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Transforming financial reporting and auditing through artificial intelligence: A Zimbabwean institutional perspective

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Abstract
Purpose: This study investigates the potential of Artificial Intelligence (AI) to enhance financial reporting and auditing practices in Zimbabwean institutions amid economic volatility and increasing transparency demands.
Research Methodology: The primary aim is to evaluate how AI-driven tools can improve the accuracy and reliability of financial information in both public and private sectors. Utilizing a mixed-methods approach, the research combines structured surveys of accounting professionals with in-depth interviews of stakeholders, including regulators and IT experts. Quantitative data were analyzed using descriptive statistics and regression models, while qualitative insights provided a deeper understanding of institutional readiness and implementation barriers.
Results: The findings indicate that AI adoption in Zimbabwe is still in its early stages, with growing awareness of its benefits, such as automation and predictive analytics. However, challenges like limited digital infrastructure, high costs, skill shortages, and regulatory uncertainty impede widespread adoption.
Conclusions: The study concludes that while AI holds transformative potential for financial reporting and auditing, a strategic and phased approach is crucial for successful integration.
Limitations: Include a small sample size in certain sectors and reliance on self-reported data, which may introduce bias.
Contributions: Despite these challenges, the research contributes significantly to the literature on AI in accounting in emerging economies, offering policy recommendations and practical frameworks to assist Zimbabwean institutions in leveraging AI for improved financial governance and oversight.

Keywords: *Artificial Intelligence, Auditing, Digital Transformation, Financial Reporting, Institutional Readiness*

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1. Introduction

The rapid advancement of digital technologies has transformed financial reporting and auditing globally, with Artificial Intelligence (AI) emerging as a key driver of efficiency, accuracy, and transparency. AI enables the automation of accounting tasks, real-time anomaly detection, and enhanced audit quality (Mbizi et al., 2022). While developed economies are progressively integrating AI into enterprise systems, its application in emerging economies such as Zimbabwe remains limited and underexplored, creating a significant research gap (Mpofu, 2024; Thakkar, Fanuel, Datta, Bhadra,

& Dabhade, 2025). Zimbabwe's institutional landscape, marked by fiscal instability, evolving regulations, and growing demands for accountability, intensifies the need for technological innovation in financial oversight.

Recent studies by Kokina, Blanchette, Davenport, and Pachamanova (2025) highlight persistent challenges, including weak digital infrastructure, inadequate technical skills, and institutional inertia, which impede AI adoption in financial reporting and auditing processes. However, these challenges present a strategic opportunity to leverage AI to strengthen financial governance, transparency, and anti-corruption frameworks across African public and private institutions. This study investigates the institutional readiness of Zimbabwean organizations to integrate AI into their financial reporting and auditing processes. It explores adoption levels, perceived benefits and risks, and contextual factors shaping implementation. This study contributes to the African discourse on digital transformation and financial governance by offering practical insights into how AI can enhance accountability, improve financial integrity, and foster institutional resilience in Zimbabwe and similar economies.

1.1 Background to the study

The increasing complexity and volume of financial data have compelled organizations worldwide to explore advanced technologies to enhance financial reporting and auditing processes. Artificial Intelligence (AI), characterized by its capabilities in machine learning, natural language processing, and data analytics, offers substantial opportunities to automate routine tasks, identify anomalies, and improve the overall quality of financial information (Ismail et al., 2024). In developed economies, AI has been progressively adopted to support auditors and accountants in ensuring accuracy, compliance, and timely reporting (Warren, Moffitt, & Byrnes, 2015).

In contrast, emerging economies, including Zimbabwe, face unique challenges in adopting AI technologies in the accounting and auditing domains. Zimbabwe's economic environment is marked by persistent fiscal instability, hyperinflationary pressures, and fluctuating regulatory frameworks, all of which complicate financial management and oversight (Kour & Schutte, 2024). Public institutions, in particular, have struggled with financial transparency and accountability, exacerbated by limited technological infrastructure and human capital constraints (Chilunjika & Chilunjika, 2024).

Despite these challenges, there is a growing recognition among Zimbabwean financial institutions and regulatory bodies increasingly recognize the potential benefits of AI and digital transformation. AI-powered tools promise enhanced fraud detection capabilities, real-time audit monitoring, and improved compliance with International Financial Reporting Standards (IFRS) (Leocádio, Malheiro, & Reis, 2024). However, empirical research examining the current state of AI adoption, institutional readiness, and contextual barriers in Zimbabwe remains limited. Therefore, this study seeks to fill this gap by providing an in-depth analysis of how AI technologies are integrated into financial reporting and auditing within Zimbabwean institutions. Understanding these dynamics is critical for designing policies and frameworks that support effective AI deployment, thereby enhancing financial governance and promoting sustainable development in Zimbabwe's public and private sectors.

1.2 Problem Statement

Despite the recognized global benefits of Artificial Intelligence (AI) in enhancing the accuracy, efficiency, and transparency of financial reporting and auditing, Zimbabwean institutions have been slow to adopt these technologies. The country's unique economic challenges, including fiscal instability, limited digital infrastructure, skills shortages, and regulatory uncertainties, have hindered the effective integration of AI tools into financial governance processes (Maguraushe & Matanda, 2024; ul Haq, Suki, Zaigham, Masood, & Rajput, 2025). This gap results in continued inefficiencies, increased risks of financial misstatements, and weak audit quality, particularly in the public sector, where accountability demands are urgent. Consequently, there is limited empirical evidence on the current state of AI adoption, institutional readiness, and barriers to AI adoption within Zimbabwe's financial reporting and auditing frameworks. This study seeks to address this knowledge gap by investigating how AI can be effectively leveraged to transform financial reporting and auditing practices in Zimbabwean institutions, thereby enhancing financial transparency and accountability.

1.3 Research Questions

1. What is the current level of adoption of Artificial Intelligence (AI) in financial reporting and auditing within Zimbabwean public and private institutions?
2. What are the perceived benefits and risks associated with integrating AI into financial reporting and auditing processes in Zimbabwe?
3. What institutional, technological, and regulatory factors influence the readiness of Zimbabwean institutions to adopt AI in financial reporting and auditing?
4. How can AI adoption improve financial governance, transparency, and accountability in Zimbabwe's public and private sectors?

1.4 Research Objectives

1. To assess the current adoption levels of AI technologies in financial reporting and auditing in Zimbabwean institutions.
2. To identify the perceived benefits and challenges of AI integration in financial reporting and auditing processes.
3. To examine the institutional, technological, and regulatory factors affecting AI readiness in Zimbabwe's financial sector.
4. To evaluate how AI adoption can enhance financial governance, accuracy, and accountability in public and private institutions.

1.5 Hypothesis

H1: Higher levels of institutional readiness positively influence the adoption of Artificial Intelligence in financial reporting and auditing in Zimbabwean institutions.
H2: The adoption of Artificial Intelligence in financial reporting and auditing is positively associated with improvements in financial reporting accuracy, audit quality, and transparency in Zimbabwean institutions.

2. Literature Review

Globally, the advent of Artificial Intelligence (AI) has gained momentum in the accounting and auditing professions, offering transformative potential for financial reporting. AI technologies such as machine learning, natural language processing, and robotic process automation are increasingly applied to enhance data accuracy, automate repetitive tasks, improve fraud detection, and support predictive analytics in audit engagements (Maphosa, 2024; Zakaria, Hassan, Othman, Zakaria, & Kasim, 2017). These technologies facilitate a shift from backward-looking to forward-looking and continuous reporting frameworks, responding to the growing demand for real-time and transparent financial information. In financial reporting, AI automates journal entries, ledger classifications, and reconciliation processes, whereas intelligent systems can detect anomalies and flag inconsistencies more efficiently than manual procedures (Kour & Schutte, 2024).

In auditing, AI enables real-time risk assessments and enhances audit quality by analyzing entire data populations rather than relying on samples (Matenda, Sibanda, Chikodza, & Gumbo, 2023; Yoon, Hoogduin, & Zhang, 2015). Globally, AI is positioned as a tool to increase efficiency and uphold financial integrity and stakeholder trust. In contrast, AI adoption in developing countries, such as Zimbabwe, remains limited. Infrastructure deficits, economic constraints, and human capital shortages impede digital transformation (Chadha, Gera, Khera, & Sharma, 2023). Zimbabwe's public sector has historically struggled with financial mismanagement, delayed audit reporting, and weak, internal controls.

Although some automation initiatives, such as SAP systems, have been introduced in select state-owned enterprises, AI-driven technologies remain largely unexplored. Institutional readiness is further constrained by limited technical expertise, underinvestment in ICT infrastructure, and the absence of regulatory frameworks that support AI integration (Ikponmwoba et al., 2020). Studies from other African contexts, such as Nigeria and Kenya, underscore that successful AI adoption depends heavily on organizational culture, leadership support, and the availability of high-quality data (Katekwe, 2025;

Mienye, Sun, & Ileberi, 2024). These findings suggest that technological capability alone is insufficient, and that institutional and contextual factors critically shape adoption outcomes.

2.1 Conceptual Framework

The conceptual framework for transforming financial reporting and auditing through Artificial Intelligence (AI) from a Zimbabwean institutional perspective addresses the pressing challenges faced in these domains. The current landscape in Zimbabwe is marked by inefficiencies, a lack of transparency, and a shortage of skilled professionals, making it essential to explore how AI can enhance the accuracy, efficiency, and reliability of financial processes (Mheuka, 2024). Central to this framework are various AI technologies, including machine learning for predictive analytics and anomaly detection, natural language processing (NLP) for automating document analysis, and robotic process automation (RPA) for streamlining repetitive tasks.

Additionally, the institutional environment plays a critical role, requiring an understanding of the current regulatory framework, capacity-building initiatives for professionals, and active stakeholder engagement to encourage AI solution adoption. Data governance is another cornerstone of the framework, emphasizing the necessity of ensuring high-quality data inputs, addressing privacy concerns, and establishing ethical guidelines for the use of AI. An effective implementation strategy is essential, which may involve initiating pilot projects in selected institutions, developing change management strategies to overcome resistance, and adopting continuous learning practices to refine AI applications over time (Maicon, 2023).

The successful integration of AI into financial reporting and auditing is anticipated to yield significant outcomes, such as enhanced accuracy through reduced human error, increased efficiency with faster reporting cycles, improved decision-making facilitated by advanced analytics, and greater transparency that fosters trust among stakeholders (Kudiwahove, 2025). However, challenges such as resistance to change, resource limitations, and regulatory compliance must be addressed using targeted mitigation strategies, including comprehensive training programs, partnerships for infrastructure support, and close collaboration with regulators. Conclusively, this framework outlines the transformative potential of AI in Zimbabwe's financial reporting and auditing landscape, highlighting the importance of a collaborative approach among all stakeholders to fully realize the benefits of technological integration in these critical sectors (Dako, Onalaja, Nwachukwu, Bankole, & Lateefat, 2020).

2.2 Conceptual diagram

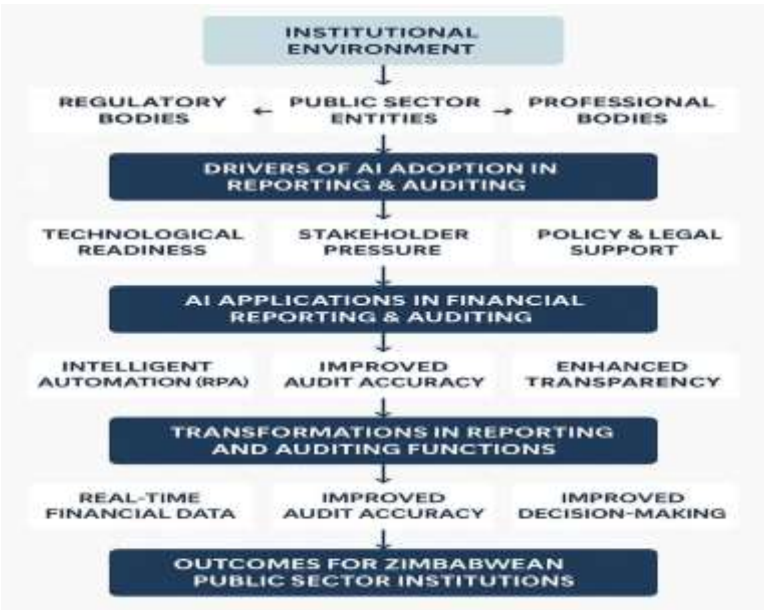

Figure 1. Conceptual Diagram
Source: Authors Compilation

The conceptual diagram illustrates how artificial intelligence (AI) can transform financial reporting and auditing within Zimbabwe's public sector institutions by tracing the process from the institutional context to measurable outcomes. The institutional environment, which includes the regulatory framework, political dynamics, and technological infrastructure that influence how public entities operate, is the foundation (Mudavanhu, P, 2019). Within this environment, three key institutional actors, regulatory bodies, public sector entities, and professional bodies, interact and collectively shape policies and practices around financial accountability (Shava & Mhlanga, 2023).

These actors both influence and are influenced by the drivers of AI adoption, which include technological readiness (such as digital infrastructure and skilled human resources), stakeholder pressure (from citizens, donors, and watchdog groups), and policy or legal support that encourages innovation and safeguards the ethical use of AI tools. These drivers facilitate the integration of various AI technologies into financial reporting and auditing processes. Notable among these are intelligent automation (such as robotic process automation for repetitive tasks), improved audit accuracy through machine learning and anomaly detection, and enhanced transparency through AI-powered data visualization and natural language processing.

As these tools are adopted, they bring about significant changes in reporting and auditing functions. For instance, financial data become accessible in real time, audits are more precise and efficient, and decision-making processes are strengthened through timely and reliable insights. The ultimate outcomes of these changes for Zimbabwean public sector institutions include increased accountability, where institutions can better demonstrate how public resources are utilized; greater public trust, as transparency enhances the credibility of financial reports; and better decision-making, supported by the availability of accurate and timely financial information. The diagram highlights that AI, when embedded within a supportive institutional framework, has the potential to transform public financial management and contribute meaningfully to good governance in Zimbabwe.

2.3 Theoretical framework

This study is anchored in two interrelated theoretical foundations: the Technology-Organisation-Environment (TOE) Framework and Institutional Theory. These frameworks provide a comprehensive lens to understand the multifaceted factors that influence the adoption and effective implementation of Artificial Intelligence (AI) in financial reporting and auditing within Zimbabwean institutions. The TOE Framework, developed by Tornatzky and Fleischer (1990), posits that the adoption of technological innovations is influenced by three contextual dimensions: technological, organizational, and environmental. The technological context refers to both existing and emerging technologies relevant to an organization, including their availability, usability, and perceived advantages. In this study, AI technologies, such as machine learning, natural language processing, and automation tools, were evaluated in terms of their capacity to enhance reporting accuracy, audit efficiency, and risk detection.

The organizational context encompasses the internal characteristics of the institution, such as size, structure, financial resources, leadership support, and the competence of human capital. In Zimbabwe, many institutions, particularly in the public sector, face constraints such as skills shortages, weak digital infrastructure, and resistance to change, which can impede AI adoption. The environmental context includes external pressures, such as government regulations, economic stability, competitive forces, and industry standards. In Zimbabwe, fluctuating monetary policies, regulatory uncertainty, and limited AI policy guidance significantly shape the environment in which institutions operate. Complementing TOE is Institutional Theory, which explains how organizations conform to external expectations due to institutional pressures.

According to DiMaggio and Powell (1983), institutions are influenced by three types of pressure: coercive, normative, and mimetic. Coercive pressures arise from government mandates and legal requirements, normative pressures stem from professional norms and ethical standards, and mimetic pressures involve the imitation of successful practices by peers. In the context of financial reporting and auditing in Zimbabwe, these institutional forces can either hinder or accelerate AI adoption, depending on how aligned they are with organizational capacity and technological readiness. By integrating these two theoretical perspectives, this study provides a robust framework for assessing how AI adoption is shaped by internal capabilities, external environments, and institutional expectations. This dual-theory approach helps explain not only whether and how AI is being adopted but also why certain institutions succeed or struggle to implement these technologies. This study further informs policy recommendations aimed at improving institutional readiness and aligning regulatory environments with technological advancements in financial governance.

2.4 Empirical Review

Empirical studies on the application of Artificial Intelligence (AI) in financial reporting and auditing have grown significantly in recent years, with most research concentrated in developed economies. These studies generally demonstrate the transformative potential of AI in improving audit quality, enhancing reporting accuracy, and reducing fraud using advanced analytics and real-time data processing. However, empirical evidence from developing countries, particularly Africa and Zimbabwe, remains limited, highlighting a critical knowledge gap that this study aims to address. Chilunjika and Chilunjika (2024), conducted one of the pioneering empirical studies in Zimbabwe, examining how AI is applied in accounting practices. Their study revealed that AI-enabled tools improved data classification, automated routine transactions, and provided predictive insights into financial planning.

Dabengwa (2017) found that audit firms using AI technologies were more effective at identifying anomalies and risks in large datasets than those using traditional methods. These findings support the notion that AI significantly enhances audit efficiency and financial-reporting reliability. In developing countries, a study by Umar and Hassan (2022) in Nigeria and Kenya showed that institutional readiness, staff competence, and regulatory support are critical determinants of successful AI adoption in public financial management. The researchers observed that while technological tools were available, poor infrastructure, lack of training, and limited awareness impeded their widespread use.

Their findings underscore the importance of aligning technological innovations with organizational and environmental contexts, which are core elements of the TOE framework. From a Southern African perspective, Mudzamba and Chikodzi (2020) explored the digitization of audit processes in Zimbabwe's public sector. They noted that while some state-owned enterprises had begun adopting basic digital tools, such as SAP and accounting software, the integration of AI for advanced auditing and financial analytics was virtually nonexistent. The challenges identified included high implementation costs, the absence of national AI strategies, poor data governance, and resistance to change among accounting professionals. Another relevant study by Mapuranga and Chigova (2021) assessed technology adoption in Zimbabwean private sector firms. They found that although awareness of AI applications in accounting was increasing, adoption remained low because of a lack of skilled personnel and inadequate investment in digital infrastructure.

These findings align with Institutional Theory, which emphasizes the influence of normative and coercive pressures, such as professional standards and government regulations, on institutional behavior. Moreover, Deloitte (2020) highlighted how AI improves transparency and reduces audit failure by providing continuous audit capabilities, enabling auditors to test entire data populations in real time. However, the applicability of such advanced tools in resource-constrained settings, such as Zimbabwe, remains questionable without adequate capacity building and investment. Collectively, these empirical studies suggest that while the benefits of AI in financial reporting and auditing are well documented, their realization in Zimbabwean institutions is hindered by institutional, technological, and policy-related constraints. The limited number of empirical studies in Zimbabwe also highlights the pressing need for localized research to understand the specific enablers and barriers to AI adoption in the country's financial governance systems.

2.5 Research Gap

While the global literature has extensively documented the benefits of Artificial Intelligence (AI) in transforming financial reporting and auditing, such as enhanced efficiency, improved accuracy, real-time risk detection, and fraud prevention, much of this research is concentrated in developed economies with advanced digital infrastructures and strong regulatory frameworks. Empirical studies in these contexts (Kokina et al. (2025); Appelbaum, Kogan, and Vasarhelyi (2017) have shown that AI can revolutionize how financial information is processed and audited, leading to increased trust and transparency in financial governance. However, the applicability of these findings to developing countries remains uncertain, particularly in African economies such as Zimbabwe, where digital transformation is still in its infancy. A limited number of regional studies (e.g., Umar & Hassan, 2022; Mudzamba & Chikodzi, 2020) have examined AI adoption in public sector accounting, but they often provide broad overviews without a focused investigation into financial reporting and auditing practices. Moreover, very few studies have explored the unique institutional, regulatory, and technological challenges faced by Zimbabwean organizations, including skills shortages, infrastructural deficits, resistance to change, and inconsistent policy environments (Mangwanya, 2025).

In the Zimbabwean context, there is currently a lack of empirical evidence on the readiness of institutions to adopt AI, the actual extent of adoption, the perceived benefits and risks, and the measurable impact on financial reporting quality and audit effectiveness in Zimbabwe. Most organizations, particularly in the public sector, continue to rely on manual or semi-automated systems, with minimal exploration of intelligent systems for financial analysis, anomaly detection and automated auditing. Furthermore, there is insufficient research linking AI adoption to improvements in transparency, accountability, and institutional trust in Zimbabwe's economic and governance systems. This study addresses these critical gaps by providing a context-specific analysis of AI adoption in financial reporting and auditing in Zimbabwean institutions (Mpofu, 2024). It investigates not only technological factors but also the organizational and environmental conditions that shape AI implementation. This study contributes to the sparse body of knowledge in this area and offers practical insights for policymakers, financial professionals, and auditors on how to harness AI for improved financial governance in Zimbabwe.

2.6 Justification of the research

This research is timely and highly relevant, given the growing global emphasis on digitization, transparency, and accountability in financial governance. While Artificial Intelligence (AI) is being rapidly adopted in financial reporting and auditing across the world, Zimbabwean institutions have lagged behind due to structural, technological, and institutional constraints. Therefore, this study is justified on several important grounds. First, the increasing complexity and volume of financial data in both public and private sector organizations in Zimbabwe demand more advanced tools than conventional accounting systems can provide. AI offers capabilities such as real-time data analysis, anomaly detection, and predictive modeling, which can greatly improve the quality, speed, and reliability of financial reporting and auditing. Second, Zimbabwe continues to face challenges such as financial mismanagement, poor audit outcomes, and low public trust in financial disclosures, especially in the public sector.

This research can inform how AI can be leveraged to enhance audit effectiveness and transparency, thus contributing to improved financial accountability and governance. Third, there is a notable gap in the local empirical literature on AI adoption in financial reporting and auditing. Most existing studies are based in developed countries, with very few focusing on Zimbabwe or offering actionable insights into its institutional context. By addressing this knowledge gap, this study provides a Zimbabwe-specific understanding of the enablers, barriers, and institutional dynamics surrounding AI adoption (Appelbaum et al., 2017).

Fourth, this study aligns with Zimbabwe's national digital transformation agenda and Vision 2030, which emphasizes modernizing public services and promoting innovation. The insights from this study could support evidence-based policymaking and help organizations formulate strategies to effectively integrate AI into their financial functions. Finally, this study contributes to academic discourse by integrating theoretical perspectives, such as Institutional Theory and the Technology-Organization-Environment (TOE) framework, to explain the dynamics of AI adoption in Zimbabwean institutions. These findings can also serve as a reference for other emerging economies facing similar constraints.

In summary, this research is not only academically significant but also practically valuable for improving financial reporting integrity, strengthening audit practices, and supporting digital innovation in Zimbabwe's financial sector.

3. Research Methodology

This study employed a mixed-methods research design, integrating quantitative and qualitative approaches to comprehensively explore the adoption and impact of Artificial Intelligence (AI) on financial reporting and auditing within Zimbabwean institutions. A mixed-methods approach was selected to enable data triangulation, thereby enhancing the validity and richness of the research findings. Guided by a pragmatist research philosophy, an explanatory sequential design was adopted, in which quantitative data collection was followed by qualitative interviews to further explain and contextualize the initial results. The target population comprised financial managers, auditors, and IT professionals from selected public and private sector organizations, including government departments, parastatals, commercial banks, and large corporations. A stratified purposive sampling technique was employed to ensure representation across sectors and institutions in the study. Stratification was based on sector (public vs. private), organization size, and geographical location, ensuring that perspectives from both urban and semi-urban institutions were captured.

Quantitative data were collected from 120 respondents using structured questionnaires distributed electronically and in print. The survey measured institutional readiness, levels of AI adoption, perceived benefits and challenges, and the impact on audit quality and financial reporting efficiency. The demographic profile of respondents showed a balanced representation: 60% male and 40% female; 45% aged 25–34, 35% aged 35–44, and 20% aged 45 and above; 50% from the public sector and 50% from the private sector; and 70% holding at least a bachelor's degree in accounting, finance, or IT-related fields. Qualitative data were collected from 15 key informants using semi-structured interviews, providing rich insights into the organizational culture, regulatory barriers, capacity gaps, and strategic factors influencing AI integration. The qualitative sample included senior financial managers, auditors, and IT directors to ensure an in-depth understanding of institutional practices and their readiness levels.

Data analysis for the quantitative component was conducted using SPSS, applying descriptive statistics, correlation analysis, and regression to examine the relationship between AI adoption and improvements in financial reporting and auditing processes. Qualitative data were analyzed through thematic content analysis using NVivo software, allowing for systematic coding and identification of recurring patterns and themes related to technological infrastructure, institutional challenges, and policy implications. To ensure model validity and reliability, the survey instrument was piloted with a small group of professionals and reviewed by subject matter experts for clarity, relevance, and construct validity. Reliability tests yielded Cronbach's alpha scores above 0.80 for all constructs, indicating high internal consistency. Additionally, multicollinearity tests and normality checks were conducted to validate the regression assumptions. Ethical considerations were strictly observed: participants provided informed consent, were assured of confidentiality, and participated voluntarily, with the research protocol approved by the relevant ethics committee.

3.1 Ethical Considerations

Ethical integrity was a paramount concern throughout this study. Prior to data collection, ethical approval was obtained from the appropriate institutional review board to ensure compliance with the established research ethics standards. Participants were provided with detailed information about the study's purpose, objectives, and procedures to enable informed decision-making regarding their involvement. Participation was entirely voluntary, and respondents were free to withdraw at any stage without negative consequences. Confidentiality and anonymity were rigorously maintained to protect the participants' identities and sensitive institutional information. Personal identifiers were removed from the data records, and all data were stored securely, with access restricted to the research team. When reporting the findings, care was taken to present information in aggregate form or through anonymized quotes, preventing the identification of individual respondents or organizations. Informed consent was obtained from all participants before their involvement in the study. This included clear explanations of their rights, the intended use of the data, and assurance that the data would be used solely for academic purposes.

Participants were also informed about the expected duration of their involvement and the nature of the questions that they would be asked. This study was mindful of the potential power dynamics and sensitivities associated with financial reporting and auditing topics, particularly in the Zimbabwean institutional context. Efforts were made to create a respectful and non-coercive environment during the interviews and surveys. The researcher ensured cultural sensitivity and adhered to local norms and values to build trust and encourage honest responses to the questionnaire. Additionally, this research upholds the principles of honesty and transparency, avoiding any form of data fabrication, falsification, or plagiarism. Any conflicts of interest were disclosed, and the research was conducted with utmost academic rigor and professionalism.

4. Results and Discussion

Objective 1 variance in effectiveness of financial reporting and auditing

Table 1. Model Summary for Objective 1: Variance in Effectiveness of Financial Reporting and Auditing

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.781	0.610	0.594	0.522

Source: Author

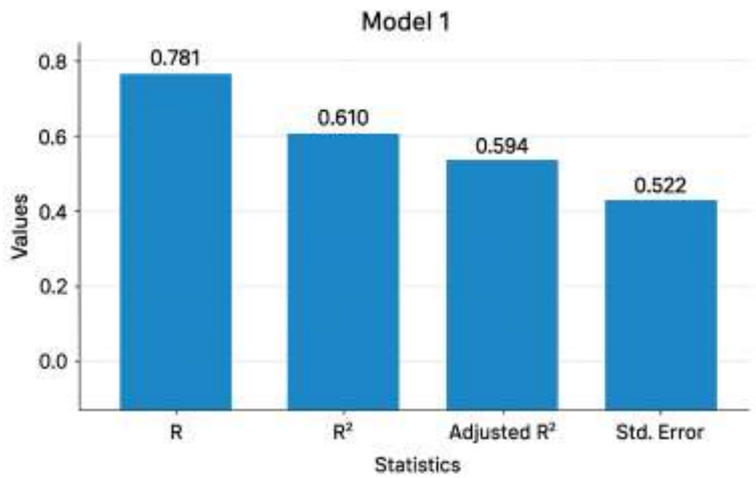

Figure 2. Model Summary Statistics for Objective 1

The regression model is quite effective, explaining approximately 61% of the changes in the outcome variable using the provided predictors. The strong correlation ($R = 0.781$) shows that the relationship between the predictors and the outcome was strong and positive. The adjusted R^2 (59.4%) confirms that this strength holds even after accounting for the number of variables used, meaning that the model is not overfitted. The prediction error (0.522) was relatively low, indicating that the model's predictions were reasonably accurate. AI adoption, staff competence, integration, management support, and regulatory compliance explain approximately 61% of the variance in the effectiveness of financial reporting and auditing.

Table 2. ANOVA Results: Overall significance of the regression model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	47.212	5	9.442	34.668	0.000
Residual	30.088	110	0.273		
Total	77.300	115			

Source: Author

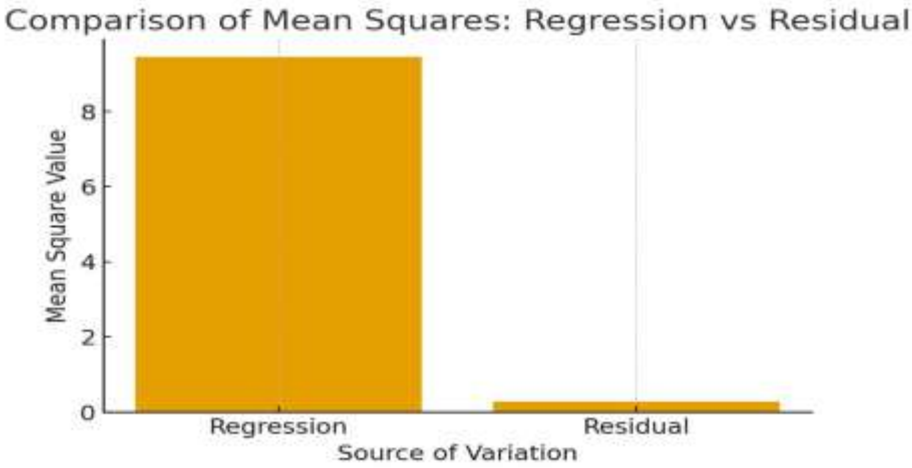

Figure 2. Comparison of Mean Squares for Regression and Residual

The mean square for the regression is 9.442, which is obtained by dividing the regression sum of squares by its degrees of freedom. The residual mean square was 0.273, calculated by dividing the residual sum of squares by its degrees of freedom. The F-statistic, which tests the overall significance of the model, was 34.668. This value is relatively large, indicating that the explained variance in the dependent variable is significantly greater than the unexplained variance. The significance value (p-value) associated with the F-test was 0.000, which is well below the conventional threshold of 0.05. This means that the regression model is statistically significant, and there is strong evidence that the independent variables, taken together, provide a meaningful explanation of the variance in the dependent variables.

Table 3. Coefficients

Predictor Variable	B	Std. Error	Beta	t	Sig.
(Constant)	1.234	0.312	—	3.955	0.000
AI Adoption Level	0.425	0.083	0.382	5.120	0.000
Staff Competence AI	0.301	0.090	0.274	3.344	0.001
System Integration AI	0.215	0.079	0.196	2.722	0.007
Top Management Support	0.142	0.067	0.138	2.119	0.036
Regulatory Compliance AI	0.096	0.063	0.102	1.524	0.130

Source: Author

Figure 3 shows a bar chart of the unstandardized coefficients (B values) for each AI-related predictor variable. AI Adoption Level (B = 0.425) had the strongest positive effect on the dependent variable, followed by Staff Competence (B = 0.301) and System Integration (B = 0.215).Meanwhile, Top Management Support and Regulatory Compliance contribute positively but to a smaller extent.

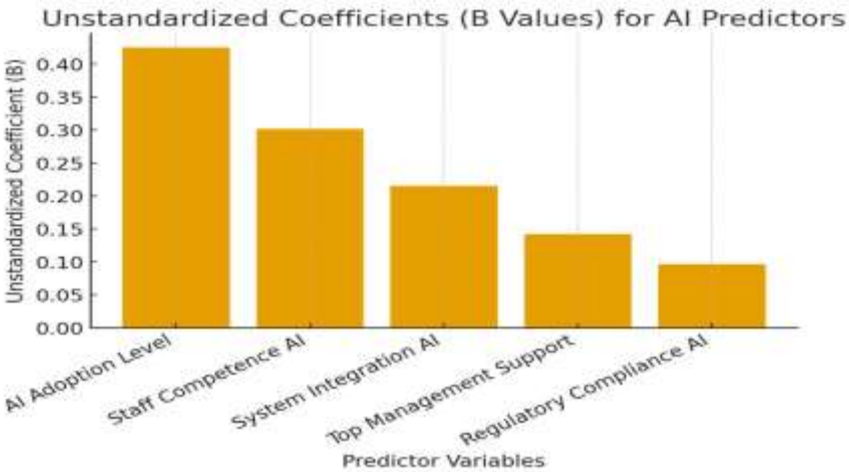

Figure 3. Unstandardized Regression Coefficients (B) for AI Predictors

The regression coefficient table provides insights into the individual contributions and statistical significance of each predictor variable in the model. The constant (intercept) had a coefficient (B) of 1.234 with a standard error of 0.312, and was statistically significant ($p = 0.000$), indicating that when all predictors were held at zero, the expected baseline value of the dependent variable was 1.234. Among the predictors, AI Adoption Level had the highest standardized beta value ($\beta = 0.382$) and a corresponding unstandardized coefficient ($B = 0.425$), with a t-value of 5.120 and a p-value of 0.000, indicating a strong, statistically significant positive effect on the dependent variable. This means that for every unit increase in the AI adoption level, the outcome variable increases by 0.425 units, holding other factors constant.

Staff competence also had a significant positive influence on the dependent variable, with $B = 0.301$, $\beta = 0.274$, $t = 3.344$, and $p = 0.001$. This suggests that as staff competence in AI improves, the dependent outcome also increases significantly. Similarly, System Integration AI had a positive and significant effect ($B = 0.215$, $\beta = 0.196$, $t = 2.722$, $p = 0.007$), indicating that better integration of AI systems contributes meaningfully to the outcome. Top Management Support is also statistically significant ($B = 0.142$, $\beta = 0.138$, $t = 2.119$, $p = 0.036$), although its effect size is smaller. This suggests that top management support for AI initiatives positively influences the dependent variable, albeit to a lesser extent than other predictors. However, Regulatory Compliance AI does not show a statistically significant effect ($B = 0.096$, $\beta = 0.102$, $t = 1.524$, $p = 0.130$), indicating that, within this model, compliance with AI-related regulations does not have a meaningful impact on the outcome at the conventional 0.05 significance level.

Table 4. ANOVA Perceived Effectiveness by Institution Type

Source	SS	df	MS	F	Sig.
Between Groups	6.985	2	3.493	5.874	0.004
Within Groups	68.032	114	0.597		
Total	75.017	116			

Source: Author

Post Hoc (Tukey HSD)
Public Sector < Private Sector ($p = 0.003$)
Audit Firms ≈ Private Sector ($p = 0.416$)
Public Sector < Audit Firms ($p = 0.048$)

The results presented are from a one-way Analysis of Variance (ANOVA), used to compare the means of three independent groups (likely Public Sector, Private Sector, and Audit Firms) on a certain dependent variable—possibly perceptions or levels of AI implementation, given your earlier context. Here is a detailed description and explanation in paragraph format, including the Tukey HSD post hoc test: The one-way ANOVA results indicate statistically significant differences between the means of the three groups. The between-groups sum of squares (SS) was 6.985 with 2 degrees of freedom (df), yielding a mean square (MS) of 3.493. The within-groups SS (representing variability within each group) was 68.032 with 114 df, giving an MS of 0.597. The F-statistic is 5.874 and the p-value (Sig.) is 0.004, which is statistically significant at the 0.05 level. This result indicates that there are significant differences between at least two of the groups in terms of the dependent variable. The Tukey HSD post hoc test was conducted to determine the differences. The results revealed that the Public Sector scored significantly lower than the Private Sector ($p = 0.003$), suggesting a meaningful difference in the average levels of the dependent variable. The Audit Firms and Private Sector did not differ significantly ($p = 0.416$), indicating a statistical similarity between these two groups. However, the Public Sector also scored significantly lower than Audit Firms ($p = 0.048$), albeit at a weaker significance level.

5. Conclusion

5.1 Conclusion

The findings from the regression and ANOVA analyses reveal that the variance in the effectiveness of financial reporting and auditing can be substantially explained by the integration of Artificial Intelligence (AI)-related factors such as adoption level, staff competence, system integration, and top management support. The overall model fit was strong, as indicated by an R value of 0.781 and an R^2 of 0.610, suggesting that 61% of the variance in financial reporting and auditing effectiveness was accounted for by the predictors included in the model. The adjusted R^2 of 0.594 further confirms that this relationship remains robust even after adjusting for model complexity, whereas the relatively low standard error of 0.522 demonstrates good predictive accuracy. The ANOVA results ($F = 34.668$, $p = 0.000$) confirm that the regression model is statistically significant, implying that the set of AI-related variables collectively has a meaningful influence on financial reporting and auditing outcomes. This implies that variations in these predictors significantly explain the differences in reporting effectiveness across institutions.

Analysis of the regression coefficients reveals that AI Adoption Level ($B = 0.425$, $p = 0.000$) exerts the strongest positive influence, followed by Staff Competence in AI ($B = 0.301$, $p = 0.001$) and System Integration ($B = 0.215$, $p = 0.007$). These findings suggest that institutions that embrace AI technologies, enhance staff skills in AI tools, and integrate these systems into their financial operations tend to achieve higher levels of reporting accuracy, efficiency, and audit reliability. Top Management Support ($B = 0.142$, $p = 0.036$) also had a positive but modest effect, highlighting the importance of leadership commitment to successful AI implementation. Conversely, Regulatory Compliance ($B = 0.096$, $p = 0.130$) did not significantly predict reporting effectiveness, indicating that compliance frameworks alone, without corresponding technological adoption and human capacity, are insufficient to drive performance improvements.

Finally, the ANOVA by institution type ($F = 5.874$, $p = 0.004$) demonstrates significant differences in perceived effectiveness across public sector, private sector, and audit firms. Post hoc tests show that the public sector lags behind both the private sector ($p = 0.003$) and audit firms ($p = 0.048$) in terms of financial reporting and auditing effectiveness, whereas the private sector and audit firms perform similarly ($p = 0.416$). These findings highlight sectoral disparities, likely reflecting differences in resource availability, technological readiness, and institutional culture. In conclusion, AI-related factors collectively explain a substantial portion of the variance in the effectiveness of financial reporting and auditing in Zimbabwe. The results underscore the critical role of AI adoption, staff competence, and system integration in improving reporting quality, while also identifying the need for stronger management support and regulatory frameworks that promote rather than merely enforce digital transformation across institutions.

5.2 Recommendations

Based on the findings of this study, several key recommendations emerge to enhance AI adoption and performance, particularly within the public sector. Firstly, there is a clear need for the public sector to develop structured AI adoption strategies aligned with national digital transformation goals. This includes identifying practical use cases, initiating pilot projects, and institutionalizing AI as a tool to improve efficiency and accountability. Given that staff competence in AI was a significant predictor of successful implementation, public institutions should invest in capacity-building initiatives through continuous training, workshops, and partnerships with academic and private entities to strengthen their internal expertise.

In addition, organizations, especially within the public sector, should prioritize improving system integration capabilities to ensure that AI tools can function effectively alongside existing legacy systems. Investing in modern digital infrastructure and adopting interoperable platforms are critical for overcoming technical bottlenecks. Equally important is the need for strong top-management support. Leadership must champion AI initiatives by allocating sufficient resources, fostering a culture of innovation and participating in strategic planning processes. Although regulatory compliance did not emerge as a significant factor in the model, it remains essential. Policymakers should shift towards enabling flexible regulations that support responsible AI adoption without stifling innovation.

Furthermore, the research highlights a performance gap between sectors, with the public sector lagging behind the private sector and audit firms. To address this disparity, cross-sector collaboration platforms should be established to facilitate knowledge sharing, technical support, and the co-development of solutions. Public-private partnerships can serve as effective mechanisms for transferring best practices and accelerating adoption. Finally, organizations should implement regular monitoring and evaluation frameworks to assess the impact of AI initiatives. This will enable evidence-based decision-making and continuous improvements. Collectively, these recommendations underscore the importance of addressing organizational, infrastructural, and leadership factors to ensure balanced and effective AI integration across all sectors of healthcare.

5.3 Suggestions

Future research should explore the longitudinal impact of AI adoption over time across different sectors, particularly within the public sector, to assess how sustained investments in staff training, system integration, and leadership support influence the long-term performance outcomes. Given that regulatory compliance was not statistically significant in this study, further qualitative investigations could uncover contextual or institutional factors that mediate its influence, especially in environments with varying levels of regulatory enforcement. Future studies could adopt a mixed-methods approach by incorporating in-depth interviews or case studies to gain richer insights into the organizational cultures and internal dynamics that shape AI implementation outcomes. Sector-specific studies focusing on areas such as health, education, or public finance would also provide more granular insights into how AI adoption differs across public-service domains. Expanding the geographical scope beyond a single country could allow for comparative regional analyses, helping to determine whether the trends observed in Zimbabwe hold true for other developing economies. Finally, future researchers should evaluate the ethical and social implications of AI adoption, particularly regarding transparency, fairness, and accountability, to ensure that technological progress aligns with public sector governance standards.

5.4 Limitations

Despite providing valuable insights into the determinants of AI adoption and performance across different sectors, this study is subject to several limitations. First, the study employed a cross-sectional design, which captured data at a single point in time, thereby limiting the ability to infer causal relationships or assess changes over time. Second, the research relied primarily on self-reported data through structured questionnaires, which may have introduced social desirability bias or inaccuracies due to respondents' perceptions rather than actual practices. Additionally, although the sample size was statistically adequate, it was restricted to specific sectors within Zimbabwe, potentially limiting the generalizability of the findings to other countries or regions with different institutional, technological, or regulatory environments. Another limitation is the exclusion of qualitative data, which could have provided a deeper context regarding internal organizational dynamics, leadership attitudes, or barriers to system integration. Furthermore, while key variables such as staff competence and system integration were included, the model may have omitted other relevant factors such as organizational culture, financial resources, and stakeholder resistance, which could influence AI adoption outcomes. Finally, regulatory compliance, although measured, was treated as a uniform construct without disaggregating its components (e.g., data protection, procurement policies), which may have diluted its significance in the model.

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