ISSN: 2958-2326

African Journal of Commercial Studies

Publisher's Home Page: https://ijcsacademia.com/

Research Paper Peer Reviewed Open Access

The Influence of Artificial Intelligence Adoption on Financial Reporting Accuracy among Selected Firms in Livingstone, Zambia

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Article Info

Volume 7, Issue 4

***Publication history*:**

Accepted on 5 May 2026;
Published: 12 August 2026

***Key Words*:**

Artificial Intelligence; Financial Reporting Accuracy; Machine Learning; Automation; Zambia

***Article Doi*:**

10.59413/ajocs/v7.i4.26

Abstract

Artificial Intelligence (AI) has increasingly transformed accounting and financial reporting through automation, enhanced data processing, error detection, and improved reliability of financial information. This study examined the influence of Artificial Intelligence adoption on financial reporting accuracy among selected firms in Livingstone, Zambia. The study specifically sought to assess the level of AI adoption in financial reporting, determine the relationship between AI adoption and financial reporting accuracy, and examine the effect of AI adoption on financial reporting accuracy. The study was underpinned by the positivist philosophy and employed a deductive approach and quantitative cross-sectional research design. Data were collected using structured questionnaires from a sample of 60 accounting and finance professionals selected through purposive and stratified sampling techniques. Data were analysed using descriptive statistics, Pearson Product-Moment Correlation and regression analysis. The findings revealed a high level of AI adoption, with an overall mean of 3.90. A strong, positive and statistically significant relationship was established between AI adoption and financial reporting accuracy ($r = 0.700$, $p < 0.001$). Regression analysis further established that AI adoption significantly influenced financial reporting accuracy, explaining 49.1% of its variation ($R^2 = 0.491$, $p < 0.001$). The five AI dimensions collectively explained 58.4% of the variation, with Natural Language Processing emerging as the significant unique predictor. The study concluded that effective AI adoption significantly enhances financial reporting accuracy. It recommended increased investment in AI technologies, continuous professional training, improved technological infrastructure, stronger cybersecurity and data governance, clear AI governance frameworks, and continued human oversight to enhance accurate and reliable financial reporting.

1. Introduction

Artificial Intelligence (AI) has emerged as an important technological development transforming accounting and financial reporting practices. Technologies such as Machine Learning (ML), Natural Language Processing (NLP), Robotic Process Automation (RPA), and intelligent data analytics are increasingly being used to automate accounting processes, detect anomalies, improve reconciliations, and enhance the accuracy and timeliness of financial information. Financial reporting is essential for organisational accountability, decision-making, regulatory compliance, and assessment of financial performance. However, traditional financial reporting processes often involve substantial manual intervention, which may result in data-entry errors, inaccurate classifications, delayed reconciliations, and financial misstatements. The increasing volume and complexity of financial transactions have therefore created a need for more efficient and reliable technological approaches to financial reporting. AI provides opportunities for organisations to improve financial reporting by automating repetitive processes, analysing large volumes of financial data, detecting unusual transactions, and reducing human errors. Despite these potential benefits, the extent of AI adoption and its contribution to financial reporting accuracy varies across organisations and countries. In developing economies, adoption may be affected by limited technological infrastructure, implementation costs, inadequate technical expertise, and organisational readiness. In Zambia, organisations are increasingly adopting digital accounting systems and other emerging technologies. However, empirical evidence on the extent of AI adoption in financial reporting and its influence on financial reporting accuracy remains limited. This study therefore examines the influence of artificial intelligence adoption on financial reporting accuracy among selected firms in Livingstone, Zambia.

DOI Link: https://doi.org/10.59413/ajocs/v7.i4.26

1.1 Background of the Study

The accounting profession has evolved significantly from manual bookkeeping to computerised accounting systems, cloud-based platforms, data analytics, and artificial intelligence. These developments have transformed how organisations capture, process, analyse, and report financial information (Alghazzawi, 2024). Globally, the increasing complexity of business transactions and growing demand for accurate and timely financial information have accelerated the adoption of AI in accounting and financial reporting. AI technologies have several applications in financial reporting. Machine learning can identify patterns and anomalies in financial data, while robotic process automation can automate repetitive activities such as data entry, invoice processing, and account reconciliations (Almasarwah, Wreikat, Marei & Alsharari, 2025). Natural language processing can assist in extracting and analysing information from financial documents. These technologies may reduce human errors, improve efficiency, strengthen anomaly detection, and enhance the reliability of financial reports. Despite these benefits, AI adoption remains uneven, particularly in developing economies where organisations may face challenges related to implementation costs, inadequate infrastructure, limited technical expertise, cybersecurity risks, and resistance to technological change. The effectiveness of AI also depends on data quality, organisational readiness, appropriate internal controls, and effective human oversight (Creswell, 2023).

In Zambia, digital transformation has increasingly influenced accounting and financial management practices through computerised accounting systems, enterprise resource planning platforms, cloud-based applications, and automated financial processes (Creswell & Clark, 2023). However, limited empirical research has examined whether the adoption of AI specifically contributes to improved financial reporting accuracy among Zambian firms. This study therefore focuses on selected firms in Livingstone, Zambia, to assess the level of AI adoption in financial reporting, determine the relationship between AI adoption and financial reporting accuracy, and examine the effect of AI adoption on financial reporting accuracy. The study seeks to provide empirical evidence that may assist accountants, financial managers, auditors, regulators, and organisations in understanding the contribution of AI to accurate and reliable financial reporting.

1.2 Problem Statement

Accurate financial reporting is essential for effective decision-making, accountability, regulatory compliance, and stakeholder confidence (Alqsass, Qubbaja, Alghizzawi, Jebreel, Dweiri & Qabajeh, 2024). However, financial reporting processes in many organisations remain susceptible to human errors, inaccurate data entry, delayed reconciliations, misclassifications, and difficulties in detecting unusual financial transactions. These challenges may compromise the reliability and accuracy of financial information used by management, investors, regulators, auditors, and other stakeholders (Anantharaman, Rozario, & Parker, 2023). Artificial Intelligence (AI) offers opportunities to improve financial reporting through automated data processing, intelligent reconciliation, anomaly detection, and real-time financial analysis. Although organisations globally are increasingly adopting AI-enabled technologies, the extent of adoption and their actual contribution to financial reporting accuracy remain unclear, particularly in developing economies (Apooyin, 2025). In Zambia, organisations are increasingly adopting digital accounting and automated financial systems. However, limited empirical evidence exists on the level of AI adoption in financial reporting and whether such adoption significantly improves financial reporting accuracy. Most existing studies have been conducted outside Zambia, making it difficult to generalise their findings to the local business environment. This creates an empirical and contextual knowledge gap regarding the relationship between AI adoption and financial reporting accuracy. Therefore, this study examines the influence of artificial intelligence adoption on financial reporting accuracy among selected firms in Livingstone, Zambia.

1.3 Research Objectives

The study was guided by the following objectives:

- To assess the level of artificial intelligence adoption in financial reporting among selected firms in Livingstone, Zambia.
- To determine the relationship between artificial intelligence adoption and financial reporting accuracy among selected firms in Livingstone, Zambia.
- To examine the effect of artificial intelligence adoption on financial reporting accuracy among selected firms in Livingstone, Zambia.

2 Literature Review

2.1 Artificial Intelligence in Accounting and Financial Reporting

Artificial Intelligence refers to computer-based technologies capable of performing tasks that traditionally require human intelligence, including learning, pattern recognition, classification, Prediction, and decision support. Within accounting and financial reporting, AI has increasingly been applied to automate financial processes, analyse large datasets, identify unusual transactions, perform reconciliations, and support financial decision-making (Awad, 2025). The increasing adoption of AI has changed the traditional role of accounting information systems. Instead of merely recording and processing transactions, modern systems can analyse financial information, identify patterns, and provide insights that support decision-making. AI applications such as Machine Learning (ML), Robotic Process Automation (RPA), and Natural Language Processing (NLP) have therefore become increasingly relevant to contemporary accounting practices. Machine learning enables systems to analyse financial data and identify patterns that may indicate errors, unusual transactions, or potential financial irregularities (Awad, R., et al. , 2025). RPA facilitates the automation of repetitive accounting activities such as transaction processing, invoice management, data entry, and account reconciliations. NLP supports the extraction and analysis of information from financial documents and other textual sources. Collectively, these technologies may improve the efficiency, consistency, and accuracy of financial reporting.

2.2 Artificial Intelligence Adoption in Financial Reporting

AI adoption refers to the extent to which organisations integrate and utilise artificial intelligence technologies within their operational and financial processes. In financial reporting, adoption may involve automated data capture, intelligent transaction classification, automated reconciliations, anomaly detection, machine learning applications, and AI-assisted preparation and analysis of financial information. The level of AI adoption differs across organisations due to variations in technological infrastructure, financial resources, management support, employee competencies, organisational readiness, and perceived benefits of technology. Larger organisations may have greater capacity to invest in sophisticated AI systems, while smaller organisations may face financial and technical barriers. (Bennett, Thompson & Rivera, 2024) observed that organisational readiness is an important factor influencing AI adoption and accounting efficiency. Similarly, (Carter & Davis, 2024) associated AI adoption with improvements in the quality of financial reporting.

These findings suggest that organisations capable of successfully integrating AI into accounting processes may experience improvements in financial information processing and reporting outcomes. However, AI adoption should not simply be understood as the availability of technology. Effective adoption requires actual integration into accounting processes, appropriate employee skills, reliable data, management support, and effective governance structures. Therefore, assessing the level of AI adoption is important in understanding the extent to which organisations are benefiting from emerging technologies.

2.3 Financial Reporting Accuracy

Financial reporting accuracy refers to the extent to which financial reports correctly and reliably represent an organisation's financial transactions, position, and performance (Davis & Carter, 2025). Accurate financial information should be free from material errors, inconsistencies, omissions, and inappropriate classifications. Financial reporting accuracy is important because stakeholders depend on financial statements when making economic and organisational decisions. Errors in financial reporting can lead to inappropriate management decisions, regulatory penalties, incorrect tax assessments, reduced investor confidence, and reputational damage. Traditional financial reporting processes involving extensive manual intervention may increase exposure to human errors. Manual data entry, reconciliation, transaction classification, and report preparation may create opportunities for mistakes, particularly where organisations process large volumes of financial information. AI-enabled technologies may improve accuracy by automating repetitive processes, validating financial data, detecting inconsistencies, and identifying unusual transactions before financial reports are finalised. (Els, 2025) linked AI applications with improvements in financial reporting quality, while (Doria, Hernández & Fajardo, 2025) identified a relationship between AI utilisation and financial reporting accuracy.

2.4 Relationship Between AI Adoption and Financial Reporting Accuracy

The relationship between AI adoption and financial reporting accuracy has received increasing academic attention. AI technologies have the potential to reduce human intervention in repetitive accounting processes and improve the ability of organisations to identify errors and inconsistencies. Automated financial systems can perform repetitive tasks consistently and process large volumes of transactions more efficiently than purely manual systems. Machine learning algorithms can identify unusual patterns within financial datasets, while automated reconciliation systems can identify discrepancies between accounting records and supporting information. Miller, (Garcia, Patel & Mohammed, 2024) observed that AI-powered financial reporting systems can Contribute to error reduction and improved decision-making. Similarly, (Jackson, Lee, & Wang, 2025) highlighted the potential of AI algorithms to improve financial reporting accuracy through enhanced data analysis and error identification. These findings suggest that higher levels of AI adoption may be associated with greater financial reporting accuracy. However, the relationship may depend on how effectively organisations integrate technology into their accounting systems and whether appropriate human oversight and internal controls are maintained.

2.5 Effect of AI Adoption on Financial Reporting Accuracy

AI adoption may influence financial reporting accuracy through automation, anomaly detection, data validation, and improved reconciliation processes. Automation reduces the need for repetitive manual data entry, thereby potentially reducing human errors. AI-supported anomaly detection can identify unusual transactions requiring further investigation before they affect financial statements. (Jens , 2023) argued that integrating AI into financial statement preparation can enhance accuracy and compliance. Similarly, (Johnson, Smith & Tran, 2024) identified AI as an important technological development with the potential to improve financial reporting quality. Despite these benefits, AI systems may also introduce risks. Poor-quality data, inappropriate algorithms, inadequate system controls, cybersecurity threats, and excessive reliance on automated outputs may negatively affect reporting outcomes. Therefore, the effect of AI on financial reporting accuracy depends not only on technology adoption but also on effective implementation, governance, data quality, and professional oversight.

2.6 Theoretical Framework

The study is guided by the Technology Acceptance Model (TAM). The Technology Acceptance Model explains the factors influencing individuals' acceptance and use of technology. The model proposes that perceived usefulness and perceived ease of use significantly influence attitudes towards technology and its eventual adoption. In the context of this study, perceived usefulness relates to the extent to which accounting and finance professionals believe that AI improves financial reporting activities, including accuracy, efficiency, error detection, and reconciliation. Perceived ease of use relates to the extent to which AI-enabled financial systems are considered understandable and manageable by users. TAM is relevant because successful adoption of AI depends partly on whether organisations and accounting professionals perceive the technology as useful and practical. Greater acceptance and utilisation of AI technologies may result in increased automation, improved error detection, and more accurate financial reporting.

2.7 Empirical Literature Gap

Existing literature generally demonstrates that AI has considerable potential to transform accounting and financial reporting. Studies have associated AI with automation, improved data processing, anomaly detection, fraud identification, regulatory compliance, and financial reporting quality. However, much of the existing empirical literature originates from developed economies and other international contexts. There remains limited empirical evidence focusing specifically on AI adoption and financial reporting accuracy among firms in Zambia. Furthermore, some previous studies have examined AI broadly in accounting, auditing, financial performance, or decision-making rather than empirically measuring the relationship and effect of AI adoption on financial reporting accuracy. This creates a geographical and empirical gap. The present study addresses this gap by assessing AI adoption and statistically examining its relationship with and effect on financial reporting accuracy among selected firms in Livingstone, Zambia.

2.8 Conceptual Framework

The conceptual framework illustrated the relationship between Artificial Intelligence Adoption, which constituted the independent variable, and Financial Reporting Accuracy, which constituted the dependent variable. The framework was developed on the assumption that the adoption and application of artificial intelligence technologies in accounting and financial reporting processes contributed to improvements in the accuracy, reliability, and consistency of financial information. In the study, Artificial Intelligence Adoption was measured through the application of Machine Learning, Robotic Process Automation, Natural Language Processing, automated financial data processing, and automated reconciliation and anomaly detection. These technologies were examined in relation to their contribution to the automation of accounting activities, processing of financial data, identification of unusual transactions, and reduction of errors associated with financial reporting processes. Financial Reporting Accuracy, as the dependent variable, was measured through the reduction of financial reporting errors, accuracy of financial reconciliations, detection of anomalies and misstatements, reliability and consistency of financial information, and accuracy of financial statements.

Independent Variable		Dependent Variable
ARTIFICIAL INTELLIGENCE ADOPTION		**FINANCIAL REPORTING ACCURACY**
Machine Learning		Reduction in Financial Reporting Errors
Robotic Process Automation		Accuracy of Financial Reconciliations
Natural Language Processing	→	Detection of Anomalies and Misstatements
Automated Financial Data Processing		Reliability and Consistency of Financial Information
Automated Reconciliation and Anomaly Detection		Accuracy of Financial Statements

Figure 1: Conceptual Framework
Source: Researcher's Conceptualisation (2026)
Source: Researcher (2026)

The conceptual framework proposed a direct relationship between Artificial Intelligence Adoption and Financial Reporting Accuracy (Mwachikoka, 2024). The study examined whether increased adoption of AI technologies contributed to improved financial data processing, more accurate reconciliation processes, enhanced detection of errors and anomalies, and reduced human errors in financial reporting. Accordingly, the framework provided the basis for examining the relationship and effect of Artificial Intelligence Adoption on Financial Reporting Accuracy among the selected firms in Livingstone, Zambia.

3 Methodology

3.1 Philosophical Underpinnings

The study was underpinned by the positivist research philosophy, which emphasised objectivity, empirical measurement, and the use of quantitative methods to examine relationships among variables (Creswell, 2023). Positivism was considered appropriate because the study sought to assess Artificial Intelligence Adoption and Financial Reporting Accuracy using measurable indicators and statistical techniques.

The philosophical orientation enabled the researcher to objectively examine the relationship between Artificial Intelligence Adoption and Financial Reporting Accuracy without manipulating the study environment. It further supported the use of structured questionnaires, numerical data, and inferential statistical techniques to draw conclusions from the findings.

3.2 Research Approach

The study adopted a deductive research approach. The deductive approach was appropriate because the study drew upon existing theoretical and empirical literature on artificial intelligence and financial reporting and examined the relationships between predetermined variables using quantitative data (Creswell & Clark, 2023). Artificial Intelligence Adoption was treated as the independent variable, while Financial Reporting Accuracy was treated as the dependent variable. The deductive approach therefore enabled the researcher to move from existing theoretical propositions to the collection and statistical analysis of empirical evidence from selected firms in Livingstone.

3.3 Research Design

The study adopted a quantitative cross-sectional research design. The quantitative design enabled the collection of numerical data required to assess the level of Artificial Intelligence Adoption and statistically examine its relationship with and effect on Financial Reporting Accuracy (Creswell, 2023). The cross-sectional design was appropriate because data were collected from respondents at a specific point in time without manipulating the study variables. This design enabled the researcher to obtain information from accounting and finance professionals working in selected firms and establish patterns and statistical relationships between the variables under investigation (Mwachikoka, 2024).

3.4 Study Area

The study was conducted among selected firms in Livingstone, Zambia. Livingstone was selected because it is Zambia's principal administrative and commercial centre and hosts a high concentration of private companies, financial institutions, multinational corporations, public institutions, and professional service organisations. The concentration of firms using computerised accounting systems, automated financial processes, and emerging digital technologies made Livingstone an appropriate geographical setting for examining Artificial Intelligence Adoption and Financial Reporting Accuracy (Naveed, Elly & Alam , 2025).

3.5 Target Population

The target population consisted of accounting and finance professionals working in selected firms in Livingstone, Zambia (Mwachikoka, 2024). The population included accountants, finance officers, financial managers, internal auditors, and other professionals directly involved in accounting and financial reporting activities. These categories of respondents were selected because they possessed relevant professional knowledge and practical experience regarding financial reporting processes, accounting information systems, automation, and the application of emerging technologies in accounting and finance.

3.6 Sample Size Determination

The sample size was determined using Cochran's formula, which provided a statistical basis for determining an appropriate sample for the quantitative study.

$$n_0 = Z^2 p(1 - p) / e^2$$

Where: n_0 = initial sample size; Z = 1.96; p = 0.5; and e = 0.05.

$$n_0 = (1.96)^2 \times 0.5(1 - 0.5) / (0.05)^2$$
$$n_0 = 384.16 \approx 384$$

Since the accessible population was finite (N = 71), the finite population correction formula was applied:

$$n = n_0 / [1 + ((n_0 - 1) / N)]$$

$$n = 384 / [1 + ((384 - 1) / 71)]$$
$$n = 384 / 6.394$$
$$n \approx 60$$

Therefore, the study used a sample size of 60 respondents drawn from the selected firms in Livingstone, Zambia.

3.7 Sampling Techniques

The study employed purposive and stratified sampling techniques. Purposive sampling was used to identify selected firms and participants who were relevant to the subject under investigation, particularly those involved in accounting, finance, financial reporting, auditing, and the use of digital financial systems. Stratified sampling was subsequently used to ensure representation of different categories of accounting and finance professionals. The respondents were drawn from categories that included accountants, finance officers, financial managers, internal auditors, and other relevant professionals involved in financial reporting activities. The combination of these sampling techniques enabled the researcher to obtain data from respondents who possessed relevant knowledge while ensuring representation of different professional categories within the study population.

3.8 Data Sources

The study utilised both primary and secondary sources of data. Primary data were obtained directly from respondents through structured questionnaires. The primary data provided information on respondents' experiences and perceptions regarding the adoption of AI technologies and their influence on financial reporting accuracy. Secondary data were obtained from relevant journal articles, books, research reports, policy documents, and other scholarly publications relating to Artificial Intelligence, accounting technologies, and financial reporting. Secondary sources were mainly used to develop the theoretical and empirical foundation of the study and support the interpretation of the findings.

3.9 Data Collection Instrument

Primary data were collected using a structured questionnaire. The questionnaire was designed in accordance with the study objectives, research questions, conceptual framework, and variables identified from the literature. The questionnaire consisted mainly of closed-ended questions measured using a five-point Likert scale, where: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree and 5 = Strongly Agree. The questionnaire was divided into sections covering respondents' demographic and professional characteristics, Artificial Intelligence Adoption, and Financial Reporting Accuracy. Artificial Intelligence Adoption was measured through indicators relating to Machine Learning, Robotic Process Automation, Natural Language Processing, automated financial data processing, and automated reconciliation and anomaly detection. Financial Reporting Accuracy was measured through indicators relating to reduction in reporting errors, accuracy of financial reconciliations, detection of anomalies and misstatements, reliability and consistency of financial information, and accuracy of financial statements.

3.10 Operationalisation of Variables

The study consisted of one principal independent variable and one dependent variable. Artificial Intelligence Adoption constituted the independent variable, while Financial Reporting Accuracy constituted the dependent variable. Artificial Intelligence Adoption was operationalised through respondents' assessment of the extent to which AI-related technologies were incorporated into accounting and financial reporting activities. The indicators included the use of machine learning applications, robotic process automation, natural language processing, automated financial data processing, and automated reconciliation and anomaly detection. Financial Reporting Accuracy was operationalised through indicators measuring the extent to which financial reporting processes resulted in fewer errors, accurate reconciliations, effective detection of anomalies and misstatements, reliable and consistent financial information, and accurate financial statements. Composite scores were generated from the relevant questionnaire items to facilitate statistical analysis of the two principal variables.

3.11 Validity of the Research Instrument

The validity of the research instrument was assessed to ensure that the questionnaire adequately measured the concepts it was intended to measure.

Content validity was established by aligning questionnaire items with the study objectives, research questions, conceptual framework, and relevant literature. The questionnaire was also reviewed for clarity, relevance, appropriateness, and adequate coverage of the variables under investigation. Necessary adjustments were made to ambiguous or unclear questions before the questionnaire was administered to the final study participants.

3.12 Reliability of the Research Instrument

The reliability of the research instrument was assessed using Cronbach's Alpha coefficient to determine the internal consistency of questionnaire items measuring Artificial Intelligence Adoption and Financial Reporting Accuracy. A Cronbach's Alpha coefficient of 0.70 or above was considered an acceptable level of reliability. A pilot assessment of the questionnaire was conducted before the main data collection exercise to identify unclear questions and improve the consistency of the measurement items. The reliability assessment ensured that items used to measure the same constructs demonstrated an acceptable degree of internal consistency before the main statistical analysis was undertaken.

3.13 Data Collection Procedure

Before data collection, the researcher obtained the necessary ethical and institutional approvals and sought permission from the relevant organisations. Potential respondents who met the inclusion criteria were identified and informed about the purpose and nature of the study. The structured questionnaires were administered to the selected respondents either physically or electronically, depending on accessibility and convenience. Respondents were provided with sufficient time to complete the questionnaires. Completed questionnaires were collected and examined for completeness and consistency. The responses were subsequently coded and prepared for statistical analysis.

3.14 Data Analysis

Quantitative data were coded, entered, cleaned, and analysed using the Statistical Package for the Social Sciences (SPSS). The analysis involved both descriptive and inferential statistical techniques, which were applied according to the three objectives of the study. For the first objective, which assessed the level of Artificial Intelligence Adoption in financial reporting, descriptive statistics comprising frequencies, percentages, means, and standard deviations were used. The results were presented using tables and appropriate graphical presentations. For the second objective, the Pearson Product-Moment Correlation analysis was conducted to determine the direction and strength of the relationship between Artificial Intelligence Adoption and Financial Reporting Accuracy. The correlation coefficient ranged from -1 to $+1$, with positive values indicating a positive relationship and negative values indicating an inverse relationship. For the third objective, linear regression analysis was conducted to determine the effect of Artificial Intelligence Adoption on Financial Reporting Accuracy. The coefficient of determination (R^2) was used to establish the proportion of variation in Financial Reporting Accuracy that was explained by Artificial Intelligence Adoption. The statistical significance of the model and regression coefficient was assessed at a 5% significance level ($p < 0.05$). The inferential findings were presented using SPSS-style Correlation, Model Summary, Analysis of Variance (ANOVA), and Coefficients tables.

3.15 Ethical Considerations

Ethical principles were observed throughout the study. Participation was voluntary, and respondents were adequately informed about the purpose of the research before participating. Informed consent was obtained from the respondents before data were collected. Confidentiality and anonymity were maintained throughout the research process. Respondents were not required to provide unnecessary personally identifiable information, and the information collected was used strictly for academic purposes. Participants were informed of their right to decline participation or withdraw from the study without any negative consequences. Research data were securely maintained and accessed only for purposes related to the study. The required ethical clearance and institutional permissions were obtained before the commencement of data collection.

4 Findings

This chapter presents and analyses findings from 60 respondents on the influence of Artificial Intelligence adoption on financial reporting accuracy among selected firms in Livingstone, Zambia. The analysis was guided by the study objectives and focused on Machine Learning, Robotic Process Automation, Natural Language Processing, Automated Financial Data Processing, and Automated Reconciliation and Anomaly Detection. Descriptive statistics, Pearson correlation and regression analysis were used to analyse the data and determine the relationship and effect of AI adoption on financial reporting accuracy.

4.1 Response Rate

Table 1: Response Rate

Response Category	Frequency	Percentage
Valid responses analysed	60	100.0%
Total	60	100.0%

Data Source: Field Data 2026

The results presented in Table 4.1 show that all 60 responses contained in the dataset were included in the analysis. The sample therefore provided an adequate basis for examining the adoption of artificial intelligence and its relationship with financial reporting accuracy among the selected firms.

4.2 Demographic and Professional Characteristics of Respondents

The demographic and professional characteristics of respondents were analysed to establish the background of the individuals who participated in the study. The characteristics examined included gender, age, education, professional role, professional experience, type of organisation, duration of using computerised accounting or digital financial systems, and knowledge of artificial intelligence applications in accounting and financial reporting.

Gender of Respondents

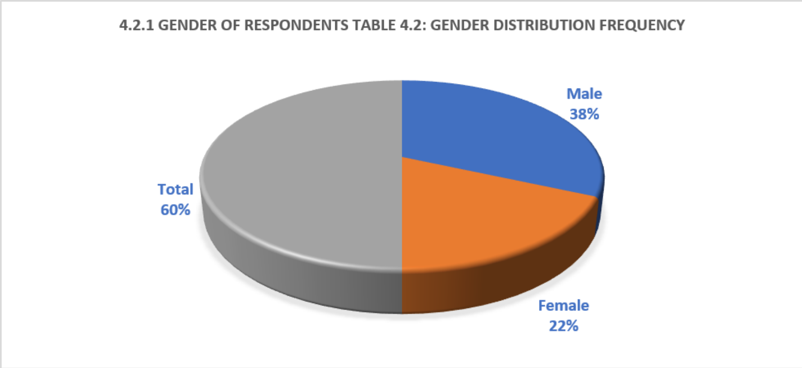

Figure 1: Gender Distribution

Data Source: Field Data 2026

The findings show that 38 respondents, representing 63.3%, were male, while 22 respondents, representing 36.7%, were female. Although male respondents constituted the majority, both genders were represented in the study.

Age Distribution of Respondents

Table 2: Age Distribution

Age Group	Frequency	Percentage
18–25 years	9	15.0%
26–35 years	25	41.7%
36–45 years	11	18.3%
46–55 years	10	16.7%
Above 55 years	5	8.3%
Total	60	100.0%

Data Source: Field Data 2026

The largest proportion of respondents was aged between 26 and 35 years, accounting for 41.7% of the sample. This was followed by respondents aged 36–45 years at 18.3%, those aged 46–55 years at 16.7%, and those aged 18–25 years at 15.0%. Respondents aged above 55 years represented 8.3%. The findings indicate that the study obtained responses from participants across different age groups, with the majority being within economically active professional age categories.

Highest Level of Education

Table 3: Educational Qualifications

Qualification	Frequency	Percentage
Diploma	6	10.0%
Bachelor's Degree	28	46.7%
Professional Qualification	16	26.7%
Master's Degree	10	16.7%
Total	60	100.0%

Data Source: Field Data 2026

The results show that 46.7% of respondents held bachelor's degrees, while 26.7% held professional qualifications. A further 16.7% held master's degrees and 10.0% held diplomas. The relatively high educational qualifications among respondents suggest that they were generally capable of understanding accounting, financial reporting and technology-related issues relevant to the study.

Professional Role of Respondents

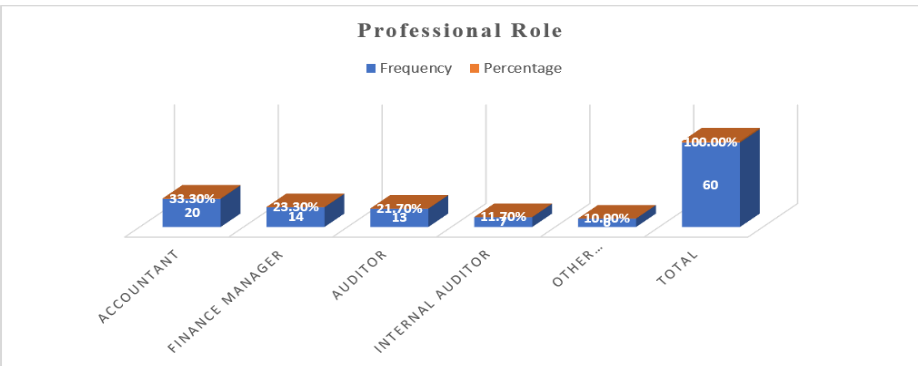

Figure 2: Professional Role
Data Source: Field Data 2026

Accountants constituted the largest group of respondents at 33.3%, followed by finance managers at 23.3% and auditors at 21.7%. Internal auditors represented 11.7%, while respondents occupying other finance and accounting roles accounted for 10.0%. These findings indicate that the respondents were predominantly professionals whose responsibilities were directly related to accounting, auditing, finance and financial reporting.

Years of Professional Experience

Table 4: Professional Experience

Years of Experience	Frequency	Percentage
Less than 3 years	6	10.0%
3–5 years	9	15.0%
6–10 years	23	38.3%
11–15 years	16	26.7%
More than 15 years	6	10.0%
Total	60	100.0%

Data Source: Field Data 2026

The majority of respondents had considerable professional experience. Specifically, 38.3% had between 6 and 10 years of experience, while 26.7% had between 11 and 15 years. A further 10.0% had more than 15 years of experience. Collectively, 75.0% of respondents had at least six years of professional experience, suggesting that the findings were informed by respondents with substantial exposure to organisational financial processes.

Type of Organisation

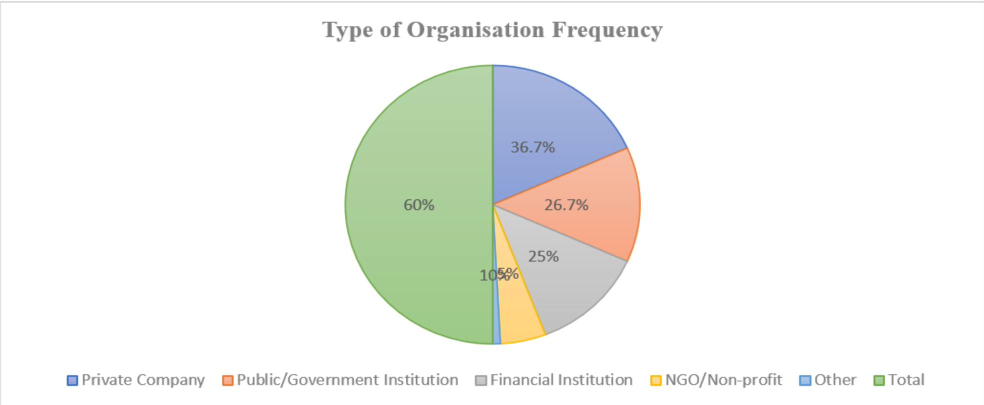

Figure 3: Type of Organisation

Data Source: Field Data 2026

Private companies constituted the largest organisational category at 36.7%, followed by public or government institutions at 26.7% and financial institutions at 25.0%. NGOs and non-profit organisations accounted for 10.0%, while other organisations accounted for 1.7%. This distribution demonstrates that the study captured experiences from different organisational settings where financial reporting and digital technologies were applied.

Duration of Using Computerised Accounting or Digital Financial Systems

Table 5: Duration of Digital Financial System Usage

Duration	Frequency	Percentage
Less than 1 year	1	1.7%
1–3 years	15	25.0%
4–6 years	22	36.7%
More than 6 years	22	36.7%
Total	60	100.0%

Data Source: Field Data 2026

The findings show that 36.7% of respondents worked in organisations that had used computerised accounting or digital financial systems for 4–6 years, while another 36.7% reported more than six years of usage. Therefore, 73.4% of respondents worked in organisations that had used such systems for at least four years. This suggests a relatively mature level of exposure to digital financial technologies among the organisations represented in the study.

Knowledge of Artificial Intelligence Applications

Table 6: Knowledge of AI Applications in Accounting and Financial Reporting

Knowledge Level	Frequency	Percentage
Very Low	1	1.7%
Low	6	10.0%
Moderate	22	36.7%
High	25	41.7%
Very High	6	10.0%

Total	60	100.0%

Data Source: Field Data 2026

The findings indicate that 41.7% of respondents rated their knowledge of AI applications as high, while 10.0% rated it as very high. A further 36.7% reported moderate knowledge. Only 11.7% reported either low or very low knowledge. Thus, 51.7% reported high or very high knowledge of AI applications, indicating that a substantial proportion of respondents possessed sufficient familiarity with AI-related technologies to provide informed responses.

Findings According to Research Objectives

4.3 Objective One: To Assess the Level of Artificial Intelligence Adoption in Financial Reporting among Selected Firms

The first objective sought to assess the level of artificial intelligence adoption in financial reporting. AI adoption was assessed using five principal dimensions: Machine Learning, Robotic Process Automation, Natural Language Processing, Automated Financial Data Processing, and Automated Reconciliation and Anomaly Detection. A five-point Likert scale was used, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Higher mean scores therefore indicated higher levels of adoption.

Table 7: Descriptive Statistics for Artificial Intelligence Adoption

AI Adoption Dimension	Mean	Interpretation
Automated Financial Data Processing	3.97	High
Robotic Process Automation	3.94	High
Machine Learning	3.93	High
Automated Reconciliation and Anomaly Detection	3.87	High
Natural Language Processing	3.82	High
Overall AI Adoption	3.90	High

Data Source: Field Data 2026

The results show that the overall mean for artificial intelligence adoption was approximately 3.90 out of 5, indicating a generally high level of AI and automation adoption among the selected firms.

Machine Learning

Machine Learning recorded an overall mean of approximately 3.93, indicating a high level of adoption. The findings suggest that intelligent analytical systems were being used to analyse patterns in financial data, identify unusual transactions, detect potential financial reporting errors, and support financial analysis and reporting decisions. The relatively high mean demonstrates that machine learning-related capabilities had become an important component of technology-supported accounting and financial reporting processes among the selected firms.

Robotic Process Automation

Robotic Process Automation recorded an overall mean of approximately 3.94, indicating high adoption. The results suggest that firms were increasingly using automation to perform repetitive and rule-based financial processes. The findings imply that automation was being applied to reduce manual processing requirements, improve processing consistency and support more efficient accounting operations.

Natural Language Processing

Natural Language Processing recorded a mean of approximately 3.82. Although this was the lowest mean among the five AI adoption dimensions, it remained above the midpoint of the five-point scale and therefore indicated a relatively high level of adoption. The result suggests that technologies associated with processing and interpreting text-based financial information were present among the selected organisations, although their adoption appeared less developed than other AI applications.

Automated Financial Data Processing

Automated Financial Data Processing recorded the highest mean score of approximately 3.97. This finding indicates that automated processing of financial information was one of the most extensively adopted technological applications among the selected firms. Such systems potentially reduce dependence on manual data entry, improve processing speed and promote greater consistency in financial information.

Automated Reconciliation and Anomaly Detection

Automated Reconciliation and Anomaly Detection recorded a mean of approximately 3.87, indicating a high level of adoption. This finding suggests that firms were using automated tools to support financial reconciliation processes and identify unusual transactions or inconsistencies in financial data.

Table 8: Overall Rating of AI Adoption

Rating	Frequency	Percentage
Moderate	14	23.3%
High	39	65.0%
Very High	7	11.7%
Total	60	100.0%

Data Source: Field Data 2026

The results show that 65.0% of respondents rated AI adoption as high, while 11.7% rated it as very high. Only 23.3% rated adoption as moderate. Therefore, 76.7% of respondents rated the overall level of AI adoption as either high or very high. These findings reinforce the descriptive mean results and demonstrate that AI and automation technologies had achieved a substantial level of adoption within accounting and financial reporting processes among the selected firms.

Financial Reporting Accuracy among Selected Firms

Financial Reporting Accuracy, the dependent variable, was measured using five dimensions: Reduction in Financial Reporting Errors, Accuracy of Financial Reconciliations, Detection of Anomalies and Misstatements, Reliability and Consistency of Financial Information, and Accuracy of Financial Statements.

Table 9: Descriptive Statistics for Financial Reporting Accuracy

Financial Reporting Accuracy Dimension	Mean	Std. Deviation	Interpretation
Reduction in Financial Reporting Errors	3.95	0.70	High
Accuracy of Financial Reconciliations	3.88	0.67	High
Detection of Anomalies and Misstatements	3.85	0.71	High
Reliability and Consistency of Financial Information	3.82	0.70	High
Accuracy of Financial Statements	3.93	0.71	High
Overall Financial Reporting Accuracy	3.89	0.49	High

Data Source: Field Data 2026

The results indicate that financial reporting accuracy was generally rated highly across all five dimensions. Reduction in financial reporting errors recorded the highest mean of 3.95, followed by accuracy of financial statements at 3.93, accuracy of financial reconciliations at 3.88, detection of anomalies and misstatements at 3.85, and reliability and consistency of financial information at 3.82. Overall, the composite mean for financial reporting accuracy was approximately 3.89, demonstrating a generally high level of financial reporting accuracy among the selected firms.

Table 10: Respondents' Overall Rating of Financial Reporting Accuracy

Rating	Frequency	Percentage
Moderate	8	13.3%
High	50	83.3%
Very High	2	3.3%
Total	60	100.0%

Data Source: Field Data 2026

The results show that 83.3% of respondents rated the accuracy of financial reporting as high and 3.3% rated it as very high. Only 13.3% rated it as moderate. Therefore, 86.6% of respondents rated financial reporting accuracy as high or very high.

4.4 Objective Two: To Determine the Relationship Between Artificial Intelligence Adoption and Financial Reporting Accuracy

The second objective sought to determine whether there was a statistically significant relationship between artificial intelligence adoption and financial reporting accuracy. Pearson Product-Moment Correlation analysis was conducted using the composite measure of AI adoption and the composite measure of financial reporting accuracy. H_0: There is no statistically significant relationship between artificial intelligence adoption and financial reporting accuracy among selected firms. H_1: There is a statistically significant relationship between artificial intelligence adoption and financial reporting accuracy among selected firms.

Table 11: Pearson Correlation Between Overall AI Adoption and Financial Reporting Accuracy

Variables	AI Adoption	Financial Reporting Accuracy
AI Adoption – Pearson Correlation	1	0.700
Sig. (2-tailed)	–	<0.001
N	60	60
Financial Reporting Accuracy – Pearson Correlation	0.700	1
Sig. (2-tailed)	<0.001	–
N	60	60

Data Source: Field Data 2026

The analysis produced a Pearson correlation coefficient of $r = 0.700$, $p < 0.001$. This indicates a strong, positive and statistically significant relationship between artificial intelligence adoption and financial reporting accuracy. The positive coefficient means that higher levels of AI adoption were associated with higher levels of financial reporting accuracy. Since the p-value was below 0.05, the null hypothesis was rejected.

Relationship Between Individual AI Adoption Dimensions and Financial Reporting Accuracy

Table 12: Correlation of AI Adoption Dimensions with Financial Reporting Accuracy

AI Adoption Dimension	Pearson r	p-value	Interpretation
Machine Learning	0.657	<0.001	Strong positive, significant
Robotic Process Automation	0.493	<0.001	Moderate positive, significant
Natural Language Processing	0.670	<0.001	Strong positive, significant
Automated Financial Data Processing	0.464	<0.001	Moderate positive, significant
Automated Reconciliation and Anomaly Detection	0.222	0.089	Weak positive, not significant

Data Source: Field Data 2026

The findings indicate that Natural Language Processing had the strongest bivariate relationship with financial reporting accuracy ($r = 0.670$, $p < 0.001$), followed closely by Machine Learning ($r = 0.657$, $p < 0.001$). Robotic Process Automation and Automated Financial Data Processing also had statistically significant positive relationships. Automated Reconciliation and Anomaly Detection recorded a weak positive relationship, but this relationship was not statistically significant at the 5% level.

4.5 Objective Three: To Examine the Effect of Artificial Intelligence Adoption on Financial Reporting Accuracy

The third objective sought to examine the effect of artificial intelligence adoption on financial reporting accuracy. Regression analysis was conducted to determine the extent to which variations in AI adoption explained variations in financial reporting accuracy. The regression model was expressed as: $FRA = \beta_0 + \beta_1(AIA) + \varepsilon$, where FRA = Financial Reporting Accuracy, AIA = Artificial Intelligence Adoption, β_0 = Constant, β_1 = Regression coefficient, and ε = Error term.

Overall Regression Model

Table 13: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.700	0.491	0.482	0.353

Data Source: Field Data 2026

The regression model produced an R value of 0.700, indicating a strong positive association between AI adoption and financial reporting accuracy. The R Square value was 0.491, meaning that approximately 49.1% of the variation in financial reporting accuracy was explained by variation in artificial intelligence adoption. The remaining 50.9% may be attributed to other factors not included in the model.

Analysis of Variance

Table 14: ANOVA for the Regression Model

Model	df	F	Sig.
Regression	1	55.862	<0.001
Residual	58		
Total	59		

Data Source: Field Data 2026

The ANOVA results show that the regression model was statistically significant, $F(1,58) = 55.862$, $p < 0.001$. This indicates that artificial intelligence adoption significantly predicted financial reporting accuracy.

Regression Coefficients

Table 15: Regression Coefficients for Overall AI Adoption

Variable	B	Std. Error	Standardised Beta	t	Sig.
Constant	1.072	0.379	–	2.825	0.006
Artificial Intelligence Adoption	0.721	0.096	0.700	7.474	<0.001

Data Source: Field Data 2026

The regression coefficient for artificial intelligence adoption was positive and statistically significant ($B = 0.721$, $\beta = 0.700$, $t = 7.474$, $p < 0.001$). The estimated regression equation was: Financial Reporting Accuracy = 1.072 + 0.721(Artificial Intelligence Adoption). This means that a one-unit increase in the composite level of artificial intelligence adoption was associated with an estimated 0.721-unit increase in financial reporting accuracy. The null hypothesis that AI adoption had no significant effect on financial reporting accuracy was therefore rejected.

4.6 Multiple Regression Analysis of AI Adoption Dimensions

To obtain a more detailed understanding of the contribution of the individual AI adoption dimensions, a multiple regression analysis was conducted using the five dimensions as predictors of financial reporting accuracy. The model was specified as: $FRA = \beta_0 + \beta_1 ML + \beta_2 RPA + \beta_3 NLP + \beta_4 AFDP + \beta_5 ARAD + \varepsilon$.

Multiple Regression Model Summary

Table 16: Multiple Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error
1	0.764	0.584	0.545	0.326

Data Source: Field Data 2026

The multiple regression model produced an R Square of 0.584, indicating that the five AI adoption dimensions collectively explained approximately 58.4% of the variation in financial reporting accuracy. The adjusted R Square was 0.545.

ANOVA for the Multiple Regression Model

Table 17: ANOVA Results

Model	df	F	Sig.
Regression	5	15.160	<0.001
Residual	54		

Total	59		

Data Source: Field Data 2026

The overall multiple regression model was statistically significant, $F(5,54) = 15.160$, $p < 0.001$. This indicates that the five dimensions of artificial intelligence adoption, when considered collectively, significantly predicted financial reporting accuracy.

Multiple Regression Coefficients

Table 18: Effect of AI Adoption Dimensions on Financial Reporting Accuracy

Predictor	B	Std. Error	t	Sig.
Constant	1.210	0.391	3.096	0.003
Machine Learning	0.203	0.124	1.640	0.107
Robotic Process Automation	0.159	0.088	1.808	0.076
Natural Language Processing	0.268	0.073	3.697	0.001
Automated Financial Data Processing	0.099	0.071	1.393	0.169
Automated Reconciliation and Anomaly Detection	-0.043	0.067	-0.634	0.529

Data Source: Field Data 2026

The multiple regression results show that Natural Language Processing emerged as the statistically significant independent predictor of financial reporting accuracy when all five AI adoption dimensions were entered simultaneously into the regression model ($B = 0.268$, $t = 3.697$, $p = 0.001$). Machine Learning, Robotic Process Automation and Automated Financial Data Processing recorded positive coefficients but did not reach statistical significance at the 5% level after controlling for the other dimensions. Automated Reconciliation and Anomaly Detection recorded a small negative coefficient in the multivariate model, but this was not statistically significant. The negative coefficient should not be interpreted as evidence that the technology reduces financial reporting accuracy; rather, it may reflect overlap among predictors when their unique contributions are estimated simultaneously.

4.7 Direct Assessment of the Influence of AI on Financial Reporting Accuracy

The questionnaire further assessed respondents' direct experiences regarding how AI and intelligent automation influenced financial reporting processes. The items examined whether AI contributed to reduced human errors, improved financial data processing, more accurate reconciliations, improved anomaly detection, increased reliability and consistency, improved financial statement accuracy and stronger internal financial controls. The responses generally showed positive perceptions regarding the contribution of AI to financial reporting accuracy. Respondents largely indicated that AI and automation improved the processing of financial information, reduced opportunities for human error and strengthened the ability of organisations to identify unusual transactions and reporting inconsistencies. The findings support the statistical results showing a significant positive relationship between AI adoption and financial reporting accuracy.

4.8 Challenges Affecting Artificial Intelligence Adoption

Table 19: Main Challenges Affecting AI Adoption

Challenge	Frequency	Percentage
High implementation costs	14	23.3%
Cybersecurity and data privacy concerns	14	23.3%
Inadequate technological infrastructure	12	20.0%
Limited staff skills and training	9	15.0%
Resistance to change	6	10.0%
Poor data quality and system integration	5	8.3%
Total	60	100.0%

Data Source: Field Data 2026

The two most frequently reported challenges were high implementation costs and cybersecurity and data privacy concerns, each identified by 23.3% of respondents. These were followed by inadequate technological infrastructure at 20.0%, limited staff skills and training at 15.0%, resistance to change at 10.0%, and poor data quality and system integration at 8.3%. The findings demonstrate that although AI adoption was generally high, firms continued to face financial, technological, human-resource and governance-related barriers.

4.9 Measures for Improving the Effective Use of AI in Financial Reporting

Table 20: Measures for Improving AI Adoption

Proposed Measure	Frequency	Percentage
Introduce clear AI governance policies and continuous human review	15	25.0%
Invest in modern technological infrastructure	11	18.3%
Increase management support and change-management initiatives	10	16.7%
Strengthen cybersecurity and data-governance controls	10	16.7%
Improve data quality and system integration	8	13.3%
Provide regular AI and digital-skills training	6	10.0%
Total	60	100.0%

Data Source: Field Data 2026

The most frequently recommended measure was the introduction of clear AI governance policies and continuous human review, identified by 25.0% of respondents. Investment in modern technological infrastructure was identified by 18.3%, while management support and change-management initiatives, as well as stronger cybersecurity and data-governance controls, were each identified by 16.7%. The findings suggest that successful AI adoption requires a comprehensive organisational approach involving technology investment, employee competence, data governance, cybersecurity, management commitment and continued human oversight.

4.10 Summary of Findings by Research Objective

Table 21: Summary of Major Findings

Research Objective	Major Finding
To assess the level of AI adoption in financial reporting	AI adoption was generally high, with an overall mean of approximately 3.90. Automated Financial Data Processing recorded the highest mean (3.97), followed by Robotic Process Automation (3.94), Machine Learning (3.93), Automated Reconciliation and Anomaly Detection (3.87), and Natural Language Processing (3.82).
To determine the relationship between AI adoption and financial reporting accuracy	AI adoption had a strong, positive and statistically significant relationship with financial reporting accuracy ($r = 0.700$, $p < 0.001$).
To examine the effect of AI adoption on financial reporting accuracy	Overall AI adoption significantly predicted financial reporting accuracy ($R^2 = 0.491$, $F = 55.862$, $p < 0.001$), explaining approximately 49.1% of the variation in financial reporting accuracy.
Additional multiple regression finding	The five AI dimensions collectively explained 58.4% of the variation in financial reporting accuracy ($R^2 = 0.584$, $p < 0.001$), with Natural Language Processing emerging as the statistically significant unique predictor in the combined model ($B = 0.268$, $p = 0.001$).

Data Source: Field Data 2026

4.11 Discussion of Findings

This chapter discusses the findings of the study on The Influence of Artificial Intelligence Adoption on Financial Reporting Accuracy among Selected Firms in Livingstone, Zambia. The discussion is organised according to the three research objectives. The findings are interpreted in relation to the study variables and existing empirical and theoretical literature on artificial intelligence adoption and financial reporting. The study conceptualised Artificial Intelligence Adoption as the independent variable, measured through Machine Learning, Robotic Process Automation, Natural Language Processing, Automated Financial Data Processing, and Automated Reconciliation and Anomaly Detection. Financial Reporting Accuracy was the dependent variable, measured through Reduction in Financial Reporting Errors, Accuracy of Financial Reconciliations, Detection of Anomalies and Misstatements, Reliability and Consistency of Financial Information, and Accuracy of Financial Statements. The discussion focuses on the meaning and implications of the descriptive, correlation and regression findings and explains how the adoption of AI technologies may contribute to the quality and accuracy of financial reporting.

Discussion of Findings in Relation to Objective One: Level of Artificial Intelligence Adoption in Financial Reporting among Selected Firms

The first objective of the study was to assess the level of artificial intelligence adoption in financial reporting among selected firms. The findings revealed that the overall level of AI adoption was relatively high, with a composite mean of approximately 3.90 out of 5. Furthermore, 65.0% of respondents rated AI adoption as high, while 11.7% rated it as very high. Collectively, 76.7% of respondents therefore perceived AI adoption within their organisations as either high or very high.

These findings suggest that the selected firms had increasingly incorporated AI-related technologies and automation into their accounting and financial reporting processes. The findings further demonstrate that AI adoption was not limited to a single technological application but extended across Machine Learning, Robotic Process Automation, Natural Language Processing, Automated Financial Data Processing, and Automated Reconciliation and Anomaly Detection. The relatively high adoption of these technologies may be attributed to the growing need for organisations to process large volumes of financial information efficiently, reduce dependence on manual accounting procedures, improve internal controls, and produce timely and reliable financial information.

Machine Learning

The findings revealed a relatively high level of Machine Learning adoption, with an overall mean of approximately 3.93. This indicates that selected firms were increasingly using or benefiting from intelligent analytical capabilities capable of identifying patterns, trends and unusual transactions within financial information. Machine Learning has considerable relevance to financial reporting because financial systems continuously generate large volumes of transactional data. Traditional manual approaches may make it difficult for accounting professionals to identify every unusual transaction or reporting inconsistency. Machine Learning algorithms can analyse historical and current financial data and identify patterns that may require further investigation. The findings are consistent with the broader literature suggesting that AI and machine learning technologies can enhance accounting processes by improving data analysis, risk identification and anomaly detection. Kokina and Davenport (2017) observed that artificial intelligence technologies were increasingly transforming accounting and auditing by automating analytical tasks and supporting professional decision-making. Similarly, Sutton, Holt and Arnold (2016) argued that artificial intelligence has significant potential to transform accounting information systems through intelligent analysis and automation. The high level of Machine Learning adoption observed in the present study therefore suggests that selected firms were gradually moving beyond conventional computerised accounting systems towards more intelligent and data-driven financial reporting processes. However, Machine Learning should complement rather than replace professional judgement, because accounting professionals remain responsible for interpreting outputs, assessing their significance and ensuring compliance with applicable accounting standards.

Robotic Process Automation

Robotic Process Automation recorded an overall mean of approximately 3.94, indicating a high level of adoption among the selected firms. This suggests that organisations were increasingly automating repetitive and rule-based accounting activities such as transaction processing, data entry, invoice processing, account matching and report preparation. The finding is significant because accounting and financial reporting traditionally involve numerous repetitive processes that can consume substantial employee time and create opportunities for human error. Robotic Process Automation can perform standardised tasks consistently and rapidly, potentially reducing manual workload and allowing accounting professionals to concentrate on analytical and strategic responsibilities. This finding is consistent with Kokina and Blanchette (2019), who found that Robotic Process Automation was increasingly being adopted within accounting functions to automate repetitive processes and improve operational efficiency. By reducing manual intervention in routine financial processes, organisations may improve consistency and reliability. Nevertheless, effective RPA implementation requires clearly defined accounting processes and appropriate internal controls. Automating a poorly designed process may reproduce existing weaknesses more rapidly, making continuous review and human oversight essential.

Natural Language Processing

Natural Language Processing recorded an overall mean of approximately 3.82. Although this represented the lowest mean among the five AI adoption dimensions, the result still indicated a relatively high level of adoption. Natural Language Processing enables computer systems to analyse, interpret and process human language contained in documents and other textual information. Within accounting and financial reporting, NLP may assist in analysing invoices, contracts, financial disclosures, audit documentation, management reports and other unstructured information. The relatively lower adoption of NLP compared with the other AI dimensions may indicate that this technology remains less established within some of the selected firms. Automated financial data processing and robotic automation may be easier to integrate into existing accounting systems because they address clearly defined transactional processes, while NLP may require more specialised systems and expertise. Despite this, NLP has considerable potential for improving financial reporting by extracting relevant information from large volumes of documents, identifying inconsistencies and supporting the preparation and review of narrative financial disclosures.

Automated Financial Data Processing

Automated Financial Data Processing recorded the highest mean among the AI adoption dimensions, at approximately 3.97. This suggests that automated processing of financial information was the most extensively adopted technological application among the selected firms. This finding is understandable because automated data processing represents one of the most direct applications of digital technology within accounting. Organisations routinely process large volumes of transactions relating to sales, purchases, payroll, banking, inventory, receivables and payables. Automating these processes can substantially reduce manual data entry and improve processing efficiency. The high adoption of automated financial data processing suggests that firms were increasingly relying on integrated accounting systems and other digital technologies to capture, process and organise financial information. This can reduce risks of transcription errors, duplication, omission and incorrect classification. However, automation does not automatically guarantee accurate information. Incorrect source data, poorly configured systems or inappropriate processing rules may still produce inaccurate outputs. Organisations must therefore combine automation with strong data-validation controls and continuous system monitoring.

Automated Reconciliation and Anomaly Detection

Automated Reconciliation and Anomaly Detection recorded a mean of approximately 3.87, indicating relatively high adoption. The finding suggests that selected firms were increasingly using automated systems to compare financial records, identify discrepancies and detect unusual transactions. Reconciliation represents a critical financial control because differences between accounting records and supporting information may indicate errors, omissions, unauthorised transactions or other irregularities. Automated reconciliation systems can compare transactions across multiple datasets and identify unmatched or unusual items for further investigation. The overall findings under the first objective therefore demonstrate that AI and automation had achieved a relatively high level of adoption among the selected firms. However, differences across the individual technologies indicate that firms were at different stages of technological maturity, with Automated Financial Data Processing being the most widely adopted dimension and Natural Language Processing recording the lowest mean.

Discussion of Findings in Relation to Objective Two: Relationship Between Artificial Intelligence Adoption and Financial Reporting Accuracy

The second objective sought to determine the relationship between artificial intelligence adoption and financial reporting accuracy among selected firms. Pearson Product-Moment Correlation analysis revealed a strong, positive and statistically significant relationship between overall AI adoption and financial reporting accuracy ($r = 0.700$, $p < 0.001$). This represents one of the central findings of the study. The positive correlation indicates that higher levels of AI adoption were associated with higher levels of financial reporting accuracy. Firms that reported greater utilisation of AI and automation technologies also tended to report better financial reporting outcomes. The finding provides empirical support for the proposition that technological advancement in accounting can contribute to improved financial information quality. AI-enabled systems can process large volumes of information consistently, identify potential errors, automate reconciliations and support the detection of unusual financial transactions. The finding is broadly consistent with Sutton et al. (2016), who argued that artificial intelligence has the potential to transform accounting through intelligent processing and analysis of financial information, and with Kokina and Davenport (2017), who noted that automation and AI technologies increasingly support accounting and auditing functions by improving analytical capabilities and reducing reliance on manual processes. The relationship may also be understood through the dimensions of financial reporting accuracy. Reduction in Financial Reporting Errors recorded a mean of 3.95; Accuracy of Financial Reconciliations recorded 3.88; Detection of Anomalies and Misstatements recorded 3.85; Reliability and Consistency of Financial Information recorded 3.82; and Accuracy of Financial Statements recorded 3.93. These results suggest that AI may contribute to financial reporting accuracy through several interconnected mechanisms.

Relationship Between Machine Learning and Financial Reporting Accuracy

Machine Learning recorded a strong positive and statistically significant correlation with financial reporting accuracy ($r = 0.657$, $p < 0.001$). This indicates that increased use of Machine Learning-related capabilities was associated with higher levels of financial reporting accuracy. Machine Learning can contribute to financial reporting by identifying patterns and exceptions that may not be easily detected through conventional manual procedures. Intelligent systems can analyse historical financial transactions and flag deviations for investigation by accounting or audit professionals. The strong relationship found in this study therefore suggests that analytical intelligence can strengthen financial reporting controls and support more accurate financial information.

Relationship Between Robotic Process Automation and Financial Reporting Accuracy

Robotic Process Automation recorded a moderate positive and statistically significant relationship with financial reporting accuracy ($r = 0.493$, $p < 0.001$). This indicates that higher levels of RPA adoption were associated with improved financial reporting accuracy. RPA may contribute to accuracy by automating repetitive tasks that would otherwise be performed manually. Manual repetition can create risks arising from fatigue, incorrect data entry and inconsistent application of procedures. Automated processes can execute predefined tasks consistently, thereby reducing some forms of operational error. This finding supports the argument by Kokina and Blanchette (2019) that RPA can transform accounting processes through automation of routine tasks.

Relationship Between Natural Language Processing and Financial Reporting Accuracy

Natural Language Processing recorded the strongest bivariate correlation with financial reporting accuracy among the individual AI dimensions ($r = 0.670$, $p < 0.001$). This finding is particularly important because NLP recorded the lowest descriptive adoption mean among the five dimensions but demonstrated the strongest individual correlation with financial reporting accuracy. The result suggests that where NLP-related capabilities were utilised effectively, they were strongly associated with improved financial reporting outcomes. NLP can analyse unstructured financial information contained in documents, contracts, invoices, reports and disclosures, helping organisations identify relevant information and detect inconsistencies. The finding suggests that firms may obtain considerable financial reporting benefits from expanding the effective use of NLP technologies.

Relationship Between Automated Financial Data Processing and Financial Reporting Accuracy

Automated Financial Data Processing recorded a moderate positive and statistically significant correlation with financial reporting accuracy ($r = 0.464$, $p < 0.001$). This demonstrates that greater automation of financial data processing was associated with higher levels of financial reporting accuracy. Automated financial data processing can reduce manual intervention in transaction capture, classification and processing, thereby reducing transcription errors, improving processing consistency and accelerating the availability of financial information. However, the moderate strength of the relationship suggests that automation alone may not be sufficient to guarantee accurate reporting. Effective internal controls, competent accounting personnel, high-quality source data and appropriate system configuration remain necessary.

Relationship Between Automated Reconciliation and Anomaly Detection and Financial Reporting Accuracy

Automated Reconciliation and Anomaly Detection recorded a weak positive relationship with financial reporting accuracy ($r = 0.222$), which was not statistically significant at the 5% level ($p = 0.089$). This finding does not necessarily mean that automated reconciliation and anomaly detection are unimportant. Rather, the evidence from the sample was insufficient to establish a statistically significant independent bivariate relationship at the conventional significance level. Some organisations may have adopted automated reconciliation tools without fully integrating them into their financial reporting processes. Alternatively, automated systems may identify anomalies, but the benefits depend on whether employees investigate and resolve the exceptions identified. The effectiveness of such systems may also depend on data quality, system configuration, employee competence and organisational follow-up procedures.

Discussion of Findings in Relation to Objective Three: Effect of Artificial Intelligence Adoption on Financial Reporting Accuracy

The third objective sought to examine the effect of artificial intelligence adoption on financial reporting accuracy among selected firms. The simple regression analysis revealed an R value of 0.700 and an R Square of 0.491. This means that artificial intelligence adoption explained approximately 49.1% of the variation in financial reporting accuracy. The regression model was statistically significant, with $F(1,58) = 55.862$, $p < 0.001$. Furthermore, AI adoption recorded a positive and statistically significant regression coefficient of $B = 0.721$, $\beta = 0.700$, $t = 7.474$, $p < 0.001$. These findings provide strong evidence that artificial intelligence adoption had a significant positive effect on financial reporting accuracy among the selected firms. The coefficient of $B = 0.721$ indicates that a one-unit increase in the overall level of AI adoption was associated with an estimated 0.721-unit increase in financial reporting accuracy. The explanatory power of 49.1% is substantial because financial reporting accuracy is influenced by numerous organisational factors, including internal controls, accounting staff competence, corporate governance, regulatory compliance, management oversight, organisational culture, data quality and auditing. AI may influence financial reporting accuracy through several mechanisms. Machine Learning may improve analytical review and pattern recognition; Robotic Process Automation may reduce manual processing errors; Natural Language Processing may support the analysis of textual financial information; Automated Financial Data Processing may improve transaction processing; and Automated Reconciliation and Anomaly Detection may strengthen financial controls.

Discussion of Multiple Regression Findings

The multiple regression analysis examined the combined effect of the five AI adoption dimensions on financial reporting accuracy. The model produced $R = 0.764$, $R^2 = 0.584$ and Adjusted $R^2 = 0.545$. This indicates that the five dimensions collectively explained approximately 58.4% of the variation in financial reporting accuracy. The overall regression model was statistically significant, with $F(5,54) = 15.160$, $p < 0.001$. This finding reinforces the conclusion that AI adoption is an important determinant of financial reporting accuracy. However, the individual regression coefficients revealed important differences in the unique contribution of each technology when all five dimensions were considered simultaneously.

Effect of Machine Learning

Machine Learning recorded a positive regression coefficient of $B = 0.203$, but its unique effect was not statistically significant at the 5% level ($p = 0.107$). This result should be interpreted alongside the strong and statistically significant bivariate correlation between Machine Learning and financial reporting accuracy. The difference suggests that although Machine Learning was strongly associated with financial reporting accuracy on its own, part of this relationship overlapped with the contribution of other AI dimensions. Consequently, the non-significant coefficient in the multiple regression model does not imply that Machine Learning is unimportant. Rather, its unique contribution became less distinct after controlling for the other AI technologies.

Effect of Robotic Process Automation

Robotic Process Automation recorded a positive coefficient of $B = 0.159$, with $p = 0.076$. Although the coefficient was positive, it did not meet the conventional 5% significance threshold when the other AI dimensions were controlled for. This finding may suggest that the contribution of RPA to financial reporting accuracy occurs partly through its interaction with other technologies. RPA primarily automates predefined tasks and may therefore depend on other systems for intelligent analysis and decision support.

Effect of Natural Language Processing

Natural Language Processing emerged as the statistically significant unique predictor of financial reporting accuracy in the multiple regression model, recording $B = 0.268$, $t = 3.697$ and $p = 0.001$. This finding is consistent with the correlation analysis, where NLP also recorded the strongest bivariate relationship with financial reporting accuracy. The result suggests that, after controlling for Machine Learning, RPA, Automated Financial Data Processing and Automated Reconciliation and Anomaly Detection, NLP retained a statistically significant unique contribution to financial reporting accuracy. This may reflect the importance of unstructured information in contemporary financial reporting. Financial reporting depends not only on numerical transactions but also on contracts, invoices, policies, explanatory notes, disclosures and other textual information.

Effect of Automated Financial Data Processing

Automated Financial Data Processing recorded a positive coefficient of B = 0.099, although the unique effect was not statistically significant ($p = 0.169$) after controlling for the other AI dimensions. This finding is noteworthy because Automated Financial Data Processing recorded the highest descriptive adoption mean. High adoption, however, does not necessarily imply that a variable will have the strongest unique predictive effect. Automated data processing may have become a relatively standard feature across many firms. Consequently, differences in financial reporting accuracy may increasingly depend on how organisations use more advanced analytical capabilities rather than simply whether basic financial processing is automated.

Effect of Automated Reconciliation and Anomaly Detection

Automated Reconciliation and Anomaly Detection recorded a small negative coefficient of B = -0.043, which was statistically non-significant ($p = 0.529$) in the multiple regression model. This result should not be interpreted as evidence that automated reconciliation reduces financial reporting accuracy. Its bivariate relationship with financial reporting accuracy was positive, although weak and statistically non-significant. The change in coefficient direction after controlling for the other AI dimensions may result from shared variance among the predictors. The practical effectiveness of automated reconciliation also depends on how organisations respond to identified discrepancies.

AI Adoption and the Dimensions of Financial Reporting Accuracy

The findings demonstrated that the overall level of financial reporting accuracy was high, with a composite mean of approximately 3.89. This result can be considered in relation to the relatively high level of AI adoption observed among the selected firms. The highest financial reporting accuracy dimension was Reduction in Financial Reporting Errors, with a mean of 3.95. Accuracy of Financial Statements recorded a mean of 3.93, Accuracy of Financial Reconciliations 3.88, Detection of Anomalies and Misstatements 3.85, and Reliability and Consistency of Financial Information 3.82. These findings indicate that AI adoption can influence financial reporting accuracy through multiple interconnected pathways rather than through a single technological mechanism.

Challenges Affecting AI Adoption and Their Implications for Financial Reporting

Despite the generally high level of AI adoption, the findings identified several challenges that could limit the effective use of AI in financial reporting. High implementation costs and cybersecurity and data privacy concerns were the most frequently reported challenges, each identified by 23.3% of respondents. Inadequate technological infrastructure was identified by 20.0%, limited staff skills and training by 15.0%, resistance to change by 10.0%, and poor data quality and system integration by 8.3%. High implementation costs may restrict organisations from acquiring advanced AI systems, maintaining technological infrastructure and employing appropriately skilled personnel. Cybersecurity and data privacy concerns are equally important because AI systems depend heavily on access to organisational data. Inadequate technological infrastructure may prevent organisations from obtaining the full benefits of AI, while limited staff skills and training may reduce the effectiveness of implementation. Resistance to change may arise where employees perceive AI as a threat, and poor data quality may undermine the reliability of AI-generated outputs. These challenges demonstrate that technology alone cannot guarantee improvements in financial reporting accuracy. Successful AI adoption requires complementary investment in people, governance, infrastructure, cybersecurity, data quality and organisational change.

Measures for Strengthening the Contribution of AI to Financial Reporting Accuracy

The findings showed that respondents considered clear AI governance policies and continuous human review the most important measure for improving AI adoption, identified by 25.0% of respondents. This finding emphasises the importance of maintaining human accountability within AI-enabled financial reporting environments. Although AI can automate processes and support decision-making, responsibility for financial reporting ultimately remains with organisational management and accounting professionals. Investment in modern technological infrastructure was identified by 18.3% of respondents. Management support and change-management initiatives and stronger cybersecurity and data-governance controls were each identified by 16.7%. Improved data quality and system integration were identified by 13.3%, while regular AI and digital-skills training was identified by 10.0%. These findings demonstrate that effective AI adoption should be approached as an organisational transformation process rather than merely as the acquisition of new software. Technology must be supported by appropriate governance, skilled employees, reliable data, strong cybersecurity, management commitment and continuous human oversight.

Overall Discussion of Findings

The overall findings demonstrate that artificial intelligence adoption had a meaningful and statistically significant association with financial reporting accuracy among the selected firms. The study established a relatively high level of AI adoption, with an overall mean of approximately 3.90. Automated Financial Data Processing recorded the highest level of adoption, followed by Robotic Process Automation, Machine Learning, Automated Reconciliation and Anomaly Detection, and Natural Language Processing. Financial reporting accuracy was similarly rated highly, with an overall mean of approximately 3.89. The correlation analysis established a strong positive relationship between AI adoption and financial reporting accuracy ($r = 0.700$, $p < 0.001$). The simple regression model further established that AI adoption explained approximately 49.1% of the variation in financial reporting accuracy, with a statistically significant positive effect ($B = 0.721$, $\beta = 0.700$, $p < 0.001$). When the five AI dimensions were considered simultaneously, they collectively explained approximately 58.4% of the variation in financial reporting accuracy. Natural Language Processing emerged as the statistically significant unique predictor in the multiple regression model. These findings demonstrate that the relationship between AI and financial reporting accuracy is multidimensional. Machine Learning supports pattern recognition and intelligent analysis; RPA automates repetitive processes; NLP processes textual and unstructured information; Automated Financial Data Processing improves transaction processing; and Automated Reconciliation and Anomaly Detection supports financial controls and exception identification. The findings further suggest that the benefits of AI depend on how effectively organisations integrate these technologies with human expertise, internal controls and governance structures. AI should therefore be regarded as an enabling technology rather than a complete substitute for professional accounting judgement. Overall, the findings support the conclusion that greater adoption and effective utilisation of artificial intelligence can contribute to improved financial reporting accuracy through reduced reporting errors, improved financial reconciliations, enhanced detection of anomalies and misstatements, increased reliability and consistency of financial information, and improved accuracy of financial statements.

5 Summary, Conclusion and Recommendations

This chapter presents the summary of the major findings, conclusion and recommendations of the study on the influence of Artificial Intelligence adoption on financial reporting accuracy among selected firms in Livingstone, Zambia.

5.1 Summary of Findings

The study established that the selected firms had a relatively high level of Artificial Intelligence adoption, with an overall mean of 3.90. AI adoption was reflected through the use of Machine Learning, Robotic Process Automation, Natural Language Processing, Automated Financial Data Processing, and Automated Reconciliation and Anomaly Detection. The study further established a strong, positive and statistically significant relationship between AI adoption and financial reporting accuracy ($r = 0.700$, $p < 0.001$). This indicated that increased adoption of AI was associated with improved financial reporting accuracy. Regression analysis showed that AI adoption explained approximately 49.1% of the variation in financial reporting accuracy. The five AI dimensions collectively explained 58.4%, with Natural Language Processing emerging as a statistically significant unique predictor of financial reporting accuracy.

5.2 Conclusion

The study concludes that Artificial Intelligence adoption has a positive and significant influence on financial reporting accuracy among selected firms in Livingstone. The adoption of AI technologies contributes to reducing financial reporting errors, improving financial reconciliations, detecting anomalies and misstatements, enhancing the reliability and consistency of financial information, and improving the accuracy of financial statements. Therefore, effective adoption and utilisation of AI can significantly strengthen the quality and accuracy of financial reporting. However, its effectiveness depends on appropriate technological infrastructure, skilled personnel, quality data, cybersecurity controls and continued human oversight.

5.3 Recommendations

Based on the findings and conclusions of the study, the following recommendations are made:

Increased Investment in Artificial Intelligence Technologies

Firms should increase investment in Artificial Intelligence technologies such as Machine Learning, Robotic Process Automation, Natural Language Processing, Automated Financial Data Processing, and Automated Reconciliation and Anomaly Detection. These technologies should be integrated into accounting and financial reporting processes to reduce manual errors, improve financial reconciliations, strengthen anomaly detection and enhance the accuracy and reliability of financial statements.

Continuous Training and Capacity Building

Firms should provide regular training and capacity-building programmes for accountants, auditors, finance managers and other employees involved in financial reporting. Training should focus on the effective use of AI-enabled accounting systems, data analytics and interpretation of AI-generated financial information. This would ensure that employees have the necessary skills to use emerging technologies effectively while maintaining appropriate professional judgement.

Strengthening Cybersecurity and Data Governance

Organisations should strengthen cybersecurity and data-governance frameworks to protect sensitive financial information processed through AI-enabled systems. Appropriate access controls, data security measures, system monitoring and regular security assessments should be implemented. Firms should also ensure that financial data used by AI systems are accurate, complete and reliable because the quality of AI-generated outputs largely depends on the quality of the underlying data.

Improvement of Technological Infrastructure and System Integration

Firms should invest in modern technological infrastructure and ensure effective integration of AI applications with existing accounting and financial information systems. Proper system integration would facilitate efficient exchange of financial information, minimise duplication and inconsistencies, and improve automated financial data processing. This would ultimately enhance the reliability and accuracy of financial reporting.

Establishment of AI Governance and Human Oversight

Firms should establish clear policies and procedures governing the use of AI in accounting and financial reporting. AI-generated financial information should be regularly reviewed and validated by qualified accounting and finance professionals before being used for financial reporting and decision-making. Maintaining human oversight would ensure accountability, support professional judgement and reduce risks arising from excessive reliance on automated systems.

Strengthening the Use of AI for Error and Anomaly Detection

Firms should strengthen the application of Machine Learning and Automated Reconciliation and Anomaly Detection in identifying financial errors, unusual transactions and potential misstatements. Automated alerts should be followed by timely investigation and corrective action by responsible accounting personnel. This would strengthen internal controls and contribute to more accurate financial statements.

Greater Utilisation of Natural Language Processing

Given the significant contribution of Natural Language Processing to financial reporting accuracy, firms should consider expanding its application in analysing contracts, invoices, financial disclosures, audit documents and other text-based financial information. Effective utilisation of NLP could improve information extraction, identification of inconsistencies and the completeness and accuracy of financial reporting.

Strengthening Management Support for AI Adoption

Senior management should provide adequate financial resources, technological support and strategic direction for the adoption of AI in financial reporting. Management should also promote employee acceptance of new technologies through effective change-management programmes. Strong management commitment would facilitate successful implementation and sustainable utilisation of AI technologies within accounting and finance functions.

Declaration of Competing Interests

The Authors declare no competing interests.

Funding

No specific funding for this study came from governmental, private, or nonprofit organisations.

Authors' Contribution Statement

Formulated and designed the study; established the research framework and technique; directed the composition of the initial manuscript draft.

Ethical considerations

The article followed all ethical standards appropriate for this kind of research.

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