Small AI for Job Creation in Emerging Economies: An Inclusive Framework

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Abstract

Employment remains the principal mechanism through which the benefits of economic growth are distributed. However, in emerging market and developing economies (EMDEs), working-age populations are expanding faster than labour markets can absorb, while employment remains concentrated in low-productivity informal sectors. This challenge may intensify as capital-intensive frontier Artificial Intelligence (AI) accelerates automation without generating sufficient employment opportunities in resource-constrained settings. This paper conceptualizes Small AI as a strategically underexplored pathway for inclusive job creation, particularly among small and medium-sized enterprises (SMEs), which account for approximately 80% of employment in developing economies. Drawing on task-based employment theory, SME productivity theory and Schumpeterian endogenous growth theory, the paper introduces the Small AI Employment Multiplier Framework (SAEMF). The framework explains how Small AI adoption can generate net employment through four interconnected channels: productivity enhancement, market expansion, enterprise formalization and complementary occupation emergence. It also provides an operational approach for activating and assessing these effects through firm-level implementation strategies, performance indicators and enabling conditions tailored to EMDE contexts. In addition, the paper translates the framework into a policy matrix for multilateral development institutions, governments and SME support organizations. By integrating theory, evidence and policy application, the study advances understanding of AI-enabled labour market transformation and offers practical guidance for inclusive growth, employment generation and sustainable development in developing economies.

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1. Introduction

The structural employment challenge confronting emerging market and developing economies (EMDEs) represents one of the most consequential development economics problems of the twenty-first century. Sub-Saharan Africa's working-age population is projected to expand more rapidly than any other developing region between 2025 and 2050, adding over 620 million people to its labour force. This figure according to World Bank (2025a) represent more than three-quarters of the net increase across all EMDEs. South Asia is also expected to expand significantly, with an increase of nearly 300 million people over the same period, while Southeast Asia and Latin America face comparable demographic pressures relative to their labour market absorption capacity (Gill & Kose, 2025; UN DESA, 2024). However, the absorptive capacity of EMDE labour markets has consistently failed to keep pace with this expansion. Globally, more than 2 billion workers are engaged in informal employment(ILO, 2023), representing approximately 58% of the global workforce. The incidence is substantially higher in developing regions, reaching 85.8% in Africa and 68.2% in Asia and the Pacific, with about 93% of all informal employment concentrated in emerging and developing economies (ILO, 2018). While employment is the primary channel through which individuals benefit from economic growth, this mechanism remains weak across most EMDEs. A large share of new labour market entrants is absorbed into low-productivity informal activities that provide limited income growth and weak poverty reduction effects. These conditions reflect a structural deficit rooted not merely in insufficient job numbers, but in the poor quality, low productivity and limited growth potential of available work. Consequently, the central labour market challenge in EMDEs is not only the creation of more jobs, but the generation of productive and inclusive employment at scale, capable of translating demographic expansion into sustained economic and social progress.

Compounding this challenge is the phenomenon of early deindustrialisation, which has progressively weakened the traditional channel through which earlier generations of economies achieved large-scale employment creation. Rodrik (2016) shows that deindustrialisation is no longer confined to advanced post-industrial economies but is increasingly evident in developing countries as well. In particular, manufacturing employment in Sub-Saharan Africa and Latin America tends to peak at much lower income levels and with smaller employment shares than those observed in earlier industrialisers, largely as a result of globalization and labor-saving technological change. Consequently, the conventional structural transformation sequence where labour moves from low-productivity agriculture into manufacturing and then into higher-value services, as experienced in Western Europe, East Asia, and China (McMillan et al., 2014; Sen, 2019) is becoming increasingly constrained or absent in many contemporary developing economies. In its place, most new labour market entrants in EMDEs are absorbed into informal microenterprises, where average labour productivity is approximately one-quarter of that in formal sector firms. Within these settings, weak market linkages, limited access to capital and restricted opportunities for firm expansion tend to reproduce rather than alleviate structural poverty (Ohnsorge & Yu, 2022; IMF, 2024). It is within this structurally constrained labour market environment that artificial intelligence has emerged, simultaneously offering opportunities for productivity enhancement while also raising legitimate concerns about employment disruption and widening inequality.

The dominant discourse on AI and employment has, however, been constructed largely through the lens of advanced economies and large-scale frontier systems. Cazzaniga et al. (2024) estimate that approximately 40% of global employment is exposed to AI, with advanced economies facing greater risks but also possessing greater capacity to harness AI's benefits. Specifically, they find that roughly 60% of jobs in advanced economies are exposed, compared to 40% in emerging market economies and 26% in low-income countries. While this differential seemingly implies lower displacement risk for EMDEs, it simultaneously signals a widening opportunity gap in harnessing AI's productivity potential. This gap has profound implications for long-run convergence. The prevailing literature, moreover, has concentrated disproportionately on automation-induced job displacement (Acemoglu & Restrepo, 2018; Autor et al., 2003), the governance of large language models and foundation AI systems (Bommasani et al., 2021), and the macroeconomic effects of frontier AI adoption in high-income contexts (OECD, 2023). Comparatively little scholarly attention has been directed toward how resource-efficient, task-specific AI systems can be configured to generate net positive employment effects within the SME-dominated, informality-intensive labour markets of developing economies. This is a significant omission. SMEs represent approximately 90% of all businesses globally and account for more than half of global employment (IFC, 2024). In developing countries, SMEs are central to economic diversification, productivity and poverty reduction (World Bank, 2024). Yet this sector remains largely absent from mainstream AI-and-employment scholarship. This constitutes a significant analytical and policy gap. This paper attempts to address this gap by positioning Small AI as a distinct analytical category and introduces the Small AI Employment Multiplier Framework (SAEMF), which models the causal pathways from Small AI adoption in SMEs to net employment generation in EMDEs.

The paper makes four distinct contributions to the literature. First, it introduces Small AI as an analytical category, distinguished from frontier AI along four dimensions namely resource efficiency, task specificity, contextual embeddedness and cost accessibility. Second, it extends existing task-based employment theory, SME productivity theory, and Schumpeterian growth theory into an integrated multiplier framework calibrated to the structural realities of EMDE labour markets. Third, it operationalizes the framework through firm-level implementation pathways and enabling conditions, supported by verified empirical evidence from documented Small AI deployments across multiple developing country contexts. Fourth, it translates the framework into an actionable policy matrix for multilateral development institutions, national governments and SME support organizations.

2. Review of Related Literature

2.1 Employment Crisis in Emerging Market and Developing Economies

The employment problem facing emerging market and developing economies (EMDEs) is structural rather than cyclical. It reflects persistent mismatches between labour supply and the productive capacity of economies to absorb workers in formal, productive employment. As shown in Table 1, Sub-Saharan Africa is projected to add approximately 450 million people to its working-age population between 2025 and 2035. This is part of a broader trajectory that will see the region add more than 620 million working-age people by 2050, representing over three-quarters of the net increase across all EMDEs (World Bank, 2025a). South Asia will add a further 350 million to its working-age population over the 2025–2035 period. Across EMDE regions, Table 1 indicates a cumulative employment gap of approximately 600 million jobs over the decade, consistent with the ILO's long-standing estimate that over 600 million new productive jobs must be created globally to keep pace with labour force growth (UN DESA, 2024). This gap is particularly concentrated in Sub-Saharan Africa and South Asia, where informal employment shares exceed 80 percent, a pattern that reflects the mutually reinforcing relationship between high informality and weak formal job creation documented by La Porta and Shleifer (2014). In addition, the magnitude of the structural shortfall exceeds the historical peak manufacturing employment levels of any industrialized economy, confirming that the traditional "manufacturing escalator" is increasingly insufficient for contemporary EMDEs, which face premature deindustrialisation at lower income levels than their predecessors (Rodrik, 2016). The situation is further compounded by the fact that labour force growth is fastest in regions where formal job creation is weakest, indicating a widening structural imbalance.

The implications of this employment deficit extend beyond economic performance to broader questions of stability and governance. Youth unemployment is particularly significant, given that young people constitute a large share of the population in most EMDEs, and is strongly associated with social instability, involuntary migration and state fragility (World Bank, 2025b; ILO, 2024). A key structural feature reinforcing this crisis is pervasive informality. Approximately 80 percent of MSMEs in developing economies operate outside the formal sector (IFC, 2025; CGAP, 2014), where productivity is estimated at less than one-third of that observed in formal firms (IFC, 2025). This creates a self-reinforcing low-productivity equilibrium. Informal firms face constrained access to credit and technology, while their workers are unable to accumulate the skills and human capital that support upward mobility (Banerjee & Duflo, 2007). De Soto (2000) further argues that this persistence is rooted in weak formal institutions, particularly insecure property rights and underdeveloped collateral systems which exclude informal actors from productive investment opportunities. Collectively, these dynamics underscore that addressing structural informality is a necessary condition for any durable solution to the employment challenge in EMDEs.

Table 1. Employment Gap Estimates by EMDE Region, 2025–2035

Region	Working-Age Pop. Growth 2025–2035 (m)	Projected New Jobs (m)	Employment Gap (m)	Gap as % of Pop. Growth	Informal Employment Share (%)
Sub-Saharan Africa	~450	~170	~280	~62%	~85%
South Asia	~350	~160	~190	~54%	~79%
Middle East & North Africa	~100	~50	~50	~50%	~63%
Latin America & Caribbean	~80	~40	~40	~50%	~49%
Southeast Asia	~120	~80	~40	~33%	~66%
Total / Average	~1,100	~500	~600	~55%	—

Source: Authors' calculations

Note. Working-age population growth estimates derived from ILO (2025) and World Bank (2025a) demographic projections. Projected new jobs computed at prevailing employment elasticities of GDP growth. Employment gap = projected working-age population growth minus projected new formal jobs. Informal employment shares from ILO ILOSTAT modelled estimates (ILO, 2023). All figures are approximate and rounded; totals may not sum exactly due to rounding.

2.2 AI and Employment: The Dominant Paradigm

The relationship between artificial intelligence (AI) and employment remains a central and contested issue in contemporary labour economics. Early contributions by Frey and Osborne (2013) estimated that approximately 47% of United States employment was at high risk of automation, initiating extensive empirical and methodological debate. Subsequent studies challenged this occupation-level approach, demonstrating that task-based rather than occupation-based analysis significantly lowers estimated displacement risks across OECD economies, with only around 9% of jobs classified as highly automatable on average across 21 countries (Arntz et al., 2016). Autor (2015) further argues that technological change has been associated not with mass unemployment but with occupational polarization, characterized by growth in high and low skill jobs alongside the displacement of routine middle-skill tasks. Building on this literature, Acemoglu and Restrepo (2019) develop the most influential framework, distinguishing between an automation effect that displaces labour and a reinstatement effect that generates new tasks. In their subsequent empirical work, they find that automation has significantly outpaced reinstatement in the United States over recent decades, accounting for between 50% and 70% of changes in the US wage structure and contributing substantially to rising wage inequality (Acemoglu & Restrepo, 2022). Cross-country evidence by Georgieff and Hyee (2022) similarly shows no uniform relationship between AI exposure and employment growth across 23 OECD economies, underscoring the importance of institutional and structural context in shaping outcomes.

More recent global evidence highlights substantial heterogeneity in AI exposure and its distributional consequences. Brynjolfsson et al. (2023) show that deployment of a generative AI conversational assistant in customer service settings increases worker productivity. This was measured by issues resolved per hour by approximately 14% on average, with the strongest gains accruing to novice and lower-skilled workers, suggesting heterogeneous labour market effects that may complement rather than simply displace lower-skilled labour. At the global level, Gmyrek (2023) find that only a small share of total employment is highly exposed to automation risk, with clerical occupations exhibiting the greatest vulnerability, with 24% of clerical tasks classified as highly exposed. Importantly, their analysis reveals strong income-level disparities such as only 0.4% of employment in low-income countries is in the category of high substitution potential, compared to 5.5% in high-income countries. Similarly, the IMF's AI Preparedness Index indicates that advanced economies are substantially better positioned for AI adoption than low-income countries, with emerging markets occupying an intermediate position (Cazzaniga et al., 2024). A pattern driven by disparities in digital infrastructure, human capital and regulatory capacity. Together, this evidence suggests that the central employment challenge for developing economies is less about widespread displacement and more about unequal access to the productivity and job-creating potential of AI-driven technological change.

2.3 AI in Developing Economies

The IMF's AI Preparedness Index, assessed across 125 countries, reveals a pronounced global divide in the capacity to adopt and benefit from artificial intelligence. Wealthier economies including advanced and some emerging market economies are substantially better positioned to harness AI, while low-income countries face compounding structural disadvantages that deepen the existing digital divide (Cazzaniga et al., 2024). These disparities are rooted in foundational infrastructure constraints. In low-income countries, fewer than 50% of the population has access to electricity. The average stands at approximately 48% and only 27% use the internet (World Bank/ESMAP, 2024; ITU, 2024). In addition, approximately 70% of 10-year-olds in low- and middle-income countries are classified as learning poor, meaning they cannot read and understand a simple text by age 10, a figure that worsened significantly as a result of pandemic-related school closures (World Bank et al., 2022). This human capital deficit substantially reduces the absorptive capacity required for effective AI deployment.

These structural constraints shape how AI interacts with labour markets in developing economies. A joint ILO–World Bank (2024) study of Latin America finds that between 26% and 38% of jobs in the region could be influenced by generative AI, but that the productivity-enhancing benefits are concentrated among formal, urban, higher-educated and higher-income workers. By contrast, informal workers who constitute the majority of young workers in the region remain largely excluded from both the risks of automation and the benefits of AI-driven transformation. This gives rise to a "neither-nor" outcome, where informal workers are neither highly exposed to displacement nor positioned to benefit from AI complementarity. In a related finding, UNCTAD (2025), drawing on evidence from its Empretec entrepreneurship network and comparative global case studies, shows that effective AI adoption in developing economies depends less on the technology itself and more on enabling ecosystem conditions, including skills, data infrastructure, access to finance, regulatory frameworks and institutional trust.

Despite these insights, a significant gap remains in the literature. Most existing studies focus on AI exposure at the occupational level rather than the employment-generating effects of AI adoption at the firm level. In particular, there is limited systematic theorization of how firm-level AI adoption, especially through productivity gains in small and medium-sized enterprises, translates into net job creation in developing economies. This gap defines the analytical space that this paper seeks to address.

2.4 SMEs as the Labour Market Core of Developing Economies

Small and medium-sized enterprises (SMEs) constitute the structural core of employment in developing economies. Globally, they account for approximately 90% of businesses, around 70% of total employment, and about 50% of GDP, with their contribution significantly higher in developing economies when informal enterprises are included (IFC, 2025b). Regional evidence reinforces this pattern. In Sub-Saharan Africa, SMEs represent more than 80% of businesses and serve as the primary source of private sector employment, with formal SMEs contributing roughly 38% of GDP, a share that increases substantially when informal activity is considered (IFC, 2024; World Bank, 2025). In Latin America, SMEs account for approximately 60% of formal productive employment and represent 99.5% of all businesses (OECD, 2024). In Southeast Asia, they constitute approximately 85–97% of enterprises and the large majority of employment. Though their contribution to value added remains below their employment share due to persistent productivity constraints. Across regions, this divergence between employment share and output contribution reflects structural limitations in access to finance, technology and markets.

Despite their central role, SMEs face entrenched constraints that shape both productivity and employment outcomes. Informal firms, in particular, are not inherently less capable but are systematically excluded from credit markets, advanced technologies and skilled labour pools, resulting in significantly lower productivity (La Porta & Shleifer, 2014). These constraints are compounded by a financing gap estimated at US$5.7 trillion across 119 emerging markets and developing economies, alongside infrastructural deficits and regulatory burdens that disproportionately affect smaller firms (IFC–World Bank, 2025; World Bank, 2025). Institutional factors further reinforce these limitations, as formal and informal rules determine transaction costs and restrict firm expansion (North, 1990), while persistent capital constraints prevent productivity-enhancing investment and entrench low-income equilibria (Banerjee & Duflo, 2007). Nevertheless, SMEs remain the dominant engine of job creation, accounting for up to 60% of employment in emerging economies and about 70% of global job creation (IFC, 2025). The World Bank (2025) further projects that most new jobs over the coming decade will originate from SMEs, particularly in Asia and Sub-Saharan Africa. This dual role as both the primary source of employment and the main locus of unrealized productivity gains positions SMEs as the critical unit of analysis for understanding how artificial intelligence can translate into inclusive employment growth in developing economies.

3. Theoretical Foundations of the SAEMF

3.1 Defining Small AI

Within this framework, *Small AI* refers to a category of artificial intelligence systems defined by four interrelated characteristics: resource efficiency, task specificity, contextual embeddedness and cost accessibility. Resource efficiency describes the ability of these systems to operate effectively under the computational, energy and connectivity limitations that are common in developing economies, where large segments of the population still lack reliable digital access (GSMA, 2023). Task specificity means that these systems are designed to perform narrowly defined functions, such as credit scoring, crop disease diagnosis or inventory management. This focus reduces data requirements, lowers implementation complexity and enables productive deployment at a lower cost, making adoption more feasible for small and medium-sized enterprises (Wang et al., 2025; khan et al, 2024; OECD, 2025). Contextual embeddedness refers to the adaptation of AI systems to local languages, institutions, digital ecosystems and business practices. This feature is particularly important in environments where informal economic activity remains dominant. The widespread adoption of mobile financial services in East Africa, most notably through the experience documented by Suri and Jack (2016), illustrates how context-sensitive digital innovations can achieve rapid uptake and generate substantial welfare gains. Cost accessibility further ensures that both deployment and operational costs remain affordable for micro, small and medium-sized enterprises operating under resource constraints.

This conception of *Small AI* differs fundamentally from frontier artificial intelligence technologies, including large language models, advanced robotic systems and large-scale industrial AI platforms. Such technologies typically depend on substantial computational infrastructure, significant capital investment and highly specialized technical expertise, resources that remain scarce across many emerging market and developing economies (Sajjadi et al., 2025; Cottier, et al. 2024). As shown in Figure 1, frontier AI is often associated with capital-intensive automation and the displacement of tasks, particularly in cognitive occupations and formal high-income economy settings. In contrast, *Small AI* is designed to complement human labour, raise productivity and support enterprise expansion within SME-dominated and frequently informal labour markets (Wang et al., 2025; Corradini et al., 2025). The distinction extends beyond technological characteristics. It is analytically critical because different forms of AI create different employment trajectories. Any framework seeking to leverage AI for inclusive job creation in EMDEs must therefore begin by recognizing this fundamental difference.

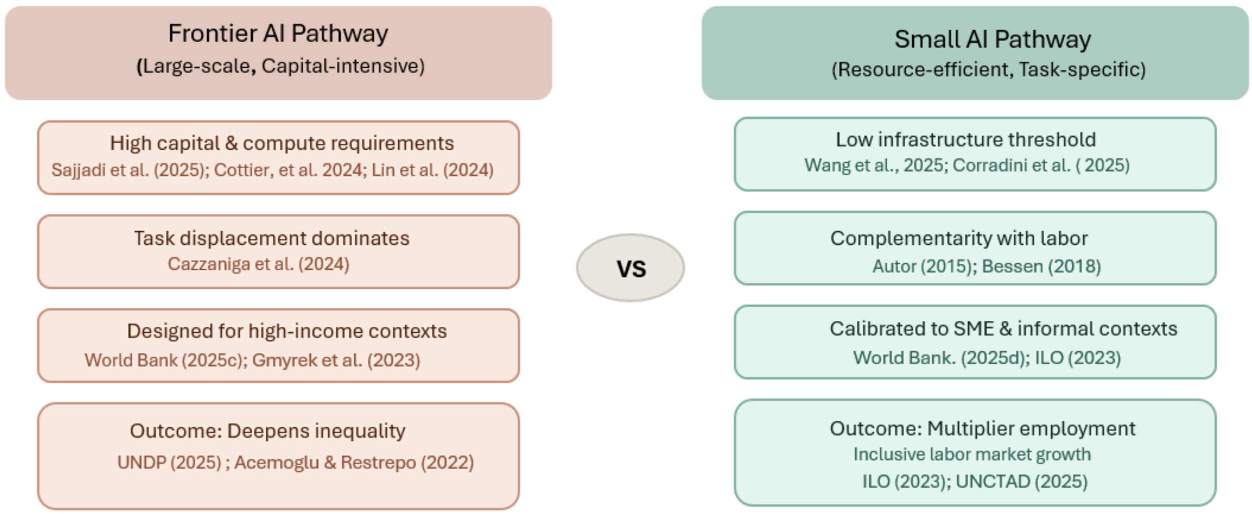

Figure 1. Frontier AI vs. Small AI: Divergent Employment Channels in Developing Economies.

Source: Authors' construction based on Acemoglu & Restrepo (2022), Wang et al. (2025), Autor (2015), ILO (2023), GSMA (2023), Cazzaniga et al. (2024), Bessen (2018), World Bank (2025d), Lin et al. (2024), Sajjadi et al. (2025)

3.2 Theoretical Pillars of the SAEMF

The Small AI Employment Multiplier Framework (SAEMF) draws on three complementary theoretical traditions that, when integrated into a single framework for employment generation in developing economies, offer a novel analytical perspective. Together, these theories explain how Small AI can influence employment through task reallocation, productivity enhancement and market expansion.

The first pillar is the *task-based theory of employment* developed by Autor et al. (2003) and subsequently extended by Acemoglu and Restrepo (2019). This framework explains how technological change reshapes labour markets by reallocating tasks between human workers and machines. It distinguishes between the automation effect, which displaces labour from existing tasks and the reinstatement effect, through which technological advances create new tasks where human labour retains a comparative advantage (Acemoglu & Restrepo, 2019). The SAEMF adapts this framework to emerging market and developing economy (EMDE) contexts by recognizing that informal small and medium-sized enterprises (SMEs) are largely characterized by relational, context-specific and physically embedded activities that are less amenable to automation than the tasks commonly found in formal labour markets of high-income economies. Empirical evidence supports this adaptation, showing that occupational exposure to AI is significantly lower in low-income countries because of differences in workforce task composition (Gmyrek et al., 2023; Chen, 2012). Within the SAEMF, the reinstatement effect underpins all employment channels and is most explicitly reflected in the creation of complementary occupations captured in Channel 4.

Building on this task-level perspective, the second pillar draws from *SME productivity theory in development economics*. This theory identifies information asymmetries, resource misallocation, inadequate infrastructure and limited access to finance as key constraints on firm productivity and employment growth in developing economies (Hsieh & Klenow, 2009; La Porta & Shleifer, 2014).

The SAEMF conceptualizes Small AI as a targeted productivity-enhancing technology capable of alleviating these constraints without the substantial capital requirements associated with frontier AI systems. By reducing information frictions and improving operational efficiency, Small AI enables firms to increase productivity, expand revenues and strengthen labour demand. This mechanism forms the basis of Channel 1 within the framework. This theoretical pillar also provides the foundation for Channel 3, which focuses on enterprise formalization. Development economics research consistently shows that many informal firms remain trapped in low-productivity equilibria, not because of a lack of entrepreneurial capability, but because they are excluded from formal credit systems, regulatory recognition and institutional support mechanisms (La Porta & Shleifer, 2014; De Soto, 2000). Building on this insight, the SAEMF proposes that Small AI can help reduce the barriers that discourage firms from entering the formal economy. In particular, Small AI applications that support digital record-keeping, tax compliance, digital payments and credit history creation can lower the transaction costs associated with formalization. As these costs decline, transitioning to formal status becomes increasingly attractive and economically viable for informal SMEs. Formalization subsequently improves access to finance, technology, business services and broader labour markets, creating opportunities for further enterprise expansion. As firms gain access to these resources, they become better positioned to increase productivity, attract investment and scale their operations. This generates a second-order employment effect, whereby newly formalized enterprises expand their workforce and create additional job opportunities while strengthening their long-term growth prospects.

The third pillar is *Schumpeterian innovation and growth theory*, originally articulated by Schumpeter (1942) and later formalized by Aghion and Howitt (1998). This tradition emphasizes that technological progress generates employment not only through productivity improvements but also through market expansion driven by entrepreneurial innovation and the creative destruction of less efficient firms. Extending this logic to SME adoption, the SAEMF proposes that productivity gains generated by Small AI can improve market access, strengthen buyer–seller relationships and stimulate demand throughout value chains. These effects create additional employment opportunities in downstream logistics, services and production activities, corresponding to Channel 2 of the framework. Together, these three theoretical pillars provide an integrated analytical foundation for the SAEMF. By linking task reallocation, productivity dynamics and market expansion, the framework explains how Small AI can generate employment multipliers that are particularly relevant to the structural conditions of EMDEs.

4. The Small AI Employment Multiplier Framework (SAEMF)

4.1 Research Phases: Design and Refinement of SAEMF

The design of the Small AI Employment Multiplier Framework (SAEMF) followed an interdisciplinary and theory-driven research process that drew upon development economics, labour market theory, technology studies and enterprise productivity research. Given the conceptual uniqueness of Small AI as an analytical category and the limited empirical base directly linking AI adoption in SMEs to employment outcomes in developing economies, the framework was constructed through an iterative design process. This process comprised three interconnected phases: establishing the research context, defining the framework design strategy and conceptualizing and specifying the framework. Figure 2 illustrates the phases involved in the design and refinement of the SAEMF.

Phase 1: Research Context

The first phase focused on defining the research problem by examining the structural employment challenges facing emerging market and developing economies (EMDEs) and assessing the limitations of existing theoretical and policy approaches. Three contextual realities shaped the scope of the study. First, labour markets in EMDEs are dominated by informal SMEs that operate under persistent constraints related to finance, technology and market access, conditions that are inadequately captured in most conventional AI-employment frameworks (La Porta & Shleifer, 2014; Hsieh & Klenow, 2009). Second, much of the existing literature treats AI as a homogeneous technology and derives its conclusions from the institutional characteristics of formal labour markets in high-income economies, limiting its applicability to developing-country contexts (Autor et al., 2003; Acemoglu & Restrepo, 2019). Third, no integrated analytical framework was identified that systematically traced the channel from AI adoption within SMEs to net employment creation in developing economies. Collectively, these observations highlighted a significant theoretical gap and justified the development of a new framework rather than the adaptation of existing models.

Phase 2: Framework Design Strategy

Having established the research context, the second phase focused on the principles guiding framework development. Three design principles were adopted. The first was theoretical pluralism. Given the complexity of employment generation in developing economies, no single theoretical perspective was considered sufficient. Consequently, the framework integrates task-based employment theory (Autor et al., 2003; Acemoglu & Restrepo, 2019), SME productivity theory in development economics (Hsieh & Klenow, 2009; La Porta & Shleifer, 2014) and Schumpeterian innovation and growth theory (Schumpeter, 1942; Aghion & Howitt, 1998) within a unified analytical structure. The second principle was contextual embeddedness. The framework was explicitly designed to reflect the realities of EMDE labour markets, including widespread informality, infrastructure deficits and the central role of SMEs, rather than relying on assumptions derived from high-income economies. The third principle was policy tractability. Beyond explaining employment dynamics, the framework was intended to provide a foundation for practical policy interventions and to support the development of a policy matrix for multilateral development institutions, national governments and SME-support organizations. In line with these principles, the design strategy specified that analysis should be conducted at the firm level. The framework therefore focuses on how Small AI adoption within individual SMEs generates employment effects, rather than examining impacts solely at the macroeconomic or occupational level, which has been the dominant approach in much of the existing AI-employment literature.

Phase 3: Framework Conceptualization and Specification

The final phase involved the conceptualization and specification of the framework. This process unfolded in three sequential steps. The first step was to define Small AI and distinguish it from frontier AI systems. Four defining characteristics were identified: resource efficiency, task specificity, contextual embeddedness and cost accessibility. Establishing these dimensions provided the conceptual foundation for treating Small AI as a distinct analytical category requiring its own employment framework. The second step involved identifying and specifying the framework's four employment channels: productivity enhancement (Channel 1), market expansion (Channel 2), enterprise formalization (Channel 3) and the creation of complementary occupations (Channel 4). Each channel was grounded in one or more of the framework's theoretical pillars and represented a distinct causal channel linking Small AI adoption to net employment generation. The third step focused on identifying the conditions required for these employment channels to operate effectively. Four enabling conditions were specified: access, affordability, applicability and capability. These conditions function as structural contingencies, meaning that the employment effects associated with each channel can only be realized when the necessary supporting conditions are present within a particular EMDE context. The outcome of this phase is the SAEMF presented in this paper: a context-sensitive and multi-channel analytical framework that links Small AI adoption in SMEs to inclusive labour market transformation in developing economies. Future research will focus on operationalizing and empirically testing the framework across selected EMDE contexts with the aim of validating its causal mechanisms and refining the accompanying policy matrix based on field evidence.

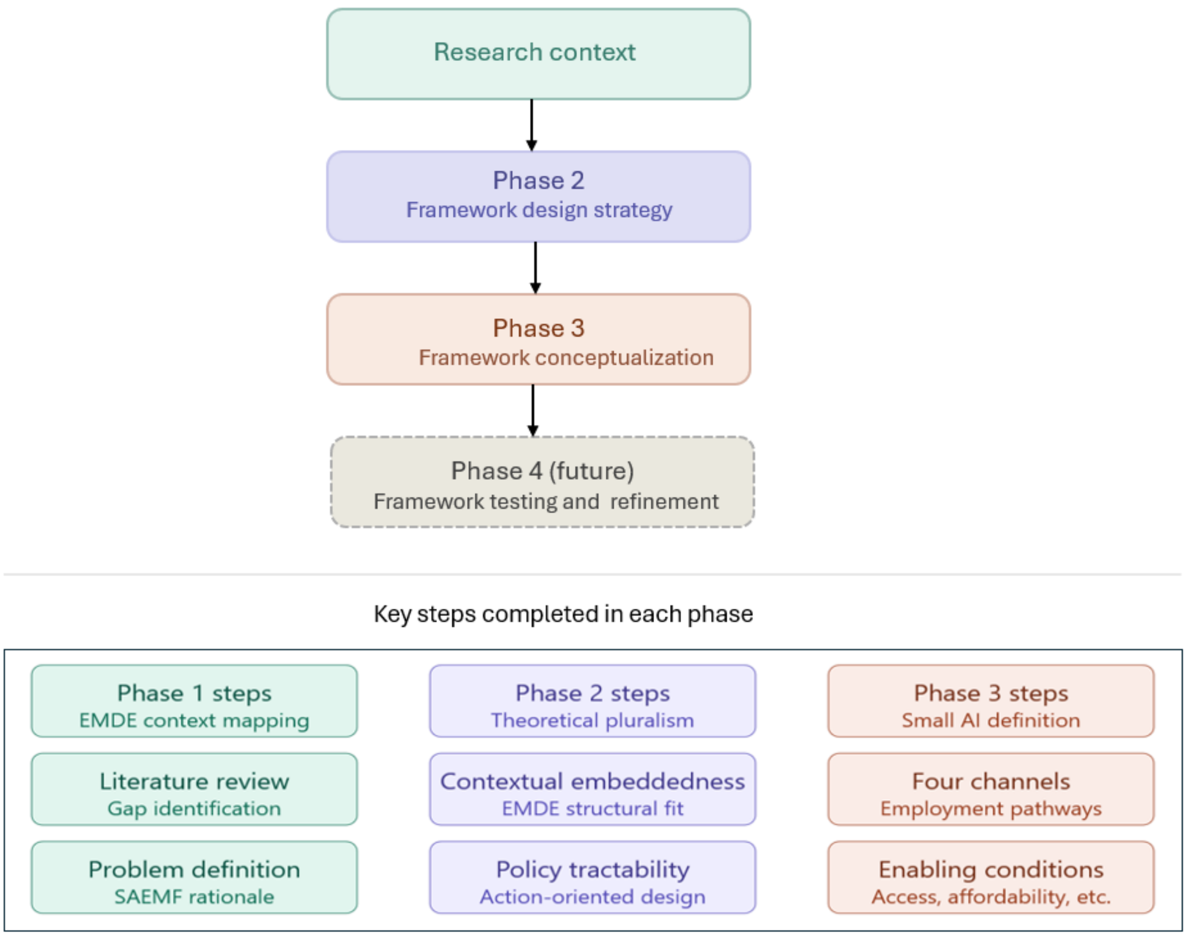

Figure 2. Research Design and Methodological Flowchart.

Source: Authors' original construction

4.2 The SAEMF Framework Architecture

The SAEMF integrates three theoretical pillars: task-based employment theory, SME productivity theory in development economics and Schumpeterian endogenous growth theory into a unified analytical framework that identifies four distinct employment channels through which Small AI shapes labour markets in developing economies. Importantly, the framework is conceptualized as a multiplier system rather than a linear causal model. Employment effects are therefore not confined to firms that directly adopt AI technologies, instead, they propagate through enterprise networks, supply chains and consumption systems, generating indirect and induced employment across multiple layers of the economy. Figure 3 presents the SAEMF architecture, showing four channels radiating from Small AI as the central node, with the employment multiplier as the convergent outcome.

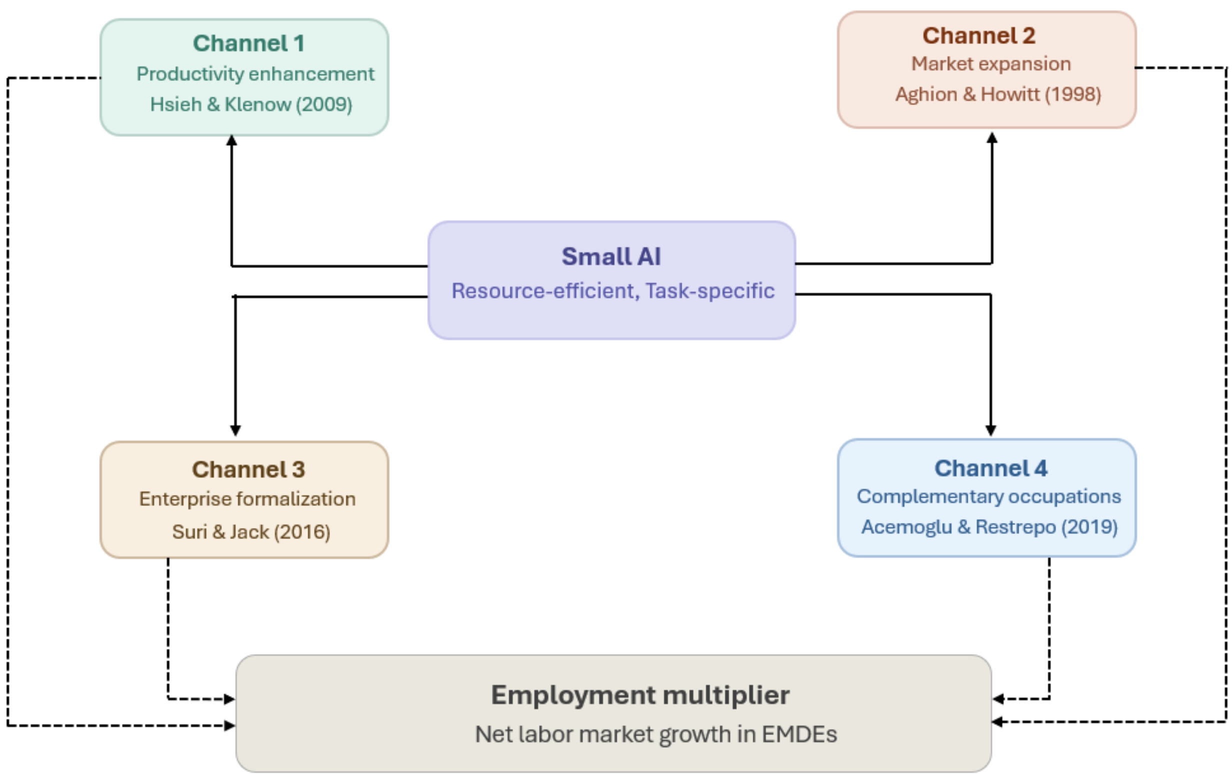

Figure 3. The SAEMF: Four Employment Channels

Source: Authors' original construction

4.3 The Four Employment Channels: Mechanisms and Operationalization

The four channels are neither mutually exclusive nor strictly sequential. In practice, Small AI deployments often activate several channels simultaneously. Their cross-channel interactions, discussed in Section 5, serve as a key source of multiplier amplification.

Channel 1: Productivity Enhancement

The primary and most direct employment channel operates through productivity enhancement. Small AI applications that automate routine, low-value tasks within SMEs such as inventory management, invoice processing, demand forecasting and quality control release owner and worker time for higher-value activities. Conventional automation frameworks often interpret such task substitution as a source of labour displacement. The SAEMF argues, however, that this interpretation is less applicable in EMDE contexts, where SMEs frequently operate below their productive potential due to information deficits, operational inefficiencies and resource constraints. In these settings, productivity gains are more likely to expand enterprise capacity than to replace existing workers. A mobile-based accounting application that reduces bookkeeping time for a micro-retailer typically does not eliminate a dedicated bookkeeping position because such a role often does not exist but instead enables the proprietor to redirect time toward sales, supplier engagement and product development. As productivity improves, firms become better positioned to increase output, expand revenues and respond to rising market opportunities. The employment effect of this channel is therefore driven not by labour-technology substitution but by the capacity of productivity-driven revenue growth to generate additional labour demand, a relationship captured by the revenue-to-labour elasticity of the enterprise (Hsieh & Klenow, 2009; La Porta & Shleifer, 2014).

Operationalization of Channel 1 begins with task mapping at the firm level. This involves identifying tasks within target SME sectors, including retail, agriculture, light manufacturing, food processing and logistics, that are routine, data amenable and currently performed inefficiently, followed by matching Small AI tools to those specific task profiles. This process must be preceded by baseline productivity measurement, which involves establishing preadoption benchmarks in output per worker, revenue per employee and owner time allocation, against which post adoption changes in firm performance and labour demand can be assessed (Brynjolfsson et al., 2023). Two documented cases illustrate this pathway at different scales. Farmerline's Darli AI, named one of TIME magazine's Best Inventions of 2024, is a multimodal AI agricultural advisor that delivers real time agronomic guidance in 27 local languages via WhatsApp and IVR to over 110,000 active users across Africa, Asia and South America, with approximately one million farmers being onboarded onto its helpline (Farmerline, 2024; GSMA, 2025). Farmerline reports that 89% of platform users recorded productivity gains, with measurable farm level income improvements consistent with the revenue to labour elasticity mechanism of Channel 1 (African PACT, 2025). Critically, productivity gains do not displace agricultural labour but create the income surplus that enables farmers to hire seasonal workers and expand cultivation. Digital Green's FarmerChat, operating across India, Kenya, Nigeria and Ethiopia, provides complementary evidence at larger scale. A J-PAL randomized evaluation in Bihar found that integrating AI video advisory into government extension services reduced the cost of inducing practice adoption from approximately USD 35 per farmer to USD 3.50, a tenfold reduction, while increasing female farmers' yields and incomes. In addition, 60% of the platform's 8.2 million users, 43% of whom are women, reported acting on AI advice within two weeks of receipt (J-PAL, 2024; Digital Green, 2024).

Key performance indicators for this channel include process efficiency gains, firm revenue growth and net new hires. The revenue-to-labour elasticity is the central empirical test of Channel 1 activation. Enabling conditions include sufficient digital literacy and device access among target SMEs, AI tools calibrated to local languages and business practices, revenue gains available for reinvestment into labour and a local workforce with the basic skills required for the higher value tasks that productivity enhancement is intended to enable.

Channel 2: Market Expansion

The second employment channel operates through market expansion. By reducing search costs, facilitating price discovery, connecting producers with buyers and enabling participation in wider markets, Small AI systems stimulate effective demand beyond the productive boundaries of individual firms. This channel is particularly significant in developing economies where market fragmentation, information asymmetries, coordination failures and high transaction costs routinely prevent productive resources from being allocated efficiently. By functioning as market enabling infrastructure that improves information flows, lowers transaction costs and enhances coordination among market participants, Small AI systems activate previously underutilized productive capacity across entire market ecosystems, generating employment in downstream logistics, processing, packaging, retail and financial services that would not exist in the absence of market connecting AI tools. Agricultural matching platforms, for instance, can connect smallholder farmers directly with wholesale buyers, increasing farm revenues while simultaneously generating employment across related value chain activities. This mechanism aligns with the market expansion logic of Schumpeterian endogenous growth theory, which emphasizes the role of innovation in enlarging markets, stimulating economic activity and generating sustained employment growth (Schumpeter, 1942; Aghion & Howitt, 1998).

Operationalization of Channel 2 requires identifying the specific coordination failure in the target EMDE context, matching an appropriate Small AI tool to that failure and quantifying the downstream employment multiplier (the number of additional jobs generated per unit of market expansion at the firm level). Twiga Foods in Kenya illustrates the full Channel 2 mechanism. Its mobile based AI enabled food distribution platform connects over 140,000 small retailers, approximately 25% of Kenya's entire informal retail industry, directly with smallholder farmers, using AI demand forecasting and GIS route optimization to reduce post-harvest losses from approximately 30% to 4%. increasing farmer incomes by up to 30% and directly employ over 10,000 people across the downstream logistics, delivery and processing ecosystem (CGIAR, 2023; Howwemadeitinafrica.com, 2024). Notably, Twiga's AI generated transaction ledger has further enabled third party credit access for both farmers and vendors, illustrating the cross channel interaction between Channel 2 and Channel 3. Lori Systems, operating across 12 African countries, provides a logistics focused complement. Its AI freight matching platform reduces coordination failures that result in trucks operating below capacity and logistics costs accounting for up to 75% of final product prices in African supply chains. It has facilitated over USD 10 billion in cargo movements and expanded the market reach of SMEs previously excluded from reliable freight infrastructure (Africa Signal, 2025; Startup List Africa, 2025).

Key performance indicators include market reach, transaction volume, supply chain activation and downstream job creation. Enabling conditions include functional digital payment infrastructure, logistics capacity to fulfil expanded demand, low bandwidth compatible AI tools and platform trust among both sellers and buyers.

Channel 3: Enterprise Formalization

The third employment channel operates through enterprise formalization. While conceptually distinct from Channels 1 and 2, it is operationally connected to both since improved productivity and expanded market access increase the incentives and capacity of informal firms to formalize. In many developing economies, a large share of employment is concentrated in informal enterprises that remain structurally excluded from formal credit systems, public procurement opportunities, export markets and regulatory protections, not because proprietors prefer informality but because formalization transaction costs are prohibitively high relative to perceived benefits (La Porta & Shleifer, 2014; De Soto, 2000). Small AI tools can reduce these costs by automating record keeping, generating auditable financial statements, facilitating digital tax compliance and producing transaction histories that serve as informational collateral for formal market participation. Mobile payment platforms with basic financial analytics, for example, have been shown to improve access to formal credit by generating verifiable transaction records for previously unbanked micro enterprises in Kenya, with similar evidence emerging across East Africa and South Asia (Suri & Jack, 2016). As enterprises gain access to formal financial and commercial networks, their expansion opportunities increase. Enterprise formalization is consistently associated with higher employment growth, improved wages, better working conditions and greater labour productivity, all positive labour market outcomes within the SAEMF.

Operationalization of Channel 3 requires mapping the most binding formalization barriers in the target context, whether administrative compliance requirements, documentation demands or cost of registration and linking AI generated records to formal financial institutions and regulatory bodies to create a credible institutional pathway from digital footprint to credit access and legal recognition. Apollo Agriculture in Kenya and Zambia demonstrates this at scale. Its machine learning system builds farmer credit profiles by combining satellite imagery, mobile transaction histories, agrodealer purchase data and repayment records, enabling instant credit decisions for over 350,000 farmers previously invisible to formal financial institutions, with users reporting average production 2.6 times higher than non-platform farmers and 84% reporting improved quality of life (Apollo Agriculture, 2024; GSMA, 2025). Pula, a Kenyan insurtech operating across 22 countries and reaching over 20 million farmers, provides a complementary formalization pathway by using high frequency satellite data and AI driven actuarial modelling to make previously uninsurable smallholder farmers insurable, while bundling insurance with farm credit and input access to progressively integrate them into formal financial networks (UNSGSA, 2023; Disrupt Africa, 2024). Pula's research shows that insurance access increases farm investment by an average of 16%, improves yields by 56% and raises household savings by up to 170%, effects consistent with the formalization employment premium predicted by Channel 3. Its USD 20 million Series B round in 2024, backed by IFC and the Bill and Melinda Gates Foundation, reflects the institutional credibility of this model (TechPoint Africa, 2024; BlueOrchard, 2024).

Key performance indicators include formalization rates, volume of formal credit extended to newly formalized SMEs, wage quality differentials between formal and informal firms and firm employment growth. Enabling conditions include a regulatory environment in which formalization offers genuine and accessible benefits, AI tools that interface directly with government registration systems and financial institutions, financial service providers willing to recognize AI generated records as creditworthy collateral and policy frameworks that incentivize early formalization.

Channel 4: Complementary Occupation Emergence

The fourth employment channel and arguably the most significant source of long term employment creation within the SAEMF operates through the emergence of complementary occupations. This channel reflects the reinstatement effect theorized by Acemoglu and Restrepo (2019), adapted here to the Small AI context. The adoption of Small AI technologies across small and medium-sized enterprises generates demand for labour associated with implementation, maintenance, customization and operation, thereby creating new occupations such as AI system technicians, data annotation specialists, digital marketing practitioners and platform-based service intermediaries that were previously absent from the labour market. The significance of this channel extends beyond the creation of new jobs. Unlike complementary occupations generated by frontier AI, which typically require multi-year university education and are concentrated in major technology hubs, Small AI adjacent roles are characterized by lower educational thresholds, geographic dispersion across rural and peri urban areas and accessibility to women, youth and informally employed workers who are disproportionately excluded from formal labour markets (Bessen, 2018; ILO, 2024). These occupations are predominantly non routine cognitive roles resistant to near term automation, accessible through short cycle vocational training and aligned with the demographic realities of EMDE labour markets. The employment effects generated through this channel are therefore both quantitative and qualitative, contributing not only to job creation but also to occupational diversification, skills upgrading and structural transformation within developing economies.

Operationalization of Channel 4 requires three sequential steps: occupational mapping of new roles generated by each Small AI deployment context, design of short cycle vocational training programmes delivered through community colleges, NGO partnerships or digital learning platforms and active labour market intermediation to match trained workers with AI deploying SMEs. Andela, founded in Lagos in 2014 and operating a talent marketplace spanning 49 African countries with over 150,000 technology professionals, demonstrates Channel 4 at the higher skill end of the occupational spectrum by identifying high potential individuals and training them in software development, AI, cloud engineering and DevOps for placement with global enterprises including Google, Meta and Microsoft, thereby systematically creating AI adjacent occupations that did not previously exist in African labour markets (Andela, 2025; IFC, 2022). In its most recent initiative, a partnership with the Cloud Native Computing Foundation, Andela trained over 5,600 African technologists in a single cohort, with plans to reach 20,000 to 30,000 by 2027; a CNCF study found that 55% of developers completing comparable programmes secured new employment as a result and 67% reported greater professional fulfilment (Andela, 2025; TechEconomy, 2024). Babajob in India illustrates the lower skill end of the same spectrum by algorithmically matching over 8.5 million informal sector workers with over 500,000 employers, creating the new occupational category of the digitally matched informal worker, with platform placed workers earning on average 20.1% more and commuting 14 minutes less per day than those placed through traditional informal networks (Tracxn, 2025). Together, these cases illustrate the full occupational range of Channel 4 from technical AI engineers to entry level informal workers, consistent with the SAEMF prediction that Small AI generates occupational diversity rather than a single job type.

Key performance indicators include documented AI adjacent roles, training uptake and placement rates, wage premiums over comparable non AI roles and demographic inclusion. Enabling conditions include rapid vocational curriculum development capacity, government and private sector recognition of AI adjacent occupational categories in national skills frameworks, sustained Small AI adoption at sufficient scale to generate consistent demand for support roles and enforceable labour standards in content intensive occupations where psychosocial harm risks are documented.

5. The SAEMF Multiplier: Cross-Channel Interactions

5.1 The Multiplier Mechanism

The aggregate employment effect of the Small AI Employment Multiplier Framework (SAEMF) exceeds the sum of the individual channel effects because activation of one channel reinforces the enabling conditions for the others. Consequently, the framework generates a system-level employment multiplier, which constitutes its central analytical contribution. This multiplier can be expressed as a stylized analytical relationship:

$$E_{total} = E_1 + E_2 + E_3 + E_4 + \sum(E_{ij})$$

where E_1through E_4represent the direct employment effects of the four channels, while $\sum(E_{ij})$ captures the cross-channel interaction effects: the additional employment generated when activation of channel i strengthens the enabling conditions for channel j, where $i \neq j$ and both i and j belong to $\{1,2,3,4\}$. This expression is a stylized heuristic decomposition rather than an empirically calibrated model. It is intended as a conceptual organizing device consistent with the additive-with-interactions logic of employment multiplier frameworks in the regional economics literature (Moretti, 2010; IMPLAN, 2025), adapted to a firm-level, multi-channel development context. The interaction term $\sum(E_{ij})$ is expected to be positive and, in well-designed Small AI deployments, substantial. Indeed, these interactions are the principal source of the multiplier effect. Empirical estimation of both the channel-specific and interaction terms therefore remains a key priority for future research agenda.

The multiplier emerges through a sequence of mutually reinforcing cross-channel interactions. First, productivity gains generated under Channel 1 create the revenue surplus needed to finance market-expansion investments and digital adoption under Channel 2. In turn, the expanded transactions facilitated by Channel 2 generate verified digital records including transaction histories, buyer–seller relationships and payment flows that serve as informational collateral for formalization and access to formal credit under Channel 3. Formalization then unlocks credit, public procurement opportunities and other growth resources, enabling investment in more advanced AI tools and the structured hiring of AI-adjacent workers under Channel 4. Finally, the AI-adjacent workforce created through Channel 4 including local technicians, platform support personnel and digital training facilitators reduces the implementation and maintenance costs of Small AI adoption. Thereby lowering the barriers to Channel 1 activation for subsequent cohorts of SMEs. Through this self-reinforcing cycle, Small AI generates a genuine employment multiplier rather than a collection of isolated firm-level productivity gains.

5.2 Empirical Illustration of the Multiplier

The Twiga Foods case provides a clear illustration of the multi-channel dynamics and multiplier amplification embedded in the SAEMF. The platform simultaneously improves farm and vendor productivity through demand forecasting and route optimization (Channel 1), while connecting previously isolated smallholder farmers and informal retailers to organized urban markets through a network of more than 35,000 vendors and 4,000 farmers (Channel 2). In addition, Twiga digitizes all platform transactions and, through partnerships with IBM and Google Cloud, applies machine learning algorithms to vendor and farmer data to generate credit scores that facilitate access to third-party microloans. This represents a directly observable interaction between Channel 2 and Channel 3 (Howwemadeitinafrica.com, 2024; Mulinge et al., 2024). At the same time, the platform creates employment in logistics coordination, data management and platform support (Channel 4). These effects reinforce one another and collectively contribute to employment expansion.

Pula, an agricultural insurtech operating across Africa and Asia that has reached more than 15 million farmers cumulatively, including 6 million insured in 2023 alone, offers a complementary example of the multiplier emerging from a different entry point (IFC, 2024). By using AI-driven agricultural insurance, Pula integrates informal smallholder farmers into formal risk-management systems (Channel 3), enabling them to invest more confidently in productive inputs and employ seasonal agricultural labour (Channel 1). Formal insurance coverage also strengthens creditworthiness and supports greater market participation (Channel 2). Simultaneously, Pula generates AI-adjacent employment at scale through its actuarial specialists, data analytics teams and more than 5,000 field enumerators responsible for farmer registration and yield assessment across African and Asian markets (Channel 4) (Pula Advisors, 2025; BlueOrchard, 2024). Together, these cases demonstrate that the SAEMF's cross-channel multiplier is not merely a theoretical construct but an observable feature of functioning Small AI deployments in EMDEs, one that would be systematically underestimated by single-channel analyses.

6. Enabling Conditions for SAEMF Activation

6.1 The Four Enabling Conditions

The employment-generating potential of the four Small AI Employment Multiplier Framework (SAEMF) channels is not automatic. Rather, it depends on the presence of four structural enabling conditions: access, affordability, applicability and capability. These conditions serve as essential prerequisites for employment creation. Consequently, the multiplier effect expands when these conditions are present and constrained when they are absent. The four enabling conditions are consistent with and extend the GSMA Mobile Connectivity Index's framework of infrastructure, affordability, consumer readiness, and content and services (GSMA, 2024). However, they are adapted specifically to the employment-generation context of Small Artificial Intelligence (AI). They also closely align with the four pillars of the IMF AI Preparedness Index: digital infrastructure, human capital and labour market policies, innovation and economic integration, and regulation and ethics (Cazzaniga et al., 2024).

To operationalize these concepts, Table 2 presents the SAEMF Enabling Conditions Diagnostic Framework. The framework maps each enabling condition to its corresponding requirements, measurement indicators and the employment channels that depend most heavily on it. Indicators accompanied by specific quantitative values are drawn from verified primary sources. The remaining indicators are author-developed measurement proxies intended for field application. The framework is the authors’ original construction, informed by GSMA (2024), International Telecommunication Union (ITU) (2024), International Finance Corporation (IFC) (2025), Cazzaniga et al. (2024), and International Labour Organization (ILO) (2024).

Table 2. SAEMF Enabling Conditions Diagnostic Framework

Enabling Condition	Definition	Key Requirements	Measurement Indicators	Primary Channels Affected
Access	Physical and digital access to Small AI tools and connectivity infrastructure	Mobile broadband coverage; device availability; electricity access; local language support	Internet penetration rate (27% in low-income countries, ITU, 2024); mobile ownership rate; electricity access rate; language localization coverage of AI tools	All channels, especially Channels 1 and 2
Affordability	Financial accessibility of Small AI tools and services for MSMEs	Low-cost or subsidized AI tools; freemium and pay-as-you-go pricing models; digital payment infrastructure	AI tool cost as % of SME monthly revenue; mobile data cost per GB (mobile internet costs in Africa 12× higher than Europe, ITU, 2024); share of MSMEs with digital payment access	Channels 1 and 3
Applicability	Contextual relevance and fit of AI tools to EMDE SME tasks, sectors, and operational constraints	Task specificity; local language support; sector-specific calibration; offline functionality for low-connectivity environments	User adoption rates; task completion rates; local language coverage; availability of offline functionality	Channels 1 and 4
Capability	Human capital and institutional capacity for effective AI adoption, use, and maintenance	Digital literacy among target SME operators; vocational AI training provision; extension and support services; regulatory recognition of AI-adjacent occupational categories	Digital literacy rates; vocational training enrolment and completion rates; AI-adjacent roles recognized in national skills frameworks; training-to-placement ratios	Channel 4 primarily; all channels secondarily

Source: Authors' construction

6.2 The Enabling Conditions as a Diagnostic Instrument

The enabling-conditions framework is intended to serve as a practical diagnostic tool that policymakers, multilateral institutions and SME support organizations can use to evaluate an EMDE's readiness for Small AI-driven employment creation before implementation begins. This approach aligns with the country-level readiness assessment methodology of the GSMA Mobile Connectivity Index (GSMA, 2024) and the IMF AI Preparedness Index's use of multi-pillar scoring to identify context-specific constraints (Cazzaniga et al., 2024). For example, a country or sector may exhibit high access but low capability, characterized by widespread mobile connectivity but limited digital literacy. Such conditions are evident across many Asian low- and middle-income countries, where skills deficits remain the leading barrier to internet adoption. In these settings, Small AI deployment should be complemented by intensive training and extension support before or alongside implementation.

Similarly, a context may exhibit high affordability but low applicability, where tools are inexpensive yet poorly adapted to local languages, tasks or offline operating environments. In such cases, localisation becomes the primary constraint, as reflected in persistently low adoption rates among connected populations lacking locally relevant content and services (GSMA, 2024; ITU, 2024). The underlying diagnostic logic is that no employment channel can realize its full multiplier potential without the necessary enabling conditions. Consequently, investment sequencing should focus on addressing the most binding constraint in each context rather than applying uniform Small AI deployment strategies across structurally diverse EMDE environments.

7. Addressing Risks, Counterarguments and Limitations

7.1 Does Small AI Generate Precarious Rather Than Productive Employment?

A substantial body of research on digital labour platforms shows that algorithmic intermediation can generate employment while simultaneously creating precarious, low-paid and unstable working conditions, particularly in content moderation, crowdwork and gig-economy roles. Drawing on an International Labour Organization survey of crowdworkers, Berg (2016) finds that platform-mediated work is often characterized by income volatility, inadequate remuneration and limited access to social protection. Similarly, the International Labour Organization's World Employment and Social Outlook (ILO, 2021), based on surveys of 12,000 workers across 75 countries and five major digital labour platforms, reports that most platform workers seek additional work but are constrained by labour oversupply, algorithmic exclusion and unpredictable earnings. These challenges are especially pronounced in developing countries, where workers also face payment restrictions and geographic discrimination. The literature further documents the psychosocial harms associated with AI content moderation (Roberts, 2019), highlighting a specific subset of Channel 4 risks that requires targeted governance. This critique is directly relevant to Channel 4 of the SAEMF. Accordingly, the framework incorporates enforceable labour standards including minimum earnings thresholds, social protection coverage and algorithmic transparency as prerequisites for Channel 4 activation, particularly in content-intensive AI-adjacent occupations. In addition, the SAEMF's employment-quality indicators such as wage premiums relative to comparable non-AI jobs, employment stability, demographic inclusion and working-condition standards are explicitly designed to assess whether Channel 4 generates productive rather than merely precarious employment.

7.2 Does Small AI Reproduce Rather Than Disrupt Value-Chain Power Asymmetries?

A second critique concerns the distribution of power within digital value chains. When Small AI platforms are owned by foreign investors or dominant domestic firms, the benefits generated through platform-enabled market expansion may be captured by intermediaries rather than shared with smallholder farmers and informal retailers, thereby reinforcing existing asymmetries in EMDE value chains. This concern is supported by evidence showing that digital value chains can be extractive when technologies and algorithms are developed in high-income economies using data sourced from developing countries while tax revenues remain disconnected from value creation (CIGI, 2021). Similar dynamics have been observed in agricultural platforms, where intermediary margins and data-ownership arrangements may disadvantage the very farmers these platforms are intended to support (Agyekumhene et al., 2018). The SAEMF recognizes this as a legitimate structural risk. However, its effects can be mitigated through platform-governance design. Platforms that incorporate data-portability rights, cooperative or multi-stakeholder ownership arrangements (Scholz, 2016), or public digital infrastructure mandates that treat data and services as public goods rather than proprietary assets are better positioned to deliver inclusive outcomes. Reflecting this concern, the policy matrix in Section 8 includes governance recommendations covering data-portability standards, user-ownership provisions and enforcement of labour standards in AI-adjacent occupations.

7.3 Can Small AI Scale Without Becoming Frontier AI?

A third concern is definitional. As Small AI tools succeed and expand, do they inevitably evolve into frontier AI systems requiring larger datasets, greater computational capacity and higher levels of capital investment? The evolution of successful digital platforms in developing economies suggests that such a trajectory is plausible. For example, mobile-money platforms initially developed for basic feature phones have progressively evolved into more sophisticated AI-enabled financial ecosystems (Suri & Jack, 2016; FSD Kenya, 2023). The SAEMF acknowledges that successful Small AI applications may eventually scale beyond their original scope. However, this does not negate their analytical distinctiveness at the deployment stage. The Small AI applications examined in this paper differ from frontier AI systems because they are task-specific, locally deployable, affordable and designed to operate under resource constraints. It is these characteristics, rather than their future evolution, that underpin their relevance for employment creation in EMDEs. This distinction is evident in the documented cases from agriculture, logistics, credit scoring and labour-market matching discussed in Section 4. Although the boundary between Small AI and frontier AI may require revision as technologies evolve and successful systems scale, this does not diminish the current analytical or policy relevance of the distinction. Policymakers can invest in Small AI deployment today without first resolving the long-term definitional question. The value of the SAEMF lies in guiding the deployment phase, while determining when a scaled Small AI system becomes frontier AI remains a useful topic for future research rather than a limitation of the framework itself.

7.4 Limitations and Future Research

This paper has three principal limitations, each of which defines a priority area for future research. First, as a conceptual framework, the SAEMF and its multiplier mechanism have not yet been tested through primary data collection. Although the examples cited are drawn from verified evaluations, organizational reports and peer-reviewed case studies, they vary in methodological rigor and were not designed to evaluate the framework's causal propositions directly. Second, the enabling-conditions diagnostic framework, while grounded in the GSMA and IMF AI-readiness literature, has not been validated across specific EMDE contexts. Consequently, both its diagnostic effectiveness and the relative importance of individual constraints remain empirical questions. Third, the multiplier expression presented in Section 5 is intended as a conceptual organizing device rather than an estimated model. The magnitude of both channel-specific effects and cross-channel interactions therefore remains an open empirical question requiring field-based research capable of identifying causal relationships and disentangling channel contributions.

8. Policy Matrix

8.1 Overview

The SAEMF can be translated into an actionable policy matrix for three primary audiences: multilateral development banks (MDBs), national governments in Emerging Market and Developing Economies (EMDEs) and Small and Medium-sized Enterprise (SME) support organizations. Table 3 presents the complete policy matrix, which organizes policy instruments by enabling condition, channel, responsible actor, implementation modality and measurable outcome. These instruments are grouped into five categories: the four enabling conditions identified in Section 6 and a cross-cutting governance category. Where instruments represent forward-looking recommendations rather than documented practices is indicated accordingly.

Table 5. SAEMF Policy Matrix

Enabling Condition	Channel	Policy Instrument	Responsible Actor	Implementation Modality	Measurable Outcome
Access	1, 2	Universal mobile broadband subsidies and community digital access points	National governments; MDBs (documented in World Bank PPP, 2024; UNESCAP, 2022)	Public investment; PPP	% population with mobile internet access; device ownership rates
Access	1, 2	Local language AI tool development mandates and incentive grants	National governments; innovation agencies standards (author-proposed instrument grounded in GSMA, 2024; ITU, 2024)	Conditional funding; procurement standards	Number of AI tools available in EMDE languages; adoption rates among target SME populations
Affordability	1, 3	Subsidized Small AI tool access programmes for	National governments; MDBs (IFC,	Voucher programmes; matching grants	Number of SMEs accessing subsidized AI tools; tool uptake rates

		SMEs below threshold revenue	2025; World Bank, 2025)		
Affordability	3	Digital payment infrastructure investment and interoperability mandates	Central banks; MDBs	Regulation; public investment (BIS, 2022; World Bank, 2024)	% SMEs with digital payment access; transaction volumes
Applicability	1, 4	Sector-specific Small AI deployment programmes for priority EMDE sectors	MDBs; national governments	Targeted investment; challenge funds	Number of sector-specific AI tools deployed; adoption and usage rates
Applicability	2	AI-enabled market infrastructure investment (matching platforms, logistics AI)	MDBs; private sector	Blended finance; public-private platforms	Market reach expansion; downstream employment created
Capability	4	National AI-adjacent vocational training programmes through TVET systems	National governments; education ministries; UNESCO-UNEVOC	Curriculum reform; training partnerships (ILO, 2024; UNESCO-UNEVOC, 2023; World Bank, 2023)	Number of workers trained; placement rates within six months; wage premiums over comparable non-AI roles
Capability	3, 4	Regulatory frameworks recognizing AI-generated financial records as formal creditworthy collateral	Central banks; financial regulators	Regulatory guidelines; pilot programmes (author-proposed instrument grounded in Apollo Agriculture, 2024; GSMA, 2025)	Number of SMEs accessing credit via AI-generated records; credit volumes
Governance	All	Small AI platform governance standards (data portability, ownership, labour standards)	National governments; MDBs; regulators	Regulation; platform licensing (Scholz, 2016; ILO, 2021)	Platform compliance rates; worker welfare indicators; data portability rates
Governance	3	Formalization incentive frameworks (progressive tax, procurement preferences)	National governments	Tax policy; procurement reform; active compliance support (De Soto, 2000; De Mel et al., 2013; Bruhn & McKenzie, 2014	Formalization rates; SME registration growth; take-up of formal credit post-registration

Source: Authors' construction. Note. MDBs = Multilateral Development Banks (World Bank Group, African Development Bank, Asian Development Bank, IDB, etc.). TVET = Technical and Vocational Education and Training. Policy instruments are illustrative rather than exhaustive. Source: Authors' original construction based on IFC (2025), ILO (2024), UNCTAD (2025), Cazzaniga et al. (2024), and De Soto (2000).

8.2 Priority Actions for Multilateral Development Institutions

Three priority actions emerge from the policy matrix for multilateral development institutions. First, Multilateral Development Banks (MDBs) should establish dedicated Small AI investment windows within their SME finance and private sector development portfolios. These windows should specifically target Small AI tools across key areas such as advisory in agriculture, health and legal, crop disease detection, inventory management, freight matching, digital skills etc., rather than treating AI investment as part of broader digital transformation programmes. For example, the African Development Bank (2025) identifies AI and digital transformation as strategic priorities in its 2024–2033 Ten-Year Strategy, while the Asian Development Bank (2025) highlights AI as a key driver of SME productivity and inclusive development across Asia. Second, MDBs should invest in SAEMF-aligned monitoring and evaluation frameworks capable of measuring direct, indirect and induced employment effects across all four channels. Such frameworks would help address the current data gap that limits rigorous assessment of AI's employment multiplier effects in EMDEs. Third, MDBs should support the development of regional Small AI ecosystems, including local-language training data commons, open-source Small AI model libraries and regional testing and certification infrastructure. These investments would lower the cost of developing and deploying Small AI tools in EMDEs and build on emerging approaches to open digital public infrastructure development.

9. Conclusion

This paper has presented Small AI as a distinct analytical category, introduced the Small AI Employment Multiplier Framework (SAEMF) as the first integrated model explaining the causal pathways linking Small AI adoption by SMEs in EMDEs to net employment creation. It shows that employment effects are amplified through cross-channel interactions that generate a genuine multiplier effect. The paper makes four principal contributions. First, it establishes Small AI defined by resource efficiency, task specificity, contextual embeddedness and cost accessibility as a conceptually distinct and analytically useful category, separate from frontier AI. Second, it integrates task-based employment theory, SME productivity theory and Schumpeterian growth theory into a multiplier framework tailored to the structural characteristics of EMDEs, including high informality, SME dominance and infrastructure constraints that existing models do not adequately address. Third, it operationalizes the framework through firm-level implementation pathways, evidence from multiple EMDE deployment contexts and an enabling-conditions diagnostic instrument. Fourth, it translates the framework into a practical policy matrix for multilateral development institutions, national governments and SME support organizations. The central argument of the paper is that the employment challenge facing EMDEs cannot be addressed by adapting AI strategies developed for high-income economies. Instead, it requires a different analytical lens grounded in the realities of informal, SME-dominated labour markets. Such a lens focuses on AI tools that can operate effectively within these constraints and identifies the pathways through which they generate employment at the scale and inclusiveness needed to address the 600 million-job gap.

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