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Original Article

Adoption of Artificial Intelligence in the Zimbabwean Manufacturing Sector: A Critical Review and Research Agenda

Thomas Masese[1], Chidochomoyo Sango[2], Yogesh Awasthi[3]
[1,2]*Department of Accounting & Finance, Africa University, Zimbabwe*
[3]*Department of Artificial Engineering, Software Engineering and Computer Science, Africa University, Zimbabwe*

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Abstract: *Artificial intelligence (AI) is reshaping manufacturing through quality control, maintenance, and supply chain planning, yet adoption in Sub Saharan Africa is uneven. The researchers synthesize evidence on AI adoption with a focus on Zimbabwe, guided by Technology Organization Environment (TOE), the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology (TAM/UTAUT), the Resource Based View (RBV), and Dynamic Capabilities. The researcher applies a transparent selection process and includes n = 26 studies: Zimbabwe (n = 2), South Africa (n = 2), Africa/regional (n = 0), and global/other (n = 22). Zimbabwe specific evidence is thin and concentrated in SMEs and a food manufacturing case. The review provides a consolidated synthesis of drivers and barriers, clarifies the methodology, and presents a practical research agenda tailored to Zimbabwe. The paper offers a compact framework linking organizational and ecosystem conditions to use cases and outcomes, and a roadmap for firm actions, policy levers, and measurement priorities to scale AI adoption.*

Keywords: *Artificial Intelligence; Digital Transformation; Industry 4.0; Manufacturing; Zimbabwe.*

I. INTRODUCTION

Zimbabwe's manufacturing sector remains central to jobs and export diversification. However, aging equipment, fragile infrastructure, and costly finance continue to constrain competitiveness, especially for SMEs (Sibanda et al., 2024). AI supports predictive maintenance, process optimization, and quality assurance, which can raise throughput and reduce waste (Brynjolfsson et al., 2021). Value often arrives after firms invest in skills, data, and redesigned processes, not at the pilot stage. Global experience shows gains from sensor enabled inspection, computer vision for defects, and AI enhanced planning. These gains require coordinated data governance, cybersecurity, and change management. In Southern Africa, studies report similar inhibitors across countries but also demonstrate feasible use cases when leadership aligns technology, processes, and people (Maisiri et al., 2021; Nzama et al., 2024). Zimbabwe specific evidence is limited. Early cases suggest performance benefits in quality and maintenance but highlight skills, integration, and funding gaps (Munongo and Pooe, 2022; Sibanda et al., 2024). This review consolidates what is known, quantifies the local evidence base, and proposes a research agenda that reflects Zimbabwe's industrial realities. See Section 5.2 for the consolidated synthesis of drivers and barriers.

II. LITERATURE REVIEW

The scope of AI in manufacturing spans machine learning, computer vision, optimization, and reinforcement learning. These tools use data from sensors, machines, enterprise systems, and external sources for tasks such as predictive maintenance, anomaly detection, and quality inspection (Lu, 2020; Bousdekis et al., 2020). Adoption outcomes vary due to managerial priorities, data quality, workforce skills, infrastructure reliability, and governance (Wamba Taguimdje et al., 2020; Mikalef et al., 2020).

A. Global Perspectives on AI Adoption in Manufacturing

Internationally, AI adoption advances alongside broader digital programs that build connectivity, data pipelines, and analytics (Bousdekis et al., 2020; Cimini et al., 2020). Firms often see delayed benefits as they accumulate data, redesign processes, and develop human capital, which creates a slow then fast path to productivity (Brynjolfsson et al., 2021). AI reshapes, rather than replaces, many roles. New tasks emerge in supervision, maintenance, and data engineering (Acemoglu and Restrepo, 2020).

The COVID 19 period accelerated digital tools for resilience. AI enhanced planning supported scenario analysis and supply network redesign (Ivanov and Dolgui, 2020; Ivanov, 2021). AI also complements lean and human in the loop practices that keep people central to decision making (Cimini et al., 2020; Tortorella et al., 2021). Key enablers include data foundations, cross functional collaboration, and governance. Constraints include legacy systems, cybersecurity risk, skills shortages, and financing hurdles, especially for SMEs (Hsu et al., 2021; Sila, 2020). Cloud based solutions lower entry barriers for some use cases (Khan et al., 2022).

B. African Experiences in AI and Industry 4.0 in Manufacturing

African research shows early stage pilots and incremental improvements. Inhibitors include limited digital skills, legacy machinery, and high equipment costs. Connectivity and infrastructure reliability also matter (Maisiri et al., 2021; Nzama et al., 2024; see Section 5.2 for consolidated synthesis). Export facing firms tend to adopt AI faster due to customer requirements. During COVID 19, pre-existing digital capabilities supported resilience, though gains were uneven (Queiroz et al., 2020). Policy strategies highlight digital economy development, but implementation gaps remain in broadband, data protection, and SME support (OECD, 2020; Stix, 2021).

C. Zimbabwean Case Evidence and Emerging Patterns

Zimbabwe specific studies are few but instructive. SMEs reported low adoption of Fourth Industrial Revolution tools during COVID 19, citing costs, skills gaps, and limited awareness. Managerial innovativeness and ICT literacy drove uptake (Munongo and Pooe, 2022). A food manufacturing case showed AI and IoT improved defect detection and process stability, but data integration and training limited scale (Sibanda et al., 2024; see Section 5.2 for consolidated synthesis). South African findings offer a relevant benchmark for managerial support, skills, and financing needs (Maisiri et al., 2021; Nzama et al., 2024).

III. THEORETICAL AND CONCEPTUAL FRAMEWORK

The analysis integrates adoption and strategy perspectives to explain AI uptake in Zimbabwean manufacturing. The Technology Organization Environment perspective frames adoption through technological readiness, organizational capacity, and environmental pressures, which aligns with evidence on how legacy systems, skills, and regulation shape digital uptake (Sila, 2020; Maisiri et al., 2021). At the user and workflow level, the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology emphasize perceived usefulness, ease of use, social influence, and facilitating conditions, and recent work adds trust and explain ability for AI in quality and maintenance decisions (Dwivedi et al., 2021; Raisch and Krakowski, 2021). From a strategic standpoint, the Resource Based View links performance to distinctive capabilities such as curated data, analytics talent, and disciplined processes that translate AI into cost, quality, and flexibility gains (Mikalef et al., 2021; Wamba Taguimdje et al., 2020). Dynamic Capabilities highlight sensing opportunities, seizing them through investment and orchestration, and transforming routines to embed AI under uncertainty, a logic that suits volatile contexts such as Zimbabwean manufacturing (Teece, 2020; Dwivedi et al., 2021).

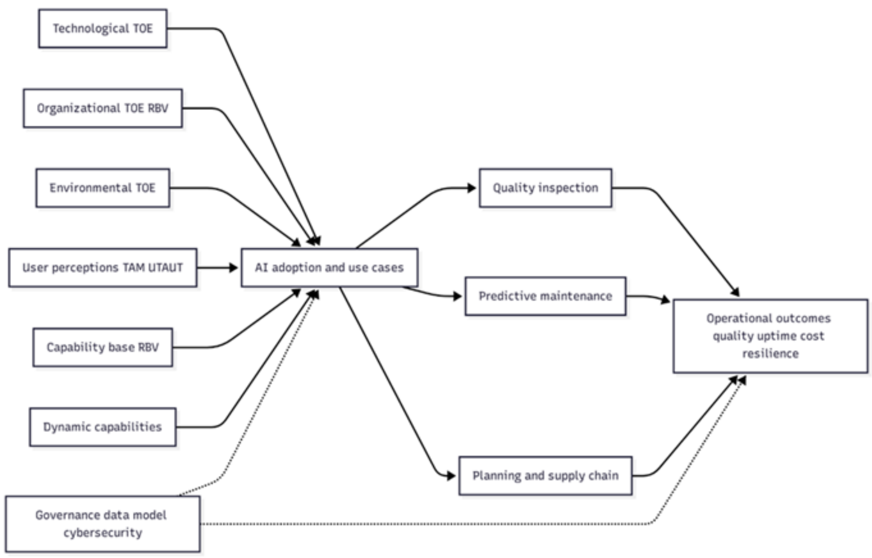

Figure 1 : Integrated Framework (TOE, TAM/UTAUT, RBV, Dynamic Capabilities): Drivers/Barriers → AI Adoption → Operational Outcomes.

Data and model governance cut across these lenses. Governance practices address data quality, cybersecurity for connected equipment, and model documentation and monitoring, which support trust and safe scaling in industrial settings with infrastructural fragility and skills limits (Hsu et al., 2021; Stix, 2021). Servitization extends the role of AI by enabling advanced services that fuse products and data driven offerings (Sjödin et al., 2020). Figure 1 presents the integrated framework from antecedents to outcomes.

A. Empirical Evidence from Zimbabwe and Southern Africa

Zimbabwean SMEs reported low 4IR adoption during COVID 19 due to cost and skills gaps. Manager innovativeness and ICT literacy supported adoption (Munongo and Pooe, 2022). A Zimbabwean food manufacturer used AI and IoT for quality control, improving detection and visibility but faced integration and training constraints (Sibanda et al., 2024). In South Africa, inhibitors include digital skills shortages and capital constraints. Export oriented sectors adopt faster due to customer pressure (Maisiri et al., 2021; Nzama et al., 2024). These patterns align with the integrated framework and underscore the need for staged capability building.

B. Research Gaps and Agenda

The review identifies five gaps for Zimbabwe. First, longitudinal plant level evidence to trace adoption sequences and outcomes is scarce (Brynjolfsson et al., 2021). Second, workforce transitions, including reskilling and job redesign, remain under examined (Acemoglu and Restrepo, 2020; Cimini et al., 2020). Furthermore, data governance and cybersecurity in industrial AI have received limited attention (Hsu et al., 2021; Stix, 2021). Moreover, the economics of AI adoption for SMEs, including total cost of ownership and payback, are poorly understood (Hottenrott and Peters, 2020). Also, policy and industry linkages that shape adoption require stronger theorization and evidence (OECD, 2020; Maisiri et al., 2021). The researcher proposes a mixed methods agenda that combines multi wave surveys with process tracing case studies across sectors such as food, wood products, metals, and textiles (Mikalef et al., 2021; Teece, 2020). Program evaluations can assess incentives and shared training platforms. Governance research should scope feasible data stewardship and cybersecurity models for local firms.

C. Research Agenda for Zimbabwean Manufacturing

Table 1 presents a concise agenda aligned to the identified gaps.

Table 1 : Research Agenda for Zimbabwean Manufacturing

Gap	Research Questions	Suggested Methods	Candidate Data Sources	Expected Contribution
Longitudinal trajectories	How do AI capabilities accumulate?	Panel surveys;	Plant logs; ERP/MES;	Sequenced adoption paths;
	What sequences yield returns?	repeated case study	interview protocols	timing of payoffs
Workforce transitions	What skills are needed at line/	Task analysis;	HR/training records; union	Reskilling models; job
	maintenance/quality roles?	skill mapping;	agreements; operator surveys	redesign templates
		quasi-experiments		
Governance & security	What minimum viable governance	Maturity assessment	Data policies; cyber incident	Context-appropriate
	practices enable trust at SMEs?	+ design science	logs; vendor SLAs	governance toolkit
Adoption economics (SMEs)	What is TCO and payback under	Cost benefit models	Financial statements; project	Investment cases;
	volatility and high borrowing?	+ matched samples	charters; lender terms	financing guidance
Policy–industry linkages	Which incentives and shared services accelerate adoption?	Program evaluation; difference in differences	Tax incentives; training vouchers; park-level services	Evidence on effective policy levers

IV. RESEARCH METHODOLOGY

The researchers conducted a critical review of AI adoption in manufacturing from 2020 to 2025, emphasizing Zimbabwe and Southern Africa while situating findings in global literature (Sila, 2020; Dwivedi et al., 2021). The researcher searched Scopus, Web of Science, IEEE Xplore, and leading publisher platforms using key search word combinations of artificial intelligence, manufacturing, quality control, predictive maintenance, digital transformation, adoption, Africa, Zimbabwe, and Southern Africa. The researcher also applied citation chaining from initial hits.

Inclusion criteria admitted empirical studies and rigorous conceptual analyses that addressed AI or advanced analytics in manufacturing or supply chains, with relevance to adoption determinants, outcomes, workforce transitions, governance, or strategy. Non-industrial domains were excluded unless clearly transferable. Given few Zimbabwe specific publications, the researcher included regional comparators and global studies with relevant mechanisms. The researcher appraised clarity of design, methods transparency, and credibility of evidence, recognizing exploratory designs in early stage contexts (Maisiri et al., 2021; Munongo and Pooe, 2022).

PRISMA style flow in prose was as follows. After screening and eligibility checks against the criteria, n = 26 studies were included: Zimbabwe (n = 2), South Africa (n = 2), Africa/regional (n = 0), and global/other (n = 22). Counts derive from the final references list.

Grey literature that included Government and industry reports likely contain relevant statistics on digital infrastructure, skills, and manufacturing upgrades were noted. The researchers did not include these but recommends incorporating them in future updates, for example national digital economy strategies and manufacturing association surveys.

Table 2 : Summary of Reviewed Studies

Author(s) & Year	Country/Region	Sector/Context	Method/Type	AI Use Case/Theme	Key Finding(s)	Relevance to Zimbabwe
Acemoglu & Restrepo 2020	Global/US	Labor/industry	Empirical	Automation & jobs	Task shifts; new roles emerge	Workforce planning
Bousdekis et al. 2020	Global	Manufacturing	Review	PHM/predictive maint.	PHM improves uptime; data key	Maintenance roadmap
Brynjolfsson et al. 2021	Global	Economy-wide	Conceptual	Productivity dynamics	Delayed gains after complements	Staged expectations
Cimini et al. 2020	Global	Manufacturing	Conceptual	Human-in-the-loop	Augmentation improves control	Operator-centric use
Dwivedi et al. 2021	Global	Decision-making	Review	AI adoption & governance	Challenges; agenda for practice	Adoption lens
Hottenrott & Peters 2020	Global/EU	Innovation	Empirical	Finance constraints	Finance affects innovation/jobs	SME finance insights
Hsu et al. 2021	Global	Manufacturing	Review	Cybersecurity (OT/IT)	ICS risks; layered controls	Security baseline
Ivanov 2021	Global	Supply chains	Conceptual	Lean–resilience–sustain.	Synergies/trade-offs in design	Plan for resilience
Ivanov & Dolgui 2020	Global	Supply networks	Conceptual	Viability/resilience	Visibility supports survivability	Scenario planning
Khan et al. 2022	Global	Manufacturing	Review	Cloud manufacturing	Cloud lowers barriers; new risks	Cloud options
Lu 2020	Global	Industry 4.0	Review	Technologies & issues	Integration challenges persist	Tech mapping
Maisiri et al. 2021	South Africa	Manufacturing	Empirical	I4.0 inhibitors	Skills, legacy, capital barriers	Regional benchmark

Mikalef et al. 2020	Global	Firms	Empirical	Big data capabilities	Capabilities mediate performance	Capability focus
Mikalef et al. 2021	Global	Firms	Empirical	AI capabilities	Positive link to performance	Investment logic
Munongo & Pooe 2022	Zimbabwe	SMEs/SCM	Empirical	4IR adoption & resilience	Low uptake; innovativeness helps	Zimbabwe evidence
Nzama et al. 2024	South Africa	Manufacturi ng	Empirical	AI influence	Benefits with workforce impacts	Labor transition
OECD 2020	Global	Policy	Report	Digital economy	Infrastructure & skills gaps	Policy context
Queiroz et al. 2020	Global	Supply chains	Review	Epidemic disruptions	Digital tools aid resilience	Risk manageme nt
Raisch & Krakowski 2021	Global	Management	Conceptual	Automation–augmentation	Balance automation & augmentation	Change leadership
Shah & Ghosh 2021	Global	Supply chains	Review	Quality 4.0	Digital quality capabilities	Quality integration
Sibanda et al. 2024	Zimbabwe	Food mfg.	Empirical	AI/IoT quality control	Better detection; scaling issues	Zimbabwe case
Sila 2020	Global	Adoption	Review	Adoption models	TOE evidence and design choices	Method & lens
Sjödin et al. 2020	Global	Manufacturi ng	Empirical	AI for servitization	Capabilities for services	Revenue models
Stix 2021	Global	Policy	Conceptual	AI policy principles	Pragmatic, actionable guidance	Governance cues
Teece 2020	Global	Strategy	Conceptual	Capability theory	Sensing/seizing/transfor ming	Orchestrati on
Wamba Taguimdje et al. 2020	Global	Firms	Empirical	AI business value	AI projects can drive performance	Business case

V. RESULTS AND DISCUSSIONS

A. State of AI Adoption in Zimbabwean Manufacturing

Evidence indicates an early and uneven adoption profile. Implementations are mostly pilots or focused use cases in quality control and process monitoring (Sibanda et al., 2024). Reported gains include fewer defects and better visibility into process variation. Many firms remain at the awareness stage due to unreliable power and connectivity, legacy machinery without digital interfaces, and limited in house data skills (Munongo and Pooe, 2022). South African studies show similar barriers, though export-oriented sectors adopt faster under customer pressure (Maisiri et al., 2021; Nzama et al., 2024). For Zimbabwe's SME heavy base, targeted applications with clear metrics offer feasible entry points. Shared platforms, vendor partnerships, and collaborative training can reduce costs and risks.

B. Drivers and Barriers of AI Adoption

Technological factors shape feasibility and scale. Sensor retrofits, cloud and edge options, and modular architectures can lower initial costs and allow incremental deployment, but legacy equipment and weak data quality raise integration complexity and undermine model performance (Khan et al., 2022; Lu, 2020; Bousdekis et al., 2020; Sila, 2020). Organizational conditions determine the pace of implementation. Clear managerial sponsorship, cross functional teams, and lean process discipline enable adoption, while shortages in data engineering and AI skills, coupled with weak change management, slow progress and increase dependence on vendors (Cimini et al., 2020; Teece, 2020; Maisiri et al., 2021; Mikalef et al., 2021). Environmental pressures act as both catalysts and constraints. Customer requirements, export standards, and competitive intensity can trigger upgrades, yet unreliable power and connectivity and a high cost of capital limit investment appetite and elongate payback periods (Nzama et al., 2024; OECD, 2020; Hsu et al., 2021; Hottenrott and Peters, 2020). Governance considerations cut across all stages. Proportionate data and model governance and industrial cybersecurity practices build trust and permit scale, whereas unclear data ownership, lack of explainability, and inadequate controls for industrial control systems deter use of AI in quality and maintenance decisions (Stix, 2021; Hsu et al., 2021; Dwivedi et al., 2021; Shah and Ghosh, 2021). Workforce transitions are pivotal. Reskilling in maintenance, data handling, and quality analytics supports human augmentation, while skills gaps and anxiety about job loss undermine adoption in the absence of transparent change plans and engagement with frontline workers (Acemoglu and Restrepo, 2020; Cimini et al., 2020; Raisch and Krakowski, 2021; Maisiri et al., 2021).

C. Performance Outcomes and the Role of Complementarities

When firms embed AI in stable processes with reliable data and trained personnel, they report fewer defects, shorter cycle times, and better maintenance scheduling (Bousdekis et al., 2020; Cimini et al., 2020). Benefits rise as complementary assets such as skills, data, and process discipline accumulate (Brynjolfsson et al., 2021). AI that complements lean practice and human oversight sustains quality and safety (Tortorella et al., 2021). In supply chains, visibility and AI supported planning improve resilience to shocks (Ivanov and Dolgui, 2020; Queiroz et al., 2020). Firm level performance effects appear when AI capabilities integrate with operational routines (Mikalef et al., 2021; Wamba Taguimdje et al., 2020).

D. Data Governance, Cybersecurity, and Ethical Considerations

Manufacturing AI needs robust practices for data quality, lineage, access controls, and model lifecycle oversight. Explainability is critical where AI informs quality and maintenance decisions (Stix, 2021; Dwivedi et al., 2021). Converging IT and OT increases exposure to cyber threats, so firms should adopt industrial control system specific controls and network segmentation (Hsu et al., 2021). SMEs may rely on vendor managed services with clear service level agreements and minimum standards to reduce burden (OECD, 2020). Ethical practice centers on transparency, accountability, and human oversight in operational decisions (Stix, 2021).

E. Workforce Transitions and Capability Development

AI changes task mixes rather than eliminating entire roles. Demand grows for skills in equipment upkeep, data handling, and quality analysis, while routine inspection automates (Acemoglu and Restrepo, 2020; Cimini et al., 2020). South African evidence identifies digital skills as a top barrier, which implies heightened urgency for Zimbabwe (Maisiri et al., 2021; Nzama et al., 2024). Effective change management involves frontline workers early, explains goals, and demonstrates value. Public and private partnerships can scale modular upskilling aligned with sector needs (OECD, 2020).

VI. IMPLICATIONS

A. Implications for Zimbabwean Firms

Firms can pursue pragmatic and staged adoption anchored in measurable use cases. The most feasible starting points are vision based quality inspection in critical processes, predictive maintenance on bottleneck equipment, and demand sensing for inventory optimization, as these applications offer clear metrics and a strong link to performance (Bousdekis et al., 2020; Sibanda et al., 2024). For each use case, firms should invest in reliable data capture and integration to ensure model inputs are stable and auditable. Demonstrating early gains can build credibility and internal support, which then eases expansion into adjacent processes as skills increase. Change leadership remains central. Managers should articulate clear objectives for AI in operations, allocate time and resources for training, and align incentives and performance measures to sustain use beyond the pilot stage, acknowledging the lag between investment and measured productivity gains that characterizes digital transformation (Brynjolfsson et al., 2021; Mikalef et al., 2021). Governance and security should be proportionate to the level of AI use. Basic data stewardship, documented model validation, and industrial cybersecurity controls for connected equipment and networks reduce risk and build trust in AI outputs, with vendor offerings and sector guidance used where in house capacity is limited (Hsu et al., 2021; Stix, 2021). Collaboration can lower costs and accelerate learning. Participation in associations, consortia, and vendor partnerships can provide access to shared training, reference architectures, and pooled solutions that reduce barriers for SMEs and diffuse successful patterns across firms facing similar constraints (OECD, 2020; Maisiri et al., 2021).

B. Implications for Policymakers and Ecosystem Actors

Policy design should address financing constraints directly and transparently. Accelerated depreciation, targeted tax credits for verified digital investments, and blended finance instruments suited to manufacturing modernization can lower the cost of capital for SMEs, with eligibility linked to productivity and employment outcomes to ensure accountability (Hottenrott and Peters, 2020; OECD, 2020). Infrastructure upgrades remain foundational. Reliable power and high quality connectivity in industrial zones, including digital industrial parks with shared cybersecurity support and data services, would raise feasibility and lower per firm costs. Skills development requires coordinated action across education and industry. Technical curricula should incorporate AI and analytics modules, while public and private partners deliver modular upskilling and apprenticeships aligned with sector roadmaps, supported by vouchers or matching grants to stimulate firm participation (Dwivedi et al., 2021; Nzama et al., 2024). Practical governance guidance should be co developed with industry bodies. Minimum data and model documentation practices, data quality standards, and baseline industrial control system cybersecurity controls, tailored to SME capacity, can raise the ecosystem baseline and reduce uncertainty (Stix, 2021; Hsu et al., 2021).

C. Implications for Research and Measurement

The thin local evidence base should be made explicit and addressed systematically. Multi case comparative studies across sectors and longitudinal plant level tracking can map trajectories, learning processes, and the accumulation of complementary assets that shape outcomes (Brynjolfsson et al., 2021; Mikalef et al., 2021). Surveys should be theory informed and include AI specific constructs such as data governance maturity, model explainability, and cybersecurity readiness to reflect the socio technical character of AI in operations (Dwivedi et al., 2021; Sila, 2020). Indicators for adoption intensity, capability maturity, and performance outcomes should be developed and maintained through collaboration among statistical agencies, industry, and academia (OECD, 2020). Table 2 lists priority questions and methods for Zimbabwe.

VII. CONCLUSIONS AND RECOMMENDATIONS

This paper delivers a tighter and transparent review of AI adoption in Zimbabwean manufacturing. It includes n = 26 studies, with only two Zimbabwe specific sources and two South African comparators. The local evidence base is therefore thin and concentrated in SMEs and a single food manufacturing case, which is a clear research gap. The review consolidates drivers and barriers into a single synthesis in Section 5.2, presents an integrated framework in Figure 1, and sets out a targeted research agenda in Table 2. The roadmap for action is concise. Firms should select a small set of high value use cases, invest in data and skills tied to those use cases, institutionalize proportionate governance and security, and leverage collaborations to reduce costs. Policymakers should target the cost of adoption with finance instruments, build reliable industrial infrastructure, scale modular skills programs, and publish practical governance guidance for industrial AI. Measurement priorities include longitudinal plant level studies and sector wide indicators of adoption and capability maturity. By aligning firm strategies with enabling policies and shared infrastructure, Zimbabwe can move from pilots to scaled AI use that improves quality, uptime, cost, and resilience. The agenda and tools provided here aim to support that transition while respecting local constraints and opportunities.

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