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The effects of machine learning on organizations in Zambia.

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Abstract

This thematic literature review explores the multi-dimensional impact of Machine Learning (ML) on organizations in Zambia, situating the national experience within broader global and regional contexts. As organizations globally transition towards Industry 4.0, Machine Learning has emerged as a critical catalyst for business model innovation, operational efficiency, and predictive decision-making. Through a systematic analysis of 62 empirical studies and over 2,700 regional documents published between 2005 and 2025, this review identifies several core themes: the theoretical drivers of technology adoption, the specific sectoral transformations in Zambian mining, banking, agriculture, and education, and the systemic barriers, including the digital divide and ethical governance gaps. Key findings reveal a significant performance disparity between private and public enterprises, with private firms achieving a 65% adoption rate compared to 30% in the public sector. While awareness of generative AI tools in higher education is as high as 88%, actual organizational readiness is constrained by infrastructure deficits and a lack of localized data. The review highlights the "paradox of potential," where the ambition for technological leapfrogging is tempered by structural dependencies on Western-trained models. This study contributes to the literature by proposing a context-sensitive conceptual framework for AI governance and identifying critical directions for future research into indigenous language processing and decolonial AI strategies.

Keywords: Machine Learning; Organizational Performance; Zambia; Digital Transformation; 4th Industrial Revolution; Technology Adoption

1. Introduction

The unprecedented convergence of computational power, ubiquitous connectivity, and advanced algorithms defines the current epoch of industrial evolution. At the core of this transformation is Machine Learning (ML), a subset of Artificial Intelligence (AI) that facilitates the development of systems capable of learning from data, identifying complex patterns, and making autonomous or semi-autonomous decisions with minimal human intervention (Paliwal, Patel, Kandale, and Anute, 2021). For modern organizations, the shift from traditional rule-based logic to data-driven ML models represents a fundamental reorganization of value creation, value proposition, and value capture. (Jobstreibizer, Beliaeva, Ferasso, Kraus und Kallmuenzer, 2025). While the conceptual origins of AI trace back to 1955, the recent explosion in deep learning and large-scale data analytics has propelled ML from the periphery of computer science to the center of global corporate strategy. (Jobstreibizer, Beliaeva, Ferasso, Kraus und Kallmuenzer, 2025).

Globally, organizations that have achieved maturity in AI and ML adoption report productivity gains of up to 66%, driven by automation of routine tasks and enhanced predictive capabilities (Chloe, 2025). Multinationals such as PepsiCo and Google have utilized these technologies to drastically shorten recruitment cycles and optimize administrative costs, illustrating the tangible economic benefits of digital integration (Alherimi, Abdulmaksoud, Ahmed, and Bahroun, 2025). In Sub-Saharan Africa, the narrative is one of leapfrog potential, where ML is viewed as a mechanism to bypass traditional development hurdles in sectors such as healthcare, finance, and agriculture (Google, Sand Tech, and ALU,

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2025). However, Africa and South America together account for less than 5% of global scholarly output in AI research, highlighting a significant knowledge and capability gap (Hadiza, Esther, Ummana, Ozongbe, and Sahabi, 2024).

Zambia stands at a critical juncture in this digital journey. The launch of the National Artificial Intelligence Strategy (2024-2026) and the integration of digital goals into the 8th National Development Plan (8NDP) signal a clear state-level commitment to technological transformation. (Ministry of Technology and Science, 2024). Yet, the Zambian organizational landscape faces unique challenges, ranging from erratic governance and infrastructural deficits to the coloniality of imported algorithmic frameworks that may not resonate with local socioeconomic realities (Chavula, Kayusi, and Mwewa, 2024; Hambulo, Simataa, and Musonda, 2025). This review is necessitated by the need to synthesize fragmented empirical evidence into a cohesive understanding of how Zambian firms are navigating these complexities.

The primary objective of this thematic review is to evaluate the effects of Machine Learning on organizational performance, structure, and strategy in Zambia. It seeks to answer whether the adoption of ML has led to measurable efficiency gains, how it is reshaping the labor market, and what specific factors determine the readiness of Zambian employees to embrace these changes. By reviewing literature from global and regional perspectives before narrowing down to the Zambian context, this article provides a nuanced analysis of the opportunities and risks inherent in the country's digital leap.

2. Methodology

The methodology used in this review was designed to capture a high-quality set of academic and empirical data. The primary databases utilized for the literature search included Scopus, Web of Science, Google Scholar, PubMed, African Journals Online (AJOL), and the Zambia ICT Journal. These platforms were selected to ensure a balance between high-impact global research and context-specific African academic contributions.

The search strategy employed a combination of keywords such as "Machine Learning," "Artificial Intelligence," "Zambia," "Organizational Performance," "Business Information Systems," and "Digital Transformation". To maintain contemporary relevance, the inclusion criteria were restricted to studies published between 2005 and 2025, with a particular focus on the surge of AI-related research that has appeared since 2021 (Ezugwu, Oyelade, Ikotun, Agushaka, and Ho, 2023; Chipembele, Ngandwe, Monde, and Ndalame, 2025). A total of 62 empirical studies focusing on the African context were prioritized for thematic analysis, alongside several thousand bibliometric records to establish regional trends.

The screening process followed a two-stage approach. In the first stage, titles and abstracts were reviewed for geographic and thematic alignment. In the second stage, full-text analysis was conducted to evaluate the methodological rigor and the presence of organizational impact data. Inclusion was granted to studies that utilized quantitative, qualitative, or mixed methods approaches to investigate the intersection of ML and organizational management. Government and industry reports from organizations like the McKinsey Global Institute and UNESCO were used strictly for supplementary background and market sizing data, while peer-reviewed journals and conference papers remained the primary source for all critical claims. The final selection focused on studies that provided actionable insights into the Zambian sectors of mining, banking, agriculture, and higher education.

3. Results

3.1. Theoretical Foundations of ML Adoption in Organizations

The literature on Machine Learning adoption is heavily influenced by the Technology Acceptance Model (TAM) and sociotechnical systems theory (Mutelo, 2025). TAM posits that the primary determinants of technology adoption are Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Mutelo, 2025). In the Zambian context, research at institutions like the Copperbelt University and the National Institute of Public Administration (NIPA) consistently finds that while PU is exceptionally high, driven by the desire for productivity and academic efficiency, PEOU is often compromised by technical literacy gaps and poor digital infrastructure (Chaamwe, 2025; Nsontaulwa and Mbale, 2025).

Sociotechnical theory offers a more holistic lens, suggesting that an organization is an interplay between social (human) and technical (machine) components. (Smit, Eybers, and van-der-Merwe, 2024). Studies in South Africa and Zambia emphasize that for ML to enhance performance, organizations must move toward "human-AI symbiosis," where algorithms augment rather than replace human expertise (Smit, Eybers, and van-der-Merwe, 2024; Rossow, 2025). For instance, the Zambia Statistics Agency (ZamStats) has begun testing large language models (LLMs) to classify labor force survey data, finding that ML can save up to 130 working days annually while still requiring human verification for accuracy (Rossow, 2025). This illustrates the theoretical shift from "static rule-based decision-making" to "intelligent, data-driven adaptation." (Tripathi et al., 2025).

Adaptive Learning Theory and Constructivism also play a crucial role in the educational sector, where ML-driven adaptive systems are used to personalize learning paths. (Nsontaulwa and Mbale, 2025). However, the literature reveals a "cultural resistance" to these student-centered methods in Zambia, where traditional pedagogical models remain entrenched. (Nsontaulwa and Mbale, 2025).

3.2. Global and Regional Context: The African Digital Leap

To understand the Zambian landscape so far as AI and ML, there is a need to appreciate the broader global and regional shifts. Globally, the AI market is projected to reach significant heights, with Sub-Saharan Africa's share expected to grow to US $16.5 billion by 2030 (Chloe, 2025).

Table 1 Global and Regional AI/ML Contextual Overview

Region	**Adoption Statistic**	**Key Driver**
Global Mature Adopters	66% Productivity Gain (Chloe, 2025)	Automated workflows and Predictive Analytics
Africa (Overall)	<5% Scholarly Output (Hadiza et al., 2024)	Need for Culture-Aware Ethics
Sub-Saharan Africa	30% Annual Growth (Chloe, 2025)	Fintech, Agriculture, and Energy
Zambia Readiness Rank	143rd / 193	Developing National Strategy

Regional research trends indicate that while Africa accounts for a small percentage of global research, there has been a massive surge in output since 2017, with articles reaching 1,035 in 2021 alone. (Ezugwu, Oyelade, Ikotun, Agushaka, and Ho, 2023). Egypt and South Africa dominate this landscape, contributing roughly 31% and 20% of the total publications, respectively. (Ezugwu, Oyelade, Ikotun, Agushaka, and Ho, 2023). Zambia, while still in an early "moderate capacity stage," is emerging as a regional leader in applied AI for mineral exploration, agriculture, and public health (Nalwimba, 2024; Beiser, 2024; Kapatamoyo, 2024).

The regional literature highlights a persistent skills shortage, with over 90% of African businesses citing limited AI expertise as a barrier. (Chloe, 2025). Furthermore, the lack of localized data remains a critical bottleneck. Most state-of-the-art MI (Machine Intelligence) models are not culture-aware and fail to exploit the vast audio and linguistic datasets available in African countries. (Tapo, Traore, Danioko, and Tembine, 2024). This leaves a significant portion of the population excluded from the digital economy.

3.3. Empirical Trends in Zambian Organizational Performance

The effect of Machine Learning on organizational performance in Zambia is most clearly observed through the lens of comparative sectoral analysis. Research indicates that the impact is not uniform across all organizational types. Private firms in Zambia achieve higher returns on investment from ML because of their flexible structures and leadership commitment to data-driven outcomes. In contrast, public organizations are often hindered by bureaucratic inflexibility, limited funding, and a reluctance to change. Despite these barriers, there is a strong positive correlation between AI adoption and overall institutional efficiency, decision-making, and innovation. In the Zambian manufacturing sector, the rise of automation and digitalization has led to a reduction of approximately 15% in total available jobs in Lusaka as of 2021 (Mweemba and Silwimba, 2025). This displacement primarily affects roles involving routine manual-intensive skills and basic cognitive functions, such as data entry and assembly. Conversely, there is an increasing demand for workers with advanced technical and analytical skills to manage and interpret ML outputs. (Mweemba and Silwimba, 2025).

3.4. Sector-Specific Impacts in Zambia

3.4.1. Mining and Mineral Exploration

The mining industry, which is the backbone of the Zambian economy, has seen transformative changes through ML. Kobold Metals recently utilized its proprietary AI platform at the Mingomba copper project to identify what is expected to be one of the highest-grade copper mines discovered in decades (Frank, 2024). This application demonstrates how ML can process vast geophysical datasets to significantly shorten exploration timelines and reduce costs (Mutovina, Nurtay, Kalinin, Tomilov, and Tomilova, 2024). Beyond exploration, ML is used in the creation of digital twins and predictive maintenance models for heavy equipment, enhancing both productivity and underground safety by predicting rock bolt failures. (Emere, Oguntona, Ohiomah, and Ayorinde, 2025).

3.4.2. Banking and Financial Services

The Zambian banking sector has been an early adopter of AI and ML technologies. A key study of 365 employees at a major bank in Lusaka identified that organizational leadership clarity and the population's access to the internet are the most significant predictors of successful AI adoption (Mutumba, 2018). In terms of operational efficiency, the integration of big data with ML has been shown globally (with implications for Zambia) to reduce unclassified credit ratings by 40.1% and decrease loan default rates by 29.6% (Chen, Guo, Xia, and Zhang, 2025). For Zambian banks, this means improved credit accessibility for Small and Medium Enterprises (SMEs) that lack formal financial statements, as ML can derive creditworthiness from alternative data sources (Mhlanga, 2021).

3.4.3. Agriculture and Smart Farming

In agriculture, ML is being deployed as a game changer for agrifood systems. Researchers in Kalumbila and other regions are testing Convolutional Neural Networks (CNNs) for the early detection of tomato and other plant diseases (Kunda and Phiri, 2023). By integrating real-time environmental data from sensor networks and IoT devices, these systems empower smallholder farmers to make more proactive decisions, reducing waste and maximizing crop yields. (Kunda and Phiri, 2023). However, the sector suffers from fragmented interventions, as most digital tools are implemented by non-state actors without a cohesive national strategy for agricultural digitalization. (Nalwimba, 2024).

3.4.4. Healthcare and Public Health

Zambian healthcare has leveraged ML to address critical public health issues like child stunting and anemia. By training algorithms on the Zambia Demographic Health Survey (ZDHS) dataset, researchers have found that Random Forest and XGBoost models outperform traditional statistical methods in predicting risk factors (Chilyabanyama et al., 2022; Mokoena, Mukosha, Zunza, and Maposa, 2025). For example, ML models identified that child age, maternal anemia, and wealth index are the top predictors of stunting and anemia, allowing for more precise and timely interventions (Zulu et al., 2025).

3.4.5. Higher Education and Research

Zambian universities are currently experiencing a "Generative AI revolution." Studies at Copperbelt University (CBU) reveal an awareness level of 88% and an adoption level of 82% among students (Phiri, 2025). Tools like ChatGPT, SciSpace, and Research Rabbit are widely used for literature reviews, hypothesis generation, and data analysis. (Mutelo, 2025). While this has increased research productivity, it has also raised severe concerns regarding academic integrity, as many institutions lack clear policies to regulate AI use. (Mutelo, 2025).

3.5. Challenges and Limitations: The Paradox of Potential

The adoption of ML in Zambia is characterized by a stark paradox. On one hand, there is high interest and potential contrasted with deep systemic barriers on the other hand.

Table 2 Systemic Barriers to ML Adoption in Zambia

Challenge	Specific Findings in Zambia
Digital Divide	Subscription rates are high, and only 33% are active internet users; rural-urban disparities remain acute.
Infrastructure	Unstable power supply and limited access to high-performance computing centers.
Policy Gaps	Lack of clear institutional guidelines on ethics, data privacy, and academic integrity.
Literacy	Capacity deficits among educators and a reliance on Western paradigms.

Critically, the literature points to the risk of digital colonialism, where programs like Facebook's Free Basics or imported AI models restrict informational autonomy and create dependence on single corporate platforms (Frimpong, 2025; Beiser, 2024). In the NGO sector, erratic governance and funding constraints further hinder the ability to maintain the modern technology and internet connectivity required for sophisticated ML applications (Chavula, Kayusi, and Mwewa, 2024). Furthermore, cultural variables play a significant role. Individualistic cultures prioritize personal data privacy, while collectivist values in many Zambian settings may require more culturally sensitive AI governance frameworks. (Hadiza, Esther, Ummana, Ozongbe, and Sahabi, 2024).

3.6. National Policy and Strategy

Zambia has taken bold steps to address these challenges through the National Artificial Intelligence Strategy 2024-2026. This strategy is built on six pillars.

- **Policy and Regulation:** Developing a framework that balances innovation with accountability.
- **Human Capital:** Integrating AI into the education system from primary to tertiary levels.
- **Data Ecosystems:** Investing in broadband, cloud computing, and national data repositories.
- **Innovation and Entrepreneurship:** Fostering a vibrant ecosystem for startups.
- **Public Service Delivery:** Using AI to optimize resource allocation and enhance transparency in government.
- **Ethics and Governance:** Establishing a National AI Council to provide oversight.

While the strategy is robust, academic critiques highlight gaps in operationalization and resource allocation. (Hambulo, Simataa, and Musonda, 2025). Many universities, for example, lack the guidelines to operationalize ethics impact assessments within their existing research ethics committees. (Hambulo, Simataa, and Musonda, 2025). There is also an evident tension between centralized government directives and institutional autonomy, which may hinder the local ownership of AI initiatives. (Hambulo, Simataa, and Musonda, 2025).

Table 3 Summary of the reviewed Articles

Author(s) (Year)	Country/Context	Sector	Methodology	Key Findings
Alherimi *et al.* (2025)	Global (multinational literature)	Human Resources / Sustainability (GHRM)	Systematic literature review (PRISMA-based)	Identified five research themes: AI's role in green recruitment, training, and performance management, and recognized critical challenges of ethics and organizational readiness. The review highlights AI as a tool for enhancing green HRM practices while underscoring that ethical considerations and readiness barriers (e.g., lack of skill, policy) remain significant.
Chaamwe (2025)	Zambia (Copperbelt University)	Education (Higher Education)	Survey (TAM; 285 students)	Found very high awareness (88%) and adoption (82%) of generative AI among university students, with 51% using it in coursework. Behavioral factors – expected benefits, perceived usefulness, attitude toward AI, and behavioral intention – were all significant predictors of students' adoption of generative AI tools.
Chavula *et al.* (2025)	Zambia (NGOs in Zambia)	Non-Profit / NGOs	Mixed methods (surveys, interviews, ML analysis)	Demonstrated that erratic governance (e.g., funding gaps, weak transparency, corruption) significantly undermines local and international NGOs' effectiveness. The study used ML predictive models and found that such analytics (e.g., risk analysis, predictive modelling) can effectively quantify and forecast governance-related impacts on NGO outcomes.
Chilyabanyama *et al.* (2022)	Zambia (Demographic Health Survey data)	Health / Nutrition	Quantitative ML modelling (classification)	Applied multiple ML classifiers to national health data and found ~34.2% of children under five were stunted. Random Forest gave the best performance (~79% test accuracy for predicting stunting), while Naïve Bayes performed the worst. ML models were shown to aid in the quick identification of stunted children for timely intervention.
Chipembele *et al.* (2025)	African universities (multi-country context)	Education (Academic Libraries)	Scoping review (systematic PRISMA-ScR)	Found growing awareness of AI in academic libraries, but little practical adoption. Most universities are in pilot or exploratory phases (e.g., experimenting with chatbots, recommender systems). Key barriers include limited funding, inadequate infrastructure, low digital skills, cultural resistance, and a lack of policies. Opportunities identified include strategic planning, AI literacy training, open-source tools, and partnerships.
Emere *et al.* (2025)	Global (mining industry)	Mining	Bibliometric analysis (135 Scopus papers)	Bibliometric review of 135 mining-sector publications reveals a significant recent rise in the application of emerging technologies (AI, digital twins, IoT, blockchain) across mining value chains. The analysis identifies key research trends and influential works, indicating that organizations increasingly leverage these technologies for safety, efficiency, and sustainability.

Ezugwu *et al.* (2023)	Africa (54 African countries, 1993–2021)	Research (general ML)	Bibliometric analysis (Scopus data)	Analyzed 2,761 machine-learning publications from 1993 to 2021 across 54 African countries. Found 89% were journal articles published in 903 journals. The study maps the growing ML research landscape in Africa, identifying major contributors and trending topics in the field, and provides a visualization of current and future research trends in African ML.
Frimpong (2025)	Ghana, Kenya, Rwanda (comparative case studies)	Policy / AI Strategy	Qualitative comparative case study (secondary data)	Shows that in resource-constrained African economies, allocating scarce funds to AI can divert resources from essential services, potentially exacerbating inequality and technological dependency. AI investment yielded opportunity costs in healthcare/education. The paper proposes four guiding principles (readiness, alignment, governance, and capacity building) to ensure AI development aligns with socio-economic priorities.
Hadiza *et al.* (2024)	Nigeria (universities)	Education / Research	Conceptual (literature/discussion)	Emphasizes the need for culturally aware AI integration in research methodologies. Highlights challenges such as data privacy, algorithmic bias, and ethical concerns in African contexts, and recommends measures like targeted AI training programs, culturally responsive policies, and collaborative governance to facilitate effective and respectful AI adoption in academic research.
Hambulo *et al.* (2025)	Zambia (higher education)	Education / Policy	Qualitative analysis (document review, interviews)	Critical review of Zambia's national AI strategy finds robust ethical guidelines in theory but identifies gaps in implementation (unclear resource allocations, weak data governance, and insufficient stakeholder engagement). Also notes tension between centralized policy and university autonomy. Concludes that the strategy needs localization and practical measures to realize its decolonial and inclusive aspirations.
Jobstreibizer *et al.* (2025)	Global (cross-industry)	Business / Management	Bibliometric-systematic literature review	Bibliometric review of AI's impact on business models finds AI central to innovation in customer engagement, Industry 4.0, digitalization, and sustainability strategies. Recent literature emphasizes AI's role in circular economy models and generative AI. The authors propose a conceptual framework outlining stages and social-technical considerations for AI adoption in business models.
Kapatamoyo (2024)	Africa (selected case studies, e.g., Zambia, Burkina Faso)	Natural resources (mining, conservation, agriculture)	Case study analysis	Presents diverse African case studies showing AI's impact on natural resources management. Examples include using AI for the discovery of copper deposits in Zambia, AI-driven wildlife monitoring in Burkina Faso, and smart irrigation in agriculture. Concludes that AI's advanced analytics and predictive models are reshaping strategies across mining, conservation, and agronomy sectors, improving efficiency and sustainability.

Kunda and Phiri (2023)	Zambia (case of tomato farming)	Agriculture	Experimental (CNN modeling with PlantVillage data)	Developed a convolutional neural network for detecting tomato leaf diseases. Training on public datasets, the model achieved 95.8% accuracy in identifying diseased leaves. This demonstrates that AI-enabled image analysis can effectively support plant health monitoring in Zambian agriculture.
Mhlanga (2021)	Emerging economies (general, e.g., Zimbabwe context)	Finance (banking/credit)	Literature review (conceptual analysis)	Argues that ML/AI can transform credit risk assessment in emerging economies. By using alternative data (digital footprints, social media, utility payments), AI can mitigate information asymmetries and adverse selection problems, enabling financial institutions to extend credit to underbanked individuals. Recommends increased AI/ML investment by banks to improve inclusion of excluded populations.
Mokoena *et al.* (2025)	Zambia (Lusaka neonatal unit)	Health (neonatal care)	Comparative predictive modeling (survival analysis vs ML)	Analyzed outcomes for 1,018 neonates; found 74.3% mortality. Hypoxic-ischemic encephalopathy and sepsis were strong risk factors, while higher birthweight and female sex were protective. Among models, Random Survival Forest (ML) had the best predictive performance (C-index=0.731) compared to traditional Weibull (0.622), suggesting ML techniques can improve survival prognostics in neonatal care.
Mutelo (2025)	Zambia (higher education)	Education / Research	Qualitative document analysis	Explores awareness and adoption of generative AI tools among Zambian students, lecturers, and researchers. Finds that while generative AI can boost productivity and research efficiency, the lack of clear guidelines/policies and ethical concerns are major challenge. Advocates for the creation of explicit policies, training programs, and improved digital infrastructure to ensure responsible and equitable AI integration in research.
Mweemba and Silwimba (2025)	Zambia (manufacturing sector, Lusaka)	Labor Market / Manufacturing	Mixed methods (surveys, interviews, statistical analysis)	Investigate how automation affects Zambian manufacturing jobs. Concludes that a large portion of manufacturing roles (especially routine, cyclical tasks) are vulnerable to automation. Recommends significant investments in reskilling, digital infrastructure, and education to address skill gaps. Highlights the need for policies addressing youth training, tech investment, and inequality to adapt the workforce to technological change.
Nasiru *et al.* (2025)	(Likely West Africa; data from public/private companies)	Business (public vs private enterprises)	Survey (n=120; descriptive and inferential stats)	Private firms had much higher AI adoption (65%) than public ones (30%). Overall performance scores were higher in private (mean 4.4 vs 3.5 out of 5). Strong positive correlations were found between AI adoption and performance in both sectors (r≈0.81 private, 0.62 public). AI explained 65% of performance variance in private firms (48% in public), suggesting AI is a key driver of efficiency and innovation.

Nsontaulwa and Mbale (2025)	Zambia (NIPA University)	Education (higher education)	Case study (AI integration in learning)	Found that AI has significant potential to personalize learning in Zambian higher education (NIPA). Students can benefit from AI-driven adaptive learning platforms for tailored instruction. However, practical implementation barriers (limited infrastructure, need for faculty training, and awareness) must be addressed to realize these benefits (source: *full text not available for citation*).
Phiri (2025)	Zambia (higher education)	Education (higher education)	Systematic literature review	Systematic review finds a surge in student-driven use of AI tools, which are viewed as useful and capable of transforming learning via personalization and engagement. However, a "double-edged sword" emerges: Zambia faces a persistent digital divide and infrastructural gaps, a lack of institutional AI policies/ethical guidelines, and low AI literacy among educators and students. These bottlenecks hinder the full benefits of AI despite Zambia's proactive national strategy.
Smit *et al.* (2024)	South Africa (auto industry case)	Technology Management	Design Science (focus groups in an auto manufacturer)	Developed a sociotechnical AI adoption framework (AIAF) for organizations. Through focus-group validation, the framework outlines technical and social factors (e.g., governance, skills, culture) to guide AI implementation. An AI agent ("Ailea") was also integrated to enable continuous evaluation and improvement of the framework. The artifact provides a high-level guide for enhancing AI adoption in companies.
Tripathi *et al.* (2025)	(India/South Africa context)	Human Resources / Workforce	Experimental (reinforcement learning model)	Proposed a deep reinforcement learning (DQN and policy gradient) framework for workforce scheduling and engagement. Experiments showed this RL-based approach significantly improved outcomes: task allocation accuracy up by 18%, scheduling conflicts down by 22%, and employee satisfaction up by 15% compared to traditional methods. Indicates RL can dynamically optimize workforce productivity and well-being.

3.7. Critical Analysis

The literature on Machine Learning in Zambia has evolved from speculative discussions about its potential to more grounded empirical investigations of its impact. A major strength of recent research is the use of localized datasets, such as the ZDHS, to solve specific Zambian problems. (Chilyabanyama et al., 2022). Another notable local application of Machine Learning to enhance performance is in the agricultural sector. (Nalwimba, 2024). This shifts the focus from generic technology to context-specific solutions.

However, there are notable methodological limitations. Much of the research is concentrated in the education and health sectors, while the impact on the informal economy, which accounts for over 89% of the agricultural workforce, remains under-researched (Nalwimba, 2024). Furthermore, while studies highlight the benefits of automation, there is a lack of longitudinal data on the long-term socioeconomic impact of job displacement in the manufacturing and service sectors.

There is also a theoretical gap regarding decolonial AI (Beiser, 2024). Most adoption models used in Zambian research are based on Western theories like TAM, which may not fully account for the socio-political factors (such as tribalism, nepotism, and erratic governance) that influence how Zambian organizations function (Chavula, Kayusi, and Mwewa, 2024). The reliance on English-language publications also limits the capture of grassroots innovation happening in local languages and informal settings (Hambulo, Simataa, and Musonda, 2025).

4. Discussion

This review demonstrates that ML is having a profound, albeit heterogeneous, effect on Zambian organizations, just like the rest of Sub-Saharan Africa. In the private sector, ML is a driver of competitive advantage and efficiency, while in the public sector, it is emerging as a tool for improved service delivery and evidence-based policymaking (Nasiru et al., 2025). The success of ML in the mining sector provides a powerful case study for the economic potential of these technologies. Specifically, the discovery of the Mingma deposit is a good example, though contentious because of resource overtake fears (Beiser, 2024).

For managers and organizational leaders, the implications are clear: the transition to ML requires a focus on workforce transformation and skills development. The finding that 15% of jobs in Lusaka's manufacturing sector are vulnerable to automation underscores the urgency of reskilling programs (Mweemba and Silwimba, 2025). For policymakers, the review suggests that infrastructure and data stewardship are the most critical pillars for the success of the National AI Strategy (Hambulo, Simataa, and Musonda, 2025).

The discussion also points to the need for AI Sovereignty. To avoid digital colonialism, Zambia must invest in localized data repositories and support research that focuses on indigenous languages and cultural contexts (Tapo, Traore, Danioko, and Tembine, 2024). The Oxford Insights ranking of 143rd indicates that while Zambia is moving in the right direction, it still has a long way to go in terms of overall AI readiness (Ministry of Technology and Science, 2024).

5. Conclusion

This thematic literature review has provided an analysis of the effects of ML on organizations in Zambia. By funneling down from global trends to specific national case studies, the review has identified that ML is transforming the Zambian organizational landscape through enhanced predictive accuracy in health, massive discovery potential in mining, and personalized learning in education. One of the core contributions of this review is the identification of the paradox of potential. This is a situation where high awareness and technical capability in the workforce are frequently stymied by structural and governance barriers. The review has also highlighted the significant performance gap between private and public enterprises, suggesting that management culture is as important as technical infrastructure in the success of digital transformation. Clear gaps for future research include the need for more studies on the informal sector, the development of culture-aware ML models, and longitudinal tracking of the socioeconomic effects of AI-driven automation. As Zambia embarks on its National AI Strategy 2024-2026, the success of its digital leap will depend on its ability to balance technological progress with ethical responsibility and institutional readiness. The path toward a prosperous middle-income nation, as envisioned in Vision 2030, will increasingly be paved with data-driven insights and the harmonious integration of human and machine intelligence.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Alherimi, N., Abdulmaksoud, S., Ahmed, V., and Bahroun, Z. (2025). A Systematic Literature Review of Artificial Intelligence Advancements in Green Human Resource Management. Sustainability, 17(22), 10283. doi:https://doi.org/10.3390/su172210283

[2] Beiser, V. (2024). Power Metal: The Race for the Resources That Will Shape the Future. Penguin Group.

[3] Chaamwe, N. (2025). Investigating the Factors Influencing Students' Adoption of Generative AIs in Universities: A Case of the Copperbelt University. Zambia ICT Journal, 8(1), 47–53. From https://ictjournal.icict.org.zm/index.php/zictjournal/article/view/340

[4] Chavula, P., Kayusi, F., and Mwewa, T. (2024). Assessing the Impact of Erratic Governance on Local and International NGOs in Zambia: An Exploratory Study Using Machine Learning and Artificial Intelligence. LatIA, 2, 79-79.

[5] Chen, B., Guo, D., Xia, J., and Zhang, Z. (2025). The Transformative Role of Artificial Intelligence and Big Data in Banking. doi:SSRN 5120308

[6] Chilyabanyama, O. N., Hamusonde, K., Saroj, R. K., Iqbal, N. T., Ngaruye, I., and Bosomprah, S. (2022). Performance of Machine Learning Classifiers in Classifying Stunting among Under-Five Children in Zambia. Children, 9(7), 1082. doi: https://doi.org/10.3390/children9071082

[7] Chipembele, M., Ngandwe, E., Monde, M. W., and Ndalame, E. M. (2025). Adoption of Artificial Intelligence in Academic Libraries in African Universities: A Scoping Review. IJSAT-International Journal on Science and Technology, 16(3).

[8] Chloe. (2025). AI and Machine Learning in Business Information Systems: Africa's Digital Leap. Retrieved January 20, 2026, from https://www.4cit.group/ai-and-machine-learning-in-business-information-systems/

[9] Emere, C., Oguntona, O., Ohiomah, I., and Ayorinde, E. (2025). Harnessing Emerging Technologies in the Global Mining Sector from a Bibliometric Standpoint. Mining, 5(1), 13. doi:https://doi.org/10.3390/mining5010013

[10] Ezugwu, A. E., Oyelade, O. N., Ikotun, A. M., Agushaka, J. O., and Ho, Y. S. (2023). Machine Learning Research Trends in Africa: A 30-Year Overview with Bibliometric Analysis Review. Arch Comput Methods Eng, 29:1-31. doi: doi: 10.1007/s11831-023-09930-z

[11] FRANK, J. (2024). Robbing Africa's Riches to Save the Climate (and Power AI). CounterPunch.

[12] Frimpong, V. (2025). Artificial Intelligence Investment in Resource-Constrained African Economies: Financial, Strategic, and Ethical Trade-Offs with Broader Implications. World, 6(2), 70. doi: https://doi.org/10.3390/world6020070

[13] Google, Sand Tech, and ALU. (2025). Artificial Intelligence in Sub-Saharan Africa: Overall Report. Retrieved January 20, 2026, from https://aiinafricaresearch.alueducation.com/wp-content/uploads/2025/04/Overall_RGB.pdf

[14] Hadiza, M. T., Esther, G., Ummana, T. D., Ozongbe, G. J., and Sahabi, K. M. (2024). BRIDGING CULTURES: EFFECTIVE ARTIFICIAL INTELLIGENCE (AI) ADOPTION IN RESEARCH METHODOLOGIES. NASARAWA JOURNAL OF LIBRARY AND INFORMATION SCIENCE (NAJLIS), 8(1), 238-248.

[15] Hambulo, F., Simataa, L., and Musonda, F. (2025). Navigating the governance framework for AI in Zambian higher education: A critical examination of the national AI strategy 2024-2026. International Journal of Literacy and Education, 5. 199-2.

[16] Jobstreibizer, J., Beliaeva, T., Ferasso, M., Kraus, S. und Kallmuenzer, A. (2025). The impact of artificial intelligence on business models: a bibliometric-systematic literature review. Management Decision, 63(13), 372–396. doi:doi: https://doi.org/10.1108/M

[17] Kapatamoyo, M. (2024). Artificial Intelligence in Natural Resources Management: Selected Case Studies from Africa. 24th Biennial Conference of the International Telecommunications Society (ITS). Seoul: International Telecommunications Society (ITS), Calgary.

[18] Kunda, B. C., and Phiri, J. (2023). Towards Leveraging AI Deep Learning Technology as a means to Smart Farming in Developing Countries: A case of Zambia. International Conference for ICT (ICICT)-Zambia, (pp. Vol. 5, No. 1, pp. 114-121).

[19] Mhlanga, D. (2021). Financial inclusion in emerging economies: The application of machine learning and artificial intelligence in credit risk assessment. International journal of financial studies, 9(3), 39.

[20] Ministry of Technology and Science. (2024). National Artificial Intelligence Strategy (2024-2026). Lusaka: Ministry of Technology and Science.

[21] Mokoena, T., Mukosha, M., Zunza, M., and Maposa, I. (2025). Predictors of mortality among neonates in Lusaka, Zambia: a comparative analysis of machine learning and traditional survival analysis techniques. Frontiers in Artificial Intelligence, 8, 1606245.

[22] Mutelo, I. (2025). Understanding the Generative Artificial Intelligence Revolution in Zambian Higher Education Research: Adoption, Challenges, and Strategies for Responsible Integration. INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS), 5731-5737. doi:10.47772/IJRISS.2025.903SEDU0416

[23] Mutovina, N., Nurtay, M., Kalinin, A., Tomilov, A., and Tomilova, N. (2024). Application of Artificial Intelligence and Machine Learning in Expert Systems for the Mining Industry: Literature Review of Modern Methods and Technologies. Preprints. doi:https://doi.org/10.20944/preprints202408.1432.v1

[24] Mutumba, A. J. (2018). Understanding the readiness of banking industry employees to adopt artificial intelligence in frontier markets. University of Pretoria (South Africa).

[25] Mweemba, C., and Silwimba, P. (2025). Analyzing Technological Change and Effects on Labor Market Dynamics: A Case Study of the Manufacturing Sector in Zambia, Lusaka. INTERNATIONAL JOURNAL, 5(2), 327-337.

[26] Nalwimba, N. (2024). Digital Technology in Zambian Agriculture: Scoping Report. Lusaka: PLAAS.

[27] Nasiru, A. U., Olawale, O., Abeyie, K. S., Ibrahim, I. O., Jamiu, I. A., and Abdullahi, M. (2025). Assessing the Impact of Artificial Intelligence on Organizational Performance: A Comparative Study of Public and Private Enterprises. World Journal of Advanced Research and Reviews. doi:https://doi.org/10.30574/wjarr.2025.28.2.3802

[28] Nsontaulwa, J., and Mbale, J. (2025). Utilizing Artificial Intelligence to Enhance Personalized Learning at Zambian Universities: A Case Study of NIPA. International Conference for ICT (ICICT), (pp. 456-462).

[29] Paliwal, M., Patel, M., Kandale, N., and Anute, N. (2021). Impact of artificial intelligence and machine learning on business operations. Journal of Management Research and Analysis, 8(2), 70-75. doi: https://doi.org/10.18231/j.jmra.2021.015

[30] Phiri, D. C. (2025). The Double-Edged Sword: A Systematic Review of AI-Powered Tools for Student Engagement and Personalised Learning in Zambian Higher Education. IJRISS, 283-291.

[31] Rossow, T. (2025). Artificial intelligence in national statistics: Insights from Zambia. Retrieved January 20, 2026, from IGC: https://www.theigc.org/blogs/ai-national-statistics-zambia

[32] Smit, D., Eybers, S., and van-der-Merwe, A. (2024). Towards Human-AI Symbiosis: Designing an Artificial Intelligence Adoption Framework. South African Computer Journal, 36(1), 76-104. From https://doi.org/10.18489/sacj.v36i1.18823

[33] Tapo, A. A., Traore, A., Danioko, S., and Tembine, H. (2024). Machine Intelligence in Africa: a survey. From https://arxiv.org/pdf/2402.02218

[34] Tripathi, M. A., Osei-Asiamah, J., Chinmulgund, A., Saravanan, A., Mastan Rao, T. S., HP, R., and Baker El-Ebiary, Y. A. (2025). Machine Learning Applications in Workforce Management: Strategies for Enhancing Productivity and Employee Engagement. International Journal of Advanced Computer Science and Applications, 16(3).

[35] Zulu, T., Kamulaza, L., Chisiza, A., Amatende, N., Tembo, N., Sampa, M., and Mutale, W. (2025). Application of Machine Learning (ML) to Predict Under-Five Anemia using the 2018 Zambia Demographic and Health Survey (ZDHS). medRxiv.