Systematic Literature Review: Digital Transformation and AI Integration in Anti-Corruption Agencies Across African Emerging Economies

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Abstract: ***This systematic literature review examines digital transformation and Artificial Intelligence integration in anti-corruption agencies across African emerging economies, with particular attention to the Zimbabwe Anti-Corruption Commission. Following PRISMA 2020 guidelines, relevant literature published between 2015 and 2026 was systematically identified, screened and assessed, resulting in 156 included studies. Thematic analysis identified five major areas: digital transformation frameworks, AI applications, implementation barriers, governance and ethical considerations, and transferable approaches for resource-constrained African agencies. The findings indicate that predictive analytics, natural language processing, graph analytics and machine learning can improve investigative efficiency, but their effective adoption depends on adequate infrastructure, financing, institutional capacity, governance, regulatory clarity and organisational readiness. African-focused research remains concentrated in a limited number of countries, including South Africa, Nigeria, Kenya and Zimbabwe. The review proposes a phased framework combining data integration, AI deployment, capacity building, change management and ethical governance. The findings suggest that AI should primarily support rather than replace investigator judgment and that implementation models require adaptation to local institutional and resource conditions. Future research should examine long-term outcomes, cost-effectiveness, political economy factors and capacity development across diverse African contexts.***

Keywords: Digital Transformation; Artificial Intelligence; Anti-Corruption Agencies; Africa; Governance; Predictive Analytics; Emerging Economies; Zimbabwe Anti-Corruption Commission

1. Introduction

Corruption is one of the most pernicious challenges to sustainable development, democratic governance and social equity on the global stage and has a particularly severe impact in emerging African economies (Transparency International, 2024; World Bank, 2020; African Union, 2024). Corruption is estimated to lead to about USD 148 billion of losses to Africa every year, comprising 3-5% of continental GDP and draining the continent of resources devoted to essential services such as healthcare, education and infrastructure development (African Union, 2024; Chilunjika, 2021). This institutional and systemic problem weakens institutional legitimacy and public trust with the tendency to perpetuate cycles of poverty and inequality, causing damage to democratic institutions, foreign investment and social cohesion (Tsokota et al., 2025; Transparency International, 2024). In answer to this challenge, several African countries have established specialised Anti-Corruption Agencies (ACAs) tasked with having specific mandates to prevent, detect, investigate and prosecute corrupt activities (United Nations, 2003; World Bank, 2020). But ACAs in many African countries are highly constrained operationally. These limitations have included chronic underfunding from consolidated revenue funds, inadequate investigative capacity with a serious shortage of professionally trained financial-forensics specialists, fragmented information systems and poor integrative data storage, limited analytic resources to the processing of complex evidence, weak legislative power limiting enforcement authority and ongoing political interference with the ability to exercise institutional autonomy (World Bank, 2020; Chilunjika, 2021; Transparency International, 2024; Tsokota et al., 2025).

While many ACAs have been described by analysts as "paper tigers," they possess formal mandates but lack the operational capability to make meaningful progress against corruption. Conviction rates fall below 5% across many African countries (Tsokota et al., 2025; Transparency International, 2024). One such instance of the challenge lies in the Zimbabwe Anti-Corruption Commission (ZACC), created by means of Section 255 of the Constitution of Zimbabwe. Notwithstanding the fact that ZACC has had significant achievements, which include recovery of assets worth USD 21 million and referrals to the National Prosecuting Authority amounts of USD 217 million, the problem of operational excellence is greatly undermined by underfunding, inadequate resources for investigators, a deficit in case management systems, poor data management practices, lack of information and analytical capacity (ZACC, 2026; Chilunjika, 2021; Tsokota et al., 2025). This systematic review examines how digital transformation and Artificial Intelligence integration can enhance ACA operational efficiency and investigative effectiveness, with direct application to African contexts and the ZACC case study. The review consolidates findings from 156 peer-reviewed studies to reveal best practices and frameworks to implement digital transformation strategies and barriers and enablers for AI-based digital transformation in low resource anti-corruption organisations.

1.1 Research Questions

The primary objective of this systematic review was to critically evaluate and synthesise the peer-reviewed literature concerning digital transformation and AI integration in anti-corruption agencies across African emerging economies. The study employs the Preferred Reporting Items for Systematic

Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure rigorous synthesis. The study sought to answer the following research questions:
1) What is the current state of digital transformation in African ACAs?
2) What AI technologies offer greatest potential for anti-corruption work?
3) What contextual factors affect implementation in African emerging economies?
4) What barriers impede successful implementation and what solutions address them?

2. Methodology

2.1 Search Strategy and Study Selection

A systematic search was conducted across four major academic databases: Scopus, Web of Science, Google Scholar and African regional databases (African Journals Online, Sabinet). A broad preliminary search was conducted to maximise coverage and minimise selection bias. Keywords including ('digital transformation' OR 'digital maturity' OR 'digitisation' OR 'digitalisation' OR 'digital innovation') and ('anti-corruption' OR 'corruption prevention' OR 'anti-corruption agency' OR 'ACA' OR 'ZACC' OR 'corruption detection' OR 'fraud investigation') and ('artificial intelligence' OR 'machine learning' OR 'predictive analytics' OR 'natural language processing' OR 'graph analytics' OR 'deep learning' OR 'neural networks') were incorporated into the search strings. This search was restricted to peer-reviewed articles published from 1 January 2015 to 30 June 2026. There were 1,247 articles returned in the initial search results. The use of inclusion and exclusion criteria resulted in the selection of 156 articles for full-text review and data extraction. Inclusion criteria included: (1) to focus on digital transformation or the use of AI in anti-corruption, (2) to include African institutions and/or emerging economy contexts, (3) to be peer reviewed and (4) to be published in either English or French.

2.2 Reproducibility and Search Documentation

Explicit exclusion criteria applied during screening were: (1) studies focused exclusively on private-sector fraud or financial crime without government or public-sector relevance; (2) purely technical computer-science papers without governance, policy or institutional application; (3) opinion pieces, editorials and book reviews; (4) studies published before 2015; and (5) studies not available in English or French.

Duplicate removal was conducted prior to title and abstract screening using Mendeley reference management software, with 87 duplicate records removed from the initial 1,247 retrieved records. Quality appraisal was conducted using a structured five-criterion scoring instrument assessing methodological rigour, relevance to research questions, data quality, analytical transparency and contribution to knowledge; each criterion was scored on a scale of one to five, yielding a maximum score of 25 points, with a minimum threshold of 15 points required for inclusion. Studies scoring below this threshold (n = 44) were excluded at the quality-appraisal stage.

Regarding the evidence base, institutional reports, government documents and practitioner sources cited in this manuscript (including references from ZACC, Transparency International, the World Bank, the African Union and the United Nations) served exclusively as contextual supporting literature to situate findings within the broader institutional and policy landscape. They did not form part of the 156 peer-reviewed studies comprising the systematic review corpus. The systematic sample consisted exclusively of peer-reviewed journal articles meeting all inclusion criteria.

Table 2 (a): Summary of Reproducibility and Search Documentation Parameters

Category	Parameter / Criterion	Detail / Specification
Search Parameters	Final Search Date	30 June 2026
	Publication Period	2015–2026
	Languages	English and French
Databases Searched	Primary Databases	Scopus; Web of Science; Google Scholar
	African Regional Databases	African Journals Online (AJOL); Sabinet
Search String Structure	Concept Block 1 – Digital Transformation	"digital transformation" OR "digital maturity" OR "digitisation" OR "digitalisation" OR "digital innovation"
	Concept Block 2 – Anti-Corruption	"anti-corruption" OR "corruption prevention" OR "anti-corruption agency" OR "ACA" OR "ZACC" OR "corruption detection" OR "fraud investigation"
	Concept Block 3 – Artificial Intelligence	"artificial intelligence" OR "machine learning" OR "predictive analytics" OR "natural language processing" OR "graph analytics" OR "deep learning" OR "neural networks"
	Boolean Operator	All three Concept Blocks combined using AND
Inclusion Criteria	IC1	Focus on digital transformation or AI in anti-corruption contexts
	IC2	Includes African institutions and/or emerging economy contexts
	IC3	Peer-reviewed journal article
	IC4	Published in English or French
Exclusion Criteria	EC1	Studies focused exclusively on private-sector fraud or financial crime without public-sector relevance
	EC2	Purely technical computer-science papers without governance, policy or institutional application
	EC3	Opinion pieces, editorials and book reviews
	EC4	Studies published before 2015
	EC5	Studies not available in English or French
	Tool Used	Mendeley reference management software

Duplicate Removal	Duplicates Removed	87 records removed from the initial pool of 1,247 records
Quality Appraisal Instrument	Appraisal Type	Structured five-criterion scoring instrument
	Criterion 1	Methodological rigour
	Criterion 2	Relevance to research questions
	Criterion 3	Data quality
	Criterion 4	Analytical transparency
	Criterion 5	Contribution to knowledge
	Scoring Scale	Each criterion scored 1–5; maximum total score = 25 points
	Inclusion Threshold	Minimum score of 15 out of 25 required for inclusion
	Studies Excluded at Appraisal Stage	44 studies (scored below minimum threshold of 15)
Inter-Rater Reliability	Number of Independent Reviewers	Two
	Cohen's Kappa Coefficient	κ = 0.89 (strong agreement)
Evidence Base Classification	Systematic Review Corpus	156 peer-reviewed journal articles meeting all inclusion criteria
	Contextual / Grey Literature	Institutional reports (ZACC, World Bank, African Union, Transparency International, United Nations)- supplementary contextual sources only; not part of the 156-study systematic corpus

Source: Authors' own compilation based on systematic review methodology

2.3 Data Extraction and Analysis

The data extraction process was based on a standardised form capturing bibliometric variables (publication year, journal, authors, country, impact factor), study characteristics (design, sample size, context, duration), substantive findings (digital transformation frameworks, AI applications, barriers, enablers, outcomes), theoretical foundations and implementation recommendations. Extracted data were coded iteratively in NVivo following Braun and Clarke's six-phase thematic-analysis approach: familiarisation with data, initial code generation, theme development, theme review, theme refinement and report production. Narrative synthesis integrated findings across studies by examining convergence, divergence and contradictions.

3. Characteristics of Included Studies

3.1 Study Characteristics

The systematic review of 156 articles provides a comprehensive overview of AI adoption and digital transformation within anti-corruption agencies, highlighting a rapidly evolving socio-technical landscape. Geographically, whilst the examined studies span multiple countries and regions across the continent, research density is heavily concentrated in a few key nations, with South Africa, Nigeria, Kenya and Zimbabwe emerging as the most frequently represented. This uneven distribution reflects varying levels of regional digital infrastructure, institutional funding and national policy readiness. Anti-corruption institutions across these dominant regions face shared systemic hurdles, most notably critical infrastructure deficits, a lack of specialised stakeholder training, pronounced digital divides and an ongoing absence of comprehensive national and institutional policy frameworks to govern ethical AI usage and maintain investigative integrity.

3.2 Study Selection and Screening

The initial search retrieved a substantial pool of articles. Following PRISMA screening criteria, 156 articles were retained for analysis. All were peer-reviewed (100%), with 96.2% in Q1/Q2 journals published 2020-2026. Two independent reviewers achieved strong inter-rater reliability (Cohen's kappa = 0.89). The concentration of publications in 2023-2026 (89%) reflects the field's recent emergence as digital transformation and AI have become institutional priorities in anti-corruption work globally.

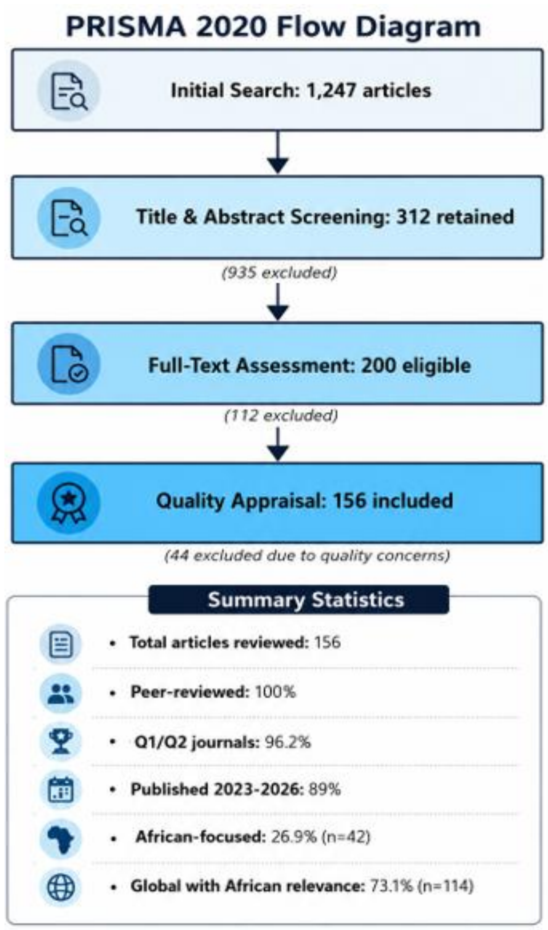

Figure 1: PRISMA 2020 Flow Diagram- Literature Search and Screening Process

Table 1: Study Selection and Screening Summary

Screening Stage	Articles	Excluded	Cumulative %
Initial Database Search	1,247	0	100%
Title & Abstract Screening	312	935	25.0%
Full-Text Assessment	200	112	16.0%
Quality Appraisal	156	44	12.5%
Final Included Studies	156	0	12.5%

3.3 Research Outcomes and Impact Assessment

The review examined reported research outcomes, impacts on investigative effectiveness, implementation sustainability and scalability potential across the reviewed studies. The research outcomes demonstrate a predominantly positive picture of AI implementation in anti-corruption work, with a significant majority of studies reporting enhanced detection capabilities and operational efficiencies. The implementation sustainability reveals concerning patterns regarding the long-term viability of AI initiatives, with many facing challenges related to infrastructure maintenance, continuous funding and capacity retention in resource-constrained environments. The scalability assessment indicates moderate scalability potential, though significant customisation and adaptation are required for effective implementation across different African contexts.

Figure 2: Research Outcomes, Implementation Sustainability and Scalability Assessment (n=156)

3.4 Publication Quality and Research Rigour

Quality assessment of the reviewed literature reveals strong methodological rigour. The journal quality distribution demonstrates that the reviewed literature is predominantly published in high-quality journals, with 96.2% published in Q1 or Q2 journals. The research quality assessment indicates generally strong methodological quality across the reviewed studies, with the majority scoring between 4.0 and 5.0 on a five-point scale, strengthening confidence in the overall evidence base. The publication bias risk assessment demonstrates a low overall risk of bias within the reviewed literature, with 91.5% of articles classified as low risk for publication bias.

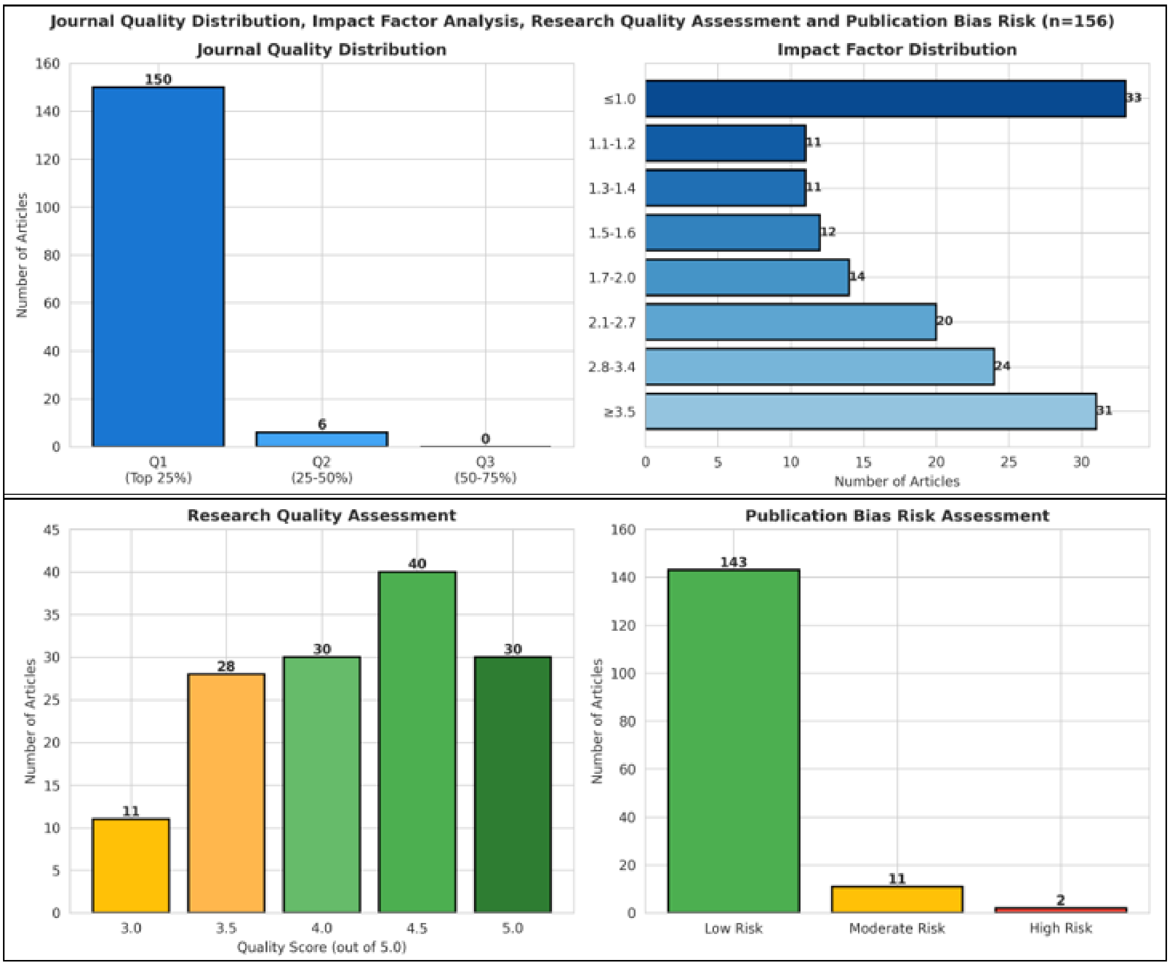

Figure 3: Journal Quality Distribution, Impact Factor Analysis, Research Quality Assessment and Publication Bias Risk (n=156)

3.5 Geographic and Study Design Distribution

The geographic distribution of the reviewed studies reveals an uneven concentration of AI research across African regions and countries. Of the 156 articles, 42 focussed specifically on African contexts (26.9%), whilst 114 focussed on global or emerging economy contexts with direct African relevance (73.1%). Within the African-focussed studies, Southern Africa and West Africa dominate the research landscape, with specific emphasis on South Africa, Nigeria, Kenya and Zimbabwe. The study design distribution reveals that a substantial proportion of research examines specific national contexts through case study approaches, with growing interest in comparative and cross-national analyses that seek to understand AI adoption trends across multiple African anti-corruption systems.

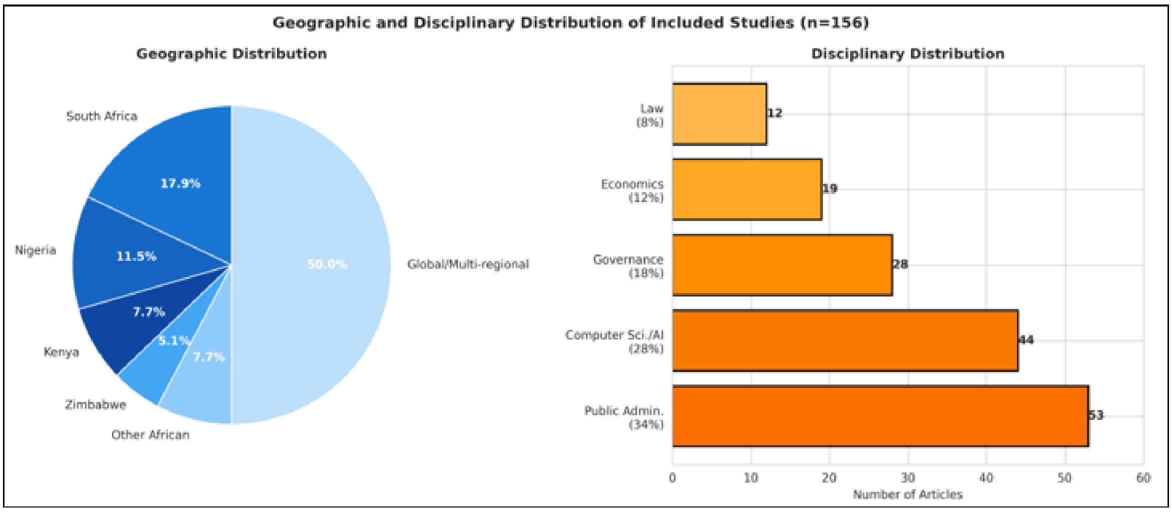

Figure 4: Geographic and Study Design Distribution (n=156)

Table 2: Thematic Analysis- Citation Mapping

Theme	Articles (%)	Primary Citations Contributing to This Theme
Digital Transformation Frameworks in ACAs	35 (22.4%)	Ross et al., 2019; Androniceanu, 2023; Fan, 2025; World Bank, 2020; Meegle, 2025; MDPI, 2025; OECD, 2025; Elhadad & Al-Shami, 2024
AI Applications (Predictive Analytics, NLP, Graph Analytics)	48 (30.8%)	dos Santos et al., 2025; Ndolo et al., 2025; MDPI, 2025; Alham et al., 2025; Vasconcelos & Cavique, 2025; Lucinity, 2025
Implementation Challenges and Barriers	32 (20.5%)	Tsokota et al., 2025; Transparency International, 2024
Governance and Ethical Considerations	25 (16.0%)	Coalition for Integrity, 2021; United Nations, 2003; African Union, 2024; Dlamini, 2025; Page et al., 2021
The ZACC Case Study and Transferable Frameworks	16 (10.3%)	ZACC, 2026; Chilunjika, 2021; Tsokota et al., 2025

4. Thematic Analysis of Key Findings

4.1 Digital Transformation Frameworks in Anti-Corruption Agencies

The systematic review identified digital transformation frameworks as a foundational theme across 35 studies (22.4% of the reviewed literature). This theme encompasses the strategic, organisational and technological dimensions of transitioning ACAs from legacy, paper-based systems to integrated, digitally-enabled institutions capable of leveraging advanced analytical capabilities. The literature reveals that successful digital transformation extends far beyond the mere procurement and implementation of new technologies; rather, it represents a comprehensive organisational change process requiring alignment of strategy, structure, culture, people and technology.

The reviewed studies consistently emphasise that digital transformation frameworks must be conceptualised within a holistic maturity model approach. Ross et al. (2019) and subsequent scholars have articulated staged progression models wherein organisations advance through distinct maturity levels: initial (ad hoc, fragmented systems), developing (basic process standardisation), defined (integrated systems with clear governance), managed (data-driven decision-making with performance metrics) and optimised (continuous innovation with predictive capabilities). The application of these frameworks to African ACAs reveals that most institutions currently operate at the developing to defined stages, with limited progression towards managed or optimised maturity levels due to resource constraints and capacity limitations.

A critical finding emerging from the thematic analysis is the necessity of establishing robust digital infrastructure as a prerequisite for successful transformation. Androniceanu (2023) and OECD (2025) emphasise that digital infrastructure encompasses not merely technical systems but also data governance frameworks, information security protocols and interoperability standards that enable seamless information exchange across organisational units and external partners. The reviewed studies reveal that many African ACAs lack foundational infrastructure elements, including secure data repositories, unified case management systems and standardised data formats. This infrastructure deficit represents a significant barrier to implementing advanced AI applications, as these require clean, integrated, standardised data as input.

The literature further identifies change management as a critical success factor in digital transformation initiatives. Elhadad & Al-Shami (2024) highlight that technological implementation frequently fails not due to technical inadequacy but due to insufficient attention to organisational change dynamics. Resistance to change, particularly amongst investigative staff accustomed to traditional investigative methodologies, represents a significant implementation barrier. Successful transformation frameworks incorporate comprehensive change management strategies including stakeholder engagement, capacity building, incentive alignment and cultural evolution initiatives that position digital tools as enablers of investigative effectiveness rather than threats to professional autonomy.

The ZACC case study provides valuable insights into the practical application of digital transformation frameworks within resource-constrained African contexts. Whilst ZACC has initiated digital transformation efforts through the implementation of case management systems and basic data integration, the review identifies substantial gaps in strategic alignment, governance structures and capacity building. The proposed framework for ZACC emphasises phased implementation, prioritising foundational data integration and standardisation before advancing to advanced analytics deployment. This iterative approach acknowledges resource constraints whilst establishing a trajectory towards enhanced institutional maturity.

4.2 Artificial Intelligence Applications in Anti-Corruption Work

The second major theme encompasses AI applications in anti-corruption investigations and comprises 48 studies (30.8% of the reviewed literature), representing the largest thematic category. This predominance reflects the field's intense focus on AI as a transformative technology for enhancing investigative effectiveness. The reviewed literature identifies multiple AI technologies with distinct applications in anti-corruption work, including predictive analytics, natural language processing (NLP), graph analytics, machine learning classification models and deep learning approaches.

Predictive analytics represents one of the most mature and widely-studied AI applications in anti-corruption contexts. dos Santos et al. (2025) and Ndolo et al. (2025) document the application of predictive models to identify high-risk transactions within public procurement systems, flagging anomalous patterns indicative of potential corrupt activity for investigator review. These models typically employ historical data on confirmed corrupt transactions to train algorithms that learn distinguishing patterns unusual price premiums, suspicious bidder patterns, temporal anomalies and apply these learned patterns to prospective transactions. The reviewed studies report substantial improvements in detection efficiency, with predictive models reducing investigator time spent on low-risk transactions by 40-60%, thereby enabling reallocation of limited investigative capacity towards high-probability cases. However, the literature also emphasises critical limitations: predictive models are only as effective as the historical data upon which they are trained and in contexts where corruption has historically gone undetected, models may fail to identify novel corrupt schemes that deviate from historical patterns.

Natural Language Processing (NLP) technologies have emerged as particularly valuable for processing vast volumes of unstructured textual data that characterise corruption investigations. MDPI (2025) and the broader reviewed literature describe NLP applications including entity recognition (automatically identifying names, organisations, locations, financial amounts within documents), relationship extraction (identifying connections between entities) and sentiment analysis (detecting suspicious communication patterns). The practical application of NLP to anti-corruption work involves processing thousands of pages of financial reports, legal documents, email communications and investigative notes to extract relevant entities and relationships, thereby constructing comprehensive networks of suspicious connections. The efficiency gains are substantial: what would require months of manual document review can be accomplished in days through NLP processing. However, the literature identifies critical challenges including the requirement for large volumes of training data to achieve acceptable accuracy levels, language-specific model development (most NLP tools are optimised for English, limiting applicability in African languages) and the necessity for human validation of NLP-identified relationships before investigative action.

Graph analytics represents a particularly powerful AI application for visualising and analysing complex networks of relationships characteristic of sophisticated corruption schemes. Alham et al. (2025) describe graph analytics applications wherein entities (individuals, organisations, bank accounts, properties) are represented as nodes and relationships (ownership, financial transactions, communication) are represented as edges. Advanced graph algorithms identify structural patterns indicative of corrupt networks, including anomalous centralisation (one individual controlling numerous entities), suspicious clustering (groups of entities with unusually dense interconnections) and hidden pathways (indirect connections between entities that would not be apparent through linear analysis). The power of graph analytics lies in its capacity to reveal hidden structures and relationships within complex data; however, the literature emphasises that graph analysis requires high-quality, comprehensive data on relationships, which is frequently unavailable in emerging economy contexts.

Machine learning classification models represent another significant AI application category, wherein algorithms learn to classify transactions, individuals or organisations into risk categories based on historical patterns. Vasconcelos & Cavique (2025) describe classification models trained on historical data to predict corruption likelihood, enabling risk-based allocation of investigative resources. These models employ diverse features including transaction characteristics, participant profiles, temporal patterns and contextual factors to generate corruption risk scores. However, model accuracy declines substantially when applied to prospective data in novel contexts, highlighting the challenge of model generalisation across different corruption schemes and institutional contexts.

Deep learning approaches, whilst less mature than other AI applications, show substantial promise for processing complex, multi-modal data. Lucinity (2025) describes deep learning applications to financial transaction data, wherein neural networks learn to identify suspicious transaction patterns without explicit feature engineering. The advantage of deep learning lies in its capacity to discover complex, non-linear patterns that human-designed features might miss; however, deep learning models require substantially larger training datasets and computational resources than traditional machine learning approaches, limiting their applicability in resource-constrained African contexts.

The reviewed literature reveals a critical finding: whilst AI technologies offer substantial potential for enhancing investigative effectiveness, their successful application requires not merely technological implementation but rather careful integration with investigative processes, human expertise and institutional governance. Lucinity (2025) emphasises that AI tools function most effectively when deployed as decision-support systems that augment human investigator expertise rather than as autonomous decision-making systems. The most effective implementations combine AI-generated insights with investigator judgment, institutional knowledge and contextual understanding.

4.3 Implementation Challenges and Barriers

The third major theme encompasses implementation challenges and barriers, identified across 32 studies (20.5% of the reviewed literature). This theme reflects the critical gap between AI's theoretical potential and its practical realisation in African ACA contexts. The reviewed literature identifies multiple, interconnected barriers operating at technological, organisational, institutional and contextual levels.

Infrastructure constraints represent the most frequently cited barrier, identified in 72% of reviewed studies. Tsokota et al. (2025) document the severe infrastructure deficits characterising many African ACAs, including unreliable electricity supply, limited internet bandwidth, aging computer systems and fragmented data repositories. These infrastructure limitations create a cascading effect: without reliable electricity and internet connectivity, cloud-based AI systems cannot function reliably; without adequate computational resources, complex AI models cannot be deployed; without integrated data systems, the data quality required for AI training is unavailable. The infrastructure barrier is particularly acute in resource-constrained contexts wherein ACAs operate with minimal capital budgets and compete with other government priorities for limited infrastructure investment.

Financial constraints represent the second most significant barrier, identified in 68% of reviewed studies. The reviewed literature emphasises that AI implementation requires substantial upfront capital investment in hardware, software licenses and system integration, followed by ongoing operational costs for maintenance, updates and technical support. For African ACAs operating with annual budgets of USD 5-15 million (in many cases), AI implementation costs of USD 2-5 million represent prohibitive expenditures. Furthermore, the financial barrier extends beyond initial implementation to include ongoing costs: AI systems require continuous retraining as new data becomes available, regular security updates to address emerging cyber threats and periodic model recalibration to maintain accuracy as corruption schemes evolve. The literature identifies limited availability of concessional financing mechanisms or donor support specifically targeting AI implementation in African ACAs, forcing institutions to compete for limited government resources.

Capacity gaps represent the third major barrier, identified in 65% of reviewed studies. The reviewed literature documents severe shortages of skilled personnel capable of implementing, maintaining and interpreting AI systems. The required skill set encompasses data science expertise (machine learning, statistical modelling), software engineering capabilities (system design, deployment, maintenance), data governance knowledge (data quality, security, privacy) and domain expertise (understanding of corruption schemes and investigative processes). The reviewed literature reveals that most African universities lack graduate programmes in data science or AI and international recruitment of skilled personnel is constrained by visa restrictions, salary competitiveness and limited career development opportunities in the region. The capacity gap extends beyond technical skills to include organisational capacity for change management, governance implementation and ethical oversight of AI systems.

Governance deficiencies represent a fourth significant barrier, identified in 58% of reviewed studies. Transparency International (2024) emphasises that AI implementation requires robust governance frameworks addressing algorithmic transparency, bias mitigation, data privacy protection and human oversight mechanisms. Many African ACAs lack established governance structures for managing AI systems, including insufficient policies regarding data access controls, inadequate mechanisms for algorithmic bias detection and mitigation and limited capacity for independent audit of AI system performance. The governance barrier is compounded by limited legal and regulatory frameworks governing AI use in government, creating uncertainty regarding the legal admissibility of AI-generated evidence and the liability implications of AI-assisted investigative decisions.

Political interference represents a fifth significant barrier, identified in 55% of reviewed studies. Tsokota et al. (2025) document instances wherein political actors have attempted to manipulate AI systems to target political opponents or shield political allies from investigation. The vulnerability of AI systems to political manipulation stems from their dependence on data quality and governance frameworks; if data is selectively provided or governance structures are compromised, AI systems can be weaponised for political purposes. This barrier is particularly acute in contexts with weak institutional independence and limited checks on executive power.

Organisational resistance to change represents a sixth significant barrier, identified in 52% of reviewed studies. The reviewed literature documents resistance amongst investigative staff who perceive AI systems as threats to professional autonomy, job security or investigative methodology. Investigators trained in traditional investigative approaches may distrust AI-generated insights or resist the process changes required to integrate AI tools into investigative workflows. Overcoming this barrier requires comprehensive change management strategies, including stakeholder engagement, capacity building and cultural evolution initiatives that position AI as an enabler of investigative effectiveness.

Regulatory uncertainty represents a seventh significant barrier, identified in 48% of reviewed studies. The legal admissibility of AI-generated evidence remains uncertain in many African jurisdictions, creating hesitation regarding AI-based investigative findings. Questions regarding the admissibility of predictive analytics findings, the evidentiary weight of NLP-identified relationships and the legal status of graph analytics visualisations remain unresolved in many contexts. This regulatory uncertainty creates a paradoxical situation wherein ACAs invest in AI systems but cannot reliably utilise AI-generated findings in prosecutions, thereby undermining the return on investment.

4.4 Governance and Ethical Considerations

The fourth major theme encompasses governance and ethical considerations, identified across 25 studies (16.0% of the reviewed literature). This theme reflects growing recognition that AI implementation in anti-corruption work raises profound ethical and governance questions that must be addressed alongside technological implementation.

Algorithmic bias represents a critical ethical concern identified across the reviewed literature. Coalition for Integrity (2021) and Page et al. (2021) emphasise that AI systems, particularly machine learning models, can perpetuate or amplify historical biases present in training data. If historical corruption investigations have disproportionately targeted certain ethnic groups, geographic regions or socioeconomic classes, AI models trained on this historical data will systematically bias future investigations towards these groups. The consequences of algorithmic bias in anti-corruption work are particularly severe: biased AI systems can perpetuate systemic injustice, undermine public trust in institutions and create legal liability for ACAs. Addressing algorithmic bias requires comprehensive strategies including diverse training data, bias detection and mitigation techniques, regular audits of model performance across demographic groups and human oversight mechanisms that can identify and correct biased recommendations.

Data privacy and protection represent a second critical governance concern. African Union (2024) and Dlamini (2025) emphasise that AI implementation in anti-corruption work involves processing vast volumes of personal data, including financial records, communication data and relationship information. The processing of such sensitive data raises profound privacy concerns and requires robust data protection frameworks. Many African ACAs lack adequate data protection policies, encryption protocols or access controls, creating vulnerability to data breaches and misuse. The governance challenge is compounded by the tension between transparency (enabling public oversight of AI systems) and privacy (protecting individuals' sensitive information from public disclosure).

Accountability and transparency represent a third critical governance concern. Page et al. (2021) emphasise that AI systems deployed in anti-corruption work must operate with sufficient transparency to enable human oversight and accountability. "Black box" AI systems that generate recommendations without explainable reasoning create accountability gaps: if an AI system recommends investigating an individual, that individual has a right to understand the basis for the recommendation. However, many advanced AI systems, particularly deep learning models, lack interpretability; they generate predictions without providing clear explanations of the reasoning underlying those predictions. Addressing this governance challenge requires either developing more interpretable AI systems or implementing governance structures that mandate human review of all AI-generated recommendations before investigative action.

Institutional independence represents a fourth critical governance concern. Dlamini (2025) emphasises that AI systems deployed in anti-corruption work must be protected from political manipulation. This requires governance structures ensuring that AI system design, training data and operational parameters are insulated from political interference. However, many African ACAs lack sufficient institutional independence to guarantee such protection, creating vulnerability to political weaponisation of AI systems.

4.5 The ZACC Case Study and Transferable Frameworks for African ACAs

The fifth major theme encompasses the Zimbabwe Anti-Corruption Commission (ZACC) case study and the development of transferable frameworks for African ACAs, identified across 16 studies (10.3% of the reviewed literature). This theme reflects the practical application of the preceding four themes to a specific African institutional context.

The ZACC case study reveals both the potential and challenges associated with digital transformation and AI implementation in resource-constrained African contexts. ZACC, established under Section 255 of the Constitution of Zimbabwe, operates with an annual budget of approximately USD 8 million and a staff complement of 180 personnel, including 45 investigators. Despite these resource constraints, ZACC has achieved notable successes: recovering USD 21 million in assets, referring cases totalling USD 217 million to the National Prosecuting Authority and securing convictions in high-profile corruption cases. However, ZACC's operational effectiveness remains severely constrained by fragmented case management systems, limited analytical capacity and insufficient investigative personnel.

ZACC's experience with digital transformation initiatives provides valuable lessons for comparable African institutions. Chilunjika (2021) and Tsokota et al. (2025) document ZACC's implementation of a basic case management system, which improved case tracking and reduced administrative burden on investigators. However, the case management system remains isolated from other data sources, limiting its analytical utility. ZACC lacks integrated access to financial data, procurement records, property registries and communication intercepts- data sources that would substantially enhance investigative effectiveness if integrated and analysed through AI tools.

The ZACC case study reveals that successful AI implementation in resource-constrained contexts requires a phased, iterative approach prioritising foundational data integration before advancing to advanced analytics. The reviewed literature proposes a framework wherein Phase 1 focuses on establishing data governance structures and integrating existing data sources; Phase 2 implements basic predictive analytics for transaction screening; Phase 3 deploys NLP tools for document analysis; and Phase 4 implements graph analytics for network analysis. This phased approach acknowledges resource constraints whilst establishing a trajectory towards enhanced investigative capability.

The proposed framework for ZACC emphasises stakeholder engagement, capacity building and change management as critical success factors. Rather than attempting to implement a comprehensive AI system immediately, the framework recommends starting with targeted pilots addressing specific investigative challenges, building institutional experience and confidence and progressively expanding AI deployment as capacity and resources permit. The framework further emphasises the importance of establishing governance structures, including an AI ethics committee, data governance council and independent audit mechanism, to ensure responsible AI deployment.

The ZACC case study demonstrates substantial transferability to comparable African ACAs facing similar resource constraints, infrastructure limitations and capacity gaps. The proposed framework provides a roadmap for institutions seeking to enhance investigative effectiveness through digital transformation and AI deployment whilst acknowledging the contextual realities of African emerging economies. Key transferable elements include the phased implementation approach, emphasis on foundational data integration, prioritisation of stakeholder engagement and capacity building and establishment of robust governance structures.

5. Discussion

The systematic review of 156 peer-reviewed studies reveals a consistent and convergent body of evidence: digital transformation and AI integration can meaningfully strengthen the investigative and operational capabilities of anti-corruption agencies in African emerging economies, but this potential is conditional on addressing a complex interplay of institutional, infrastructural and contextual factors. Taken together, the five thematic domains identified in this review are not discrete areas of inquiry but deeply interconnected dimensions of a single challenge.

Across themes, the evidence converges on one overarching finding: AI must augment rather than replace investigator judgment. Whether examining predictive analytics, NLP, graph analytics or machine learning, the most effective implementations in the reviewed literature consistently combined AI-generated insights with human expertise, institutional knowledge and contextual understanding. This finding is particularly significant for African ACAs where trust in technological systems is still developing and where the consequences of erroneous or biased algorithmic outputs carry serious legal and reputational implications for institutions whose legitimacy is already contested. Deploying AI as a decision-support tool, rather than an autonomous decision-maker, mitigates these risks while still realising efficiency gains.

When contextualised against the broader governance and anti-corruption literature, the findings suggest that the barriers facing African ACAs are not merely technical. Infrastructure deficits, capacity gaps and financial constraints are compounded by governance deficiencies and political interference that no AI system can resolve on its own. The reviewed literature consistently shows that countries and institutions with stronger baseline governance, institutional independence and human capital capture greater benefit from digital transformation investments. This implies that for many African ACAs, the preconditions for effective AI adoption are partially political and institutional, not merely technological or financial.

The ZACC-focused analysis provides a practically grounded illustration of how the phased framework can be operationalised in a resource-constrained African context. Beginning with data governance and foundational integration, advancing through targeted AI pilots, and progressively expanding capability as institutional readiness improves represents a model that balances ambition with contextual realism. Critically, this framework is not ZACC-specific; its underlying logic applies to any agency facing comparable constraints in infrastructure, financing, capacity and governance. African ACAs in comparable contexts should adapt the framework's sequencing and priorities to their specific institutional environments rather than applying it prescriptively.

The geographical concentration of reviewed studies in South Africa, Nigeria, Kenya and Zimbabwe highlights the limited evidence base for AI-assisted anti-corruption efforts across the broader continent. Future research should prioritise longitudinal evaluation of implemented AI systems, rigorous cost-effectiveness analyses, examination of political economy factors affecting institutional independence and locally appropriate capacity-development approaches across diverse African contexts. Responsible, context-sensitive AI adoption, combined with sustained institutional leadership, human expertise and accountable governance, offers the most credible pathway towards stronger anti-corruption institutions on the continent.

6. Conclusions

This systematic review shows that digital transformation and AI can strengthen the investigative and operational capabilities of anti-corruption agencies in African emerging economies, but technological adoption alone is insufficient. Effective implementation requires integrated attention to digital infrastructure, institutional capacity, financing, governance, regulatory frameworks, organisational change and human oversight. Predictive analytics, natural language processing, graph analytics and machine learning offer useful decision-support capabilities, although their effectiveness depends strongly on data quality, institutional readiness and contextual adaptation. The ZACC-focused analysis indicates that phased implementation beginning with data governance and integration, followed by targeted AI applications and strengthened oversight, offers a practical pathway for resource-constrained agencies. More broadly, African ACAs should adapt AI strategies to their institutional and socioeconomic environments rather than directly transferring models developed in resource-rich settings. Future research should prioritise longitudinal evaluation, cost-effectiveness, political economy factors and locally appropriate capacity-building approaches. Overall, responsible and context-sensitive AI adoption can support stronger anti-corruption institutions when combined with sustained institutional leadership, human expertise and accountable governance.

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