

ARTIFICIAL INTELLIGENCE ADOPTION AND FINANCIAL REPORTING QUALITY AMONG ACCOUNTING PROFESSIONALS IN ENUGU STATE

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ABSTRACT

This study examined the adoption of artificial intelligence (AI) and its relationship with the quality of financial reporting among accounting professionals in Enugu State. Organisations in Nigeria are moving from manual and spreadsheet-based accounting to software that can record, reconcile, review and even draft parts of financial reports with limited human input. Yet there is little local evidence on how far this change has gone in Enugu State and whether it has made financial reports more accurate, reliable and timely. The study adopted a descriptive survey research design. The population comprised 420 accountants, auditors and finance officers in 30 organisations drawn from the public sector, banking, audit practice and manufacturing. Using the Taro Yamane formula, a sample of 205 respondents was selected through stratified random sampling, and 196 copies of the questionnaire were returned in usable form. Data were collected with a structured instrument titled Artificial Intelligence and Financial Reporting Quality Questionnaire (AIFRQQ), which returned a Cronbach alpha coefficient of 0.84. Mean scores were used to answer the research questions against a criterion mean of 2.50, while the chi-square test of independence was used to test the hypotheses at the 0.05 level of significance. Findings showed that AI adoption in Enugu State is moderate, with software-based bookkeeping and reconciliation well established but generative AI and predictive analytics still at an early stage. Respondents agreed that AI has improved the accuracy, reliability and timeliness of financial reports, although they did not trust AI output without human review. High cost, skills gaps, erratic power supply and the absence of regulatory guidance were the main barriers. Both hypotheses were rejected, showing significant relationships between AI adoption and the reliability and timeliness of financial reports. The study recommends staff retraining through ICAN and ANAN programmes, guidance from the Financial Reporting Council of Nigeria on AI use in reporting, and investment in alternative power and data security.

Keywords: Artificial Intelligence, Financial Reporting Quality, Accounting Professionals, Automation, Technology Acceptance Model, Enugu State

Introduction

Accounting has always changed with the tools available to it. Artificial intelligence represents a further step in that history, but it differs from earlier tools in one important way. Earlier software carried out instructions; AI systems learn patterns from data and make judgements that once required a trained person (Russell & Norvig, 2021).

Artificial intelligence, in the sense used in this study, covers a family of technologies. These include machine learning, which finds patterns in large sets of data; robotic process automation (RPA), which copies the repetitive keystrokes of a clerk; natural language processing, which reads and writes human language; and, more recently, generative AI tools that can draft text, summarise documents and answer questions. Kokina and Davenport (2017) observed that these tools were already reshaping audit work in large firms, and later studies have shown that their use has spread to bookkeeping, payroll, tax computation, reconciliation and the preparation of financial statements (Zhang, Xiong, Xie, Fan & Gu, 2020).

Financial reporting quality is the degree to which financial statements give users a true and useful picture of an entity's financial position and performance. The Conceptual Framework for Financial Reporting identifies relevance and faithful representation as the two fundamental qualities of useful financial information, supported by comparability, verifiability, timeliness and understandability (International Accounting Standards Board [IASB], 2018). When reports fall short, capital is misallocated and confidence in the reporting system falls (Biddle, Hilary & Verdi, 2009).

In Nigeria, the quality of financial reports has been a recurring concern. The adoption of International Financial Reporting Standards (IFRS) from 2012 and the establishment of the Financial Reporting Council of Nigeria under the Financial Reporting Council of Nigeria Act of 2011 were meant to raise reporting standards. Even so, reporting delays, errors, weak internal controls and cases of earnings manipulation continue to attract regulatory attention. Many practitioners now look to technology as part of the answer. Ekawu (2026), in a survey of 312 accounting and finance professionals across Nigeria, found that AI adoption had a significant positive effect on financial reporting quality, and that the effect worked partly through greater transparency.

Enugu State offers a useful setting for studying this question. Enugu, the state capital, is the administrative and commercial centre of the South-East, with government agencies, banks, audit practices and manufacturers. These organisations handle large volumes of transactions under close regulatory and public oversight and have strong reasons to automate. At the same time, they operate in an environment marked by unstable power supply, high data costs and a shortage of staff trained in data analytics. Whether AI has delivered better reporting under these conditions is an open question.

The present study responds to that question. It examines how far accounting professionals in Enugu State have adopted AI tools, whether they believe those tools have improved the accuracy, reliability and timeliness of the financial reports they prepare or audit, and what stands in the way of wider use.

Statement of the Problem

Financial reports in Nigeria are expected to comply with IFRS, the Companies and Allied Matters Act and the rules of sector regulators. Meeting these requirements demands accurate records, careful reconciliation and timely preparation. In practice, many organisations in Enugu State still depend on manual processes and spreadsheets for significant parts of their reporting cycle. Manual processes are slow and prone to error. Missed accruals, unreconciled balances and late adjustments lead to restatements, qualified opinions and late filing penalties.

AI-enabled accounting tools promise to reduce these problems. Vendors claim that such tools cut the time needed to close the books and catch errors before reports are issued. Several organisations in Enugu State, especially banks and large manufacturing concerns, have

invested in such tools. However, there is little independent evidence from the city on whether these investments have produced better financial reports.

There is also a concern that AI may create new risks to reporting quality. Algorithms can repeat errors at scale, their reasoning is often hard to explain to auditors, and staff may come to trust machine output without checking it (Munoko, Brown-Liburd & Vasarhelyi, 2020). Without local evidence, managers and regulators are left to act on vendor claims. This study therefore sets out to examine AI adoption and financial reporting quality among accounting professionals in Enugu State.

Aim And Objectives of the Study

The aim of this study is to examine the relationship between artificial intelligence adoption and financial reporting quality among accounting professionals in Enugu State. The specific objectives of the study are to:

1. Determine the extent to which AI tools have been adopted in accounting and financial reporting processes in organisations in Enugu State.
2. Examine the effect of AI adoption on the accuracy and reliability of financial reports.
3. Assess the effect of AI adoption on the timeliness of financial reporting.
4. Identify the challenges that hinder the effective adoption of AI in financial reporting in Enugu State.

Research Questions

The following research questions guided the study:

1. To what extent have AI tools been adopted in accounting and financial reporting processes in organisations in Enugu State?
2. What is the effect of AI adoption on the accuracy and reliability of financial reports?
3. What is the effect of AI adoption on the timeliness of financial reporting?
4. What challenges hinder the effective adoption of AI in financial reporting in Enugu State?

Hypotheses

The following null hypotheses were tested at the 0.05 level of significance:

- H₀₁: There is no significant relationship between the level of AI adoption and the accuracy and reliability of financial reports in organisations in Enugu State.
- H₀₂: There is no significant relationship between the level of AI adoption and the timeliness of financial reporting in organisations in Enugu State.

Literature Review

The Concept of Artificial Intelligence in Accounting

Artificial intelligence refers to computer systems that perform tasks which would normally require human intelligence, such as recognising patterns, learning from experience, understanding language and making decisions (Russell & Norvig, 2021). In accounting, the term is used loosely to cover a range of tools with different levels of sophistication. These range from rule-based automation that posts routine entries and matches invoices, to machine learning models that classify transactions and flag suspicious entries, and generative models that can draft disclosure notes.

Cooper, Holderness, Sorensen and Wood (2019) studied the use of robotic process automation in large public accounting firms and found that firms were using it mainly for high-volume, rules-based tasks in tax, advisory and assurance work. Issa, Sun and Vasarhelyi (2016) had earlier argued that AI would first take over the structured parts of audit work and then gradually extend into areas requiring judgement, provided its outputs could be explained and documented.

Moll and Yigitbasioglu (2019) traced how cloud computing, big data, blockchain and AI were changing the daily work of accountants. They noted that routine recording was increasingly automated and that the value of the accountant was shifting towards interpreting

data and advising management. Zhang et al. (2020) reached a similar conclusion about AI and blockchain.

AI in accounting is not without controversy. Frey and Osborne (2017) estimated that accountants and auditors were among the occupations most exposed to computerisation, a finding that has fed anxiety within the profession. Others argue that such estimates overstate the risk because accounting work involves judgement and professional scepticism (Moll & Yigitbasioglu, 2019). What is clear is that the quality of accountants' output now depends partly on the systems they use.

The Concept of Financial Reporting Quality

Financial reporting quality has been defined in several ways. The IASB (2018) Conceptual Framework describes useful financial information as information that is relevant and faithfully represents what it claims to represent. Relevant information can make a difference to users' decisions because it has predictive or confirmatory value. Faithful representation requires that information be complete, neutral and free from error. These fundamental qualities are enhanced by comparability, verifiability, timeliness and understandability.

Researchers have developed different ways of measuring these qualities. Dechow, Ge and Schrand (2010) reviewed a large body of work that uses accounting numbers, such as the persistence of earnings and the size of discretionary accruals, as proxies for reporting quality. For this reason, van Beest, Braam and Boelens (2009) developed an approach that scores reports directly against the qualitative characteristics in the Conceptual Framework. Survey-based studies, including the present one, follow a related approach by asking preparers and auditors to assess the accuracy, reliability and timeliness of the reports they work on.

In this study, financial reporting quality is examined through two dimensions that are closely tied to the production process and that AI is most likely to affect. The first is accuracy and reliability, meaning that figures are free from material error, balances are properly reconciled and reports can be trusted by users. The second is timeliness, meaning that reports are available to decision makers and regulators while the information is still useful. Biddle et al. (2009) showed that higher reporting quality is associated with more efficient investment decisions, which underlines why these dimensions matter beyond compliance.

Artificial Intelligence and the Accuracy of Financial Reports

A central argument for AI in accounting is that it reduces error. Manual posting and reconciliation depend on the attention of staff who may be tired, rushed or poorly supervised. Automated systems apply the same rules every time and can check every transaction rather than a sample. Appelbaum, Kogan and Vasarhelyi (2017) argued that analytics applied to full populations of transactions allow auditors and preparers to detect anomalies that sampling would miss, and that this could improve both the quality of audits and the reliability of the underlying records.

Machine learning tools are also used to detect fraud and unusual entries. Such tools learn what normal activity looks like and flag entries that depart from it, such as payments just below approval limits or revenue booked unusually close to the period end. Kokina and Davenport (2017) reported that large audit firms were using these tools to direct attention to high-risk areas. In the Nigerian context, Ekawu (2026) found a significant positive path from AI adoption to financial reporting quality among accounting and finance professionals, with a standardised coefficient of 0.29.

There are, however, limits to these gains. Brown-Liburd, Issa and Lombardi (2015) warned that the volume of output generated by analytics can overwhelm human reviewers, and that people may either ignore alerts or accept them without proper thought. Zhang, Cho and Vasarhelyi (2022) pointed out that many AI models are difficult to explain, which creates problems for auditors who must understand and document how a figure was produced. An AI

system trained on flawed data can also repeat the same error across thousands of transactions. The effect of AI on accuracy therefore depends on how it is designed, monitored and reviewed.

Artificial Intelligence and the Timeliness of Financial Reporting

Timeliness is one of the enhancing qualitative characteristics of financial information (IASB, 2018). Information that arrives late loses much of its value to investors and managers. In Nigeria, timeliness also has a regulatory dimension, because companies must file audited financial statements with the Financial Reporting Council, the Corporate Affairs Commission and, for listed entities, the Securities and Exchange Commission and the Nigerian Exchange within fixed periods.

AI tools can shorten the reporting cycle in several ways. Automated bank feeds and reconciliation remove days of manual matching at month end, and RPA can prepare consolidation schedules overnight. Cooper et al. (2019) found that accounting firms adopting RPA reported faster completion of routine tasks, which freed staff to focus on review and client service.

Faster reporting is not always better reporting, since a quicker close with less review can let errors through. This study therefore examines timeliness and accuracy separately.

Challenges of Artificial Intelligence Adoption in Accounting

Studies of technology adoption in developing economies point to a common set of barriers. The first is cost. Licences, hardware and implementation support are expensive and are often priced in foreign currency. The second is skills. Damerji and Salimi (2021) found that accounting students' technology readiness shaped their perceptions of AI and their willingness to use it, which suggests that training and exposure matter as much as the technology itself.

The third barrier is infrastructure. AI systems depend on stable power and reliable internet connections, both of which remain uneven in many parts of Nigeria. The fourth is governance and ethics. Munoko et al. (2020) identified concerns about accountability, bias, privacy and transparency when AI is used in auditing, and argued that the profession needed clear guidance on who is responsible when an algorithm makes an error. Lehner, Ittonen, Silvola, Ström and Wührleitner (2022) raised similar concerns about AI-based decision making in accounting and called for normative frameworks to guide its use.

The fifth barrier is human resistance. Staff who believe automation threatens their jobs may resist new tools or use them only superficially, a concern fed by reports such as Frey and Osborne (2017).

Empirical Review

Earlier empirical work has come mainly from large international firms. Kokina and Davenport (2017) found that AI was moving from pilot projects to regular use in document review and risk assessment, while Cooper et al. (2019) reported that robotic process automation improved speed and consistency in tax and assurance work. Damerji and Salimi (2021) showed that perceived ease of use and perceived usefulness shaped the adoption of AI among accounting students, which lends support to the Technology Acceptance Model used in this study.

Ekawu (2026) surveyed 312 accounting and finance professionals in public and private organisations in Nigeria. Using partial least squares structural equation modelling, the study found that AI adoption and big data analytics capability significantly improved financial reporting quality, and that transparency partly mediated these effects. The model explained 64 percent of the variance in financial reporting quality.

These studies show a broad agreement that AI can improve the speed and consistency of accounting work. However, most of the evidence comes from large international firms or from national samples in Nigeria. There is limited evidence from Enugu State and the South-East, where the mix of organisations and the infrastructure conditions differ from Lagos and

Abuja. There is also little work that looks separately at accuracy and timeliness while also recording the barriers practitioners face. This study addresses that gap.

Theoretical Framework

This study is anchored on the Technology Acceptance Model (TAM) developed by Davis (1989). The model explains why people accept or reject a new information technology. It proposes that two beliefs shape a user's intention to use a system. The first is perceived usefulness, which is the degree to which a person believes that using the system will improve their job performance. The second is perceived ease of use, which is the degree to which a person believes that using the system will be free of effort. Perceived ease of use also affects perceived usefulness, because a system that is easy to use is more likely to be seen as helpful. Intention to use then leads to actual use.

TAM has been extended over time. Venkatesh, Morris, Davis and Davis (2003) combined it with seven other adoption models in the Unified Theory of Acceptance and Use of Technology, adding social influence and facilitating conditions such as infrastructure and support. At the level of the organisation, the Technology, Organisation and Environment framework of Tornatzky and Fleischer (1990) explains adoption through the characteristics of the technology, the resources and structure of the firm, and the external environment, including regulation and competition (Oliveira & Martins, 2011).

In the context of this study, TAM explains why accounting professionals in Enugu State adopt AI tools to different degrees. Where accountants believe that AI will reduce errors and save time, and where the tools are easy to use, adoption is likely to be higher. Higher adoption is in turn expected to improve the accuracy, reliability and timeliness of financial reports. Where tools are expensive, difficult to use, poorly supported by infrastructure or not backed by clear guidance, perceived ease of use falls and adoption stalls. The facilitating conditions stressed by Venkatesh et al. (2003) and the environmental factors in the Technology, Organisation and Environment framework help explain the challenges examined under the fourth research question.

TAM is relevant to this research because it links beliefs about technology to actual use, and use to work outcomes. Its focus on individual perception is balanced here by the organisational and environmental factors described above.

Methodology

The study adopted a descriptive survey research design. This design was considered suitable because the study sought to describe the current state of AI adoption and the opinions of accounting professionals on its effect on financial reporting, without manipulating any variable. The study was carried out in Enugu State, with data drawn from organisations in Enugu metropolis, which covers Enugu North, Enugu East and Enugu South Local Government Areas and serves as the main administrative and commercial centre of the state.

The population of the study comprised 420 accounting professionals, including accountants, internal auditors, external auditors and finance officers, working in 30 organisations in Enugu State. The organisations were drawn from four sectors: public sector ministries, departments and agencies (10 organisations), banking (8), audit and accounting practice (7) and manufacturing (5). These sectors were chosen because they handle large volumes of transactions and are subject to regular financial reporting obligations. The sample size was determined using the Taro Yamane (1967) formula at a 0.05 margin of error, which gave 205 respondents. Stratified random sampling was used to allocate the sample across the four sectors in proportion to their share of the population, and respondents within each organisation were selected by simple random sampling from staff lists provided by the heads of finance.

The instrument for data collection was a structured questionnaire titled Artificial Intelligence and Financial Reporting Quality Questionnaire (AIFRQQ). It had five sections.

Section A collected demographic information on gender, professional qualification, years of experience and sector. Section B contained six items on the extent of AI adoption. Section C contained six items on accuracy and reliability of financial reports. Section D contained five items on timeliness of financial reporting, and Section E contained six items on the challenges of AI adoption. Items in Sections B to E were rated on a four-point Likert scale of Strongly Agree (4), Agree (3), Disagree (2) and Strongly Disagree (1).

The instrument was validated by two lecturers in accounting and one in measurement and evaluation, who checked the items for clarity, relevance and coverage of the research questions. To establish reliability, the questionnaire was administered to 20 accounting professionals in Awka, Anambra State, who were not part of the study sample. Cronbach's (1951) alpha method gave an overall reliability coefficient of 0.84, which is above the 0.70 threshold commonly accepted for research instruments (Nunnally, 1978).

The researcher and two trained research assistants administered the questionnaire in person over five weeks,. Of the 205 copies distributed, 196 were returned correctly completed, giving a response rate of 95.6 percent. Data were analysed with the Statistical Package for the Social Sciences (SPSS). Frequency counts and percentages were used for demographic data. Mean scores were used to answer the research questions, and a mean of 2.50 and above was taken as agreement while a mean below 2.50 was taken as disagreement. For the hypotheses, respondents were grouped into high, moderate and low levels of AI adoption and of each reporting quality dimension based on their section scores, and the chi-square test of independence was applied at the 0.05 level of significance. Cramér's V was used to report the strength of any significant relationship.

Results

Demographic Characteristics of Respondents

Table 1: Demographic Characteristics of Respondents (n = 196)

Variable	Category	Frequency	Percentage (%)
Gender	Male	112	57.1
	Female	84	42.9
Professional qualification	ICAN	82	41.8
	ANAN	44	22.4
	ACCA/Other international	28	14.3
	Degree only (no professional qualification)	42	21.4
Years of experience	1-5 years	48	24.5
	6-10 years	61	31.1
	11-15 years	47	24.0
	Above 15 years	40	20.4
Sector	Public sector (MDAs)	66	33.7
	Banking	56	28.6
	Audit and accounting practice	44	22.4
	Manufacturing	30	15.3

Table 1 shows that male respondents (57.1%) slightly outnumbered female respondents (42.9%). Most respondents held a professional qualification from ICAN (41.8%)

or ANAN (22.4%), while 14.3 percent held ACCA or another international qualification. More than half had between 6 and 15 years of experience. The public sector accounted for the largest share of respondents (33.7%), followed by banking (28.6%), audit and accounting practice (22.4%) and manufacturing (15.3%).

Analysis of Research Questions

Research Question One: To what extent have AI tools been adopted in accounting and financial reporting processes in organisations in Enugu State?

Table 2: Mean Scores on the Extent of AI Adoption in Accounting and Financial Reporting Processes

S/N	Items	SA	A	D	SD	Total	$\bar{x}$	Decision
1	My organisation uses AI-enabled accounting software for bookkeeping and transaction recording.	68	79	33	16	591	3.02	Agree
2	AI tools are used for automated bank and account reconciliation in my organisation.	61	74	40	21	567	2.89	Agree
3	Machine learning tools are used to detect unusual transactions and possible fraud.	39	58	63	36	492	2.51	Agree
4	Robotic process automation handles routine tasks such as invoice processing and payroll.	47	66	52	31	521	2.66	Agree
5	Generative AI tools are used to draft notes, narratives or management commentary in financial reports.	28	49	71	48	449	2.29	Disagree
6	Predictive analytics is used for forecasting, budgeting and impairment estimates.	33	55	67	41	472	2.41	Disagree
Grand Mean							2.63	Agree

Criterion mean = 2.50; SA = Strongly Agree, A = Agree, D = Disagree, SD = Strongly Disagree

Table 2 shows that four of the six items recorded mean scores at or above the criterion of 2.50. AI-enabled bookkeeping software (3.02), automated reconciliation (2.89), robotic process automation (2.66) and machine learning based fraud detection (2.51) are in use in many of the organisations studied, although the last of these only just reached the criterion. The use of generative AI for drafting report narratives (2.29) and predictive analytics for forecasting and impairment estimates (2.41) fell below the criterion. The grand mean of 2.63 indicates a moderate extent of AI adoption. Adoption is strongest in routine, rules-based tasks and weakest in areas that call for judgement.

Research Question Two: What is the effect of AI adoption on the accuracy and reliability of financial reports?

Table 3: Mean Scores on the Effect of AI Adoption on the Accuracy and Reliability of Financial Reports

S/N	Items	SA	A	D	SD	Total	$\bar{x}$	Decision
7	AI tools have reduced arithmetic and posting errors in our financial records.	82	86	19	9	633	3.23	Agree
8	Automated reconciliation has improved the reliability of account balances.	77	89	21	9	626	3.19	Agree
9	AI-assisted review helps us identify misstatements before reports are issued.	64	90	29	13	597	3.05	Agree
10	Financial statements prepared with AI support comply better with IFRS requirements.	51	83	43	19	558	2.85	Agree
11	AI anomaly detection has strengthened internal control over financial reporting.	58	87	34	17	578	2.95	Agree
12	I trust figures generated by AI tools without further human review.	17	31	82	66	391	1.99	Disagree
Grand Mean							2.88	Agree

Criterion mean = 2.50; SA = Strongly Agree, A = Agree, D = Disagree, SD = Strongly Disagree

Table 3 shows that respondents agreed with the first five items, with mean scores ranging from 2.85 to 3.23. Item 12, however, had a mean of 1.99, showing that respondents did not trust AI-generated figures without human review. The grand mean of 2.88 indicates that AI adoption has improved the accuracy and reliability of financial reports, but that professionals still see review and judgement as necessary.

Research Question Three: What is the effect of AI adoption on the timeliness of financial reporting?

Table 4: Mean Scores on the Effect of AI Adoption on the Timeliness of Financial Reporting

S/N	Items	SA	A	D	SD	Total	$\bar{x}$	Decision
13	AI tools have shortened the time needed to close the books at month end.	88	81	18	9	640	3.27	Agree
14	Our annual financial statements are now ready earlier than before AI adoption.	66	84	31	15	593	3.03	Agree
15	Real-time dashboards allow management to see financial results as they happen.	59	80	38	19	571	2.91	Agree
16	Automated reporting helps us meet statutory and regulatory filing deadlines.	71	83	28	14	603	3.08	Agree
17	Less time is spent on data entry, leaving more time for analysis.	90	79	17	10	641	3.27	Agree
Grand Mean							3.11	Agree

Criterion mean = 2.50; SA = Strongly Agree, A = Agree, D = Disagree, SD = Strongly Disagree

Table 4 shows that all five items recorded mean scores above 2.50, with a grand mean of 3.11, the highest of the three outcome tables. Respondents agreed most strongly that less time is now spent on data entry (3.27) and that the month-end close is shorter (3.27). Automated reporting

also helps them meet regulatory filing deadlines (3.08). The lowest mean (2.91) related to real-time dashboards.

Research Question Four: What challenges hinder the effective adoption of AI in financial reporting in Enugu State?

Table 5: Mean Scores on the Challenges Hindering Effective AI Adoption in Financial Reporting

S/N	Items	SA	A	D	SD	Total	$\bar{x}$	Decision
18	The cost of acquiring and maintaining AI accounting software is high.	104	68	15	9	659	3.36	Agree
19	Many accounting staff lack the skills to use AI tools effectively.	97	73	18	8	651	3.32	Agree
20	Erratic power supply and poor internet connectivity disrupt AI-based systems.	112	61	14	9	668	3.41	Agree
21	There is no clear regulatory guidance on the use of AI in financial reporting in Nigeria.	93	72	21	10	640	3.27	Agree
22	Concerns about data privacy and cybersecurity slow down AI adoption.	86	79	22	9	634	3.23	Agree
23	Some staff resist AI because they fear job loss.	74	70	35	17	593	3.03	Agree
Grand Mean							3.27	Agree

Criterion mean = 2.50; SA = Strongly Agree, A = Agree, D = Disagree, SD = Strongly Disagree

Table 5 shows that all six items recorded high mean scores, with a grand mean of 3.27. Erratic power supply and poor internet connectivity had the highest mean (3.41), followed by the high cost of software (3.36) and the lack of skills among accounting staff (3.32). The lack of regulatory guidance (3.27) and data security concerns (3.23) followed. Fear of job loss had the lowest mean (3.03), although it was still well above the criterion.

TESTING OF HYPOTHESES

Hypothesis One (H_{01}): There is no significant relationship between the level of AI adoption and the accuracy and reliability of financial reports in organisations in Enugu State.

Table 6: Cross-Tabulation of AI Adoption Level and Accuracy/Reliability of Financial Reports

AI adoption level	Reliability: High	Reliability: Moderate	Reliability: Low	Total
High	38 (23.34)	17 (23.96)	6 (13.69)	61
Moderate	29 (32.14)	41 (33.00)	14 (18.86)	84
Low	8 (19.52)	19 (20.04)	24 (11.45)	51
Total	75	77	44	196

Expected frequencies are shown in brackets.

Table 7: Chi-Square Test for Hypothesis One

N	df	χ^2 cal	χ^2 crit	p-value	Cramér's V	Decision
196	4	39.66	9.49	< .001	0.32	H ₀₁ Rejected

Table 7 shows a calculated chi-square value of 39.66 against a critical value of 9.49 at 4 degrees of freedom. Since the calculated value is greater than the critical value and the p-value is below 0.05, the null hypothesis is rejected. There is a significant relationship between the level of AI adoption and the accuracy and reliability of financial reports. Cramér's V of 0.32 indicates a moderate relationship. Table 6 shows that 62.3 percent of respondents in the high adoption group rated reliability as high, compared with 15.7 percent in the low adoption group.

Hypothesis Two (H₀₂): There is no significant relationship between the level of AI adoption and the timeliness of financial reporting in organisations in Enugu State.

Table 8: Cross-Tabulation of AI Adoption Level and Timeliness of Financial Reporting

AI adoption level	Timeliness: High	Timeliness: Moderate	Timeliness: Low	Total
High	41 (25.21)	15 (23.03)	5 (12.76)	61
Moderate	31 (34.71)	39 (31.71)	14 (17.57)	84
Low	9 (21.08)	20 (19.26)	22 (10.67)	51
Total	81	74	41	196

Expected frequencies are shown in brackets.

Table 9: Chi-Square Test for Hypothesis Two

N	df	χ^2 cal	χ^2 crit	p-value	Cramér's V	Decision
196	4	39.19	9.49	< .001	0.32	H ₀₂ Rejected

Table 9 shows a calculated chi-square value of 39.19, which is greater than the critical value of 9.49 at 4 degrees of freedom, with a p-value below 0.05. The null hypothesis is therefore rejected. There is a significant relationship between the level of AI adoption and the timeliness of financial reporting, and Cramér's V of 0.32 again indicates a moderate relationship. As Table 8 shows, 67.2 percent of respondents in the high adoption group rated timeliness as high, against 17.6 percent in the low adoption group.

Discussion of Findings

The first finding is that AI adoption among accounting professionals in Enugu State is moderate. Tools for bookkeeping, reconciliation and routine automation are in common use, but predictive analytics and generative AI have not yet become part of normal reporting work. This pattern agrees with Cooper et al. (2019) and with the view of Issa et al. (2016) that AI moves from structured work to judgement-based work over time. The low use of generative AI suggests that organisations remain cautious about using it for disclosures that carry legal weight.

The second finding is that AI adoption has improved the accuracy and reliability of financial reports, and the first hypothesis confirmed a significant relationship between the two. Respondents in organisations with high adoption were far more likely to rate their reports as reliable. This is consistent with Appelbaum et al. (2017), who argued that analysing full populations of transactions improves error detection, and with Ekawu (2026), who found a positive effect of AI on financial reporting quality in Nigeria. An equally important result is that respondents did not trust AI output without human review. This reflects the concerns raised

by Brown-Liburd et al. (2015) and Zhang et al. (2022) about over-reliance and the difficulty of explaining machine output. Professionals in Enugu State appear to see AI as an aid to judgement, not a replacement for it.

The third finding is that AI has improved the timeliness of financial reporting, with the highest grand mean among the outcome variables. The second hypothesis confirmed a significant relationship between adoption and timeliness. Shorter month-end closes and less time on data entry are the most visible benefits. This matches Cooper et al. (2019), who reported faster task completion after RPA adoption.

The fourth finding concerns the barriers to adoption. Power supply and internet connectivity emerged as the most serious challenge, followed by cost and skills. These results reflect the facilitating conditions stressed by Venkatesh et al. (2003) and the organisational and environmental factors in the framework of Tornatzky and Fleischer (1990). The skills gap supports the argument of Damerji and Salimi (2021) that readiness shapes adoption. The absence of regulatory guidance echoes the call by Munoko et al. (2020) and Lehner et al. (2022) for clear rules on accountability and ethics when AI is used in accounting. Fear of job loss ranked lowest, suggesting that professionals worry less about replacement than about having the tools and training to use AI well.

Taken together, the findings support the Technology Acceptance Model, and the rejection of both hypotheses shows that the benefits reported are linked to the level of adoption rather than to general optimism about technology.

Conclusion

This study has shown that artificial intelligence is already part of accounting practice in Enugu State, although its use is uneven. Routine tasks such as bookkeeping, reconciliation and invoice processing are widely automated, while advanced applications such as predictive analytics and generative AI remain limited. Where AI has been adopted, accounting professionals report more accurate and reliable financial statements and a faster reporting cycle, and statistical tests confirmed significant relationships between the level of adoption and both dimensions of reporting quality. At the same time, professionals continue to see human review as necessary, and the benefits of AI are held back by poor infrastructure, high costs, skills gaps and the absence of regulatory guidance.

Recommendations

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

1. The Financial Reporting Council of Nigeria, working with the Institute of Chartered Accountants of Nigeria (ICAN) and the Association of National Accountants of Nigeria (ANAN), should issue guidance on the use of AI in the preparation and audit of financial reports. The guidance should cover documentation of AI processes, human review requirements and responsibility for errors.
2. ICAN and ANAN should include practical AI and data analytics modules in their continuing professional development programmes, and universities in Enugu State should introduce such content into undergraduate accounting curricula.
3. Organisations should retain clear human review steps over AI-generated figures and disclosures, and internal auditors should test the controls around AI systems as part of their regular work.
4. Firms should invest in alternative power sources and reliable internet connections for their finance functions, and should consider cloud-based AI tools with local data backup to reduce the effect of outages.
5. Smaller firms should consider shared or subscription-based AI services to reduce up-front costs, and business associations in Enugu should explore group licensing arrangements with software vendors.

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