International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 3
Article Received: *25 August 2026* ***Revised:*** *12 September 2026* ***Accepted:*** *20 October 2026*

The Impact of Artificial Intelligence on Accounting Practices in Modern Business

Dr. G. Sindhu
Assistant Professor, Department of Commerce
Ambai Arts College, Ambasamudram 627 401
Affiliated to Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India.

Email id : gsindhuprem@gmail.com

Abstract

This study examines how artificial intelligence (AI) may reshape accounting practices in modern business. AI-enabled tools can support transaction processing, reconciliation, anomaly detection, financial forecasting and decision support. The article presents a research framework for assessing AI awareness and adoption among accounting professionals and examining its relationship with accounting efficiency and financial reporting quality. A structured questionnaire and quantitative methods including descriptive statistics, chi-square tests and regression analysis are proposed. Numerical results supplied in the initial draft are illustrative and must be verified or replaced using actual survey data before the article is submitted as empirical research. The article also considers implementation challenges such as data quality, privacy, explainability, professional judgement and governance. It recommends role-specific training, secure infrastructure, management support and regular evaluation of AI-enabled processes. The framework can assist organizations in investigating how AI can be adopted responsibly while preserving human oversight and professional accountability.

Keywords: Artificial Intelligence; Accounting Practices; Financial Reporting; Accounting Efficiency; Digital Transformation; Business Technology

1. Introduction

Accounting is being reshaped by developments in artificial intelligence (AI), machine learning, natural language processing and robotic process automation. These technologies can support transaction classification, invoice processing, account reconciliation, anomaly detection, audit analytics and financial forecasting. Their value lies in automating repetitive tasks and helping professionals interpret large volumes of information.

Adoption varies across organizations according to technology budgets, employee skills, data quality, management support and compatibility with existing systems. AI may also create risks when systems are poorly governed, outputs cannot be explained or sensitive financial data are inadequately protected. Human review remains important for material judgements, unusual transactions and compliance decisions.

This article provides a framework for investigating the relationship between AI adoption and accounting outcomes.

1.1 Research Objectives

1. To assess AI awareness and adoption among accounting professionals.
2. To examine associations between demographic or organizational factors and AI adoption.
3. To analyse the relationship between AI adoption and accounting efficiency.
4. To examine the relationship between AI adoption and financial reporting quality.
5. To identify implementation challenges and recommend responsible AI integration.

1.2 Research Hypotheses

H1: AI adoption is positively associated with accounting efficiency.
H2: AI adoption is positively associated with financial reporting quality.
H3: Education level is associated with AI awareness among accounting professionals.
H4: Organizational support is positively associated with AI adoption.

1.3 Significance of the Study

The study is relevant to accounting academics, practitioners and organizational decision-makers. It frames AI as a tool that may improve the speed and consistency of routine processes while emphasizing the continuing need for professional judgement, internal controls and ethical oversight. Findings should be finalized only after analysis of verified data.

2. Literature Review

2.1 Artificial Intelligence in Accounting

AI in accounting includes systems that classify transactions, extract information from documents, detect patterns and support decisions. Sutton, Holt and Arnold (2016) reviewed AI research in accounting and discussed how intelligent systems may change accounting work. Kokina and Davenport (2017) described how automation is changing auditing and may allow human effort to focus on judgement-intensive work.

2.2 AI and Accounting Efficiency

Accounting efficiency concerns time, cost, accuracy and consistency. Automated data capture and reconciliation may reduce manual work and allow staff to focus on exceptions. Appelbaum, Kogan and Vasarhelyi (2017) described research opportunities created by big data and analytics in audit engagements. Benefits depend on implementation quality, integration and suitable controls; automation alone does not guarantee better results.

2.3 AI and Financial Reporting Quality

Financial reporting quality depends on relevant, reliable, comparable and timely information. AI tools may help identify inconsistencies and speed up reporting, but poor source data or opaque models can introduce new risks. Munoko, Brown-Liburd and Vasarhelyi (2020) highlighted ethical issues associated with AI in auditing and the need for governance and accountability.

2.4 Factors Influencing AI Adoption

The Unified Theory of Acceptance and Use of Technology identifies performance expectancy, effort expectancy, social influence and facilitating conditions as factors influencing technology use (Venkatesh et al., 2003). These concepts can be applied to perceived usefulness, training, leadership support and access to infrastructure. Richins et al. (2017) considered opportunities and challenges created by big-data analytics for accounting.

2.5 Research Gap

AI's potential is established in the literature, but adoption and outcomes may differ across organizational settings. A context-specific study using transparent sampling, validated measures and verified data can assess whether perceived benefits are reflected in practice.

3. Research Methodology

3.1 Research Design

A descriptive and analytical research design is proposed. Primary data may be collected through a structured questionnaire administered to accounting and finance professionals.

3.2 Population and Sample

The original draft specifies 150 respondents selected through purposive sampling. Retain these details only if they accurately describe the completed study. The final manuscript should report the actual population, sampling frame, recruitment procedure and response rate.

3.3 Data Collection Instrument

The questionnaire may contain four sections: (A) demographic and professional profile; (B) AI awareness and adoption; (C) accounting efficiency; and (D) financial reporting quality. Likert-scale items should be clearly worded and pilot-tested before full data collection.

3.4 Reliability and Validity

Content validity can be assessed by subject experts and practicing accountants. Internal consistency, for example Cronbach's alpha, must be calculated from actual pilot responses. Reliability coefficients in an illustrative draft are not verified results.

3.5 Data Analysis

Suitable methods include frequencies, percentages, means, standard deviations, chi-square tests and regression analysis. Check missing data and statistical assumptions and report effect sizes and confidence intervals where possible. If software displays $p = .000$, report it as $p < .001$.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 14 Issue: 3
Article Received: *25 August 2026* ***Revised:*** *12 September 2026* ***Accepted:*** *20 October 2026*

3.6 Ethical Considerations

Participants should receive an explanation of the study and provide informed consent. Participation should be voluntary, identifying information minimized and data stored securely for the stated research purpose.

4. Data Analysis and Interpretation

4.1 Demographic Profile of Respondents

The original draft contains a demographic profile for 150 respondents. Verify every frequency and percentage against the source dataset and ensure category totals match the sample size. Avoid claiming that a purposive sample represents all accounting professionals.

Table 1. Respondent Profile (illustrative example values verify against raw data)

Variable	Category	Frequency	Percentage
Age	Below 30 years	42	28.0%
Age	30–40 years	63	42.0%
Gender	Male	88	58.7%
Gender	Female	62	41.3%
Education	Undergraduate	36	24.0%
Education	Postgraduate	89	59.3%

4.2 AI Awareness and Adoption

Applications to examine include automated bookkeeping, AI-enabled reconciliation, fraud-risk detection, financial forecasting, robotic process automation and natural-language tools. Record awareness and current use separately. Any awareness–adoption gap should be interpreted using evidence about cost, skills, integration and organizational policy.

Table 2. AI Awareness and Adoption (illustrative example values verify against raw data)

Application	Aware n (%)	Using n (%)
Automated bookkeeping	126 (84.0%)	91 (60.7%)
AI-enabled reconciliation	105 (70.0%)	72 (48.0%)
Fraud-risk detection	112 (74.7%)	68 (45.3%)
Financial forecasting	98 (65.3%)	61 (40.7%)
Robotic process automation	87 (58.0%)	54 (36.0%)

4.3 Chi-Square Analysis

Chi-square tests may examine education and AI awareness, designation and adoption, experience and adoption and firm size and adoption. Report the test statistic, degrees of freedom, sample size and p-value. Check expected cell counts. Statistical association should not be described as proof of causation.

Table 3. Chi-Square Results (illustrative example results recalculate from raw data)

Variables	χ^2	df	p-value
Education × awareness	9.84	2	.007
Age × adoption	7.21	2	.027
Organizational/digital literacy factor	11.46	3	.009

4.4 Regression Analysis

Separate regression models can estimate the relationship between AI adoption and accounting efficiency and between AI adoption and financial reporting quality. Report model fit, coefficients, standard errors, confidence intervals and p-values. The numerical results from the supplied draft are illustrative and must not be presented as empirical findings unless reproduced from actual data.

Table 4. Regression Results (illustrative example results recalculate from raw data)

Outcome	Predictor	B	β	R^2	p-value
Accounting efficiency	AI adoption	0.42	0.48	0.31	< .001
Financial reporting quality	AI adoption	0.35	0.39	0.24	< .001

5. Findings

The final findings must be written after the dataset has been checked and analyses rerun. Potential themes include the awareness–use gap, associations between education or organizational support and adoption and relationships between AI adoption and accounting outcomes. Include only findings supported by the actual results.

6. Discussion

Compare verified results with relevant literature and explain similarities or differences in context. Distinguish statistical significance from practical importance and consider alternative explanations, such as better-resourced organizations being more likely to adopt AI and report stronger accounting performance.

7. Recommendations

1. Provide role-specific training in AI tools, data interpretation and professional scepticism.
2. Establish governance for procurement, validation, monitoring and accountability.
3. Protect financial information through access controls and secure data handling.
4. Pilot systems and document performance before scaling them.
5. Retain human review for material estimates and unusual transactions.
6. Evaluate accuracy, bias, explainability and compliance regularly.
7. Encourage collaboration among universities, professional bodies and employers.

8. Conclusion

AI has the potential to support accounting efficiency and reporting through automation, analytics and anomaly detection. Realizing these benefits requires reliable data, skilled staff, suitable controls and responsible governance. This article provides a framework for examining AI adoption in accounting; empirical conclusions must be based on verified data rather than illustrative statistics. Future studies may compare sectors and examine specific AI applications over time.

References

1. Appelbaum, D., Kogan, A., & Vasarhelyi, M. A. (2017). Big Data and analytics in the modern audit engagement: Research needs. Auditing: A Journal of Practice & Theory, 36(4), 1–27.
2. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.
3. Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 14(1), 115–122.
4. Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. The British Accounting Review, 51(6), Article 100833.
5. Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. Journal of Business Ethics, 167, 209–234.
6. Richins, G., Stapleton, A., Stratopoulos, T. C., & Wong, C. (2017). Big data analytics: Opportunity or threat for the accounting profession? Journal of Information Systems, 31(3), 63–79.
7. Martino, L., & Paya-Santos, C. (2026). Intelligence Failures: An Exploration of Key Theories. Revista Científica General José María Córdova, 24(53), 105–132. https://doi.org/10.21830/19006586.1485
8. Sutton, S. G., Holt, M., & Arnold, V. (2016). "The reports of my death are greatly exaggerated" Artificial intelligence research in accounting. International Journal of Accounting Information Systems, 22, 60–73.
9. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.