Artificial intelligence and the conditions for productive employment in South Africa

Postgraduate category

Word count: 3,382, excluding references

1 Introduction

South Africa's response to artificial intelligence should begin with the difficulty of turning productive potential into opportunities to earn a living. In the third quarter of 2026, the official unemployment rate stood at 33.7%, while only 39.7% of people aged 15–64 were employed (Statistics South Africa: 2026). AI enters this labour market with the capacity to improve particular tasks, but also to reorganise work around fewer employees. Its contribution to development will therefore depend on how firms use the technology and on whether people can participate in the resulting production.

This essay argues that South Africa should organise its response around complementary investments that make AI useful: workers' knowledge, firms' capacity to reorganise production, and institutions that link learning to employment. Education, industrial policy and fiscal incentives must address these relationships together. However, the need for complementary investment does not automatically justify a subsidy. Public support should focus on transferable skills, shared implementation knowledge and adjustment assistance that private adoption would provide inadequately. Firms should ordinarily finance investments whose benefits they can capture.

The proposed approach accepts that some jobs will change or disappear. Its purpose is to expand productive opportunities while making adjustment costs a matter of public policy.

2 From task productivity to productive employment

2.1 The conditions for wider gains

Labour productivity measures output per unit of labour input, commonly per worker or per hour worked; it reflects capital, technology and organisation as well as employees' effort (OECD: n.d.). Higher output per worker can accompany expanding production, but it can also arise when employment falls faster than output. Consequently, productivity growth is an incomplete measure of a development strategy's success. Output and quality must be examined alongside earnings, recruitment and the prospects of displaced workers. The distinction is already evident locally: the Reserve Bank reports that weaker labour absorption largely explained faster formal

non-agricultural productivity growth in the first quarter of 2026 (SARB: 2026). This does not establish an AI effect; it demonstrates why the productivity ratio alone cannot settle the employment question.

AI reshapes this relationship by altering tasks within occupations. Automation can displace labour, while lower costs, expanding demand and new tasks can increase it. The balance depends on the direction of technological change and the economy's capacity to absorb workers into other activities (Acemoglu and Restrepo: 2019). A study of 5,172 customer-support agents found that an AI assistant increased issues resolved per hour by 15% on average, with larger gains among less experienced workers (Brynjolfsson, Li and Raymond: 2025). This demonstrates a route through which technology can spread expertise. It does not establish that the employer will need more agents.

Nor does access to a tool establish that a firm can use it productively. Brynjolfsson, Rock and Syverson (2021) explain that general-purpose technologies require complementary investments in processes and human capital, whose returns take time to materialise. A worker who can identify an erroneous automated classification still needs reliable records, time to investigate, and authority to correct it. Education develops the judgement involved; workplace organisation determines whether that judgement improves production. This interdependence is the organising principle of the reforms proposed here.

2.2 South Africa's unequal starting point

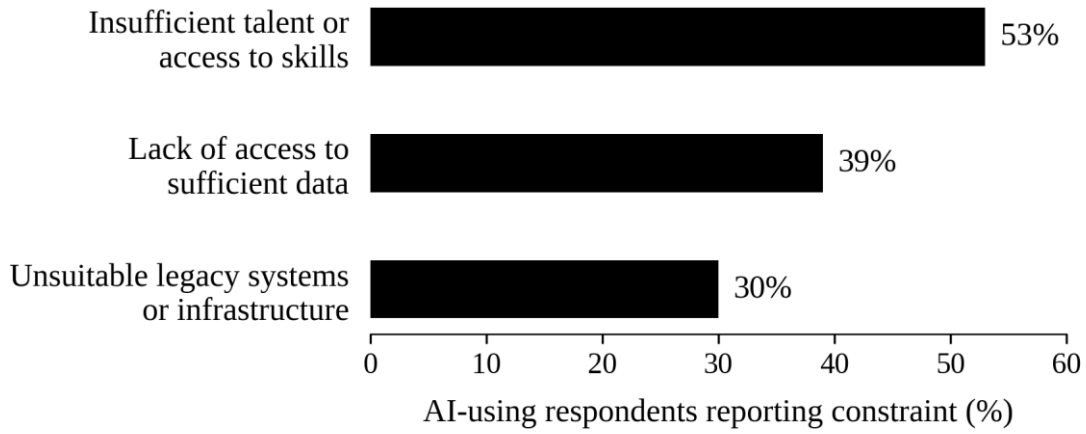
South African evidence cautions against assuming either inevitable job losses or automatic shared prosperity. Using administrative manufacturing data, Kilumelume et al. (2025) find that automation increased output, employment and wages at adopting firms, but put pressure on employment and wages at non-adopting firms in the same industry and municipality. Although this concerns earlier automation rather than generative AI, it highlights an important distinction: successful adopters can grow while competitive adjustment imposes costs elsewhere. Counting jobs only at supported firms would miss part of this process.

The capacity to benefit is also unevenly distributed. By mapping occupational tasks to South Africa's 2019 employment data, Pizzinelli et al. (2023) find that nearly 40% of workers are in occupations with relatively high AI exposure, about half of them with greater potential for complementarity. Exposure measures technical possibilities, not expected job losses. In addition, tertiary-qualified workers held 66.2% of non-routine analytical jobs in formal private employment in 2019, despite making up only 20% of that workforce (Bhorat et al.: 2023). Although both analyses use employment data from before generative AI became widespread,

they show why opportunity cannot be inferred from exposure alone. People with limited access to qualifications may be excluded from new complementary roles, even when their current jobs face little direct automation.

OECD analysis links South Africa's weak job creation to barriers to firm entry and expansion, skills shortages, and infrastructure failures (OECD: 2025). Figure 1 shows selected constraints reported even by existing AI users in finance. Skills, usable data, and compatible systems all matter. These voluntary survey responses are neither national prevalence estimates nor causal explanations of adoption, but they highlight practical complements that a strategy focused solely on purchasing technology would overlook (Hlophe and Mabetha: 2025).

Figure 1 Selected constraints reported by South African financial-sector AI users, 2024



Source: Author's chart from Hlophe and Mabetha (2025: 35), Figure 13. Voluntary survey, October–December 2024; 220 AI-using respondents. Multiple responses permitted.

The policy implication is selective coordination. General education and accessible employment services serve a public purpose beyond any single firm. Shared demonstrations and transferable training can likewise benefit organisations beyond those that fund them. By contrast, a profitable proprietary application may not need a subsidy. Distinguishing between these cases allows the state to address unequal participation without treating every barrier to private investment as a claim on the budget (Brollo et al.: 2024).

3 Education that connects learning to work

3.1 Building independent judgement

Immediate occupational skills shortages and the long-term foundations for learning call for different responses. Foundational learning shapes who can interpret information and later develop occupational expertise. In PIRLS 2021, 81% of South African Grade 4 learners did not

reach the Low International Benchmark for reading comprehension (Department of Basic Education: 2023). An AI strategy that overlooks this foundation risks concentrating benefits among those already equipped to learn. Protecting literacy and numeracy is therefore essential to broadening future participation, though it cannot address the immediate adjustment needs of today's workers..

Technology should reinforce that educational commitment. A South African randomised evaluation found that a package of classroom coaching, lesson plans and materials improved reading outcomes by about 0.24 standard deviations after two years, compared with the control group (Cilliers et al.: 2020). This offers a credible benchmark for evaluating proposed digital interventions. An application that cheaply generates completed exercises does not necessarily lead to more learning.

The distinction matters particularly for generative AI. In a Turkish high-school mathematics experiment, unrestricted GPT assistance improved practice performance but lowered scores on unaided tests taken immediately afterwards by 17%; a tutor with instructional safeguards had no detectable effect on unaided performance (Bastani et al.: 2025). These findings cannot predict outcomes in South African classrooms, but the educational warning is relevant: assistance can displace the practice that builds independent competence. The Department of Basic Education and provinces should therefore test supervised applications in specific subjects, with teacher preparation and assessments completed without AI. Procurement decisions should be based on retained learning, including performance in local languages, rather than usage alone.

3.2 Making occupational learning usable and portable

For existing workers and new entrants, the immediate priority is to link learning with changes in production. The World Bank's mapping of South Africa's digital-skills pipeline identifies gaps in relevance, practical experience and geography, as well as weak alignment between training provision and employer demand (Antunes de Carvalho et al.: 2026). Expanding course enrolment without addressing these gaps could increase the number of credentials while doing little to ease firms' constraints or improve learners' employment prospects.

The Department of Higher Education and Training should accordingly organise occupational partnerships around identified work problems. Colleges, Sector Education and Training Authorities, and employers could develop assessed modules that combine domain knowledge with practical AI use. In bookkeeping, for example, competence would include reconciling accounts and investigating incorrect classifications. Employers would provide supervised practice and paid learning time; providers would assess whether workers can explain and correct

the result independently. Training would thus prepare people to exercise judgement within the redesigned workplace, rather than simply operate an interface.

Assessment should also make competence visible beyond a worker's current employer. In an experiment in Johannesburg involving young jobseekers, shareable skills certificates increased employment by 5.2 percentage points over a control-group rate of 30.9% after three to four months (Carranza et al.: 2022). The intervention communicated skills participants already had; it did not teach AI or demonstrate net job creation across the economy. This supports the use of recognised, portable evidence of competence, but certification cannot make up for inadequate instruction or a shortage of vacancies. Public funding should therefore link assessments to placement services and publish outcomes on progression and earnings, interpreting results in light of participants' starting circumstances.

This proposal can build on DHET's existing post-school plan, which gives SETAs roles in industry engagement and workplace learning and calls for standardised funding timelines (DHET: 2023). These commitments provide an institutional starting point, but do not demonstrate delivery. Initial partnerships should involve providers with proven teaching capacity and clear employer demand, with commissioning deadlines and externally assessed work samples. A single agreement should link the employer's production objectives, paid learning and transition commitments, ensuring responsibility does not fall between separate training and investment schemes.

Such portability also explains why employers may underinvest in training whose benefits another firm can capture. Public co-funding can address that gap, while employers remain responsible for supervision and firm-specific instruction. Entrants need protected opportunities to acquire experience as routine tasks change; otherwise, efficient task completion today may weaken the supply of experienced workers tomorrow (The Economist: 2026a). These arrangements will succeed only where firms organise work so that learning is used.

4 Industrial policy that makes learning productive

4.1 Diagnosing the investment that firms need

Industrial support should start by identifying the production constraint that keeps existing knowledge and resources from delivering better output. Figure 1 suggests that the answer may lie in records, systems or expertise, rather than in a new model. Across South Africa's wider economy, unreliable electricity, logistics and limited market access can also restrict expansion (OECD: 2025). Diagnostics must therefore be able to recommend basic management

improvements or an alternative investment. An AI programme that rewards software purchases regardless of the underlying problem would break the link between public spending and productive capability.

Diagnostics must also assess the entire workflow. The Economist's account of AI-assisted invoicing at Johnson & Johnson describes how faster processing left more work waiting in finance (The Economist: 2026b). This is an illustration, not causal evidence, but it makes the coordination problem tangible. Faster completion of one task has limited value if review becomes the next bottleneck. Evaluation should consider completed, reliable output and the costs of checking it. Providers should help managers and workers redesign these connections together.

The distinction between adopting AI and benefiting from it is supported by an experiment involving 640 Kenyan entrepreneurs. Access to an AI business adviser produced no statistically detectable average improvement in business performance, though outcomes varied according to firms' initial performance (Otis et al.: 2026). Advice that helps a better-equipped firm may be ineffective or even harmful for others. Readiness should shape the assistance offered, not serve as a reason to withhold all support from weaker firms.

The Department of Trade, Industry and Competition should draw on existing technical institutions to bring together diagnostics, demonstrations and workplace learning. The CSIR's manufacturing services and learning factories offer an institutional starting point for practical training tied to production systems (CSIR: n.d.). However, they do not show that adequate capacity already exists nationwide. Initial contracts should therefore identify available providers, sectors and staff, and require findings that can be reused. Sharing knowledge about failed applications can help other firms avoid costly mistakes, offering a clearer public benefit than subsidising routine subscriptions.

4.2 Connecting firm expansion to worker opportunity

The employment effects of support depend on the production strategy it enables. In a randomised study of small firms around Cape Town, both marketing and finance training increased profits, while marketing training produced a larger employment increase after one year, with gains concentrated in part-time work (Anderson, Chandy and Zia: 2018). Although not an AI intervention, this study shows that profitability can improve through different changes in production and demand. Industrial policy should examine whether an application helps a firm improve quality, enter markets or develop services, alongside any savings in labour costs.

Business-process services illustrate the practical stakes. AI assistance could help South African agents resolve complex cases and win additional contracts. However, research on South African

contact centres shows that firms' economic upgrading need not improve workers' conditions (Anwar and Graham, 2019). Foreign clients may retain much of the gain, while employers intensify work. Support agreements should therefore link the production plan to paid learning, consultation and explicit arrangements for changing responsibilities. Worker input can identify errors and unrealistic performance demands; it does not, by itself, guarantee a fair distribution.

Access to this support must nevertheless be carefully designed. Selecting only firms that are immediately ready to invest would favour established businesses and could reinforce the unequal starting point identified earlier. A preparatory stage should help smaller firms improve their records and management before they apply for investment assistance. But inclusion should not mean approving unsuitable projects. Publish applicant and award distributions, select advisers competitively, and separate their diagnostic role from commissions on software sales. This makes wider access compatible with a rigorous test of productive use..

Support should leave firms and workers able to apply what they learn when contracts or suppliers change. Publicly supported projects should provide transferable training and practical access to operational data, while procurement should avoid unnecessary dependence on a single vendor. These safeguards for continued learning also narrow the fiscal question: which elements create benefits beyond the assisted firm, and which should remain a private expense?

5 Fiscal incentives for additional public value

5.1 Selecting the public contribution

The strongest objection to a new initiative is the opportunity cost of scarce funding and administrative capacity. The Parliamentary Budget Office reports revised debt-service costs of R441.5 billion for 2026/27, while emphasising the ongoing demands on public services and development spending (Parliamentary Budget Office: 2026). Funding an AI project could divert resources from teaching, maintenance or infrastructure—areas with a stronger claim. The response must therefore explain why a particular intervention is preferable to these alternatives. Calling the expenditure innovative or labelling it a pilot does not answer that question..

Fiscal instruments should match the diagnosis. Firms should normally finance commercially attractive integration and software themselves. When the barrier is access to finance for a viable investment, credit may be more appropriate than a grant. Public funding is more defensible for shared testing, transferable occupational learning, and adjustment assistance, or when a transparent distributional objective justifies supporting excluded groups. Even then, co-financing signals a willingness to invest; it does not prove that public support changes behaviour.

Grants should fund additional benefits, not reimburse investments that would proceed without support (Brollo et al.: 2024).

A further objection is that ordinary business support could deliver these benefits without an AI-specific intervention. This is persuasive when the underlying need is bookkeeping, maintenance, or market access. Assistance should therefore be technology-neutral during diagnosis, with AI used only when it addresses the problem identified. A limited experiment is justified when uncertainty about implementation or transferable learning prevents worthwhile investment, and when the knowledge gained can inform other firms. The case for experimentation is weaker if existing services can resolve the constraint at lower cost.

Existing tax instruments address only part of the problem. Section 11D's 150% deduction applies to qualifying, approved research and development; it does not provide general reimbursement for AI adoption (SARS: 2025). Extending tax relief to ordinary purchases could reward investments firms would make anyway, while providing little immediate support to firms without taxable profits. A more coherent response is to preserve legitimate research support and direct complementary assistance towards demonstrated learning and coordination gaps.

South Africa's experience offers a warning about both design and evidence. A review of the R&D incentive by Treasury and the Department of Science and Innovation found that an impact evaluation could match only 18 supported firms with 14 comparison firms, making definitive conclusions impossible. It also noted that competition between firms may have driven up remuneration for scarce research skills (National Treasury and DSI: 2021). This does not prove that the incentive failed. Rather, it shows why eligible expenditure is an inadequate measure of outcomes and why efforts to increase demand for skills must be matched by investment in their supply.

5.2 Funding adjustment and testing continuation

The dtic's planned incentive review offers an opportunity to incorporate these lessons into existing arrangements (Department of Trade, Industry and Competition: 2026). Treasury and the department should begin by costing a limited cohort that combines technical assistance, assessed learning and evaluation. The appropriation should cover administration and worker adjustment, identify displaced expenditure, and require a fresh decision before any expansion. No specific ceiling can be justified without these cost estimates. If the appraisal finds that strengthening existing technical services is preferable to adding grants, the budget should reflect that evidence.

Adjustment support warrants a distinct justification. As evidence from South African automation suggests, workers can suffer losses from restructuring even when adoption increases output at

adopting firms (Kilumelume et al.: 2025). Participating employers should fund agreed paid learning and supervision. Existing public employment services should connect displaced workers—including those from unsupported firms—to assessed training and vacancies. Transport or care assistance may be needed to enable participation. Eligibility should not depend on proving that AI alone caused displacement. This protection recognises the distributional costs of change without promising that every task or job will remain.

Evaluation should capture these broader effects. Before assistance begins, applicants should report their planned investment, as well as baseline production and employment. If equally eligible applications exceed capacity, random allocation or randomly phased access can provide a credible comparison. Comparing technical assistance alone with technical assistance plus a grant would show whether the subsidy adds enough value. Collecting these data from the outset addresses a weakness identified in the R&D review, rather than making evaluation a requirement only after funds have been spent (National Treasury and DSI: 2021).

Continuation should depend on whether reliable output and worker outcomes improve enough to justify the full costs of investment, delivery and adjustment. Alongside losses at competing firms, where measurable, assessments should consider earnings, recruitment and where displaced workers go. A supported firm does not have to preserve every position, but it must honour its commitments to learning and transition. Training certificates and higher profits for beneficiaries, however, cannot establish public value on their own. Publishing unsuccessful results and ending ineffective support would make the programme's learning objective enforceable. Since organisational investment takes time, early reviews should assess implementation and learning, followed by later assessments of production and employment. Slow initial returns should prompt investigation—not automatic cancellation or indefinite renewal (Brynjolfsson, Rock and Syverson: 2021).

6 Conclusion

AI can increase productive capacity while leaving many people unable to share in its benefits. South Africa should respond by linking educational capability to how production is organised, and by funding areas that private investment would otherwise neglect. Training subsidies do not guarantee that workplaces will use new skills productively, just as lower production costs alone do not give displaced workers a path into new jobs. Learning, business growth and adjustment must therefore be considered together. The test is whether public intervention creates additional productive opportunities at a justifiable cost.

7 Recommendations

The 2027 budget should fund appraisal and costing through the dtic's incentive review, with a first cohort proceeding only if its benefits justify the costs. Treasury should set clear limits and renewal conditions. DHET and technical providers should link assessed occupational learning to participating firms' production plans, while DBE protects foundational teaching. Expansion should be guided by published evidence of additional output and worker benefits—including displacement costs—not by the number of tools purchased or grants awarded.

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