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Review Article

AI-Driven Insights for Detecting Corruption Risks in Ethiopian Public Sectors: A Systematic Literature Review

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Abstract

This systematic literature review examines AI-driven methods and evidence for detecting corruption risks in the public sectors of Ethiopia and neighboring East African countries. Corruption remains a significant challenge to effective public-sector governance, economic development, and the efficient delivery of public services in Ethiopia and East African countries. The increasing availability of digital government data and advances in artificial intelligence (AI) provide new opportunities to identify corruption challenges, detect anomalies, and strengthen transparency and accountability. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-guided search, screening, and selection procedures, relevant studies were identified from Scopus, Web of Science, PubMed, Google Scholar, and regional grey literature repositories. The review synthesizes evidence from 28 studies published between 2010 and 2025 that investigate the application of AI, machine learning (ML), network analysis, anomaly detection, and related computational approaches to corruption-risk identification. The review targeted on four major public-sector domains: public procurement, financial auditing, payroll management, and asset management. Key themes examined include the types and quality of data used, pre-processing and feature-engineering practices, dominant AI and ML algorithms, evaluation metrics, model interoperability, and the practical feasibility of implementation in low-resource environments. The results indicate growing interest in AI-enabled corruption detection, particularly through anomaly detection, classification, predictive modeling, and network-based approaches. However, the evidence base remains limited by fragmented datasets, insufficient data quality, limited access to government records, insufficient technical capacity, and the absence of standardized evaluation frameworks. Ethical concerns, including privacy, algorithmic bias, transparency, accountability, and the potential misuse of automated decision-support systems, also require careful consideration. In general, AI can complement, rather than replace, institutional anti-corruption mechanisms. For Ethiopia, priority should be given to strengthening public-sector data infrastructure, improving data governance and interoperability, developing interpret able and context-sensitive AI models, and establishing controlled pilot projects for procurement and financial-integrity monitoring. Sustained collaboration among policymakers, anti-corruption agencies, universities, technology experts, and international partners, together with capacity building and ethical safeguards, is essential for responsible and effective adoption of AI-driven corruption-risk detection systems.

Keywords

Artificial Intelligence, Corruption Detection, Public Sector, Ethiopia

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1. Introduction

Corruption in public sectors undermines service delivery and erodes public trust. Recent advances in AI and ML offer new opportunities to identify corruption risks at scale by detecting anomalies, suspicious bidder networks, and irregular financial flows [7, 9]. However, adoption in East Africa and Ethiopia specifically faces challenges including limited digitized records, data fragmentation, and governance constraints. This review maps the current state of AI applications for corruption detection relevant to Ethiopian public institutions and situates them within regional evidence and implementation lessons.

Artificial Intelligence (AI) is a trending force of change in the delivery of the public service worldwide. Applications of AI like chatbots, predictive analytics, and intelligent decision-support systems have been incorporated into government processes to streamline administrative activities, make them accountable and responsive [10, 11]. In the developed nations, the buying of AI has led to quantifiable results. As another example, AI-based fraud-detecting systems in the United Kingdom alone are reported to have reduced the losses by more than 300 million since 2016 [12]. Nonetheless, the application of AI in developing countries has been characterized by issues of infrastructural gaps, skills shortages, and ethical issues that purport to intensify the prevailing governance issues [8, 13, 16].

2. Objectives

1) To identify empirical AI/ML studies that detect corruption or fraud in public-sector contexts in Ethiopia and East Africa.
2) To analyze algorithms, data sources, evaluation approaches, and reported effectiveness.
3) To synthesize barriers, enablers, and ethical considerations for deploying AI-driven corruption risk detection in Ethiopia.

3. Methods

3.1. Protocol and Reporting

The researcher of the study followed PRISMA 2020 guidelines for systematic reviews and registered a protocol (internal) that defined search strings, inclusion/exclusion criteria, and extraction fields (population/context, AI method, data types, evaluation metrics, and findings).

3.2. Search Strategy

Databases searched (from inception to July 2025): Scopus, Web of Science, IEEE Xplore, PubMed/PMC, Google Scholar (first 200 hits), Research Gate, and grey literature from anti-corruption agencies, think-tanks, and UN/World Bank repositories. Search terms combined keywords for AI ("artificial intelligence", "machine learning", "anomaly detection", "network analysis", "NLP") and corruption detection ("corruption", "fraud", "procurement fraud", "integrity risk") together with geographic terms ("Ethiopia", "East Africa", "Kenya", "Uganda", "Tanzania"). Snowballing (backward/forward citation) and targeted searches for Ethiopia-specific studies were performed.

Table 1. *The search strategy of the paper.*

Component	Description
Databases Searched	Scopus, Web of Science, IEEE Xplore, PubMed/PMC, Google Scholar (first 200 hits), ResearchGate, UN & World Bank repositories, regional grey literature
Core Search Strings	(“artificial intelligence” OR “machine learning” OR “deep learning” OR “anomaly detection” OR “network analysis” OR “NLP”) AND (“corruption” OR “fraud” OR “procurement fraud” OR “integrity risk”) AND (“Ethiopia” OR “East Africa” OR “Kenya” OR “Uganda” OR “Tanzania”)
Additional Search Techniques	Backward and forward citation tracking; manual review of key journals; targeted searches in anti-corruption agency archives
Inclusion Criteria	AI/ML-based corruption or fraud detection studies; public sector focus; East Africa/Ethiopia context; empirical or methodological; English language
Exclusion Criteria	Opinion papers; purely legal analyses; private-sector fraud only; non-AI governance papers
Validation Approach	Two-reviewer cross-checking, consistency testing, pilot sample validation

3.3. Inclusion and Exclusion Criteria

Included: empirical or methodological studies applying AI/ML or network methods to detect corruption, fraud, or integrity risks in public-sector contexts within Ethiopia or East Africa; conference papers, journal articles, technical reports, and credible working papers in English. Excluded: opinion pieces without methodological content, purely legal analyses, or studies focused solely on private-sector fraud outside public procurement or public service delivery.

3.4. Screening and Data Extraction

Two reviewers screened titles/abstracts and full texts. Disagreements were resolved by discussion. Extracted fields: authors, year, country, data source, AI method, ground truth labeling, evaluation metrics (precision, recall, ROC-AUC), and implementation notes.

3.5. Quality Assessment

We appraised methodological quality using a bespoke checklist emphasizing dataset description, train/test separation, baseline comparisons, transparency of model features, and discussion of ethical risks.

4. Results

4.1. Study Selection

The initial search returned 1,842 records; after deduplication and screening, 28 studies met inclusion criteria. (A PRISMA flow diagram was generated during screening.)

4.2. Study Characteristics

Of the 28 studies: 12 targeted procurement fraud detection, 5 focused on audit and payroll anomaly detection, 6 used network analysis to detect collusion and suspicious bidder networks, and 5 investigated natural-language processing (NLP) approaches for analyzing tenders, contracts, and declarations of interest. While few studies were Ethiopia-specific, regional evidence from Kenya, South Africa, and cross-country reviews provided transferable lessons [6].

4.3. Data Sources and Quality

Common data sources: public procurement databases (contract awards, tender notices), financial transaction registers, payroll systems, corporate registries, and unstructured documents (contracts, minutes). A recurrent limitation was data incompleteness, inconsistent identifiers across databases (making entity resolution hard), and lack of labeled corruption instances for supervised learning.

4.4. Algorithms and Approaches

Supervised learning: logistic regression, random forests, gradient boosting machines were commonly used where labeled instances existed. Studies report competitive performance but caution over overfitting to historical case [1, 3, 4, 7].

Unsupervised methods and anomaly detection: clustering (k-means), isolation forests, and auto encoders were used to flag outliers when labels were absent.

Network analysis: community detection, centrality measures, and bipartite projection methods identified suspicious bidder clusters and potential collusion.

NLP: transformers and classical text-mining methods extracted red-flag phrases, semantic similarity between documents, and inconsistencies in bid descriptions [5, 7, 9].

4.5. Evaluation Practices

Evaluation often relied on historical cases or expert-labeled samples. Metrics varied widely; precision at top-k, ROC-AUC, and confusion-matrix derived metrics were common. Several studies emphasized the importance of using precision for operational triaging of suspicious cases.

4.6. Implementation Barriers in East Africa and Ethiopia

Key barriers: limited digitization of procurement and financial records; lack of unique identifiers; fragmented agency systems; limited technical capacity in anti-corruption agencies; legal and political constraints on data sharing; and concerns about algorithmic fairness and accountability [10, 13, 16].

4.7. Ethical and Governance Considerations

Studies highlighted risks of biased outputs when historical enforcement is biased, privacy risks when combining datasets, and the need for transparent, interpretable models that can be audited and understood by investigators [11, 13, 16].

5. Discussions

5.1. Synthesis of Evidence

There is growing evidence that AI methods, particularly network analysis combined with supervised models, can identify procurement irregularities and collusion with useful accuracy. However, success is contingent on data quality, labeling, and institutional capacity to investigate flagged cases [1-3].

Although numerous studies highlight the potential of AI to detect corruption risks in public sectors, several empirical studies present rebuttals and cautionary perspectives that must be considered. Some scholars argue that AI systems are only as reliable as the quality, completeness, and integrity of the data used to train them [4, 8, 10]. In many developing countries, including Ethiopia, public sector data are often fragmented, incomplete, or inconsistently documented, which may reduce the effectiveness and accuracy of AI-driven corruption detection systems. Furthermore, empirical research indicates that AI tools may inadvertently reproduce existing institutional biases embedded in historical datasets, thereby reinforcing systemic inequities rather than mitigating corruption risks.

Additionally, other studies emphasize institutional and organizational barriers as significant limitations to AI implementation. These include insufficient technological infrastructure, lack of skilled human resources, limited financial capacity, and resistance to technological change within public institutions [3, 4]. Some empirical findings also question the practical applicability of AI models, noting that while AI demonstrates high predictive performance in controlled experimental settings, its effectiveness in real-world public sector environments remains constrained by governance challenges, weak regulatory frameworks, and lack of transparency.

Moreover, critics argue that AI should not be viewed as a standalone solution to corruption but rather as a complementary tool that supports traditional anti-corruption mechanisms such as audits, legal enforcement, and institutional reforms. Without strong governance structures, accountability systems, and ethical oversight, AI-driven systems may fail to produce meaningful anti-corruption outcomes [4, 8, 10, 14, 15].

Therefore, while AI presents promising opportunities for detecting corruption risks, the empirical literature also underscores important rebuttals related to data limitations, institutional readiness, implementation barriers, and ethical concerns. These contradictory findings suggest that successful adoption of AI in the Ethiopian public sector requires not only technological advancement but also parallel improvements in data governance, institutional capacity, regulatory frameworks, and organizational readiness.

5.2. Implications for Ethiopian Public Sector

Ethiopia can benefit from targeted pilots focusing on procurement integrity in sectors where procurement data are more digitized (e.g., major infrastructure or centralized procurement agencies). Co-developing models with anti-corruption institutions and auditors will help ensure operational relevance and trust.

5.3. Recommendations

Data strategy: standardize procurement and financial data (unique identifiers), improve digitization, and create secure data-sharing frameworks.

Pilot interpretable models: start with rule-based plus tree-ensemble hybrids and network analysis for collusion detection; evaluate using precision.

Capacity building: Train anti-corruption agents in data literacy, model interpretation, and investigative follow-ups.

Ethical safeguards: Conduct bias impact assessments, maintain human-in-the-loop decision processes, and document model governance.

Research Agenda: develop labeled datasets for benchmarking, explore transfer learning from regional models, and assess socio-technical impacts.

6. Limitations of This Review

Limitations include potential publication bias, English-language restriction, and the rapid emergence of new studies after our cut-off date (July 2025). Limited Ethiopia-specific peer-reviewed work meant we relied partly on credible grey literature and regional studies for transferable insights.

7. Conclusion

AI-driven approaches present promising tools to detect corruption risks in Ethiopian public sectors, especially for procurement and network-based collusion. Realizing benefits requires investment in data infrastructure, legal frameworks for data access, and co-designed, interpretable models aligned with investigative capacity.

Abbreviations

AI	Artificial Intelligence
NLP	Natural Language Processing
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ML	Machine Learning
ROC-AUC	Receiver Operating Characteristic-Area Under the Curve
IEEE	Institute of Electrical and Electronics Engineers
PubMed/PMC	PubMed Central
UN	United Nation

Author Contributions

Tigist Mintesnot Tewabe: Conceptualization, Data duration, Formal Analysis, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Conflicts of Interest

The author declares no conflicts of interest.

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