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Reimagining South Africa's Economic Policy for an AI-Driven Future

Education, industrial transformation and fiscal incentives for inclusive productivity growth.

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1. Introduction

A business can invest in artificial intelligence (AI) and still fail to become more productive. The technology may not suit the production process, workers may not know how to use it, data may be unreliable, or management may leave workflows unchanged. A competitor using the same software may raise output, improve quality and reach new markets. The difference lies less in the technology than in the economic and institutional environment around it.

That distinction is acute for South Africa. AI is arriving in an economy with persistent unemployment, deep educational inequality, weak investment and wide gaps in firm capability. Unemployment reached 33.6% in the second quarter of 2026, with roughly 8.5 million people unemployed (Statistics South Africa, 2026a). Debt-service costs absorb 21.3% of revenue, which limits what the state can spend on any new programme (National Treasury, 2026). AI policy therefore cannot be judged by its capacity to cut business costs alone. It must ask who can adopt the technology, which tasks it displaces, where new activities emerge and whether productivity gains broaden economic participation.

This essay asks: how should South Africa redesign education, industrial policy and fiscal incentives to achieve AI-driven productivity growth while limiting labour-market disruption? It argues that South Africa's AI challenge is a productive-capacity and diffusion problem, not a technology deficit. Value will depend less on how quickly firms acquire AI than on whether they hold the skills, capital and organisational capability to convert it into sustained productivity.

The approach is as follows. Section 2 draws on classical and endogenous growth theory and task-based labour economics to identify what determines whether AI raises productivity and who benefits. Section 3 tests South Africa's readiness against firm-level, labour-market and educational evidence. Sections 4 to 6 examine education, industrial policy and fiscal incentives in turn, drawing on OECD and Korean experience. Section 7

evaluates feasibility and sets out recommendations. One limitation should be stated: South African evidence on AI specifically is thin, so adjacent evidence on digital technology and automation is used with caution.

2. The Economics of Artificial Intelligence and Productivity Growth

2.1 Productivity, specialisation and creative destruction

Smith (1776) linked the division of labour to productivity and the extent of the market. AI can deepen that process by lowering coordination costs and processing information that once demanded substantial labour, through demand forecasting, quality inspection and inventory management. Yet gains are not automatic. Solow's (1957) growth accounting separates output growth driven by capital and labour from growth in total factor productivity (TFP), which captures how efficiently inputs are combined. A firm that buys AI software has raised its inputs; it has not shown higher TFP until the same resources yield more or better output.

Schumpeter's (1942) creative destruction adds a distributional dimension. Innovation opens new markets and methods but weakens established firms and devalues particular skills. AI is therefore both a productivity opportunity and a process of restructuring. The policy question is not how to prevent change but how to strengthen the capacity of firms and workers to join the activities that emerge.

2.2 Knowledge, learning and complementary investment

Romer (1990) places knowledge and innovation at the centre of long-run growth, while Arrow (1962) shows that learning-by-doing raises productivity beyond the initial investment. Firms are thus sites of learning, not passive purchasers of technology: a small processor that learns to use data to reduce waste builds capabilities that improve other parts of its business. Brynjolfsson, Rock and Syverson (2021) explain why this learning takes time. General-purpose technologies require complementary investment in skills, data, management and process redesign, so measured productivity may fall before it rises. Subsidising licences without funding implementation can therefore produce visible adoption with little economic return. Figure 1 illustrates the pattern: output per worker stagnates or dips while firms absorb implementation and learning costs, then rises above its earlier path as complements mature. The curve is conceptual but it explains why early adoption data can mislead and why Section 7 requires 12 to 24 months of evaluation.

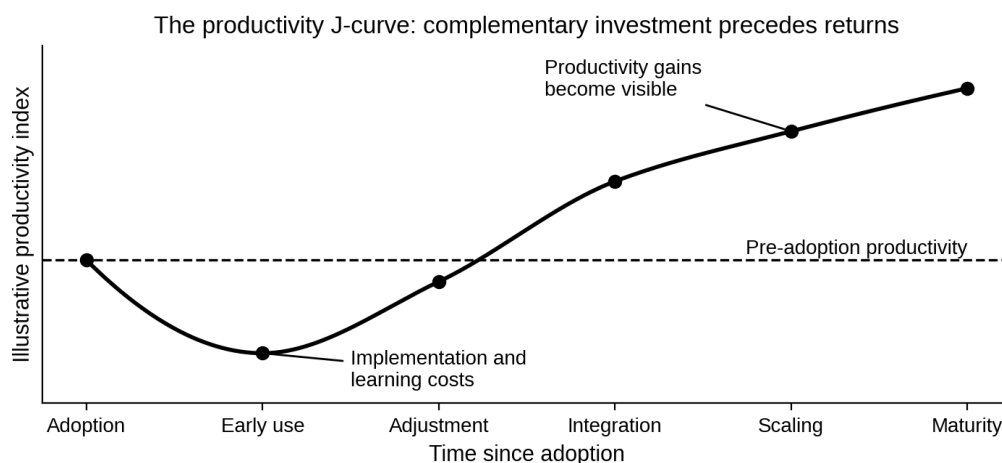


Figure 1. Illustrative productivity J-curve. The curve is conceptual, not an estimate for South African firms. Source: Author's illustration based on Brynjolfsson, Rock and Syverson (2021).

The same logic applies to people. Nelson and Phelps (1966) argue that education matters not only for current productivity but for the ability to understand and implement new technology and that this adaptive capacity is greatest where education is strongest. For South Africa, AI education should prioritise analytical reasoning, occupational knowledge and the ability to judge machine output, not coding alone.

2.3 Labour displacement, task creation and the demand for skills

Acemoglu and Restrepo (2019) distinguish a displacement effect, where capital takes over tasks, from a reinstatement effect, where new tasks create labour demand. Employment outcomes depend on whether reinstatement keeps pace, which in turn depends on investment, market demand, skills and institutions. A logistics firm may need fewer routine schedulers but more data managers, whose jobs may demand different qualifications and sit in different communities. If AI complements advanced analytical skills while substituting routine tasks, returns to skills and capital rise relative to the wages of workers whose tasks are easy to automate. Distribution is therefore shaped by retraining access and bargaining power, not by technology alone.

3. South Africa's Readiness for an AI-Driven Economy

Readiness begins with growth. Figure 2 shows that real GDP growth averaged about 1.1% a year over 2022 to 2025 and Treasury now forecasts 1.2% for 2026, down from the 1.6% it projected in February (Statistics South Africa, 2026b; Magubane, 2026). With unemployment at 33.6%, growth near 1% leaves little room for labour absorption. In

Solow's terms, faster growth must come largely from higher TFP, meaning more output from existing resources. That is the gain AI promises but as Section 2 showed, it is delivered only through complementary skills, data and organisation.

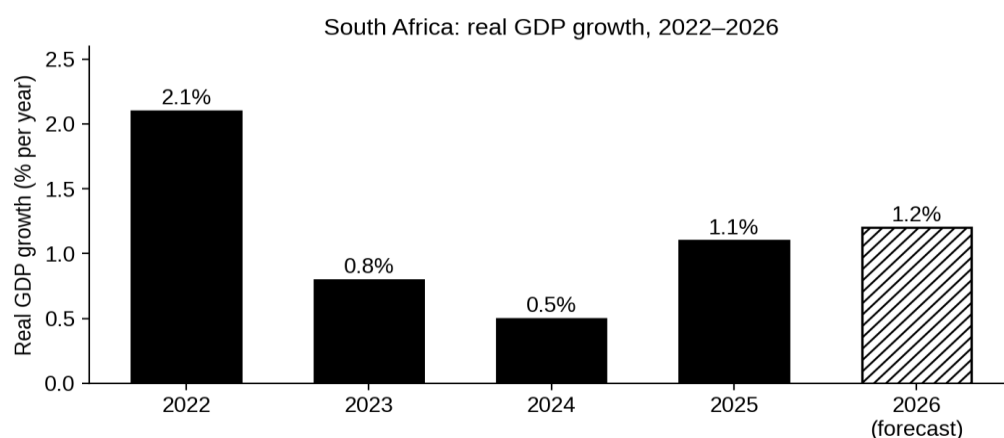


Figure 2. South Africa's real GDP growth, 2022–2026 (% per year). Bars for 2022–2025 are outcomes; the hatched 2026 bar is Treasury's October 2026 forecast.

Sources: Statistics South Africa (2026b); Magubane (2026).

3.1 Skills and educational inequality

The foundation for adaptive capacity is weak. In the 2021 Progress in International Reading Literacy Study, 81% of Grade 4 learners could not read for meaning in any language, up from 78% in 2016 and South Africa ranked last of the participating countries (Spaull, 2023). Declines were concentrated in African-language schools and inequality between no-fee and fee-charging schools widened. On Nelson and Phelps's logic, learners who cannot read fluently will struggle to adapt to AI-enabled work, so any AI skills strategy built on this base without repairing it will fail.

3.2 Industrial capacity and unequal firm-level adoption

Avenyo, Bell and Nyamwena (2024), using survey data on 516 manufacturing firms, find that innovation, foreign ownership, export exposure and higher-skilled human capital are associated with digital adoption, while capital constraints inhibit it. The study covers digital technologies broadly, not AI but it shows that firms start the transition with unequal capabilities. This invites cumulative advantage: capable firms adopt, grow and reinvest, while smaller firms remain trapped by limited resources and low productivity. The OECD (2024) finds similar concentration of AI adoption among larger, more productive firms in its member economies.

Kilumelume et al. (2025), using administrative data and an event-study design, find that South African manufacturers adopting automation roughly doubled production and value added within four years, with higher value added per worker, TFP, employment and average wages. Crucially, they find no significant spillovers to non-adopting firms in the same industry and location. The findings concern automation, not generative AI but they show that productivity and employment can rise together inside expanding firms while diffusion beyond them is not guaranteed.

3.3 Labour-market vulnerability and the digital divide

The labour-market risk is real. Giwa and Ngepah (2024) find a negative long-run relationship between AI investment and low-skilled employment in South Africa, using quarterly data for 2012 to 2021. Aggregate time series cannot show that each AI application destroys low-skilled jobs but they undermine the assumption that markets will protect vulnerable workers automatically. This sits alongside Kilumelume et al. (2025) without contradiction: the studies cover different technologies, samples and mechanisms.

Connectivity compounds the problem. Statistics South Africa (2025) reports that 82.1% of households had internet access by some means in 2024, much of it presumably through mobile devices but only 17.4% had a fixed-line connection at home. Mobile access supports communication but constrains the sustained, data-intensive use that AI-enabled learning and work require. Finally, the 2026 draft National AI Policy was withdrawn after fictitious references were found in it (South African Government, 2026). The episode shows that AI governance requires verification, technical expertise and accountable institutions.

4. Redesigning Education for an AI-Enabled Workforce

4.1 Curriculum reform

Not everyone must become a programmer. Most workers will create value by combining AI with expertise in agriculture, accounting, engineering, logistics or healthcare. A workable strategy distinguishes three tiers: foundational AI literacy, occupational application and specialist technical development. At school level, literacy, mathematics and reasoning come first, supplemented by teaching learners to question AI output and recognise error, bias and privacy risk. Section 3.1 implies that early-grade reading is itself

AI policy. Teacher capacity matters as much as content: curriculum change that outruns teachers' own confidence with the technology will produce compliance, not learning.

4.2 Technical and vocational education

TVET colleges are the natural vehicle for occupational application and the 2026 Budget allocates R15.0 billion to them (National Treasury, 2026). Colleges should co-design applied projects with employers, so that an agro-processing student, for instance, tests demand forecasting on a real plant's data. Paid, supervised placements link learning to business need and, through the extension model in Section 5, give unemployed graduates practical experience. The constraint is employer engagement, since placements only teach if firms have real problems and data to offer, which is another reason for the extension model to anchor them.

4.3 Lifelong learning, reskilling and worker adaptability

Workers already employed need short modular courses tied to changes in their actual tasks. Employers and SETA-supported programmes could co-finance paid apprenticeships in which participants demonstrate competence by solving a real workplace problem. Training should be judged by outcomes (employment transitions, earnings, workplace use and employer satisfaction), not enrolment. A portable record of assessed capabilities could help employers recognise skills, provided it rests on demonstrated competence rather than another certificate of uncertain value. Displaced low-skilled workers are the group most exposed (Giwa and Ngepah, 2024) and the least able to fund unpaid study, so reskilling for them should be short, tied to adjacent tasks they can plausibly move into and accompanied by income support during transition rather than asking them to retrain as data specialists.

5. Reorienting Industrial Policy Towards AI-Driven Productivity

5.1 Sector-specific adoption

Support should concentrate where AI offers a credible advantage over simpler tools. Agro-processing, manufacturing and logistics are natural starting points. A food processor might test demand forecasting to cut overproduction and inventory costs; a manufacturer, predictive maintenance to reduce downtime; a fresh-produce wholesaler, stock forecasting to reduce spoilage. These uses matter in an agri-food economy where losses, variable supply and coordination problems affect both viability and food

availability. Each should be assessed against data requirements, cost, reliability and non-AI alternatives.

5.2 SME support and technological diffusion

Because diffusion does not happen automatically (Kilumelume et al., 2025), it must be engineered. Smaller firms face information and coordination failures: they struggle to evaluate suppliers, while vendors have incentives to sell rather than independently assess suitability. South Africa should pilot AI productivity extension services, modelled on agricultural extension, delivered through TVET colleges, universities and existing business-support bodies. Advisers would diagnose problems, test solutions and verify results.

Korea's AI Voucher Programme offers a precedent. It helps eligible firms buy services from registered providers and builds a domestic supplier market. An OECD case study reports more than 1,000 supported projects and an independent evaluation finding average employment gains of about six percentage points among beneficiaries, persisting for up to three years (OECD, 2025a). The result should not be read as a South African forecast, given different industrial structure and state capacity. The transferable lesson is to lower adoption costs, connect firms to capable providers and evaluate. OECD survey evidence (2025b) also suggests firms mostly use generative AI to improve existing employees' performance rather than cut headcount, although these are self-reported findings, not causal estimates.

5.3 Domestic innovation and industrial competitiveness

South Africa should not try to compete in frontier model development. Its comparative opportunity lies in applications and adaptation: tools trained on local languages, agricultural and logistics data and sector problems that global vendors neglect. Public procurement and accredited-provider lists can build that supplier base. Rodrik (2004) frames industrial policy as a discovery process in which government and firms learn together, which requires support to be tied to performance and withdrawn where it fails.

6. Redesigning Fiscal Incentives for Inclusive Technological Growth

6.1 Targeted tax incentives

Blanket deductions for AI purchases risk subsidising investments that large firms would make anyway. The economic case for intervention rests on additionality: public support

must change the scale, timing or quality of investment. Before creating new tax expenditure, Treasury should review whether existing instruments, such as the research-and-development deduction and the Employment Tax Incentive, can be adapted for this purpose. With unemployment above 33%, every rand of tax expenditure must demonstrate public value beyond the firm's own return. Adapting existing instruments also avoids adding complexity to a tax system that smaller firms already find costly to navigate.

6.2 AI adoption grants

Grants or vouchers should be capped, co-funded and paid against verified milestones, with money following implementation rather than software licences. Firms would identify the operational problem, establish a baseline and commit to milestones. Co-funding screens for genuine commitment and payment through accredited providers reduces fraud. A small agro-processor, for example, might receive a matched voucher covering part of an adviser-diagnosed project, with the balance released only once agreed waste or downtime targets are verified. Larger firms, which can finance adoption themselves, would receive little or no grant support.

6.3 Training subsidies and conditional incentives

Where workers' tasks are materially affected, firms should submit a credible plan for training, redeployment or transition support. Requiring net job creation would be a mistake, as it could deter productivity-enhancing investment or reward hiring that firms do not need. Support should instead be tiered: basic assistance for viable projects, with enhanced support for demonstrable worker training, redeployment, market expansion or local supplier development. Skills Development Levy resources already flow to SETAs and could be channelled towards such conditions.

6.4 Fiscal risks and accountability

Fiscal space is narrow, so the main risks are windfall gains, administrative capture, vendor lock-in and open-ended commitments. Time limits, co-funding, transparent selection, independent evaluation and clawback for misrepresentation are the necessary safeguards. Any programme lacking them should not proceed. There is also a political-economy risk: incentives that are easy to start tend to be hard to end, so every instrument should carry a sunset date and a pre-agreed test for renewal.

7. Recommendations

My position is that South Africa should adopt a sequenced, pilot-first strategy funded largely by reprioritisation. It should neither introduce a national AI subsidy nor leave adoption to the market, which the evidence on unequal diffusion suggests would widen firm-level gaps. Four recommendations follow.

- R1.** Prioritise foundational learning and occupational application in education. Early-grade reading and mathematics should take precedence over any new compulsory coding curriculum. TVET and SETA funding should favour paid, employer-linked placements assessed on demonstrated competence.
- R2.** Launch a two-year AI productivity extension pilot in agro-processing, manufacturing and logistics, deliberately including SMEs and cooperatives. An indicative envelope of about R300 million over two years, roughly 1% of the R30.1 billion allocated to Skills Development Levy institutions in the 2026 Budget (National Treasury, 2026), is affordable if reallocated from existing business-support and skills budgets. This figure is my own illustrative proposal, not a costed estimate.
- R3.** Make fiscal support conditional and tiered by adapting existing incentives before creating new ones, with capped, co-funded, milestone-based payments and transition plans where tasks change.
- R4.** Build evaluation capacity first. Each participating firm should record a pre-intervention baseline and report for 12 to 24 months on output and value added per worker, unit costs, waste, wages, employment, training and survival, compared with similar non-participants or a phased rollout.

Feasibility. Affordability is manageable only because the pilot reallocates rather than expands spending; a new national subsidy would be hard to justify while debt service consumes more than one-fifth of revenue. Institutional capacity is the binding constraint. SETA performance is uneven, the market of accredited AI providers is thin and the withdrawn AI policy shows weak verification. The pilot should therefore start small, in regions with existing training capacity and business demand. Unintended consequences include subsidy capture by firms that would have invested anyway, displacement without transition support and programmes tilting toward better-connected firms. Table 1 matches each recommendation to a lead institution, supporting partners and indicative timing. Sequencing matters. The first year should secure evaluation design, provider accreditation and foundational-learning priorities; the pilot should then run for two years;

and a decision gate should follow, scaling support only where additionality, productivity gains and worker outcomes have been independently verified.

Table 1. Implementation priorities and institutional responsibilities

Priority	Lead institution	Supporting partners	Timing
Foundational learning and occupational AI curriculum	Department of Basic Education; Department of Higher Education and Training	SETAs, TVET colleges, employers	Year 1 onwards
AI productivity extension pilot	Department of Trade, Industry and Competition (the dtic)	SEDA, Technology Innovation Agency, TVET colleges, industry associations	Years 1–3
Conditional, tiered fiscal support	National Treasury	SARS, the dtic, SETAs	Design in Year 1
Independent evaluation and decision gate	National Treasury, with independent academic evaluators	Statistics South Africa, participating firms	Baseline Year 1; review Year 3

Conditions for success and failure. The approach succeeds if baselines and independent evaluation are enforced, if smaller firms are genuinely included, if conditions are tight enough to deliver additionality and if government is willing to end what does not work. It fails if it degenerates into a blanket subsidy, if AI training outpaces foundational learning, if providers capture the programme, or if distributional outcomes are not measured. Preserving every existing task at the expense of competitiveness is not a sustainable employment strategy; neither is calling a programme inclusive because output rose while workers lost hours or earnings.

8. Conclusion

The essay set out to establish how education, industrial policy and fiscal incentives should be redesigned so that AI raises productivity without needlessly disrupting labour

markets. Solow and the productivity J-curve show that adoption is not productivity; Romer, Arrow and Nelson and Phelps show that learning and adaptive human capital are what convert technology into growth; and Schumpeter and Acemoglu and Restrepo show that displacement and new task creation occur together but not at the same pace or for the same workers.

South African evidence confirmed that these mechanisms apply. Adoption tracks firm capability and access to capital; automation has lifted productivity, employment and wages in adopting manufacturers without spilling over to others; and separate evidence raises concern for low-skilled workers. Weak foundational learning and limited fixed connectivity narrow the base on which adaptation depends. These findings are consistent: they describe the same underlying problem of unequal capacity. International experience, notably Korea's voucher programme, showed that demand-side support can work when it is tied to providers and evaluation.

South Africa can harness AI and limit labour-market disruption but only by treating diffusion and capability as the objective, with education, industrial policy and fiscal incentives working together under disciplined evaluation. Disruption can be limited and managed, not eliminated. Success should be measured not by software purchased or money spent but by whether firms become more productive, workers acquire skills the labour market values and productive capability spreads beyond a small group of leading firms.

9. References

- Acemoglu, D. and Restrepo, P. (2019) 'Automation and new tasks: How technology displaces and reinstates labor', *Journal of Economic Perspectives*, 33(2), pp. 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Arrow, K.J. (1962) 'The economic implications of learning by doing', *Review of Economic Studies*, 29(3), pp. 155–173. <https://doi.org/10.2307/2295952>
- Avenyo, E.K., Bell, J.F. and Nyamwena, J. (2024) 'Determinants of digital technologies' adoption in South African manufacturing: Evidence from a firm-level survey', *South African Journal of Economics*, 92(2), pp. 235–259. <https://doi.org/10.1111/saje.12378>
- Brynjolfsson, E., Rock, D. and Syverson, C. (2021) 'The productivity J-curve: How intangibles complement general purpose technologies', *American Economic Journal: Macroeconomics*, 13(1), pp. 333–372. <https://doi.org/10.1257/mac.20180386>
- Giwa, F. and Ngepah, N. (2024) 'The relationship between artificial intelligence and low-skilled employment in South Africa', *Heliyon*, 10(23), e40640. <https://doi.org/10.1016/j.heliyon.2024.e40640>
- Kilumelume, M., Mensah, J.T., Nsabimana, A. and Sen, K. (2025) 'Automation, firms and workers: Evidence from South Africa', *UNU-WIDER Working Paper 2025/61*. Helsinki: UNU-WIDER. <https://doi.org/10.35188/UNU-WIDER/2025/620-9>
- Magubane, K. (2026) 'MTBPS 2026 | Government to allocate R10bn for El Niño response', *TimesLIVE*, 21 October. Available at: <https://www.timeslive.co.za/news/south-africa/2026-10-21-mtbps-2026-government-to-allocate-r10bn-for-el-nino-response/> (Accessed: 30 October 2026).
- National Treasury (2026) *Budget Review 2026*. Pretoria: National Treasury. Available at: <https://www.treasury.gov.za/documents/National%20Budget/2026/review/FullBR.pdf> (Accessed: 30 October 2026).
- Nelson, R.R. and Phelps, E.S. (1966) 'Investment in humans, technological diffusion and economic growth', *American Economic Review*, 56(1/2), pp. 69–75.
- OECD (2024) *Fostering an inclusive digital transformation as AI spreads among firms*. OECD Policy Briefs, No. 8. Paris: OECD Publishing. <https://doi.org/10.1787/5876200c-en>

- OECD (2025a) 'Korea's AI Voucher Programme', in *SME Technology Adoption in the United Kingdom*. Paris: OECD Publishing. Available at: https://www.oecd.org/en/publications/sme-technology-adoption-in-the-united-kingdom_cecfb794-en/korea-s-ai-voucher-programme_02177759-en.html (Accessed: 30 October 2026).
- OECD (2025b) *Generative AI and the SME Workforce: New Survey Evidence*. Paris: OECD Publishing. <https://doi.org/10.1787/2d08b99d-en>
- Rodrik, D. (2004) 'Industrial policy for the twenty-first century', *CEPR Discussion Paper No. 4767*. London: Centre for Economic Policy Research.
- Romer, P.M. (1990) 'Endogenous technological change', *Journal of Political Economy*, 98(5, Part 2), pp. S71–S102. <https://doi.org/10.1086/261725>
- Schumpeter, J.A. (1942) *Capitalism, Socialism and Democracy*. New York: Harper & Brothers.
- Smith, A. (1776) *An Inquiry into the Nature and Causes of the Wealth of Nations*. London: W. Strahan and T. Cadell.
- Solow, R.M. (1957) 'Technical change and the aggregate production function', *Review of Economics and Statistics*, 39(3), pp. 312–320. <https://doi.org/10.2307/1926047>
- South African Government (2026) 'Minister announces withdrawal of draft AI Policy', *SANews*, 26 April. Available at: <https://www.sanews.gov.za/node/81049> (Accessed: 30 October 2026).
- Spaull, N. (2023) '10 main findings from PIRLS 2021 South Africa', *Nic Spaull*, 18 May. Available at: <https://nicspaull.com/2023/05/18/10-main-findings-from-pirls-2021-south-africa> (Accessed: 30 October 2026).
- Statistics South Africa (2025) *General Household Survey 2024*. Statistical Release P0318. Pretoria: Statistics South Africa.
- Statistics South Africa (2026a) *Quarterly Labour Force Survey, Quarter 2: 2026*. Statistical Release P0211. Pretoria: Statistics South Africa.
- Statistics South Africa (2026b) *Gross Domestic Product: Fourth Quarter 2025*. Pretoria: Statistics South Africa. Released 10 March 2026.