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How should South Africa redesign education, industrial policy, and fiscal incentives to harness artificial intelligence for productivity growth while limiting labour market disruptions?

1. Introduction

Artificial intelligence (AI) is changing how goods and services are produced. Machine-learning systems lower the cost of prediction, so they can spot defects, speed up routine analysis and support decisions in sectors from agriculture to financial services (Agrawal, Gans and Goldfarb, 2018). Early evidence suggests these tools can raise productivity, especially for less experienced workers (Brynjolfsson, Li and Raymond, 2025). The same capabilities can also replace tasks that workers now perform. Whether the net effect on employment is positive depends on whether technology creates enough new tasks to offset those it automates (Acemoglu and Restrepo, 2019; Autor, 2015). Early cross-country estimates suggest that a large share of jobs is exposed to AI, and that exposure is greater in advanced economies than in low-income ones (Cazzaniga et al., 2024).

For South Africa this question is pressing. The economy needs faster productivity growth, but the labour market has little room to absorb disruption. Statistics South Africa reported that the official unemployment rate rose to 33.6 per cent in the second quarter of 2026, which corresponds to about 8.5 million unemployed people (Statistics South Africa, 2026). The youth unemployment rate rose by 1.5 percentage points to 47.4 per cent. Many young people therefore enter the labour market with no prior formal job to fall back on, and displaced workers would have few alternatives. Fiscal space is also tight. The 2026 Budget Review forecasts real GDP growth of 1.6 per cent in 2026, rising to 2 per cent by 2028 (National Treasury, 2026).

This essay discusses how South Africa can shape the spread of AI so that it expands productive opportunities instead of simply displacing workers. It argues that the real choice is not whether to permit AI, but how to guide its adoption. It proposes a differentiated, employment-sensitive strategy built on four pillars: Education and skills, Industrial policy, Fiscal incentives and Worker transition support. The essay proceeds from South Africa's economic constraints to the theory of technological change, international experience, education reform, sector selection, fiscal design and labour-market adjustment.

2. Background: AI and South Africa's structural economic constraints

Artificial intelligence (AI) refers to computational methods that perform tasks such as classification, prediction, natural-language processing and pattern recognition. Generative AI can also produce text, code and images, while narrower applications already support maintenance planning, demand forecasting and quality inspection. The economic effects depend less on the technology than on how it is embedded in organisations, what complementary investments accompany it, and which tasks stay under human control. Measured productivity gains typically lag adoption because firms must first invest in data, processes and skills (Brynjolfsson, Rock and Syverson, 2021). It is also important to distinguish a job's exposure to AI from its disappearance. Jobs are bundles of tasks, and automating some tasks can change an occupation without eliminating it, particularly where new tasks are created alongside (Arntz, Gregory and Zierahn, 2016; Acemoglu and Restrepo, 2019; Cazzaniga et al., 2024).

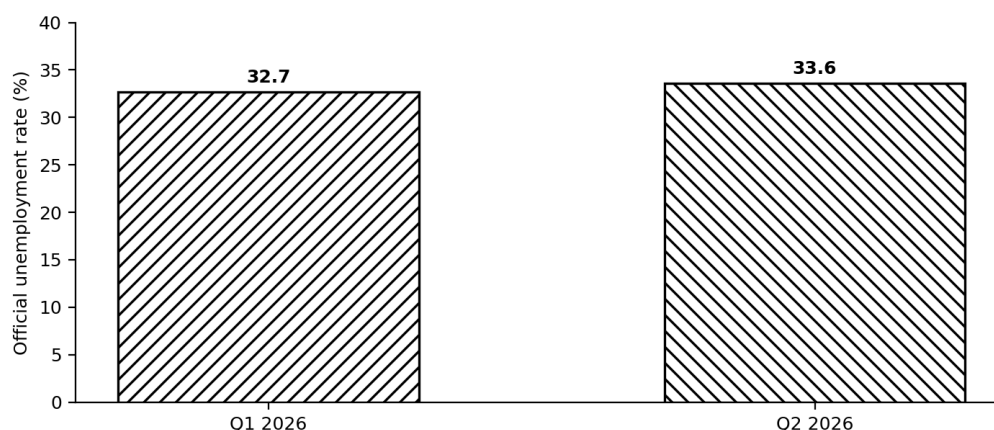
South Africa's production structure pairs sophisticated finance and professional services with many small firms, widespread informal work and uneven access to reliable infrastructure. This dualism affects how AI spreads. Large enterprises can usually finance software, cloud services, cybersecurity and staff development. Smaller firms often lack the cash flow, managerial capability or data to adopt the same tools, a pattern found in technology adoption across developing economies (Cirera and Maloney, 2017). A uniform tax deduction would therefore tend to favour firms that are already technologically advanced and do little for those facing the largest barriers to adoption.

Advanced AI tools depend on literacy, numeracy, problem-solving and the ability to evaluate information. Foundational learning is weak: in the 2021 Progress in International Reading Literacy Study (PIRLS), 81 per cent of Grade 4 learners could not read for meaning in any language, up from 78 per cent in 2016 (Mullis et al., 2023; Spaul, 2023). Introducing AI software without strengthening these basic capabilities risks substituting a new device for genuine learning. Unequal connectivity and teacher support can also widen the gap between well-resourced and poorly resourced schools. Education reform should therefore be sequenced around foundational learning, teacher readiness, infrastructure and practical assessment.

Electricity reliability, transport performance, broadband access, competition and administrative capacity determine whether an efficiency gain inside one firm becomes an economy-wide productivity gain. AI cannot compensate for goods that cannot reach a port or for a business without reliable connectivity. The government itself treats these constraints as central: the 2026 Budget Review ties its growth forecast, reaching 2 per cent by 2028, to continued structural reforms (National Treasury, 2026). It also projects public infrastructure spending above R1 trillion over the medium term. AI industrial policy should therefore complement these infrastructure and competition reforms, not divert resources from them.

3. Current economic overview: unemployment, growth and fiscal space

The official unemployment rate rose from 32.7 per cent in the first quarter of 2026 to 33.6 per cent in the second quarter. The increase is not evidence of AI-related displacement. It is evidence of the difficult starting conditions in which any technological transition would occur.

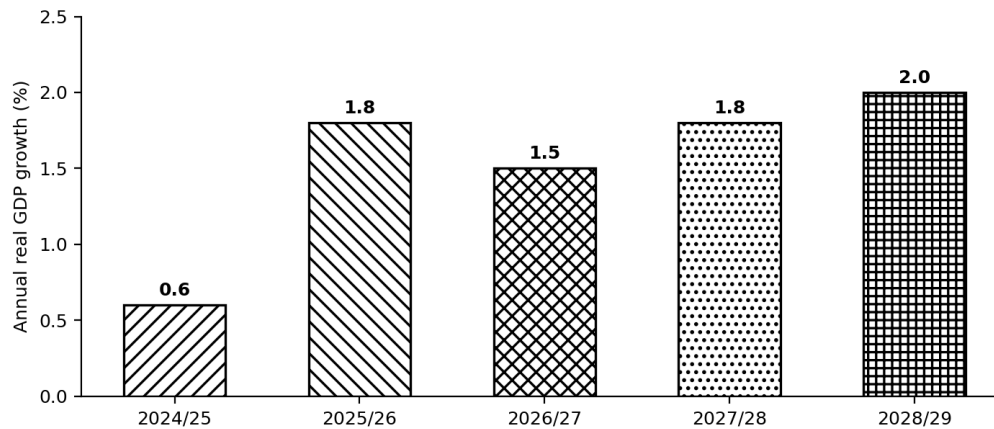


Source: Statistics South Africa (2026).

Figure 1. Official unemployment, South Africa, Q1–Q2 2026.

The National Treasury's 2026 Budget Review estimated real GDP growth of 1.8 per cent in 2025/26 and forecast 1.5 per cent in 2026/27, followed by 1.8 and 2.0 per cent in the subsequent two fiscal years. These figures are projections from the budget document, not realised outcomes.

Figure 2. Real GDP growth: published actuals, estimates and forecasts.



Source: National Treasury (2026).

Fiscal discipline is especially important because public support for AI may compete with basic education, electricity networks, water, transport and existing social commitments. A subsidy that merely transfers revenue to a company that would have invested anyway has a high opportunity cost.

4. Theoretical framework: technological change, growth and employment

Endogenous growth theory explains productivity improvement as the result of deliberate knowledge accumulation, innovation and investment in human capital, not as an outside force (Romer, 1990; Aghion and Howitt, 1992). Within this framework, AI matters because it can lower the cost of experimentation, make better use of information and give more firms access to specialised expertise. Yet the existence of a model does not guarantee a productivity gain. Benefits arise only when organisations reorganise work around the technology, which in turn depends on complementary skills, competition and investment (Brynjolfsson, Rock and Syverson, 2021). Skills are the most important of these complements. Human capital theory treats education and training as investments that raise productive capability (Becker, 1964), and the ability to adopt and adapt new technology rises with educational attainment (Nelson and Phelps, 1966). In an AI transition, the relevant capabilities include foundational literacy and mathematics, digital fluency, domain knowledge and judgement. Workers who can supervise and interpret AI outputs are likely to become more productive. Those whose work consists mainly of automatable tasks may face falling demand unless they can acquire

complementary skills (Goldin and Katz, 2008). Education policy therefore affects both the size of the aggregate gain and how it is distributed.

The task-based framework explains why these effects differ across occupations (Autor, Levy and Murnane, 2003; Acemoglu and Restrepo, 2019). Technology does not replace whole jobs. It substitutes for specific tasks, and this can lower labour demand in some activities. Three other forces work against that loss. Cheaper production can expand output and raise demand for labour elsewhere. AI can complement workers by making complex activities easier. New tasks and occupations can emerge. Employment outcomes therefore depend on the balance between displacement and these offsetting forces, and they cannot be inferred from technical exposure alone.

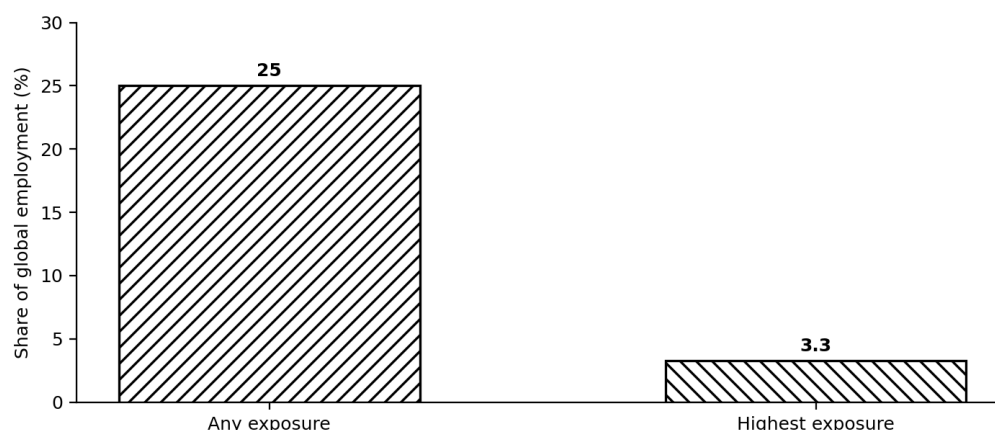
The offsetting forces materialise depends partly on where AI is applied, which brings in structural transformation. Long-run growth requires labour and resources to move into activities with higher productivity (McMillan and Rodrik, 2011). Hirschman's (1958) backward and forward linkages show why support for one activity can spill over to its suppliers and downstream users. AI-enabled cold-chain management, for example, could cut food losses and raise demand for processing, transport and retail services. Spillovers of this kind provide a stronger basis for selective public support than private productivity gains alone, and they point policy towards applications that strengthen domestic production networks.

Spillovers are also what make public intervention defensible. Markets tend to underinvest where firms cannot capture all the benefits of training, research, shared data infrastructure or technology demonstration. Credit constraints and coordination failures can further slow adoption among smaller firms. Intervention is not free of risk, however. Governments face their own information problems and may pick weak projects or subsidise politically connected firms (Krueger, 1974). Support should therefore be additional, meaning that it changes firm behaviour instead of rewarding investment that would have happened anyway (Hall and Van Reenen, 2000). Industrial policy is more likely to succeed when it is treated as a process of discovery between state and business, with clear conditions and accountability (Rodrik, 2004).

5. International experience and lessons for South Africa

International experience provides design lessons, not proof that AI has reduced national unemployment. The International Labour Organization estimates that one in four workers worldwide are in occupations with some generative-AI exposure, while 3.3 per cent are in its highest exposure category. The categories are nested, and exposure does not mean job loss.

Figure 3: Global occupational exposure to generative AI (share of global employment, per cent)



Source: ILO (2025), Working Paper 140. The 3.3 per cent group is included within the 25 per cent group.

Singapore, Germany, South Korea and Finland each offer a partial lesson for South Africa, and none can be copied wholesale. Singapore links early AI literacy in schools, teacher guidance and adult retraining through Skills Future, and the transferable point is that connection, not its labour-market results (Singapore Ministry of Education, 2026). Germany shows the value of employer participation in curriculum design, apprenticeships and technical support for smaller manufacturers, but its schemes are costly and operate in a different fiscal and labour-market environment. South Korea's AI-enabled digital learning highlights implementation risks, including teacher preparation, assessment quality, procurement and unequal access, while Finland's guidance on responsible AI in education stresses clear rules and educator judgement. Taken together, these cases support a staged approach in which South Africa runs modest pilots, forms measurable partnerships, and evaluates educational outcomes before requiring widespread adoption.

6. Redesigning education for an AI-enabled economy

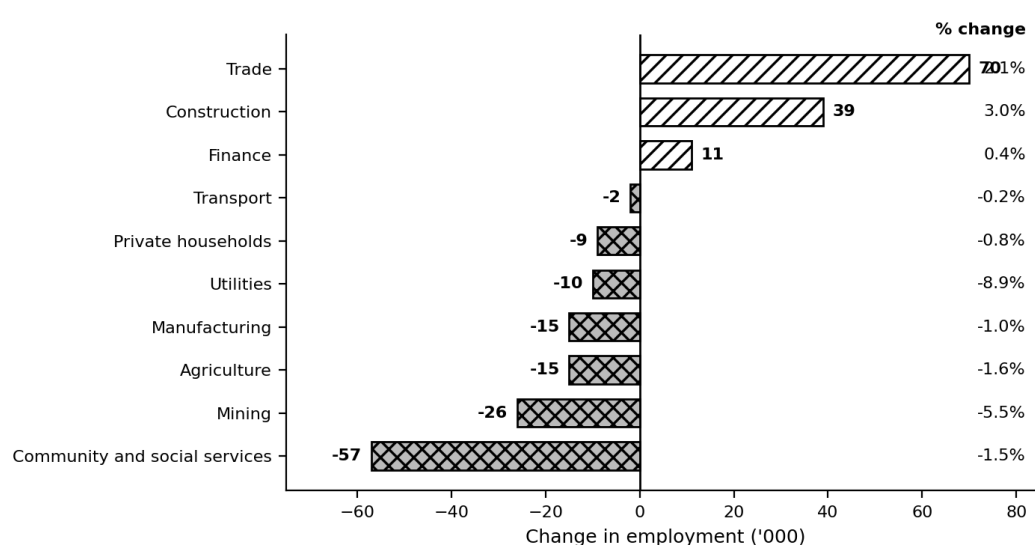
Education is central to AI-driven productivity growth, as human capital improves technological adoption and workforce adaptability (Becker, 1964; Nelson and Phelps, 1966). However, South Africa's educational inequalities remain a challenge, with 81% of Grade 4 learners unable to read for meaning in 2021 (Mullis et al., 2023; Spaull, 2023). The following reforms are proposed:

- Basic education reform: Introduce AI literacy progressively, prioritising foundational literacy, numeracy and computational thinking in primary schools, followed by coding, data interpretation and responsible AI use in secondary schools.
- Pilot AI education programmes: Implement targeted pilots in urban, township and rural schools, assessing learning outcomes, costs and accessibility before nationwide implementation (Bloom, Van Reenen and Williams, 2019).
- Teacher development: Provide training in AI-assisted teaching, digital assessment and data protection, while maintaining teachers' responsibility for critical thinking, learner evaluation and academic integrity.
- TVET and university curriculum reform: Integrate industry-specific AI skills into vocational and higher education, including predictive maintenance in manufacturing, precision farming in agriculture and digital optimisation in logistics (Autor, Levy and Murnane, 2003).
- Workforce reskilling: Strengthen collaboration between Sector Education and Training Authorities (SETAs), employers and universities to provide accredited short courses aligned with labour market demand and emerging occupations (Acemoglu and Restrepo, 2019).
- Equitable digital access: Expand shared digital infrastructure, community learning centres and affordable connectivity, prioritising disadvantaged communities and supporting AI applications in South African languages (Cirera and Maloney, 2017).
- Monitoring and accountability: Evaluate education reforms through measurable improvements in learning outcomes, skills acquisition, employment transitions and programme costs before expanding public investment (Rodrik, 2004).

7. Industrial policy: choosing where AI can raise productivity and employment

A differentiated industrial policy should compare sectors on productivity potential, employment spillovers, domestic linkages, readiness and the need for public assistance. The ranking should be evidence-led and updated as technology changes. It should not presume that every agricultural application is labor-intensive or that every financial application is labour-saving. Recent industry employment changes provide context for an employment-sensitive AI policy.

Figure 4. Quarter-on-quarter change in employment by industry, Q1–Q2 2026 (thousands)



Source: Statistics South Africa, Quarterly Labour Force Survey, Q2 2026

The figure indicates that trade gained approximately 70,000 jobs (2.1%) and construction gained 39,000 jobs (3.0%). By contrast, manufacturing and agriculture each lost approximately 15,000 jobs, corresponding to declines of 1.0% and 1.6%, respectively. Mining recorded a decline of about 26,000 jobs (5.5%), while community and social services experienced a reduction of approximately 57,000 jobs (1.5%). Finance recorded a modest gain of 11,000 jobs (0.4%).

These quarterly movements are not evidence of AI-driven job losses. Seasonal patterns, demand and investment conditions may explain changes. The figure establishes employment vulnerabilities rather than causation.

7.1 Implications for sector-specific AI adoption

In agriculture, AI-enabled crop monitoring, weather and yield forecasting, and decision-support tools could improve resource use and help producers respond to climatic uncertainty. Yet the benefits may be concentrated among larger commercial producers unless smaller farms can access connectivity, equipment, extension services and training.

In manufacturing, AI applications such as predictive maintenance, quality inspection and production scheduling could reduce downtime and improve competitiveness. However, automation of routine production tasks could also reduce demand for certain occupations. Support for industrial upgrading should consequently be linked to workplace learning, technical qualifications and supplier development.

Mining presents a different set of opportunities and risks. AI-assisted maintenance, geological analysis and safety monitoring could improve operational efficiency and workplace conditions, but the scope for task substitution requires careful assessment. Given the sector's employment decline in the supplied figure, AI investment proposals should be assessed for their implications for occupational restructuring and the availability of retraining and redeployment pathways.

7.2 Connecting employment performance to productivity evidence

The proposed differentiated approach should therefore evaluate AI projects against three tests: whether they address a demonstrable productivity constraint, whether they produce wider economic benefits that justify public support, and whether credible measures exist to assist workers whose tasks are affected. Where AI complements labour, policy can focus on diffusion and skills. Where automation risks are substantial, incentives should be paired with retraining, job-placement assistance and monitoring of employment outcomes.

8. Fiscal incentives: a disciplined approach to AI adoption

South Africa should prioritise targeted fiscal incentives over blanket tax holidays, which may benefit established firms, subsidise investments that would occur anyway, and exclude financially constrained SMEs (Hall and Van Reenen, 2000; Cirera and Maloney, 2017). The following measures are proposed:

- Conditional tax incentives: Introduce temporary, capped tax allowances for AI investments linked to productivity improvements, accredited worker training and

cybersecurity safeguards. Support should target additional investment rather than subsidise existing plans.

- SME grants and vouchers: Provide matching grants to smaller firms for AI software, technology integration and workforce training, particularly where tax deductions offer limited benefits.
- AI technology extension services: Establish shared advisory services through universities, TVET colleges and industrial-support agencies to help SMEs assess AI applications, investment costs and technological readiness (Rodrik, 2004).
- Fiscal sustainability and accountability: Finance initial programmes through reprioritisation of existing budgets, with transparent eligibility criteria, spending limits and independent evaluations to assess productivity, employment and investment outcomes (Bloom, Van Reenen and Williams, 2019).
- Employment protection: Link fiscal support to worker reskilling and transition programmes to minimise labour displacement while encouraging productive technological change (Brynjolfsson, Rock and Syverson, 2021).

9. Policy recommendations and Conclusion

AI offers South Africa a chance to raise productivity and firm competitiveness, but it also adds adjustment pressure to a labour market with 33.6 per cent unemployment and a youth rate of 47.4 per cent (Statistics South Africa, 2026). Policy should not aim to maximise adoption or to preserve every existing task. Its aim should be to ensure that productivity gains create new economic activity while workers keep real opportunities to adapt.

First, the state should strengthen foundational education before it expands AI in classrooms. With 81 per cent of Grade 4 learners unable to read for meaning (Mullis et al., 2023), AI tools cannot substitute for basic literacy and numeracy. AI literacy should be introduced through evaluated pilots with explicit teacher support. Second, TVET, university and workplace training should be aligned with the tasks emerging in agriculture, manufacturing, logistics and digital services, so that skills match demand. Third, industrial support should go to projects that show productivity potential, domestic spillovers and feasible worker transitions, in line with the linkage argument in Section 4. Fourth, broad AI subsidies should give way to capped, temporary and independently evaluated incentives that reward additional investment and skills development. This reflects both the weak rationale for blanket subsidies and a fiscal position in which Treasury projects growth of only 2 per cent by 2028 (National Treasury, 2026).

These measures should be delivered through existing institutions wherever possible. Their legitimacy depends on transparent budgets, independent assessment and public evidence that they improve outcomes, and Parliament and Treasury should be able to test them against the indicators set out in this paper. Policy should also treat AI as one part of South Africa's wider productivity agenda, alongside electricity, transport, education, competition and state capability, because AI cannot compensate for failures in any of these.

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