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Ethical Concerns and Operational Implications of Artificial Intelligence in the Accounting Profession

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Abstract
AI is changing accounting by increasing the speed, accuracy, and analytical capacity of financial operations. This study examines how machine learning, data analytics, robotic process automation, auditing, reporting, forecasting, and professional decision making are used in financial analysis. The study assesses the institutional notification of AI use in accounting as well as its operational advantages. According to the study, artificial intelligence can enhance audit processes, uncover anomalous financial patterns, expedite repetitive activities, assist real-time reporting, and increase the accuracy of financial projections. However, its application also raises issues with algorithmic bias, data quality, information security and accountability for automated decisions. The paper evaluates that while AI can help with accounting procedures, it should not replace the professional skepticism and critical thinking of accounting practitioners. Effective implementation requires strong data governance, explainable algorithms, ongoing human monitoring, ethical standards, and clarity regarding roles. The study also explains the increasing demand for accounting people to acquire knowledge of data analytics, artificial intelligence and ethical technology management. The paper proposes an integrated approach which connects artificial intelligence with accounting applications and governance mechanism. The study concludes that responsible use of AI can improve financial authenticity and accuracy.

Keywords: Artificial Intelligence, Accounting, Machine Learning, Auditing, Data Analytics

1. Introduction

1.1 Background of Study

Accounting has been undergoing a digital transformation from paper-based ledger systems and workflows to corporate systems, and intelligent automation and reporting tools (Fülöp et al., 2023; Odonkor et al., 2024). In traditional accounting system, the focus was given to manual data entry and clerical workflows which were very time consuming and prone to errors (Smith, 2018; Fating et al., 2025). In contrast to this, modern accounting system uses Artificial Intelligence, Machine learning, Natural Language processing to perform all accounting operations such as data entry, invoice coding (Oyeniyi et al., 2024; Jones & Free, 2026). Error rates and manual processing times have decreased after the procedure was automated (Moffitt et al., 2018; Kokina & Davenport, 2017). Most significantly, this technical transformation enables accounting professionals to switch from transaction processing to strategic advising roles, including corporate governance, financial risk analysis, predictive modeling, and executive decision support. (Leitner-Hanetseder et al., 2021; Luo et al., 2018).

1.2 Problem Statement

While the advantages of using AI in accounting are well established, the swift integration of AI-powered tools introduces substantial ethical, legal, and structural risks (Fülöp et al., 2023; Parra Rodriguez, 2022). The basic working of AI systems is based on statistical pattern matching and mathematical calculations. These automatic tools are non-aware and don't think for themselves, donot have a moral sense, or don't have a sense of deliberation (Stahl et al., 2021; Fülöp et al., 2023). Accordingly, algorithms cannot demonstrate genuine professional skepticism or use context-specific critical judgment in the face of unusual financial situations (Munoko et al., 2020; Jones & Free, 2026).

In addition, automated software cannot accept legal or regulatory responsibility for financial misstatements, reporting omissions or frauds (Parra Rodriguez, 2022). Human accounting practitioners, corporate officers, and software engineers are the ones who are fully accountable for the accuracy of the financials and regulatory compliance (Fülöp et al., 2023). Large financial datasets also amplify cyber-attacks, concerns about data privacy and security, and the threat of "black box", or opacity, as well as workforce displacement anxiety (Ionescu et al., 2022; El Hajj & Hammoud, 2023). In the absence of proper governance, it is possible to compromise the ethical principles and the public perception due to the short-term pressure to reduce the process costs (Fülöp et al., 2023).

1.3 Research Questions

This research paper checks three specific research questions to address these emerging issues (RQs)
RQ1: In which specific accounting processes are AI tools currently used and how familiar are practitioners with these systems?
RQ2: What are the operational, environmental, social risks associated with AI usage in accounting firms? (Di Vaio et al., 2020; Fülöp et al., 2023)
RQ3: What ethical principles must govern AI systems to align automated capabilities with human professional integrity and public trust? (Ashok et al., 2022; Parra Rodriguez, 2022)

1.4 Research Aims, Objectives and SDG Alignment

The main objective of this research paper is to evaluate the operational capacities and institutional implications of AI usage in accounting practices. The specific objectives are (1) to analyze the main AI technologies used across accounting functions, (2) to check associated ethical and governance risk and (3) to propose an integrated framework linking technological capability with professional competencies and regulatory oversight (Fating et al., 2025; Fülöp et al., 2023).
This study also connects the Sustainable Development Goals (SDGs) of the United Nations with technology governance in accounting. SDG 8 (Decent Work and Economic Growth) is supported by automated process efficiency; SDG 9 (Industry, Innovation, and Infrastructure) is advanced by real-time data infrastructure; SDG 16 (Peace, Justice, and Strong Institutions) is supported by transparent financial controls; and SDG 17 (Partnerships for the Goals) is aligned with interdisciplinary collaboration (Peng et al., 2023).

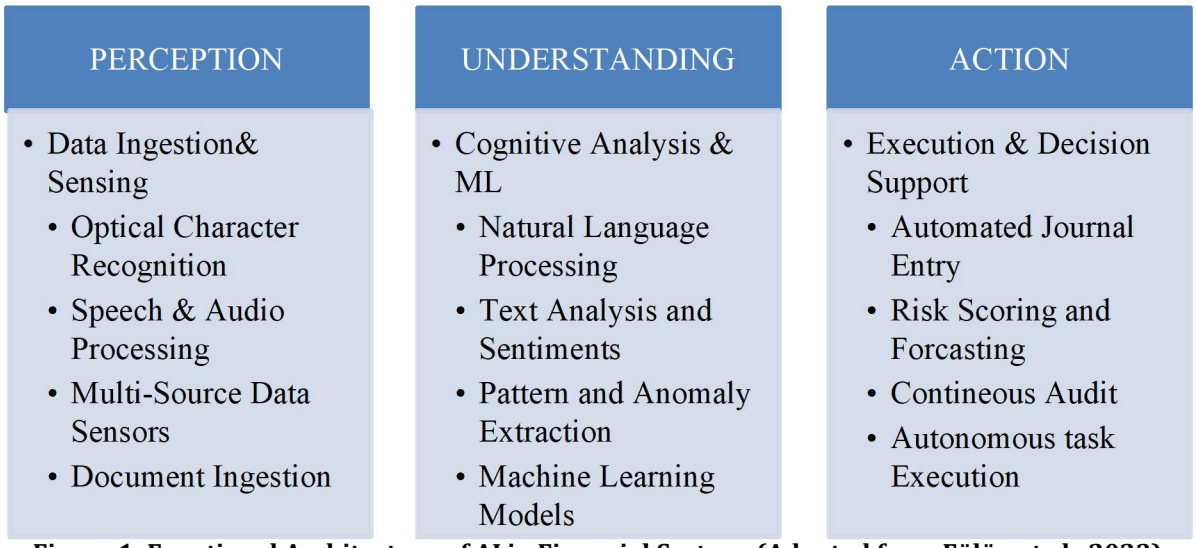

Figure 1: Functional Architecture of AI in Financial Systems(Adapted from Fülöp et al., 2023)

2. Literature Review

2.1 Theoretical frameworks governing Technological Adoption

There are several theoretical frameworks that are used to study technological adoption in the accounting discipline:

- **Technology Acceptance Model (TAM):** This was developed by Davis (1989) that suggests the adoption of a technology is a function of perceived usefulness and perceived ease of use. In accounting, there are AI tools that are used when there is a clear improvement in efficiency and accuracy in the system, and there are AI tools that are resisted because they are complex or threatening (Lopes et al., 2023; Fating et al., 2025).
- **Resource-Based View (RBV):** It is a theory that originated from Barney (1991) which states that long-term competitive advantage is created by valuable resources, resources that are rare, and resources that are non-substitutable. Proprietary AI algorithms and data pipelines serve as strategic assets, enhancing analytical insight and organizational agility (Fating et al., 2025).
- **The Socio-Technical Systems**: Theory was first introduced by Trist and Bamforth (1951), which focused on the need for concurrent attention to the technical tools, employee skills, and workflow structures needed for technological success (Zirnig et al., 2021).
- **System of Professions and Boundary Work:** Based on Abbott (1988), professionals maintain their authority by controlling legitimate diagnosis and inference. When predictive models become very accurate, accountants do

"boundary work" to explain financial statements and to have moral control(Jones & Free, 2026).

- **Digital Maslow Hierarchy:** Adapted by Spiekermann (2015), this model frames digital transformation around basic human needs, positioning knowledge and freedom as prerequisites, and data security, privacy, and trust at the core of adoption.

The following diagram presents the presents the Maslow's hierarchy of needs for the digital accounting age (Spiekermann, 2015 & Fülöp et al., 2023)

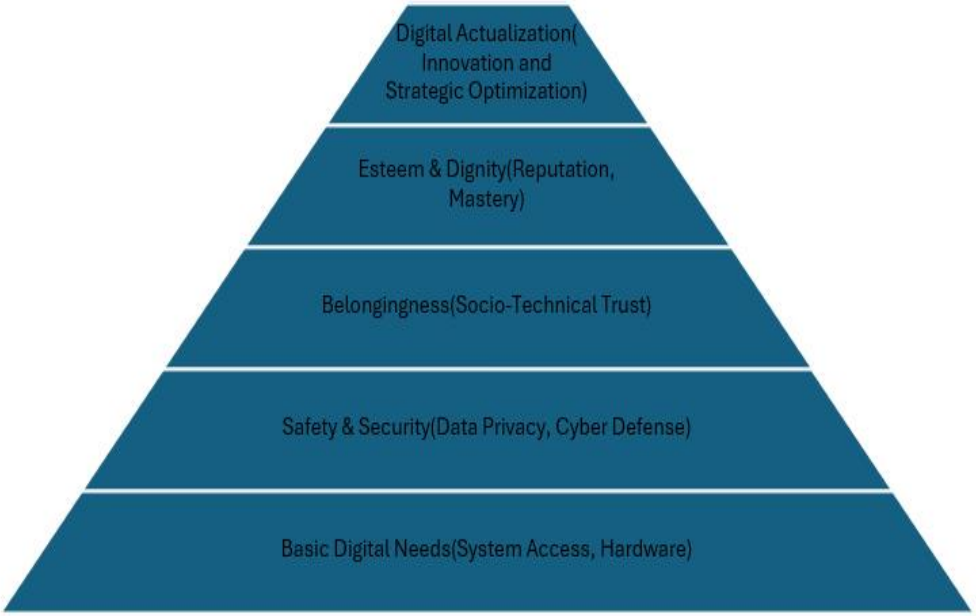

Figure 2: Maslow Pyramid for Digital Accounting Age

2.2 Epistemic Shift and Core Technologies

Four technology clusters are driving digital transformation in accounting:

- Robotic Process Automation(RPA) performs high-volume, rule-based clerical tasks(Moffitt et al., 2018).
- Machine learning(ML) generates non-linear patterns from data for scoring risk and predicting bankruptcy (Bao et al., 2020; Rajaratnum et al., 2025).
- Natural Language Processing(NLP) pull out disclosures from unstructured data(Bochkay et al., 2023).
- Predictive Analytics is moving accounting from recording the past to predicting the future of finance(Goel et al., 2023).

All these tools collectively present an epistemic shift from traditional accounting to future accounting(Jones & Free, 2026).

2.3 Operational Applications, Audit Quality and Explainability

Empirical studies have reported a range of gains in areas of accounting. RPA and ML can save upto 60% processing errors and task lead times (Kokina & Davenport, 2017). AI tools in auditing allow for 100% population testing, which helps avoid sampling risk, and helps identify subtle transaction anomalies (Issa et al., 2016). The predictive power of the ML models extends to helping predict corporate distress, loss reserves, and going-concern failures, which are superior to the predictive power of human managers (Ding et al., 2020; Rajaratnum et al., 2025). But deep learning models give rise to black-box opacity. This means that to meet the audit requirements, organizations need to implement Explainable AI (XAI) methods, such as SHAP and LIME, to ensure that algorithmic results are auditable and interpretable (Zhang et al., 2022).

3. Research Methodology

3.1 Research Design and Qualitative Content Analysis

This study uses the secondary qualitative research design that gives a structured review of the academic literature and accounting standards and empirical information through interview (Saunders et al., 2019; Fülöp et al., 2023). The analysis follows the procedure of the rule-based qualitative content analysis (Mayring's et al., 2015) and six phases of thematic model, which is a systematic coding and synthesis of text passages (Braun and Clarke's et al., 2006).

3.2 Source Selection and Empirical Dataset

The empirical material is based on a structured data set consisting of 12 semi-structured interviews(145 transcipt pages) where the heads of the accounting firm, controlling managers and financial IT specialists have participated (Fülöp et al., 2023). For the transcripts, NVivo 12 software was used to determine the reference frequencies and node density by research questions.

4. Empirical Results and Findings

4.1 Profile of Interviewees

The empirical sample consisted of 12 accounting and financial IT professionals who worked in a variety of organizational roles, age groups and experience levels (Fülöp et al., 2023). Table 1 gives the detailed profile breakdown.

Table 1. Profile of Interviewed Accounting Professionals (Fülöp et al., 2023)

ID	Department	Age Group	Years Experience	Duration
1.	Employer in Accounting IT Dept.	30-35	9 Years	24.17 min
2	Employer in Controlling Dept.	30–35	10 Years	21:30 min
3	Income Invoice Responsible	40–45	15 Years	23:45 min
4	Import / Export Department	40–45	17 Years	25:30 min
5	Employer in Accounting IT Dept.	30–35	8 Years	20:45 min
6	Head of Financial Accounting	45–50	24 Years	26:30 min
7	Employer in Accounting Dept.	25–30	5 Years	17:45 min
8	Employer in Controlling & IT Dept.	30–35	8 Years	21:35 min
9	Head of Financial Accounting	35–40	14 Years	24:15 min
10	Head of Financial Accounting	45–50	25 Years	22:10 min
11	Employer in Controlling & IT Dept.	35–40	17 Years	26:15 min
12	Head of Financial Accounting	35–40	13 Years	23:10 min

4.2 RQ1 Results: Processes Utilizing AI

NVivo coding shows that respondents actively use AI across three primary operational categories: Data Processing (9 nodes / 63 references), Data Storage (5 nodes / 43 references and Data Analysis and Forcasting(4 nodes / 37 references)) (Fülöp et al., 2023). Interviewees stated that general automation is prevalent, but many accountants struggle to distinguish between basic digitization, RPA and machine learning.

4.3 RQ2 Results: Indication of AI Risks

The analysis of the answers to RQ2 reveals that the most important concern is the legal and compliance risk (6 nodes / 53 references), more precisely client data liability in case of cyber-attacks (Fülöp et al., 2023). Other important risk categories are Algorithmic Discrimination (4 nodes / 34 references), Future Technology & Job Displacement Anxiety (3 nodes / 27 references), Environmental Concerns (4 nodes / 23 references), Reputational Risk (3 nodes / 23 references), and Social Impact (3 nodes / 21 references).

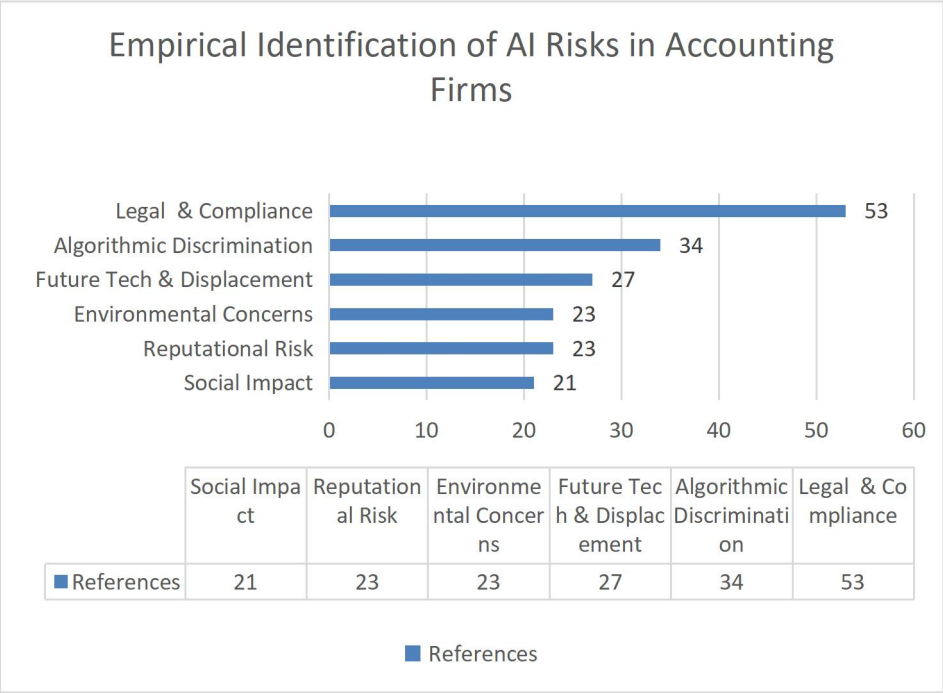

Figure 3. Empirical Identification of AI Risks in Accounting Firms

4.3 RQ3 Results: Ethical Principles versus Machine Rules

Respondents emphasized that in the case of machines they are governed by pre-programmed instructions and do not have moral sense and are unable to take responsibility for mistakes, therefore human governance is necessary in all cases. When the professional standards are compared with AI capabilities, It highlights the total number of references against the two codes: 60 references to accountants professional ethical standards versus 54 references to AI technical standards (Fülöp et al., 2023).

4.4 Quantitative Operational Efficiency Gains

Through automation, there are substantial gains in operations which are highlighted by secondary data. In the field of vendor payments, RPA implementation saved up to 97.8% of time and 55% of the cost of employee processing (Arnaz & Harahap, 2021). In the same way, the time for processing routine tasks saw a 60% reduction after the introduction of AI (Kokina & Davenport, 2017).

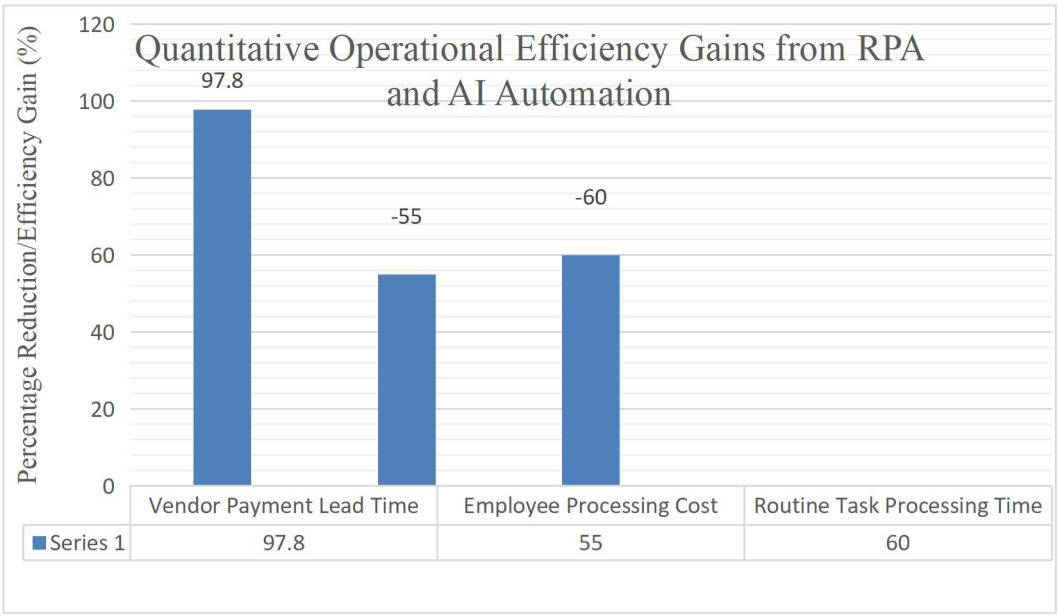

Figure 4: Quantitative Efficiency Improvements from RPA and AI Implementation (Source: Arnaz & Harahap, 2021; Kokina & Davenport, 2017)

5. Ethical Governance, Legal Liabilities and Implementation Framework

5.1 Legal Liability, Algorithmic Neutrality, and XAI

European regulatory frameworks need rigorous producer liability, mandatory civil liability insurance, and optional or required Certificates of Ethical Compliance (CECA) for high-risk systems in order to close legal liability gaps(Parra Rodriguez, 2022). Thorough pre-deployment testing is necessary for algorithmic neutrality in order to remove discriminatory bias from automated credit allocation and risk rating.

5.2 Data Privacy, Cybersecurity, and Corporate Digital Responsibility

The widespread availability of digital accounting data has led to data breaches and cyberattacks. To manage digital technology in an ethical and sustainable manner, businesses should implement corporate digital responsibility (CDR) and obey strict privacy laws, such the General Data Protection Regulation (GDPR), in order to preserve institutional credibility((Spiekermann, 2015, Parra Rodriguez, 2022).

5.3 Workforce Evolution and Lifelong Learning

Skill mismatches can be redressed by rethinking through lifelong learning by practitioners. A participatory design approach to introducing AI, within a triadic model (technology, work, individual) maintains employee psychological ownership, autonomy, and job satisfaction during digital transition(Zirnig et al., 2021; Fülöp et al., 2023).

5.4 Integrated SDG Strategic Implementation Matrix

The integrated implementation structure that links AI capabilities, ethical governance procedures, accounting applications, professional skill development, and SDG targets is described in Table 2.

Table 2. Integrated SDG Strategic Implementation Matrix (Peng et al., 2023; Parra Rodriguez, 2022)

SDG Goel	AI Capability	Accounting Application	Governance Mechanism	Skill Focus
SDG 8: Decent Work & Growth	RPA & Automated Workflows	Invoice coding, reconciliations, expense tracking	Human-in-the-loop oversight & triadic design	Process management & digital literacy
SDG 9: Industry & Innovation	Machine Learning & NLP	100% population audit, text disclosure mining	XAI (SHAP/LIME) & algorithm audits	Data analytics & model interpretation
SDG 16: Strong Institutions	Predictive Analytics & Anomaly Models	Fraud detection, going-concern & misstatement prediction	GDPR, strict liability rules	Tech ethics governance & Cybersecurity
SDG 17: Partnerships for Goals	Interdisciplinary Systems Integration	Cross-functional reporting & ESG metrics integration	Proactive collaboration between accountants & IT	Interdisciplinary communication & advisory

6. Conclusion and Recommendations

6.1 Main Findings

There are considerable advantages in terms of speed, transaction accuracy, ongoing audit and predictive risk scoring for AI technologies in accounting. However, machines cannot take legal or regulatory responsibility because automated tools lack consciousness, moral deliberation and genuine skepticism. Finally, the ultimate responsibility will be with human professionals, requiring a hybrid intelligence model where humans take control of intelligence interpretation and ethical oversight, while AI processes data.

6.2 Recommendations

- **Phased Enterprise Implementation:** Companies should use AI technologies gradually, beginning with simple administrative chores and working their way up to more sophisticated predictive decision assistance.
- **Modernize Financial Education:** Universities should include data analytics, cybersecurity and technology ethics in the traditional degree programs.
- **Include Explainability and Ethical Governance:** To guarantee compliance

and auditability, companies must mandate Explainable AI Frameworks and human in loops protocols.

6.3 Limitations and Future Scope

The conceptual method and qualitative synthesis are the basis of this research. Future research should be longitudinal, empirical studies which track changes in accountants' professional identity and job satisfaction over time, as generative AI is integrated into everyday work. Empirical evaluation of the XAI model in developing countries and small and medium sized businesses (SMEs) should also be performed.

References

1. Abbott, A. (1988). The System of Professions: An Essay on the Division of Expert Labor. University of Chicago Press.
2. Arnaz, R., & Harahap, M. E. (2021). Analysis of implementation of robotic process automation: A case study in PT X. Business Innovation and Engineering Conference (BIEC 2020), 61–64.
3. Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical framework for Artificial Intelligence and digital technologies. International Journal of Information Management, 62, 102433.
4. Bao, Z., Ke, B., Li, B., Yu, Y., & Zhang, J. (2020). Detecting accounting fraud in publicly traded U.S. firms using a machine learning approach. Journal of Accounting Research, 58(1), 199–235.
5. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.
6. Bochkay, K., Brown, S. V., Leone, A. J., & Tucker, J. W. (2023). Textual analysis in accounting: What's next? Contemporary Accounting Research, 40(2), 765–805.
7. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.
8. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.
9. Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. Journal of Business Research, 121, 283–314.
10. Ding, K., Lev, B., Peng, X., Sun, T., & Vasarhelyi, M. A. (2020). Machine learning improves accounting estimates: Evidence from insurance payments. Review of Accounting Studies, 25(3), 1098–1134.
11. El Hajj, M., & Hammoud, J. (2023). Unveiling the influence of artificial intelligence and machine learning on financial markets. Journal of Risk and Financial Management, 16(10), 434.
12. Fating, P. P., Pusadkar, A. V., & Gajabe, N. M. (2025). Artificial intelligence applications in modern accounting systems. Educational Studies, 15(4), 160–178.
13. Fülöp, M. T., Topor, D. I., Ionescu, C. A., Cifuentes-Faura, J., & Măgdaş, N. (2023). Ethical concerns associated with artificial intelligence in the accounting profession: A curse or a blessing? Journal of Business Economics and Management, 24(2), 387–404.
14. Goel, M., Tomar, P. K., Vinjamuri, L. P., Reddy, G. S., Al-Taee, M., & Alazzam, M. B. (2023). Using AI for predictive analytics in financial management. 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 963–967.
15. Ionescu, A. M., Clipa, A. M., Turnea, E. S., Clipa, C. I., Bedrule-Grigoruţă, M. V., & Roth, S. (2022). The impact of innovation framework conditions on corporate digital technology integration. Journal of Business Economics and Management, 23(5), 1037–1059.
16. Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. Journal of Emerging Technologies in Accounting, 13(1), 1–20.
17. Jones, S., & Free, C. (2026). What accountants need to know about artificial intelligence and machine learning: A review and call for future research. Journal of Accounting Literature, 48(5), 133–158.
18. Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence in accounting. Journal of Emerging Technologies in Accounting, 14(1), 115–122.
19. Leitner-Hanetseder, S., Lehner, O. M., Eisl, C., & Forstenlechner, C. (2021). A profession in transition: Actors, tasks and roles in AI-based accounting. Journal of Applied Accounting Research, 22(3), 539–556.
20. Lopes, A. P. D. C., de Oliveira, D. F., Marques, C. G. C., & Dos Santos, A. C. B. N. (2023). Technological acceptance of robotic process automation software by

accounting professionals. 18th Iberian Conference on Information Systems and Technologies (CISTI), 1–6.
21. Luo, J., Meng, Q., & Cai, Y. (2018). Analysis of the impact of artificial intelligence application on the development of accounting industry. Open Journal of Business and Management, 6(4), 850–856.
22. Mayring, P. (2015). Qualitative content analysis: Theoretical background and procedures. In Approaches to Qualitative Research in Mathematics Education (pp. 365–380). Springer.
23. Moffitt, K., Rozario, A., & Vasarhelyi, M. A. (2018). Robotic process automation for auditing. International Journal of Accounting Information Systems, 28, 53–66.
24. Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. Journal of Business Ethics, 167(2), 209–234.
25. Odonkor, B., Kaggwa, S., Uwaoma, P. U., Hassan, A. O., & Farayola, O. A. (2024). The impact of AI on accounting practices: A review. World Journal of Advanced Research and Reviews, 21(1), 172–188.
26. Oyeniyi, L. D., Ugochukwu, C. E., & Mhlongo, N. Z. (2024). Robotic process automation in routine accounting tasks: A review and efficiency analysis. World Journal of Advanced Research and Reviews, 22(1), 695–711.
27. Parra Rodriguez, C. (2022). Ethical principles in the use of artificial intelligence in the financial sector from a European perspective. Studia Prawnicze KUL, 1(89), 199–221.
28. Peng, Y., Ahmad, S. F., Ahmad, A. Y. B., Al Shaikh, M. S., Daoud, M. K., & Alhamdi, F. M. H. (2023). Riding the waves of artificial intelligence in advancing accounting and its implications for sustainable development goals. Sustainability, 15(19), 14165.
29. Rajaratnum, B., Neo, E., Jones, S., Redchenko, P., & Zhou, S. (2025). When machines surpass experts: Epistemic authority displacement in professional judgment. University of Sydney Working Paper.
30. Saunders, M., Lewis, P., & Thornhill, A. (2019). Research Methods for Business Students. Pearson Education.
31. Smith, S. S. (2018). Digitization and financial reporting: How technology innovation may drive the shift toward continuous accounting. Accounting and Finance Research, 7(3), 240–250.
32. Spiekermann, S. (2015). Ethical IT Innovation: A Value-Based System Design Approach. Auerbach Publications.
33. Stahl, B. C., Andreou, A., Brey, P., Hatzakis, T., Kirichenko, A., Macnish, K., & Wright, D. (2021). Artificial intelligence for human flourishing: Beyond principles for machine learning. Journal of Business Research, 124, 374–388.
34. Trist, E., & Bamforth, K. (1951). Some social and psychological consequences of the longwall method of coal-getting. Human Relations, 4(3), 3–38.
35. Zhang, C., Cho, S., & Vasarhelyi, M. (2022). Explainable artificial intelligence (XAI) in auditing. International Journal of Accounting Information Systems, 46, 100572.
36. Zirnig, C., Jungtäubl, M., & Ruiner, C. (2021). Menschengerechte Gestaltung von KI bei Dienstleistungsarbeit. In Künstliche Intelligenz im Dienstleistungsmanagement (pp. 235–258). Springer Gabler.
37. Singh, A. R., & Sharma, R. (2025). Prevailing trends and innovations in machine learning techniques and applications. International Journal on Science and Technology (IJSAT), 16(2).
38. Sharma, R., Bajaj, K., Singh, A. R., Narang, V., & Singh, A. (2025). Navigating AI bias: Challenges, mitigation, and ethical implications. Economic Sciences, 21(5), 207–217. https://doi.org/10.69889/tt8vsa10
39. Sharma, R., & Mahajan, R. (2026). Privacy-preserving artificial intelligence: Balancing innovation and user protection. RMSG (Rashtrakavi Maithili Sharan Gupt) Publication, 1(6). https://www.rmsgpublication.in/rmsgpublicationin
40. Sharma, R., Raj, A., & Mahajan, R. (2026, February). Ethical AI, data privacy and responsible AI practices. 1st International Conference on Artificial Intelligence and Data Science, Anu Bose Institute of Technology for Women & Rademics Research Institute, Paloncha, Telangana, India.
41. Sharma, R., & Bajaj, K. (2026, January). Role of AI in securing smart cities. 2nd International Conference on Recent Trends in Science, Engineering and Technology, Jagannath University, Jaipur, Rajasthan, India.
42. Sharma, R., & Bajaj, K. (2026, January). AI

driven cyber security: Detection and prevention of cyber threats. 2nd International Conference on Recent Trends in Science, Engineering and Technology, Jagannath University, Jaipur, Rajasthan, India.

43. Sharma, R., & Bajaj, K. (2026, January). Role of management practices in achieving sustainability through smart manufacturing and industry 4.0. 2nd International Conference on Recent Trends in Science, Engineering and Technology, Jagannath University, Jaipur, Rajasthan, India.