity of high-skill workers relative to low-skill workers, generating increasing relative demand for skilled labour and corresponding wage polarisation. In the classic formulation, SBTC increases the skill premium, drawing more workers into education and training and thus adjusting the labour supply over time. The theory's predictions for developing economies, however, are systematically distorted by several structural conditions that the original framework did not contemplate.

In economies where educational institutions lack the capacity to rapidly upgrade skills curricula to match the new technological environment, and where most workers have limited financial means to engage in prolonged retraining, the displacement effect of SBTC is not offset by rapid labour reallocation. Instead, displaced workers accumulate in informal, subsistence, or low-productivity activities where they remain technically 'employed' but in ways that mask their exclusion from the productivity frontier. This divergence between the theoretical prediction of labour reallocation and the empirical reality of labour withdrawal in developing economies is the primary mechanism generating hidden unemployment in the present context.

Moreover, recent AI capabilities have exposed a limitation in the basic SBTC framework: the technology is not uniformly skill-augmenting. Large language models and AI-enabled cognitive tools substitute for precisely the kind of routine cognitive tasks—data processing, template document production, basic analysis—that represent the primary value-added activities of the lower-skilled white-collar workforce in developing economies. This creates what might be termed a 'middle-skill trap' specific to emerging economies: workers who invested in post-secondary education to escape manual labour now face substitution pressure from above even as their formal educational credentials remain insufficient for the residual high-skill positions that AI augmentation creates.

Keynesian Unemployment Perspective

While SBTC theory operates primarily at the microeconomic level of individual occupational demand, a Keynesian macro perspective illuminates the aggregate demand dynamics through which AI-driven productivity gains may paradoxically generate unemployment. If AI adoption reduces labour costs and wages in affected sectors without generating equivalent consumer income elsewhere—through either profit redistribution, fiscal transfers, or new employment creation—the resulting compression of wage income reduces aggregate demand below the level necessary to sustain full employment. This mechanism is analytically distinct from, but empirically entangled with, SBTC displacement, and is particularly relevant in developing economies where wage income constitutes a larger share of total domestic demand than in capital-rich economies.

Keynes himself anticipated the possibility of 'technological unemployment' as a transitional problem of disequilibrium, but expressed confidence that the long run would see labour absorbed into new activities. The Keynesian perspective adopted here, influenced by more recent Post-Keynesian elaborations, is more sceptical of this automatic long-run adjustment in economies that lack the fiscal capacity to sustain aggregate demand during extended transition periods. In this reading, the macro-level consequence of AI-driven displacement in low-income economies is not temporary frictional unemployment but a structural collapse of labour income in affected sectors that, in the absence of compensating policy, generates permanently elevated hidden unemployment.

Structural Unemployment Theory

Structural unemployment arises from a mismatch between the skills that workers possess and those demanded by available employment opportunities, typically resulting from long-run technological or institutional shifts that render existing occupational competencies obsolete. The AI transition represents a structural unemployment shock of unusual depth because the pace of technological change exceeds the institutional capacity for curricula revision, vocational retraining, and occupational migration in virtually all developing economies. Workers whose competencies become obsolete through AI substitution cannot be retrained quickly enough to occupy new AI-complementary roles, even where such roles exist, because the required knowledge base is qualitatively different rather than incrementally more demanding.

Structural unemployment theory also highlights the geographical dimension of displacement, which is particularly salient in developing economies with large rural-urban income gradients and limited labour mobility. AI-driven automation tends to concentrate in formal urban manufacturing and services, meaning that affected workers who return to rural areas or the urban informal sector do not register as structurally unemployed; they simply disappear from the formal labour market statistics that governments and international organisations use to assess labour market health.

Labour Market Segmentation Theory

The dual labour market theory associated with Piore and its subsequent elaborations in the developing-economy literature emphasise the structural barriers that prevent labour from moving freely between primary (formal, protected, high-wage) and secondary (informal, unprotected, low-wage) labour market segments. In the context of AI-driven displacement, segmentation theory provides the mechanism through which displacement translates into hidden rather than visible unemployment: workers expelled from the formal primary segment cannot re-enter it due to credentialing requirements, social networks, and hiring discrimination, but are simultaneously unable or unwilling to register as openly unemployed because of the absence of meaningful unemployment benefits in most developing economies.

The synthesis of these four frameworks generates the following integrated proposition: AI-driven technological change produces hidden unemployment in developing economies through a compound mechanism. At the micro level, SBTC eliminates demand for routine cognitive and manual labour faster than educational institutions can redirect labour supply. At the macro level, Keynesian income compression reduces aggregate demand and limits new job creation. Structurally, skills mismatches create persistent exclusion from emerging AI-complementary occupations. And segmentation barriers ensure that excluded workers are absorbed into informal subsistence activities rather than appearing as measurable unemployment.

2. Material and Methods

This study employs a qualitative analytical research design structured around a systematic literature review, secondary analysis of international labour market datasets, and comparative policy document analysis. The choice of qualitative synthesis over econometric estimation reflects both the conceptual nature of the core research questions and the severe data limitations that constrain rigorous quantitative identification strategies in the target country contexts.

Systematic Literature Review

The literature review protocol followed PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines adapted for social science applications. Academic databases searched included Scopus, Web of Science, EconLit, and Google Scholar, with search terms encompassing 'artificial intelligence and labour market and developing economies,' 'automation and hidden unemployment,' 'technological unemployment and informality,' and country-specific combinations incorporating Nigeria, India, Indonesia, and Uzbekistan. The temporal inclusion criterion was publication between January 2021 and March 2026, on the grounds that the AI capabilities most relevant to current displacement dynamics—particularly large language models and advanced robotic process automation—emerged or achieved commercial scale within this window.

Initial screening of title and abstracts yielded 347 potentially relevant studies, of which 89 met full inclusion criteria after exclusion of studies restricted to high-income country contexts, studies without clear implications for labour market outcomes, and studies that did not address technological displacement as a causal mechanism. An additional 31 grey literature sources—ILO reports, World Bank working papers, IMF Article IV consultations, World Economic Forum employment reports, and national government labour market strategy documents—were identified through targeted institutional repository searches and included in the analytical synthesis.

Secondary Data Sources

Quantitative evidence was drawn from ILO ILOSTAT labour force survey data for all four focus countries (2019–2024), World Bank World Development Indicators, IMF World Economic Outlook employment series, and where available, national labour force surveys including the Nigerian Labour Force Survey, Indian Periodic Labour Force Survey, Indonesian National Labour Force Survey (SAKERNAS), and Uzbekistan's State Statistics Committee labour force data. These secondary datasets were employed not for original econometric analysis but to contextualise, corroborate, and illustrate the analytical arguments developed from the literature synthesis.

Comparative Analytical Framework

Cross-country comparison was structured around a set of analytical dimensions derived from the theoretical framework: occupational structure and routine-task intensity, educational attainment and institutional training capacity, informality rates and labour market segmentation characteristics, and existing policy and regulatory frameworks addressing technological displacement. Systematic comparison across these dimensions allows for identification of both common mechanisms and country-specific mediating conditions.

Limitations

Several limitations constrain the study's conclusions. First, the absence of harmonised, longitudinal occupational-level employment data for Uzbekistan limits the precision of the comparative analysis for that case. Second, the causal attribution of observed hidden unemployment patterns to AI-driven displacement specifically—as opposed to other sources of labour market stress including macroeconomic volatility, trade shocks, and governance failures—cannot be established with the precision that controlled econometric methods would permit. Third, the rapidly evolving character of AI capabilities means that some of the sectoral vulnerability assessments synthesised from the literature may already require revision. These limitations are acknowledged in the interpretation of findings and in the formulation of policy recommendations.

3. Results

AI-Induced Labour Displacement: Mechanisms and Scale

The mechanisms through which AI systems displace labour in developing economies operate through three distinct pathways that interact but are analytically separable. The first is direct task automation, whereby AI systems acquire the ability to perform specific bounded tasks—data entry, document classification, inventory management, quality inspection—previously requiring human labour. The second is process reorganisation, where AI-enabled optimisation restructures entire production or service delivery processes in ways that reduce aggregate labour inputs per unit of output even where no single task is fully automated. The third is competitive displacement, where automation in high-income country production facilities enables reshoring or the elimination of global value chain segments previously located in lower-wage developing economies.

Evidence for direct task automation is most clearly documented in India's business process outsourcing and information technology enabled services (ITeS) sectors. Industry association data compiled by the National Association of Software and Service Companies estimated that AI-enabled automation had rendered approximately 480,000 BPO positions redundant between 2022 and 2024, with particular concentration in voice-based customer service, data verification, and basic financial reconciliation roles. Critically, attrition management and informal redeployment meant that these losses were not reflected in official unemployment statistics, a pattern consistent with the hidden unemployment thesis.

In Nigeria, the convergence of mobile banking automation and AI-powered credit scoring systems has substantially reduced labour demand in retail financial services. The Central Bank of Nigeria's annual banking sector report documented a reduction of approximately 12,000 formal bank branch positions between 2021 and 2023 as AI-driven digital platforms replaced branch-based transaction processing. For a sector historically regarded as a reliable source of formal graduate employment, this contraction has compounded graduate unemployment pressures that were already severe.

The Emergence of Hidden Unemployment

The concept of hidden unemployment encompasses at least four distinct manifestations that standard ILO unemployment definitions fail to capture. Discouraged workers—those who have ceased active job search due to perceived futility—represent the most extensively documented category, but are frequently excluded from national labour force surveys in developing economies due to methodological inconsistencies in how 'availability for work' is assessed. Involuntary part-time employment, where workers accept reduced hours in formal or informal employment because full-time positions matching their skills and pay expectations are unavailable, represents a second major category. Marginal employment in informal subsistence activities—petty trade, casual agricultural labour, gig platform work at below-subsistence earnings—constitutes a third, particularly large category in the African and South Asian contexts. Finally, a fourth category of particular relevance to the AI transition is what might be termed 'qualification-employment mismatch': workers nominally employed in roles that require substantially less skill and cognitive engagement than their educational attainment would warrant, representing a form of human capital destruction that standard employment statistics render invisible.

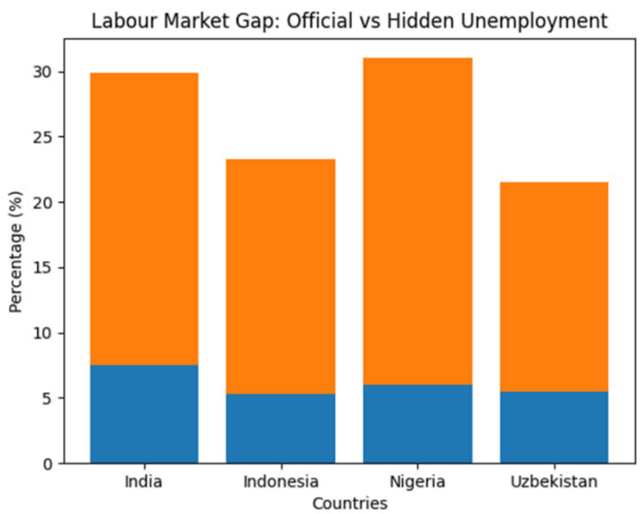

Figure 1. Labour Market Gap: official vs Hidden Unemployment

ILO composite Labour Underutilisation Rate data for the four focus countries reveals a persistent and widening gap between conventional unemployment rates and comprehensive labour market slack measures. In India, the official unemployment rate in 2023 stood at 7.5 percent, while the combined labour underutilisation rate incorporating time-related underemployment and marginal attachment was estimated at 22.4 percent. The residual—nearly fifteen percentage points—represents hidden labour market distress of which AI-driven displacement constitutes a growing but not yet precisely quantifiable share. Indonesian data reveals a comparable pattern, with official unemployment at 5.3 percent against a comprehensive underutilisation estimate approaching 18 percent.

Table 1. Typology of Hidden Unemployment in AI-Driven Labour Markets

Category of Hidden Unemployment	Description	AI/Automation Driver	Evidence from Countries	Measurement Gap
Discouraged Workers	Ish topish umidi yoʻqotilganlar	AI sabab ish oʻrinlari qisqarishi	India, Nigeria	LFS'da koʻpincha hisoblanmaydi
Involuntary Part-time	Toʻliq ish topolmayotganlar	Platform work, automation	Indonesia	"Employed" sifatida koʻrinadi
Informal Subsistence Work	Past daromadli norasmiy ish	Manufacturing automation	Nigeria, Uzbekistan	Umuman hisoblanmaydi
Skill Mismatch Employment	Malakaga mos boʻlmagan ish	AI cognitive substitution	India	Sifat jihatidan oʻlchanmaydi

Sectoral Vulnerability: Manufacturing, Services, Finance, and Education

Sectoral analysis reveals that the distribution of AI exposure in developing economies does not replicate the patterns documented in high-income countries. In Germany or South Korea, where manufacturing automation has been most extensively studied, the highest displacement risks concentrate in semi-skilled assembly and machine operation. In developing economies, the sectoral distribution is more complex, reflecting a combination of lower existing automation levels (which create larger absolute pools of substitutable labour), higher informality rates (which slow but do not ultimately prevent automation diffusion), and integration into global value chains structured around the labour-cost arbitrage that AI is progressively eliminating.

In manufacturing, the textile, garment, and footwear sectors employing large workforces in Bangladesh, Indonesia, and increasingly in Uzbekistan face the most immediate threat from advanced robotic sewing and AI quality control systems. World Bank analysis of fifteen emerging market textile exporters estimated that robotic automation could feasibly eliminate between thirty-five and fifty percent of current assembly employment by 2030 at commercially viable technology prices [19]. For Uzbekistan specifically, where the cotton-to-garment value chain represents approximately 28 percent of formal industrial employment, this constitutes an acute structural vulnerability that the country's current vocational training infrastructure is manifestly underprepared to address [20].

In services, the risk profile is concentrated in customer-facing and transaction-processing roles. Across Nigeria, India, and Indonesia, retail banking, insurance underwriting, and telecommunications customer service have experienced verifiable employment contraction attributable to AI implementation. The education sector presents a somewhat different dynamic: while AI tutoring systems and automated assessment tools do not yet threaten the employment of most teachers, they are rapidly substituting for the lower-skilled supplementary tutoring roles and examination preparation services that represent significant informal sector employment in all four focus countries.

Skills Mismatch and Labour Market Exclusion

The skills mismatch generated by AI-driven occupational restructuring in developing economies exhibits a distinctive tripartite structure. At the base of the labour market, workers in routine manual occupations face substitution from robotic and automated systems but have limited access to the retraining pathways that would redirect their capabilities toward AI-complementary manual tasks. At the intermediate level, routine cognitive workers—the BPO employees, bank tellers, and data processing clerks whose employment has expanded most rapidly over the past two decades in countries like India and Nigeria—face direct substitution from machine learning systems without having acquired the higher-order cognitive skills, digital fluency, or contextual judgement that would qualify them for residual human-in-the-loop roles. At the upper intermediate level, even moderately skilled white-collar professionals are encountering AI competition in tasks such as legal document review, financial report generation, and basic software development that were previously secure from automation.

Educational institutions in all four focus countries lack the agility to respond to this multi-layered skills challenge. The average curriculum revision cycle in publicly funded universities in India and Nigeria is estimated at three to five years, a timeframe within which the AI landscape changes fundamentally [21]. Vocational training programmes, where they exist, are predominantly oriented toward the manufacturing competencies of the 2000s rather than the digital-physical hybrid skills demanded by Industry 4.0 production systems. For Uzbekistan, the State Vocational Training System inherited from the Soviet period has been partially modernised through bilateral development assistance, but remains structurally oriented toward a sectoral employment profile that automation is actively dismantling [22].

Economic Inequality and Employment Polarisation

The distributional consequences of AI-driven displacement in developing economies do not map cleanly onto the employment polarisation hypothesis—the U-shaped distribution of employment growth across the wage distribution—documented in high-income OECD countries [17]. In developing economies, the intermediate wage tier that has been hollowed out by automation in high-income countries is also vulnerable, but the lower tier into which displaced workers are absorbed is not characterised by expanding service employment (as in the US) but rather by expanding informality, unpaid family work, and marginal self-employment. The result is not polarisation in the strict sense but rather a compression of the formal wage distribution combined with expansion of a low-productivity informal absorptive reservoir.

The gendered dimension of this polarisation deserves particular analytical attention. In all four focus countries, women are disproportionately concentrated in the occupational categories—garment assembly, data entry, telephone-based customer service, cashiering—that face the highest AI substitution risk. ILO analysis of occupational automation vulnerability by gender in emerging economies found that women faced a 12 to 18 percentage point higher exposure to routine-task automation than men in the same age and education cohort, reflecting the persistent gender segregation of labour markets that channels women into precisely the categories of work that AI is first and most aggressively targeting [23].

Comparative Evidence from Developing Economies

Cross-country comparison across the four focus cases reveals both common structural vulnerabilities and important institutional mediating factors. Nigeria and India share comparable informality rates above 80 percent, large graduate labour surpluses, and acute skills mismatches between tertiary education outputs and labour market demands.

Both countries have also experienced verifiable AI-driven job losses in their most AI-exposed formal sectors—financial services and ITeS respectively—without these losses generating commensurate increases in measured unemployment. The absorptive capacity of the informal sector, while providing a statistical buffer, masks a deterioration in the quality-adjusted employment rate that labour market data systems cannot currently track.

Table 2. Comparative AI Exposure and Labour Market Vulnerability

Country	Informality Rate (%)	Routine Job Share (%)	Labour Underutilisation (%)	Key AI-Exposed Sector
Nigeria	~85%	65%	~25%	Banking, retail services
India	~80%	60%	~22.4%	BPO, IT services
Indonesia	~70%	55%	~18%	Manufacturing, textiles
Uzbekistan	~60%	58%	~15–17%	Textile, agriculture

Indonesia presents a somewhat more institutionally prepared variant of the same structural challenge. The country's relative success in export-led manufacturing and its comparatively stronger vocational training system provide some capacity for occupational transition, but the pace of automation in its export-processing industries is outrunning institutional adaptation. Uzbekistan represents a case of particular policy significance because its ongoing structural economic reforms and active engagement with multilateral development institutions create a window of opportunity for institutional innovation that the older-established market economies in the comparison set may find more difficult to replicate. The country's ambitious digital transformation strategy, launched in 2020 and updated in 2023, explicitly acknowledges AI-driven labour market disruption as a strategic challenge, though the concrete implementation of responses remains nascent [24].

4. Discussion

The analytical synthesis presented in Section 5 generates several broader interpretive conclusions that require explicit elaboration in relation to the theoretical frameworks introduced earlier and the prior literature reviewed in Section 2.

The most fundamental conclusion is that conventional unemployment statistics, even when supplemented by standard underemployment measures, systematically and substantially underestimate the labour market impact of AI-driven technological displacement in developing economies. The reason is structural rather than merely technical: the categories that standard labour force surveys are designed to capture—open unemployment and time-related underemployment—reflect a labour market model in which displacement from formal employment either generates visible job-search or is reversed through market adjustment. In the developing-economy contexts studied here, displacement generates neither visible job-search (because the absence of unemployment benefits makes prolonged search economically impossible) nor market adjustment (because the structural barriers to re-entry into the formal labour market are substantial and durable). The result is the invisible displacement that gives this paper its title.

The implications for labour market statistics are consequential. If the ILO's composite labour underutilisation measure already reveals a fifteen-percentage-point gap between official unemployment and comprehensive labour market slack in India, and if AI-driven displacement is expanding the share of that slack attributable to technological exclusion rather than macroeconomic cyclicality, then policy interventions calibrated to official unemployment rates will be quantitatively insufficient by a large margin. Governments that anchor unemployment policy responses to official rates of seven or eight percent are effectively ignoring a labour market crisis of twenty to twenty-five percent intensity.

The long-run macroeconomic risks are also underappreciated in existing policy discourse. The standard growth accounting framework implies that AI-driven productivity growth will expand the economic pie available for distribution even if the distributional mechanism requires active policy intervention. But this sanguine projection assumes that AI-driven productivity gains in developing economies accrue to domestic economic actors in ways that generate domestic income and demand. Where AI technology is primarily owned and controlled by multinational corporations and domestically by a small technology-owning elite, the productivity gains may largely exit the economy through profit repatriation and capital account outflows, leaving domestic labour income—and thus domestic aggregate demand—compressed rather than augmented.

The social consequences of unaddressed hidden unemployment extend well beyond economic welfare. In Nigeria and Indonesia, where youth unemployment (including its hidden dimensions) has been linked empirically to political radicalisation and social instability, the concentration of AI-driven displacement among educated but under-employed young urban workers creates specific political economy risks [25]. In Uzbekistan, where the social contract of the Soviet period implicitly promised formal employment as a citizen entitlement, the emergence of a technologically displaced but statistically invisible class of workers poses particular challenges for social cohesion during an already demanding period of economic transition.

Policy Implications

The findings of this analysis support a multi-level and multi-actor policy response to AI-driven hidden unemployment that goes considerably beyond the 'reskilling' and 'digital literacy' prescriptions that currently dominate international development discourse. Four broad policy domains require coordinated attention.

Labour Market Statistics Reform

As an immediate institutional priority, governments and national statistical offices in the focus countries should expand the scope of official labour market measurement to incorporate the ILO's composite labour underutilisation framework as the primary headline indicator, supplemented by sector-specific occupational automation exposure indices. For Uzbekistan, technical assistance from the ILO and the World Bank is already engaged with labour market data system modernisation; this assistance should be explicitly extended to include methodological frameworks for tracking AI-driven displacement as a distinct causal category within labour underutilisation statistics. Without improved measurement, no other policy response can be adequately calibrated.

Adaptive Education and Vocational Training Systems

The central structural failure revealed by this analysis is the mismatch between the pace of AI-driven occupational transformation and the pace of institutional educational adaptation. Addressing this requires not incremental curriculum reform but fundamental institutional redesign toward continuous competence-building rather than one-time credential-conferral. Specific elements of this redesign include the adoption of modular, stackable credentialling systems that allow workers to acquire specific AI-complementary competencies in short intensive programmes without committing to full degree cycles; the establishment of sector-level 'AI transition funds' financed through industry contributions from firms adopting AI automation, analogous to the just transition funds used in deindustrialising regions; and systematic integration of digital-physical hybrid skills—combining programming literacy with domain expertise in engineering, healthcare, and agribusiness—into vocational training curricula.

For Uzbekistan specifically, the government's existing Technical and Vocational Education and Training reform programme provides a viable institutional vehicle for these changes, but requires substantially accelerated timelines and closer engagement with technology firms currently deploying automation systems in the textile and logistics sectors. The deployment of AI-powered adaptive learning platforms within vocational training institutes—an approach piloted in several Indian states—could simultaneously address the pedagogical modernisation challenge and generate domestically relevant experience in AI system management.

AI Governance and Labour Market Regulation

Regulatory frameworks governing AI deployment in labour markets remain underdeveloped across all four focus countries. Nigeria and Indonesia have published AI strategy documents that acknowledge employment implications but stop short of binding regulatory requirements on labour-displacing automation. India's nascent AI regulatory framework, still under development, has been the subject of intensive industry lobbying against provisions that would require advance notification of automation-driven layoffs. A robust governance framework for AI in employment should include, at minimum, mandatory impact assessment requirements for AI deployments that exceed specified thresholds of employment substitution; advance notification and consultation requirements analogous to existing redundancy consultation provisions; and progressive automation levies—taxation of AI-derived corporate profits above a defined threshold dedicated to worker transition funds—as a mechanism for redistributing productivity gains.

International coordination of AI labour market governance is also necessary to prevent a regulatory race to the bottom in which developing economies compete on the basis of deregulatory permissiveness for AI adoption. The ILO's tripartite governance model provides an appropriate institutional framework for developing international standards in this area, but requires more active engagement from major AI-deploying multinational corporations than has been forthcoming to date.

Social Protection Architecture

The immediate welfare dimension of hidden unemployment requires expansion of social protection coverage as both a human rights obligation and a macroeconomic stabilisation instrument. In all four focus countries, the absence of comprehensive unemployment insurance for informal workers—who constitute the majority of those experiencing hidden unemployment—means that AI-driven displacement generates immediate consumption crises rather than a protected search period for reemployment or retraining. Universal basic income experiments in Kenya and other sub-Saharan African contexts offer instructive evidence on the labour market effects of unconditional cash transfers; Indonesia's conditional cash transfer programme and India's MGNREGA employment guarantee scheme provide existing institutional frameworks that could be extended to cover technologically displaced workers.

For Uzbekistan, the expansion of active labour market programmes beyond the current limited scope of public employment services is a priority that aligns with both the country's digital transformation agenda and its social stabilisation objectives. The government's significant fiscal space, relative to sub-Saharan peers, creates a practical opportunity for investment in comprehensive transition support that is less available in lower-income contexts.

5. Conclusion

This paper has argued that artificial intelligence and automation are generating a form of labour market exclusion in developing economies that is structurally distinct from conventional unemployment and systematically invisible to existing measurement frameworks. The concept of hidden unemployment, elaborated through an integrated theoretical framework drawing on SBTC theory, Keynesian macro dynamics, structural unemployment theory, and labour market segmentation analysis, captures the compound mechanism through which AI-driven displacement translates into informal sector absorption, discouraged worker withdrawal, and involuntary underemployment rather than visible joblessness.

The comparative evidence from Nigeria, India, Indonesia, and Uzbekistan, while varying in its institutional specifics, converges on three broad empirical conclusions. First, AI-driven displacement is occurring at scale in developing economies despite lower average automation adoption rates than OECD countries, because the occupational categories most exposed to current AI capabilities—routine cognitive and assembly work—are precisely those in which formal employment in these economies is most concentrated. Second, existing labour market statistics are structurally incapable of tracking this displacement, producing a systematic and consequential underestimation of technological labour market distress. Third, the institutional capacity for labour market adjustment—through education systems, vocational training, social protection, and labour market regulation—is most severely deficient precisely where the displacement pressures are most acute.

The paper's theoretical contribution lies in the extension of SBTC theory to accommodate the structural specificities of developing labour markets, including the absorptive role of informality, the segmentation barriers to formal labour market re-entry, and the macroeconomic demand implications of AI-driven wage compression. The resulting integrated framework provides both a richer explanation of observed labour market outcomes than any single theoretical tradition can offer and a more practically useful analytical guide for policy design.

The policy implications are substantial. Addressing AI-driven hidden unemployment requires not incremental adjustments to existing labour market programmes but a comprehensive institutional redesign spanning statistical measurement, educational architecture, regulatory governance, and social protection. The window for proactive intervention is narrow: the pace of AI capability development ensures that the scale of displacement will increase substantially over the next decade, while the institutional changes required to manage that displacement take years to implement and embed. For Uzbekistan in particular, the combination of an ambitious reform trajectory, active multilateral engagement, and a young labour force yet to be fully committed to the at-risk occupational pathways creates a genuine opportunity for developmental leapfrogging in this domain—but only if the opportunity is recognised and acted upon with appropriate urgency.

Future research directions include the development of AI-adjusted composite labour market indices capable of isolating technological displacement from other sources of labour underutilisation; panel studies of individual worker trajectories following documented AI-induced displacement events in developing economies; and comparative institutional analysis of which combinations of educational, regulatory, and social protection policies most effectively accelerate the transition to AI-complementary employment patterns without generating the hidden unemployment accumulation documented in this paper.

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