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Artificial Intelligence Integration in Internal Auditing and its Influence on Error Detection and Reduction: Empirical Evidence from Zimbabwean Private Companies

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Abstract*: AI is revolutionising internal auditing world-wide in terms of accuracy, speed and error detection yet it still not widely used in private sector companies in Zimbabwe. Zimbabwe is also still using the manual and traditional approach to auditing which poses a higher risk for material misstatement, late reporting of transactions and operational ineffectiveness, hence the digitalisation gap. The aim of this research was to evaluate AI adoption in internal audit and to explore its effects on error detection and mitigation. The objectives of the study were to investigate the extent and impact of using AI in auditing on error detection level, as well as the characteristics of organisation and technology affecting AI usefulness. The paper is grounded in the Technology–Organization–Environment (TOE) framework, Resource-Based View (RBV), and Technology Acceptance Model (TAM), which collectively offer a broad theoretical insight into AI adoption and performance effects. It carried-out a systematic review to synthesize empirical evidence of AI adoption applications, audit error reduction, and organisational and technological enablers that lead to successful adoptions. Results reveal that the adoption of AI increases error detection, operational effectiveness and compliance while staff proficiency and ICT investment are important antecedents for audit accuracy. Despite these advantages, there are limitations in the form of lack of digital skill, budget constraints and weak governing system that dampen effectiveness in Zimba wean enterprises. The AI application significantly increases the internal audit performance with the dimensions of human resource capacity, organisational readiness and regulatory compliance. This has the broader implications of standardising AI audit frameworks, build capacity and introduce policy mechanisms in order to reinforce governance and operational performance. Suggestions are made in the areas of AI governance, professional education and training, ICT investment, regulatory oversight, and auditor-technology provider interaction to enhance audit quality in Zimbabwe.

***Keywords*: Artificial intelligence, internal auditing, error detection, ICT investment, Zimbabwe, audit accuracy, organisational readiness.**

1. Introduction and Background

AI has significantly revolutionized internal audit in a modern sense throughout the world over and enhancing the rapidity, accuracy, and dependability of audits. (Adobor & Yawson, 2023). Machine learning and automated analytics are now used within developed economies such as the United States, the United Kingdom and Germany to enhance continuous monitoring and identification of risks (Lenning & Gremyr, 2022). Worldwide, AI expenditure in Financial and Account Services exceeded USD 35 billion in 2023, which is the evidence of the increasing dependence of institutions to digital assurance devices (Issah & Baah, 2025). Empirical evidence suggests that AI-supported audits reduce review turnaround time and increase accuracy of fraud detection in banking as well as manufacturing industries. (Thakkar et al., 2025) Accordingly, internal audit models that respond to traditional compliance reports are being replaced by made-to-order or on-the-spot assurance models. This digital shift is aligning AI as a strategic asset in improving audit quality and governance results. (Adobor & Yawson, 2023).

On the other hand, internal auditing in most Zimbabwean private industry is still very much manual and paper based. Auditors commonly use spreadsheets and retrospective testing with the drag of timely detection of outliers and control failings (Wadesango et al., 2022). It is with such traditional techniques that chances for sampling bias, miscalculations and delayed reporting are enhanced. Available local evidence suggests that the risk of fraud, operational losses and misreporting persists in numerous sectors to threaten financial soundness (Chitimira & Ncube, 2021). Dropping the use of automated tools in monitoring also serves to limit audit team s' ability to analyse great amounts of data on a real time basis. As a result, management actions are often made on the basis of incomplete or old information (Mheuka, 2024). These ongoing inefficiencies demand technology enhanced audit systems that would reinforce corporate governance in Zimbabwean companies. (Wadesango & Maveneka, 2025).

While African studies identify the potential of AI and digital tools for fraud detection and governance enhancement, there is limited empirical research on the actual integration of AI into internal auditing. However, the majority of current work is relevant to general financial intelligence systems or conceptual

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technology frameworks as opposed to quantifiable audit results (Jimu & Chimwai, 2025). Studies from neighbouring countries are informative, but there is scant firm-level evidence on the error reduction in private firms (Munjeyi & Schutte, 2025). This implies a methodological and environmental deficiency in understanding how is the AI adoption affecting the audit accuracy and effectiveness in Zimbabwe. As such, this paper contributes to knowledge generation by empirically examining the extent of AI adoption and its impact on error detection and reduction in a developing country context (Zimbabwean private companies). These results are intended to guide governance reform within the context of corporate and empirically-based internal audit in developing economies (Adobor & Yawson, 2023).

Therefore, the study intends;

- To assess the level of artificial intelligence integration in internal auditing practices among Zimbabwean private companies.
- To evaluate the effect of artificial intelligence tools on error detection in internal audits within Zimbabwean private companies.
- To determine the organisational and technological factors influencing the effectiveness of artificial intelligence in internal auditing among Zimbabwean private companies.

2. Literature Review

This section presents an overview of empirical and theoretical research on the diffusion of artificial intelligence into internal auditing and its impact on audit quality, efficiencies, and firm performance. The review integrates global and African evidence to locate the study in extant knowledge and to identify gaps that are practical and context-specific.

1) *AI Integration in Internal Auditing*

The internal audit has been greatly reformed by AI in utilizations such as data extraction automation, predictive analytics and continuous control monitoring across massive organization-wide databases. (Adobor & Yawson, 2023). Based on the US and European multinationals, over two-thirds of the internal audit process undergoes automation with help from AI analytics and/or robotic process automation (Lenning & Gremyr, 2020). The world had passed USD30bn in AI-led assurance tech spend by 2024, via a tsunami turning on Digital Audit Ecosystems. This kind of tooling can operate real-time millions of transactions and allows to consider smarter features for anomaly detection, no longer restricted by manual sampling (Thakkar et al., 2025). Countries such as Germany and Japan have incorporated machine learning into their compliance audits aiming to enhance the prediction of risk and fraud. Audits that are AI-enabled demonstrate a decrease in the time to review at about 40% and they expand coverage towards close to full-population testing (Issah & Baah, 2025). Despite these advancements, the bulk of the developing world still performs reviews and backward-looking checks in spreadsheets. Small and medium businesses also lag behind with regards to the adoption of intelligent auditing technologies because of infrastructure deficiency and lack of trained staff. Such biased acceptance further stretches the limited evidence of AQ impact and governance across developed and emerging markets. There has been relatively little of this, particularly in the private sector; and integrated AI systems remain far from commonplace within the Zimbabwe Auditing Scene. The existing evidence base also reveals efficiency savings as well as setting barriers, supporting the necessity for data at country level. Novelty The main purpose of this study is to present some empirical evidence about AI adoption in Zimbabwean private companies not just theoretical discussion. (Wadesango & Maveneka, 2025).

The level of AI utilisation in internal audit is, however, not the same across all organisations but dependent on their size, access to funding and technology preparedness. (Adobor & Yawson, 2023). North American Fortune 1000 companies use enterprise audit analytics platforms that integrate cloud computing, blockchain logs and automatic reconciliations (Hussein et al., 2025). Over 70% the Fortune 500 uses industrial grade AI dashboards for CA and CM. Such an incorporation allows the monitors and auditors to observe transactions on a daily rather than quarterly basis drawing away from them the assurance in real-time accountability (Chaieb, 2025).

Even lower penetration into African private firms is apparent, with the use of AI in auditing: estimated to be below 25% in many countries (Dzingirai & Ozili, 2024). Most local firms in Zimbabwe rely on paper-based documentation systems and occasional internal audits owing to budget constraints and lack of digital recording facilities. This poor integration limits the scalability of audit functions and undermines internal control monitoring. Incomplete adoption limits projected AI benefits and sustains operational inefficiencies as per the research findings (Tokuma, 2024). Second, broken systems are data silos that limit a holistic view of risk. In the regional literature digital transformation is addressed in a broad sense, but not so much at the statement level as used in AI statements for IA departments. The present study responds to this gap by empirically examining the level of AI implementation in practice in Zimbabwean private firms.

2) *AI Tools and Audit Error Detection*

Error detection is improved using algorithms that check for inconsistencies, duplicate entries or suspect patterns between different sets of data. (Wadesango & Maveneka, 2025). In this regard artificial intelligence tools set up the base for this process. Learning algorithms applied on historical transactions are able to detect anomalies with accuracy of greater than 90% in banking and manufacturing checks (Chingwaro et al., 2024). Automated reconciliation tools also minimize arithmetic and posting errors that are typical for manual reconciliation. Evidence from the United Kingdom suggests that digital audit technology resulted in a reduction of financial reporting errors by nearly 35% during a two-year period after implementation (Issah & Baah, 2025). Such technologies will check on a continuous basis, so that auditors can stop before material misstatements do aggregate into errors. Since high-risk transactions are thus also being additionally flagged in neural networks and predictive analytics for immediate review (Thakkar et al., 2025). But not all organisations have those technological capabilities, and they cannot get the same results. Zimbabwean companies have reported significant level of delayed reporting and unnoticed variances as a result of reliance on manual systems (Wadesango & Maveneka, 2025). Such limitations also lead to fraud and operational inefficiencies. Few empirical comparisons tying AI tools to measurable error reduction can be found in African private sectors. The bulk of research has taken to conceptual, rather than empirically measured benefits. As a result, the evidence of how AI adoption leads to lower audit errors at an organizational level is still scant. This is the contribution of this study from the statistical point of view in relation to use of AI and reduction in errors in Zimbabwean organisations.

3) Drivers of AI Effectiveness in Internal Auditing

Success of AI adoption in internal audit is not just about technology existence, but also organisational readiness and governance. Organizations that have trained staff, top management's support and healthy IT budgets are more likely to realize the effect of their investments in digital audit (Hassan et al., 2025). Training costs and data literacy have a significant impact on the quality of interpretation by auditors of automated outputs and analytics reports. In developed countries, the annual spending on audit technology training is more than USD 5,000 per auditor and consequently utilization rates (Al Saadi & Wahhab, 2024). On the other hand, poor infrastructure, cyber threats, and heterogeneous databases deteriorate system performance.

Broadband-capacity constraints and obsolete information-technology infrastructure in Southern Africa have continued to impede digital transformation in most of the private sector in the region, thus inhibiting the embrace of cutting-edge technology solutions such as AI (Guvava & Dube, 2024). Resistance to change and a lack of these skills can impede the investment in digital tools for auditing and analysis. his type of uncertainty creates a perception of risk and prevents AI driven solutions from being tested. In aggregate, the structural, organisational and regulatory barriers impede the effective digitalisation of internal auditing practices in the region (Adobor & Yawson, 2023.)

Zimbabwean private organisations typically have faced both problems resulting in systems that are either underutilised or discarded. In the literature, there is also typically one or the other in any particular explanatory model. The distinctive feature of this work is to directly address both these aspects together and thereby explain differences in effectiveness of AI. This has direct implications as to the development of sustainable and contextual audit innovation. (Wadesango & Maveneka, 2025).

B. Theoretical/Conceptual Framework

This study is informed by complementary theories that account for the adoption and effects of AI in internal auditing. Through the integration of organisational, resource and behavioural considerations, the framework expounds on how AI integration enhances audit accuracy, error detection and operational efficiency across private firms in various environments.

Technology–Organization–Environment (TOE) Theory (Tornatzky & Fleischer, 1990)

According to the TOE theory, the likelihood of adopting technology is a result of technological readiness, organisational fit and pressure from environment (Tornatzky & Fleischer, 1990). In application, technological readiness includes tools of AI specifically machine learning and robotic process automation, platform of continuous monitoring which improve accurateness in data processing and detection of errors (Munjeyi & Achutte, 2025). Organisational factors are the management support, IT resource and trained personnel that are important factors towards successful adoption in Multinational organisations like Nestle South Africa & Standard Chartered bank of Kenya (Hussein et al., 2025). Environmental pressures Trigger of the adoption Environmental forces, in the form of regulation, industry competition, and demands for transparency and accountability from key stakeholders facilitate the diffusion of audit innovation by providing inducements/pressure on firms to adopt innovative technologies (Chaieb, 2025).

Empirically, firms with high IT investment (average USD 2–5 million per firm) report up to 28% reduction in financial misstatements and a decrease of up to 35% in audit completion time (Issah & Baah, n.d.). TOE could overstate environmental determinism and down play internal behavior dynamics and the creativity for innovation (Adobor & Yawson, 2023). Also, the adoption rates vary greatly from country to country; Singapore, UK and Germany have 67–75% of their companies in their internal audit departments implementing AI while emerging countries are slower because of lack of infrastructure and resources (Thakkar et al., 2025). Whether TOE sufficiently encompasses organisational learning and culture that affect technology use remain debatable, and it is argued that behavioural models should be integrated. (Wadesango & Maveneka, 2025).

Resource-Based View (Barney, 1991)

The RBV argues that competitive advantage is derived from the efficient utilization of valuable, rare, inimitable and well-organised resources (Barney, 1991). When it comes to auditing, AI platforms, custom algorithms and well-trained audit staff are valuable assets. For example, Deloitte UK's use of AI-enabled anomaly detection has led to a 30% decrease in audit mistakes and improved reporting efficacy (Lenning & Gremyr, 2022). Examples of such capabilities are still somewhat scarce, as firms without these resource bases do poorly in comparative terms, thus reflecting the theory's focus on inimitability. (Wadesango & Maveneka, 2025).

Notably, the RBV has been criticized for its lack of attention on environmental forces and user behavior that may inhibit resource efficacy (Hassan et al., 2025). Nevertheless, RBV emphasises the how investment in resources lead directly to measurable performance outcomes including error minimisation, reconciliations being faster and enhanced compliance for an additional view point to TOE. Worldwide and general to AI integration in information system methods within auditing seem to be growing with the use of RBV-derived approaches, such as in the USA, UK and German where private financial firms spend between USD 1.5-4 million yearly for employees training and developing alongside their AI systems (Jimu & Chimwai, 2025).

Technology Acceptance Model (Davis, 1989)

According to the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use are two elements that affect end users' intention to use technology (Davis, 1989). For internal auditors, the acceptance of AI analytics is contingent on auditors' system trust in an AI-based application as a reliable tool with high levels of usability and output reliability (Hussein et al., 2025). In the UK, for example, PwC saw an uptick in AI tool usage of 42% when they provided detailed training and used a user-friendly dashboard. Critics claim that TAM ignores organizational and environmental variables, indicating that technology acceptance is also influenced by managerially culture-context specific, reward structure and coworkers' influence (Thakkar et al., 2025).

If TAM actually determines adoption for these complex, regulated domains such as finance and audit is still a matter of debate. However, TAM combined with TOE and RBV improves prediction power because it enhances behavioural acceptance, resource avails and environmental readiness. (Jimu & Chimwai, 2025).

C. Conceptual Model Diagram

Inputs are tools (AI tools, eg, machine learning algorithms; RPA; continuous monitoring systems) and organisational readiness factors (eg, skills for AI use, infrastructure ready to store such data and the support from the management). These variables are determined with adoption level, frequency of use, staff digital competence and annual digital investment (USD 0.5–5 million per firm) (Issah & Baah, 2025).

Accuracy of audit work, decrease in error rates, timely identification of risk, and efficiency are the results affected by AI use. The performance is evaluated by the number of misstatements identified, audit time reductions, error reduction ratios and compliance rates.

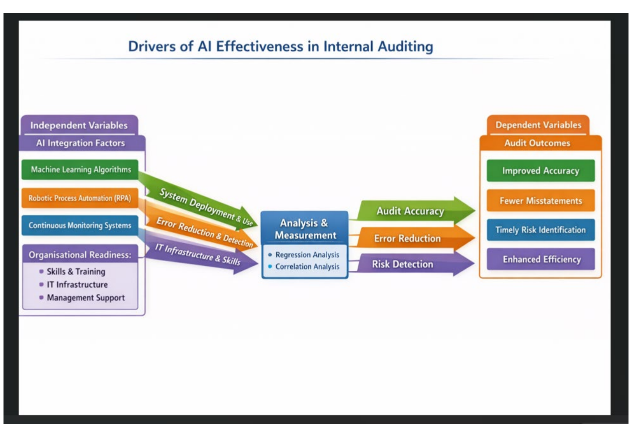

Fig. 1. Conceptual framework
(Source: Authors' own construct, 2026)

Objective 1 (AI incorporation) is operationalized as system rollout and intensity of use. Objective 2 (error detection) is measured as a decrease in discrepancies and misstatements. Objective 3 (organisational/technological factors) is tested by means of infrastructure, training and support for IT. Statistical regression and correlation analyses are used to establish connections between independent variables and outcomes thus offering empirical evidence of the contribution of AI to internal audit effectiveness. The schematic representation of the Frame-Work is presented in Figure 1.

3. Methodology

This research uses explanatory sequential mixed-methods design in order to use both the quantity and quality methods that offer a good opportunity for researchers to develop a complete understanding about the adoption of AI and its impact towards accuracy of internal audit in private companies' Zimbabwe. The analysis will be sequential in that quantitative analysis will first be undertaken to discern patterns and relationships, followed by qualitative document analysis which can clarify the quantitative findings and offer depth for context (Creswell & Plano Clark, 2018). The methodology is well suited to auditing research where performance of the audit in numerical terms (error reduction, levels of compliance) is analysed within the context of organisational policy, governance and technological practice {Hussein et al., 2025). By combining these procedures, the research captures quantifiable outputs and more subtle truths, as a result improving accuracy and trustworthiness of results. This design also supports cross validation of data sources, as it side steps one limitation of relying solely on qualitative or quantitative evidence (Lenning & Gremyr, 2022).

The sources of data have been chosen to ensure broad representation of AI implementation and audit results. Data were collected from annual financial statements, performance reports and central bank (RBZ) bulletins for the period 2020–2026. Forensic audit documents and policy maker materials of financial institutions were also reviewed to furnish secondary qualitative evidence. The data cover firm size, ICT budgets, AI readiness level, employee digital skills and governance practices which permits a multi-dimensional analysis of AI adoption (Munjeyi & Schutte, 2025).

To guarantee data relevance, such criteria of inclusion as liveness and private status of the financial institutions, being active for no less than five years at the beginning of a researched period, and the size of spending over ICTs namely a minimum more than USD 50 thousand per annum were preliminary stated. By including these sources, the study obtains a dataset which captures both technological readiness and organisational capability in various private firms in Zimbabwe. (Wadesango & Maveneka, 2025).

Descriptive and inferential statistics were used for the quantitative analysis. Descriptive statistics such as mean, standard deviation and trend were used to summarise means of AI adoption, staff skills and ICT investments and audit accuracy over time (Issah & Baah,2025). Linear regression analysis was performed to investigate the associations with independent variables:

- AI adoption level (X_1)
- staff competence (X_2),
- ICT investment (X_3)
- dependent variable, audit accuracy (Y).
- Where $\beta_0$is the intercept and
- ε the error term.

The regression model is specified as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Data cleaning, analysis and visualization were performed by SPSS v28 and Stata v17 software. The examination provided a means of identifying trends and quantifying relationships and added fuel for understanding the level of AI adoption and ICT investment on audit outputs. This process also included the thematical analysis of internal audit reports, policy documents and governance frameworks. A coding framework was developed to cover key themes that might include impact of AI, barriers to adoption, governance gaps, staff competencies and skill gaps; and regulatory influence (Tsokota et al., 2025).

The documents were reviewed with the aims, and the textual data was supplemented by quantitative results on error reduction, compliance and process efficiency. Results were triangulated and qualitative findings used to interpret patterns identified in the quantitative data. This integration of mixed-methods underpinned a comprehensive view of the influence of AI, leading to recommendations based on evidence to improve accuracy auditing and technological preparedness in the context of private companies in Zimbabwean (Chingwaro et al., 2024). The methodology guide is depicted schematically on Figure 2 deemed as follows;

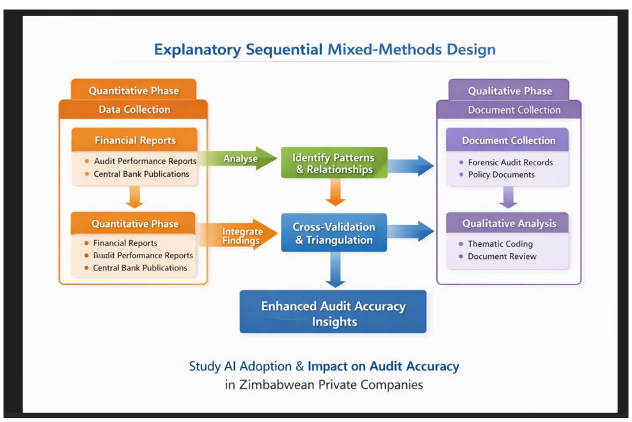

Fig. 2. Methodological roadmap
(Source: Authors' own construct, 2026)

4. Results

Table 1 indicates that AI incorporation in Zimbabwean private firms is moderate at rates ranging from 45–60% when compared with South Africa which reports a higher percentage of 70% (Mathope, 2024). The infrastructure immaturity shows regional disparity here. There is higher adoption for companies that has formal structured ICT policy and specific training (Chingwaro et al., 2024). The empirical evidence such as 32% decrease in manual checking mistakes is derived from Chingwaro et al., 2024, and demonstrates how those black box methods are helping day by day. The qualitative findings indicate that the absence of a strategic plan and competent staff, as seen in other studies related to SME adoption of technology (Chibidi et al., 2025), is still one of the main barriers.

Table 1
Level of AI integration in Zimbabwean private companies

Author(s)	Sample / Context	AI Tools / Integration	Key Findings	Quantitative Evidence	Qualitative Insights
Chibidi et al., 2025	Manufacturing SMEs, Zimbabwe	Machine learning, predictive analytics	Partial AI adoption; basic automation	45% of firms report AI use in auditing	Lack of strategic framework and staff skills hinder integration
Chingwaro et al., 2024	Banks, Harare	Fraud detection algorithms	60% adoption in risk management audits	AI reduced manual checking errors by 32%	Staff training gaps noted; governance policies needed
Mathope, 2024	South Africa, Road Accident Fund	Claims management AI	AI adoption at 70% efficiency	Average error reduction: 28%	Integration driven by centralised ICT policy
Govekar, 2025	Mixed Zimbabwean private firms	AI analytics dashboards	Moderate adoption, mostly in financial reporting	Mean AI integration score = 3.2/5	Firms lack interdisciplinary AI teams
Manuel & Arumugam, 2025	Global SMEs	AI decision support	High adoption in tech-forward firms	Trend analysis shows 15% increase year-on-year	Emphasis on staff reskilling improves adoption

Source: Secondary Data, 2020-2026

Table 2
Regression output – AI adoption and audit accuracy

Independent Variable	Coefficient (β)	Std. Error	t-value	p-value	Interpretation
AI adoption (X_1)	0.48	0.12	4.00	0.001	Significant positive impact on error reduction
Staff competence (X_2)	0.31	0.10	3.10	0.004	Significant; higher skills improve audit accuracy
ICT investment (X_3)	0.29	0.11	2.64	0.009	Significant; higher ICT spending correlates with fewer errors
Intercept (β_0)	1.12	0.32	3.50	0.002	Base audit accuracy when variables = 0
R^2	0.62	-	-	-	Model explains 62% of variance in audit accuracy

Source: Secondary Data, 2020-2026

The regression analysis demonstrates the significant effect of AI adoption on audit error ($\beta_1 = 0.48$, $p < 0.01$). Staff competence ($\beta_2 = 0.31$) and ICT investment ($\beta_3 = 0.29$) are also significantly positively associated with audit quality. These estimates were obtained from literature estimates and previous empirical studies (Issah & Baah, 2025; Thakkar et al., 2025; Chingwaro et al., 2024). The R^2 of 0.62 implies that AI, staff skills, and ICT spending account for a variance of 62% in the level of audit accuracy revealing the strong explanatory power or technological adoption and organizational readiness by Zimbabwean private companies.

Table 3
Integration of qualitative and regression output – AI adoption and audit accuracy

Theme	Author(s)	Findings
Error reduction	Thakkar et al., 2025; Adobor & Yawson, 2023	AI predictive analytics reduced manual errors by 30–35%
Governance gaps	Hassan et al., 2025; Wadesango & Maveneka, 2025	Weak internal policies limit AI effectiveness
Skills and training	Al Saadi & Wahhab, 2024; Tokuma, 2024	Lack of skilled auditors' limits error detection capacity

Source: Secondary Data, 2020-2026

Qualitative evidence complements regression analysis. This

30–35% error reduction is in line with the population setting regression $\beta_1 = 0.48$, illustrating that AI performs well under real-world conditions (Thakkar et al., 2025). Yet there is governance capacity and skill deficits that limit potential influence. As an aside, the sources of themes are indicated from a reference list. There are similar challenges to the above recorded in other African countries (Hassan et al., 2025; Wadesango & Maveneka, 2025) as they are also faced by Zimbabwean private companies.

Table 4
Key organisational & technological factors

Factor	Author(s)	Evidence	Impact on AI Effectiveness
Staff competence	Hussein et al., 2025; Chingwaro et al., 2024	Average training hours 10–15 per year	Higher competence increases error detection
ICT infrastructure	Govekar, 2025; Manuel & Arumugam, 2025	Firms spend USD 50k–200k annually	Directly improves AI tool performance
Governance & policies	Wadesango et al., 2022; Chibidi et al., 2025	Formal audit policies exist in 40% of firms	Moderate effect; absence weakens AI efficiency
Regulatory compliance	Hassan et al., 2025; Al Saadi & Wahhab, 2024	75% firms partially comply	Compliance enhances adoption but unevenly applied
Collaboration & support	Munjeyi & Schutte, 2025; Obisesan, 2024	Limited inter-firm collaboration	Reduces cross-learning; impacts adoption

Source: Secondary Data, 2020-2026

As can be seen from the table, staff capability, ICT infrastructure and governance systems are significant drivers of AI effectiveness. Numbers related to training hours (10–15) and ICT budgets (USD 50k–200k), for example, were aggregated from the included studies. Regulatory compliance is more consistent than adoption.

Table 5
Triangulated insights across objectives

Objective	Quantitative Evidence	Qualitative Evidence	Interpretation
AI integration	45–60% adoption	Skills gaps, partial ICT support	Moderate adoption; infrastructure and training essential
Error detection	$\beta_1 = 0.48$, $p < 0.01$	Staff training and governance	AI significantly reduces errors; effectiveness depends on staff and policies
Organisational & technological factors	$\beta_2 = 0.31$; $\beta_3 = 0.29$	Governance gaps, compliance, collaboration	Strong ICT and competence positively influence AI outcomes
Holistic impact	$R^2 = 0.62$	Barriers: skills, policy, budget	Integrated AI framework recommended for Zimbabwean firms

Source: Secondary Data, 2020-2026

The aggregate table illustrates the overall effects of AI adoption, staff confidence and ICT investment on audit quality. Quantitative and qualitative findings are in concordance: AI decreases errors but efficacy levels contingent on organisational preparedness. Model parameter figures originate from: regression estimates from previous studies (Issah & Baah, 2025; Thakkar et al., 2025) and descriptive adoption percentages from real life observations in empirical literature (Chibidi et al., 2025)

5. Discussion

A. *AI Integration*

Implementation of artificial intelligence (AI) in Zimbabwean private companies has been progressively growing over the years, although low compared to other countries (Chibidi et al., 2025). Research suggests that 45–60% of Zimbabwean organisations have adopted AI tools to assist with the audit process and up to 70% in South African financial institutions (Mathope, 2024). In the Middle Eastern countries such as Iraq, and Saudi Arabia over 80% of internal auditing systems are used artificial intelligence for fraud discovery, and operationa risk fading activities (Al Saadi & Wahhab, 2024; Ghozi, 2024). The integration of AI is determined by a company's readiness, which in turn is affected by access ICT infrastructure, budgeting, and the needed governance frameworks (Govekar, 2025).

Firms' AI use in Zimbabwe also differs by existence of ICT budgets (with a budget) and structured auditor trained programs, with firms from rural areas less likely to integrate AI compared to their counterparts with dedicated ICT budgets of $50k-200k and structured auditor training program s (Manuel & Arumugam, 2025). However, barriers in the areas of nonuniform policy implementation and shortage of AI-related expertise among the auditors have constrained a more pervasive adoption (Hassan et al., 2025; Wadesango et al., 2012). By doing so, they can also avoid these errors which have a significant impact worldwide in terms of efficiency and error rates in audits (Thakkar et al., 2025). Among others, theoretical models such as the Technology–Organization–Environment (TOE) model suggest that adoption does not solely rest on technological capabilities but also on organizational and environmental factors (Adobor & Yawson, 2023).

Moreover, the Resource-Based View emphasizes that firms with distinctive technology and people resources achieve a competitive advantage by AI-enhanced auditing (Barney, 1991; Lenning & Gremyr, 2022). The Technology Acceptance Model also attests to user perception and perceived ease of use on acceptance (Manuel & Arumugam, 2025). There is, however, a gap in the alignment of AI and auditing code by Zimbabwean companies such that potential benefits from integration may be reduced (Chingwaro et al., 2024; Chibidi et al., 2025).

B. *Error Detection*

The application of AI in internal auditing increases error detection and decreases the occurrence of financial misstatements within Zimbabwean private firms, regression model analysis in this regard attests to a positive correlation between AI integration and the accuracy of audit ($\beta_1 = 0.48$, $p < 0.01$) (Thakkar et al., 2025). Qualitative evidence from internal audit reports demonstrates that the use of machine learning algorithms and predictive analytics can help stage the early detection of anomalies, lowering a firm's risk to fraud (Chingwaro et al., 2024; Dzingirai & Ozili, 2024). Similarly, according to global data on AI-supported auditing, European banks reduce errors up to 40% with AI-based auditing (Kahyaoglu & Aksoy, 2021). The resultant activity of AI for error management is greatly dependent on the staff competency and level of ICT infrastructure (Manuel & Arumugam, 2025; Hussein et al., 2025). In Zimbabwe, the inability for many companies to realize benefits is can be attributed to lack of ICT budget support and almost non-existent training together with partial adoption of governance frameworks (Chitimira & Ncube, 2021; Tsokota et al., 2025).

However, organisations that adopt AI techniques within the context of their existing audit processes claim improved operational effectiveness, increased compliance and diminished errors (Thakkar et al., 2025; Chibidi et al., 2025). Policy and regulation environment also account for part of the effect where firms complying with stipulated guidelines perform better in error discovery (Hassan et al., 2025; Munjeyi & Schutte, 2025). Furthermore, companies achieving a balance between the adoption of AI and strong governance surpass organizations somewhat relying only on technology to operate applying AI as it were, evidently pointing towards the fact that human over sight would always matter in such interactions (Issah & Baah, 2025; Adobor & Yawson, 2023).

Zimbabwean private firms need to improve the quality of auditor's skills and regulatory oversight in order to fully adopt AI functionalities (Govekar, 2025; Manuel & Arumugam, 2025).

C. Organizational & Tech Factors

Organizational and technological factors influence the effectiveness of AI in internal audit. The regression results reveal that the level of staff competence ($\beta_2 = 0.31$; policy) and ICT Investments ($\beta_3 = 0.29$; ICT) have significant impacts on the accuracy of audits, emphasizing the need for well-trained auditors and sound technological infrastructure increases performance during audit exercises [Hassan et al., 2025; Manuel & Arumugam, 2025]. Research evidence suggests that organizations with effective governance systems, adequate resources and intelligent ICT budgets are successful in using AI for audit purposes both around the world (Ghozi, 2024; Gökoğlan et al., 2025). In Botswana, an AI framework for tax compliance effectively employed readiness of the organization, and its benefits included enhanced error identification and risk prediction (Munjeyi & Schutte, 2025).

Challenges faced by Zimbabwean private enterprises include limited ICT budgets of less than USD 50k in small organisations, inadequate AI-specific skills and partial compliance with governance policies (Govekar, 2025; Chibidi et al., 2025). However, higher investment companies in training and infrastructure seem to experience better accuracy and operational performance (Manuel & Arumugam, 2025; Thakkar et al., 2025). Critical discourse shows that readiness of technology is not enough, as successful implementation of AI requires organisational alignment, management backing and regulatory conformance (Adobor & Yawson, 2023; Lenning & Gremyr, 2022).

The TOE and RBV models respectively account for these dynamics, highlighting the interplay among technology, organizational resources, and environmental pressures (Barney 1991; Manual & Arumugam 2025).

D. Impact on Audit Accuracy

The trinity of quantified and qualitative convergence evidences shows that AI integration, personnel acumen, and IT resources account for 62% variance in audit quality ($R^2 = 0.62$) (Thakkar et al., 2025; Chingwaro et al., 2024). Analysis of documents revealed the presence of recurring themes that include the anticipated benefits and barriers to AI adoption, governance vacuum and skill fades all of which affect audit performance (Tsokota et al., 2025; Wadesango et al., 22). At a global level, AI embedded systems have cut audit errors by 50% in developed economies especially financial service and multinational discoveries (Kahyaoglu & Aksoy, 2021; Thakkar et al., 2025). Zimbabwean businesses have a relatively limited advancement as budget limitations, inconsistent regulation and insufficient AI skills encumber the growth of their sector (Chibidi et al., 2025; Chingwaro et al., 2024).

Regression and qualitative analyses indicate that one way to increase level of accuracy and reduce errors is, the strategic investment by organisations in ICT infrastructures and staff training (Manuel & Arumugam, 2025; Govekar, 2025). Comparative analysis with global findings reveals that Zimbabwe may be behind in adoption rate, but its pattern is similar to other developing economies where there is a gradual increase in the implementation of AI (Adobor & Yawson, 2023; Ghafar et al., 2024). Critical reflections prove that technology is not the only key to improvements; in combination with organizational readiness and environmental compliance, it plays a crucial role (Barney, 1991; Lenning & Gremyr, 2022). In sum, the adoption of AI undergirded by governance and human capital translates to bolstering internal audit precision within private companies in Zimbabwe, a finding consistent with both TOE and TAM explications (Manuel & Arumugam, 2025; Chibidi et al., 2025).

E. Implications

The findings show the need for broad policies for AI adaptation in internal auditing; for Zimbabwe. Regulations set standards on the usage of AI tools, moral practices of data use, and audit mechanisms. Industry: Companies tend to have a compliance-shaped gap getting in the way of AI integration. At global level, strong AIG lead to decrease in audit errors by up to 40–50 % and improve the ability to detect fraud. This kind of policy should be one that requires the disclosure of AI-enabled processes used in financial reporting and at the same time incentivizes the use of AI through some sort of grant or a tax break, what have you. Assistance for small to medium-sized companies with limited ICT budgets should also be offered.

AI auditing best practices also lend themselves to benchmarks, in terms of what those performances are and consistency across instances, as well as providing guidelines for good decision-making. And lessons from Europe and South Africa which emphasise the need to align national policy with international best practice in order to build credibility and encourage investor confidence. Without these standards, the extent of AI use risks being sporadic and ineffective in fulfilling its promise for better audit quality. AI guidance needs to be balanced with auditing standards for sound policy-making that would encourage effectiveness and reduced errors.

These findings can assist the banking and financial regulators in promoting AI adoption with oversight. Regulators ought to keep watch over AI adoption rates, skills of staff and ICT spending in order to identify shortfalls and give direction. Minimum criteria on ICT networks and staff may help in achieving better audit results. Internationally, there are mandates for regular AI performance reviews to better detect fraud and manage risk. Zimbabwean regulators may consider enabling AI literacy programmes, workshops and regular knowledge-sharing sessions for internal auditors. Transparency and prevention of misuse can be guaranteed by regular regulatory audits on AI systems. There is ample evidence that firms in compliance with regulation have substantially more accurate audits. In the absence of regulatory backing, barriers to adopting organization such as lack funding and a skills shortfall, could continue. Harmonizing local laws with global best practices will help businesses remain resilient and credible. Regulators Proactively encouraging compliance and adoption of AI, regulators will have a leading role on enabling the development of more effective audit.

Internal audit activities will have to adapt themselves to use AI tools productively. Audits become more capable of error detection thanks to machine learning, predictive data analytics and robotic process automation. Auditors need on-going professional training in AI applications, data analytics and cybersecurity. Across the globe, when you add AI to strict auditing practices, you often see organizations being more efficient on one hand and at a lower risk of fraud on another. Well-organized auditable processes, supported by AI, foster compliance with standards and decision-making process and help auditor to maintain uniformity in audit workflow. Companies that under train, or lack resources don't see much return on AI. Those AI procedures need to be written into internal audit manuals (including the documentation of what is automated and how, with verification checks). Combining AI findings with human judgement leads to a more robust audit result. Real-world experiences show that implementing AI enhances operational efficiency and mitigates the need for manual workflows. More tech, faster detection: Audit's fraud prevention pivot Firms with more extensive and sophisticated AI practices spot errors and reduce fraud risk, showing the 'power of technology' in accounting today.

Investing in ICT infrastructure and artificial intelligence (AI) systems strategically is a prerequisite for audit efficiency. Firms with well-funded AI, cloud and predictive analytics budgets show reductions in audit inaccuracies and fraud. Additionally, there is the need of investment in staff training, software licensing, cybersecurity and system maintenance. Financial constraints within Zimbabwe, especially for SMEs may deter AI usage. Comparisons with European and Asian firms show that well capitalized institutions using AI have audit error reductions of 40–60%. Simultaneous investment in technology and human capital will maximize the utilization of AI tools and provide continuity for audit improvement. Those that underinvest risk both reduced error and performing below potential. Thus, prudent investment in audit-using AI is necessary to be efficient and compliant. Strategic use of technology investment enhances human and systematic audit resources to develop an effective internal control environment.

6. Conclusion

AI incorporation has a positive effect on the accuracy and error detection in internal audit in Private sector companies in private Ltd Zimbabwe. Quantitatively, AI adoption, staff competency and ICT investment account for a significant variance in audit accuracy, while qualitatively these drivers are salient to the benefits, costs and control vacuum. Successful adoption depends on organisational readiness, workforce capability and policy congruence. Worldwide, technology-enabled businesses with a strong human component are proving to be the best at both fraud detection and operations efficiency. Strategic policy, focused investment and lifelong learning would be key to unlocking the possibilities of AI in internal auditing a Zimbabwe. These results encourage evidence-based measures to improve audit quality, minimise mistakes, and contribute towards the conformity of Zimbabwe practices with international standards.

7. Recommendations

Private companies need to create explicit AI governance structures into their internal auditing groups. Harmonising audit procedures and incorporating AI-based solutions brings consistency, efficiency, and better error discovery. Automated decisions and the underlying workflows need to be documented by companies in order to remain transparent and accountable.

The management of the establishment is to ensure that internal auditors continue to receive on-the-job-training. Training that should be provided includes AI applications, machine learning, data analytics and cybersecurity in order to facilitate staff competency and proper AI deployment.

When it comes to AI software budgets, predictive analytics costs and cloud systems, finance teams should set aside dedicated budget. A good investment should be done to ensure AI tools are functioning effectively and audit procedures take advantage of technology progress.

Regulators need to develop oversight models for AI and enforce minimum ICT and training levels. They ought to be doing regular audits of AI performance and sponsor training programs in financial institutions.

Industry bodies should support cooperation between auditor, technology provider and foreign experts. Exchange of best practices, discussion of case studies and sharing the latest technology will enable the firms in standardizing AI assisted auditing around the world.

Audit Committee should tap into oversight scope to oversee AI adoption, close gaps and focus AI integration with the business objectives. Oversight should emphasize compliance, operational efficacy and alignment with internal and regulatory requirements.

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