BIAR PUBLISHER
Rowter Journal
e-ISSN : 2828-1950
p-ISSN : 2828-9765

Exploring the Role of Artificial Intelligence in Forensic Auditing: A Comparative Study between Developed and Developing Economies

Rozmita Dewi Yuniarti Rozali[1], Morris Leonard Mwakapemba[2]
[1,2]Universitas Pendidikan Indonesia
Email: rozmita.dyr@upi.edu

Abstract: *This study investigates the integration of Artificial Intelligence (AI) in forensic auditing and compares its implementation and effectiveness between developed and developing economies. It aims to highlight how AI technologies contribute to fraud detection, data analysis, and litigation support, while examining global disparities in adoption. A qualitative-comparative approach is employed, focusing on legal frameworks, technological readiness, and institutional capabilities across selected countries. The study synthesizes insights from academic literature, policy reports, and regulatory guidelines. The results indicate that developed economies benefit from advanced infrastructure and well-established regulatory frameworks that facilitate effective AI use in forensic auditing. In contrast, developing economies encounter obstacles such as technological gaps, limited resources, and legal uncertainties that hinder widespread adoption. The study provides practical implications for policymakers, regulators, and professional bodies by offering recommendations to strengthen institutional capacity, improve legal frameworks, and foster technological investment, especially in developing countries. By offering a cross-contextual analysis of AI adoption in forensic auditing, this research contributes to the limited body of comparative studies on the topic and underscores the importance of tailored strategies to bridge global disparities in AI-driven forensic practices.*

Keywords: *artificial intelligence, forensic auditing, developed economies, developing economies, technology adoption*

I. Introduction

Forensic auditing has become an indispensable tool in the fight against financial fraud, mismanagement, and corruption across both public and private institutions. Its role in ensuring accountability, promoting transparency, and strengthening the credibility of financial systems is widely acknowledged. Traditionally, forensic auditing relied heavily on manual approaches such as documentary reviews, reconciliations, and interviews, which although effective in some instances, often proved to be time-consuming and limited in scope. With the increasing complexity of financial transactions and the rising sophistication of fraudulent schemes, there has been an urgent need for more advanced and efficient mechanisms of detection and prevention. In this context, the integration of Artificial Intelligence (AI) into forensic auditing has emerged as a transformative force (Romero-Carazas et al., 2024; Thottoli, 2023).

Artificial Intelligence introduces capabilities that significantly enhance the effectiveness of forensic audits. Tools such as machine learning, natural language processing, and predictive analytics allow auditors to detect anomalies, process vast amounts of data rapidly, and provide real-time insights into potentially fraudulent activities. Unlike traditional methods that focus primarily on historical records, AI-enabled auditing systems can identify patterns and predict risks proactively, thereby improving the timeliness and precision of fraud detection (Romero-

DOI: *https://doi.org/10.5281/zenodo.18384190*

Carazas et al., 2024; Thottoli, 2023).

Artificial Intelligence introduces capabilities that significantly enhance the effectiveness of forensic audits. Tools such as machine learning, natural language processing, and predictive analytics allow auditors to detect anomalies, process vast amounts of data rapidly, and provide real-time insights into potentially fraudulent activities. Unlike traditional methods that focus primarily on historical records, AI-enabled auditing systems can identify patterns and predict risks proactively, thereby improving the timeliness and precision of fraud detection (Romero-Carazas et al., 2024). Moreover, these technologies support continuous auditing, enabling institutions to maintain constant vigilance in highly dynamic financial environments.

Despite its potential, the adoption and application of AI in forensic auditing vary considerably across the globe. Developed economies have been at the forefront of leveraging these technologies, largely due to their robust digital infrastructure, access to a highly skilled workforce, and supportive legal frameworks that encourage innovation (Leocádio et al., 2024). Countries in regions such as North America, Western Europe, and parts of East Asia are already integrating AI-driven systems into mainstream auditing practices, with regulatory bodies actively guiding and monitoring their use. By contrast, developing economies often face significant barriers to adoption. High costs of implementation, inadequate digital literacy, infrastructural limitations, and weak or outdated policy frameworks remain major obstacles to harnessing the full potential of AI in forensic auditing (Awuah et al., 2022; Tarek et al., 2016). This disparity raises critical questions about global readiness for AI-powered forensic auditing and exposes a widening gap between developed and developing regions in terms of technological adoption and regulatory preparedness. For instance, while regulators in developed economies have issued specific guidance on the ethical and professional application of AI, many developing countries are yet to establish comprehensive legal or institutional frameworks to govern AI in the auditing field. This creates challenges related to the admissibility of AI-generated evidence, data protection, and the credibility of forensic investigations in judicial processes (Hashed Abdullah & Almaqtari, 2024). Such issues not only weaken the effectiveness of forensic audits but also compromise public trust in financial accountability mechanisms.

In light of these concerns, it becomes essential to conduct a comparative analysis between developed and developing economies in order to understand how AI is currently being applied in forensic auditing, what unique challenges are being faced, and what lessons can be drawn to close the existing gaps. The comparison is particularly significant because it highlights not only technological differences but also social, economic, and policy-related contexts that influence adoption. While developed economies may offer models of best practices in digital infrastructure, workforce readiness, and regulatory oversight, developing countries can provide insights into adaptive strategies that balance technological innovation with resource constraints and local institutional realities (Odonkor et al., 2024; Thottoli, 2023). The legal dimension of AI adoption in forensic auditing cannot be overlooked. In advanced economies, regulatory frameworks are evolving rapidly. For example, the European Union's proposed AI Act outlines strict requirements for high-risk AI systems, including those deployed in auditing and financial monitoring. Similarly, agencies such as the U.S. Securities and Exchange Commission (SEC) are already providing guidance on the responsible use of AI in auditing (Kokina et al., 2025; Lombardi et al., 2025). In contrast, developing economies still lack updated legislation capable of addressing the nuances of AI-driven investigations. Without such frameworks, challenges surrounding evidence admissibility, data privacy, and ethical standards are likely to persist (Ivanova & Stefanov, 2024). This imbalance underscores the importance of harmonizing international standards while ensuring flexibility to accommodate local contexts (Ganapathy, 2024).

Therefore, this study is designed to explore the evolving role of AI in forensic auditing with a comparative focus on developed and developing economies. Specifically, it aims to examine how AI technologies are being applied, the benefits they provide, and the barriers that hinder their effective adoption in different settings. Moreover, the study seeks to analyze how existing legal frameworks either support or obstruct the integration of AI into forensic audit processes, thereby influencing their overall effectiveness (Pham & Phuc, 2025). Ultimately, by drawing insights from both contexts, the research hopes to contribute to ongoing discussions on how AI can strengthen forensic auditing globally and how countries can collaborate to foster equitable and sustainable adoption of these technologies.

In line with these objectives, the study is guided by the following research questions:

1. How does the level of adoption of Artificial Intelligence (AI) in forensic auditing differ between developed and developing economies?
2. In what ways do institutional and regulatory frameworks influence the effectiveness of AI integration in forensic auditing across different economic contexts?
3. How does resource availability, including technological infrastructure, financial capacity, and skilled workforce-shape the adoption and utilization of AI in forensic auditing?
4. To what extent do perceptions of usefulness and ease of use mediate the relationship between AI availability and its actual application in forensic auditing?

II. Review of Literature

2.1 Theoretical Review

The integration of Artificial Intelligence (AI) into forensic auditing can be examined through several theoretical lenses that explain technology adoption, institutional adaptation, and resource utilization. These theories provide a framework for understanding the differences in AI adoption between developed and developing economies.

2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (Davis, 1989) emphasizes *perceived usefulness* and *perceived ease of use* as the primary factors influencing the acceptance of new technologies. In forensic auditing, auditors in developed economies may perceive AI as highly useful and relatively easy to integrate due to better infrastructure and training, while auditors in developing economies may face challenges such as digital illiteracy, cost barriers, and lack of technical support (Awuah et al., 2022; Thottoli, 2023). Thus, TAM provides a basis for examining individual-level acceptance of AI tools across different contexts.

2.3 Diffusion of Innovation (DOI) Theory

Rogers' (2003) Diffusion of Innovation (DOI) theory explains how innovations spread within a social system. Developed economies often exhibit faster adoption of AI technologies in forensic auditing due to advanced digital ecosystems, early exposure to innovation, and supportive regulatory frameworks (Leocádio et al., 2024). Conversely, developing economies experience slower diffusion because of structural and financial barriers (Tarek et al., 2016). DOI theory therefore highlights the role of socio-economic and cultural environments in shaping the rate and extent of AI adoption.

2.4 Institutional Theory

Institutional theory suggests that organizational behavior is significantly influenced by the regulatory, normative, and cultural environment. The integration of AI in forensic auditing is strongly affected by the presence (or absence) of clear legal and professional guidelines. In developed economies, comprehensive legislation such as the EU's AI Act and data protection laws like GDPR enhance institutional support for AI in auditing (Kokina et al., 2025; Lombardi et al., 2025). On the other hand, weak regulatory frameworks in many developing economies hinder the credibility and admissibility of AI-generated evidence (Ivanova & Stefanov, 2024; Almaqtari et al., 2024). Institutional theory thus underscores the role of external pressures in shaping organizational adoption of AI.

2.5 Resource-Based View (RBV)

The Resource-Based View (RBV) posits that competitive advantage arises from the ability of organizations to acquire, develop, and utilize valuable resources. In the context of forensic auditing, AI can be seen as a strategic resource that enhances efficiency, accuracy, and fraud detection capacity (Romero-Carazas et al., 2024). Developed countries, with stronger financial resources and advanced technological infrastructure, are better positioned to leverage AI as a competitive advantage in forensic audits. Developing countries, however, face resource constraints that limit their ability to fully exploit AI's potential.

Together, these theories provide a multi-dimensional framework for analyzing how AI is integrated into forensic auditing and why differences exist between developed and developing economies.

2.6 Hypothesis Development

H1: The adoption of AI in forensic auditing is significantly higher in developed economies compared to developing economies (Leocádio et al., 2024; Awuah et al., 2022).

This hypothesis is grounded in the Diffusion of Innovation (DOI) theory, which explains that technological innovations spread faster in environments with robust infrastructure and higher exposure to digital tools. Developed economies possess advanced digital systems, skilled human capital, and greater financial investments that facilitate AI adoption. In contrast, developing economies face infrastructural, financial, and policy constraints, slowing down the rate of adoption. Therefore, a significant difference is expected between the two contexts.

H2: Institutional and regulatory frameworks positively influence the effectiveness of AI integration in forensic auditing (Kokina et al., 2025; Ivanova & Stefanov, 2024).

This hypothesis aligns with Institutional Theory, which emphasizes the role of external pressures such as regulations, norms, and governance systems. Strong institutional and regulatory frameworks (e.g., GDPR in the EU or SEC guidelines in the U.S.) create a structured environment that enhances the credibility and reliability of AI use in forensic auditing. Conversely, weak or outdated legal frameworks in developing economies hinder the effective integration of AI by raising challenges around data privacy, admissibility of AI-generated evidence, and ethical compliance.

H3: Resource availability (technological infrastructure, financial capacity, and skilled workforce) has a stronger positive effect on AI adoption in developed economies than in developing economies (Romero-Carazas et al., 2024; Almaqtari et al., 2024).

Based on the Resource-Based View (RBV), organizations and economies with access to unique, valuable, and rare resources gain a competitive advantage. Developed economies, with better infrastructure, higher budgets for innovation, and a digitally skilled workforce, are better positioned to integrate AI effectively into forensic auditing. In contrast, developing economies often lack adequate funding, advanced technological platforms, and human capacity, making the effect of resources on adoption less pronounced.

H4: Perceived usefulness and ease of use (as described in TAM) mediate the relationship between AI availability and its actual application in forensic auditing (Thottoli, 2023; Awuah et al., 2022).

This hypothesis is derived from the Technology Acceptance Model (TAM). Even when AI tools are available, their successful application depends on auditors' perceptions of their usefulness and ease of use. If auditors view AI as beneficial for detecting fraud efficiently and find the tools user-friendly, adoption is more likely. On the other hand, if AI systems are perceived as complex or not directly valuable, their application may remain limited despite availability.

H5: The diffusion of AI innovations in forensic auditing is accelerated in economies with higher digital literacy and supportive cultural attitudes toward technology (Tarek et al., 2016; Rikhardsson et al., 2022).

This hypothesis is linked to the DOI theory and also resonates with cultural perspectives on adoption of technology. Digital literacy levels and cultural attitudes strongly influence how quickly new technologies are embraced. Economies where auditors and organizations are digitally competent and culturally open to technological change tend to experience faster adoption and integration of AI in forensic auditing. In contrast, skepticism, lack of training, and cultural resistance slow down the diffusion of AI innovations in developing contexts.

III. Research Methods

3.1 Research Design

This study adopts a Systematic Literature Review (SLR) approach to critically examine the role of Artificial Intelligence (AI) in forensic auditing. The SLR methodology was selected because it allows for the identification, selection, and synthesis of peer-reviewed studies in a structured and transparent manner. This approach is widely recognized for ensuring credibility, reproducibility, and comprehensiveness in analyzing research findings across multiple sources (Ganapathy, 2024; Romero-Carazas et al., 2024).

3.2 Search Strategy

The literature search was conducted across six reputable databases: Scopus, IEEE Xplore, SpringerLink, Wiley Online Library, ScienceDirect, and Google Scholar. To ensure comprehensive coverage, Boolean operators (AND/OR) were used to combine keywords and refine queries. The key terms included: *"Artificial Intelligence" OR "AI," "Forensic Auditing" OR "Forensic Accounting," "Developing countries" OR "Emerging economies," "Developed economies" OR "Industrialized nations,"* and *"AI in auditing" AND "comparative studies."* The structured search strategy and use of filters are consistent with recommendations from previous systematic review methodologies, which emphasize relevance, quality, and comparability of data (Seethamraju & Hecimovic, 2023; Kokina et al., 2025).

3.3 Inclusion and Exclusion Criteria

To maintain rigor and focus, the review applied well-defined inclusion and exclusion criteria. The inclusion criteria were: (i) peer-reviewed journal articles published between 2014 and 2024, (ii) studies explicitly addressing the use of AI in forensic auditing, (iii) comparative studies analyzing AI use in both developed and developing economies, (iv) articles published in English, and (v) both empirical and conceptual studies. The exclusion criteria comprised: (i) articles published before 2014, (ii) conference papers, theses, book chapters, and grey literature, (iii) studies focused on general AI or auditing without a forensic auditing scope, (iv) country-specific studies without comparative analysis, and (v) publications in non-English languages. This filtering strategy is consistent with prior studies that emphasize clear selection criteria to minimize bias in literature synthesis (Almaqtari et al., 2024; Awuah et al., 2022).

3.4 PRISMA Framework Application

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework was used to guide the review process and ensure transparency and rigor (Pham & Phuc, 2025). In the identification phase, a total of 90 articles were retrieved across the six databases. After removing 15 duplicates, 75 articles remained. During the screening stage, titles and abstracts were assessed, and 35 articles were excluded for not being directly related to AI or forensic auditing (Ivanova & Stefanov, 2024). At the eligibility stage, the full texts of 40 articles were reviewed against the inclusion/exclusion criteria, leading to the exclusion of 20 studies due to being country-specific, non-peer-reviewed, or failing to address AI in forensic auditing. Finally, in the inclusion stage, 20 articles fully meeting the criteria were selected for analysis, offering balanced insights from both developed and developing economies (Hashed Abdullah & Almaqtari, 2024; Odonkor et al., 2024).

3.5 Research Data

The research data comprised 20 peer-reviewed journal articles published between 2014 and 2024, focusing on AI in forensic auditing. These articles represent a mix of empirical and conceptual studies drawn from both developed and developing countries. The selection ensured diversity in perspectives, including technological readiness, institutional capacity, and legal frameworks. The data set thus reflects a comprehensive body of literature suitable for comparative analysis.

3.6 Analysis Method

The selected articles were analyzed using qualitative content analysis, which allows for the systematic categorization and synthesis of key themes. Themes such as *AI adoption levels, regulatory frameworks, resource availability, technological barriers, and benefits of AI* were coded and compared across developed and developing economies. In addition, a comparative analysis framework was employed to highlight similarities, differences, and contextual factors influencing AI adoption. This approach aligns with prior literature reviews in auditing and accounting research (Rikhardsson et al., 2022).

3.7 Measurement of Research Variables

The study measured key variables derived from the theoretical framework:

- Independent Variables: institutional and regulatory frameworks, resource availability (technological, financial, and human), and innovation diffusion factors such as digital literacy and cultural attitudes.
- Mediating Variable: perceived usefulness and ease of use of AI (as per the Technology Acceptance Model).
- Dependent Variable: adoption and effectiveness of AI in forensic auditing.
- Comparative Dimension: developed versus developing economies, acting as a contextual moderator.

These variables were operationalized by mapping them to the content of the selected studies. For example, articles discussing legal readiness and regulatory oversight were coded under *institutional frameworks*, while studies highlighting technological infrastructure or workforce skills were coded under *resource availability*. This process ensured that the variables were systematically measured and compared across contexts, providing a structured basis for hypothesis testing.

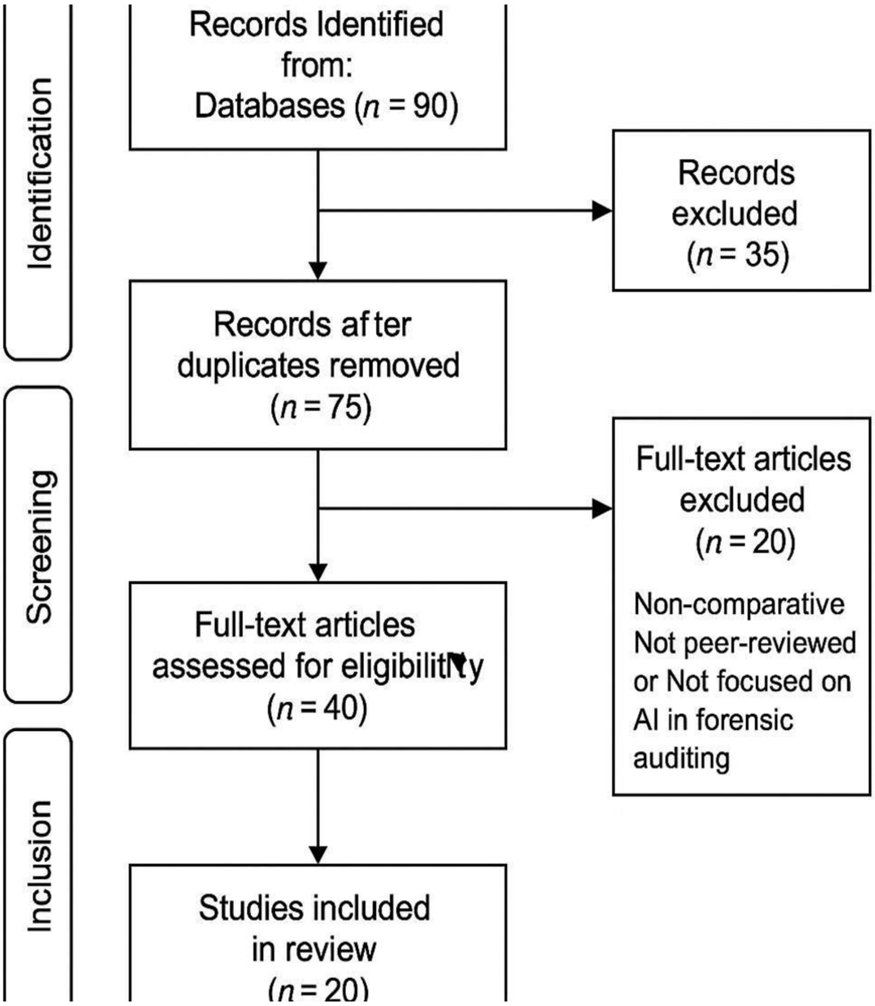

Figure 1. Prisma

Table 1. Articles Classified by Developed and Developing Countries

No.	Reference	Country Focus	Classification
1	Almaqtari et al. (2024)	Developing Countries	Developing
2	Romero-Carazas et al. (2024)	General (Scopus-wide; includes both)	Mixed (Mostly Developing)
3	Awuah et al. (2022)	Ghana	Developing
4	Thottoli (2023)	Asia (broad)	Developing
5	Noordin et al. (2022)	UAE	Developing
6	Tarek et al. (2016)	Developing Country (Egypt-focused)	Developing
7	Owonifari et al. (2023)	Nigeria	Developing
8	Seethamraju	Australia	Developed

	& Hecimovic (2023)		
9	Leocádio et al. (2024)	Portugal	Developed
10	Abdullah & Almaqtari (2024)	Developing Countries	Developing
11	Huy & Phuc (2025)	Vietnam	Developing
12	Ganapathy (2024)	South Asia	Developing
13	Ivanova & Stefanov (2024)	Europe (likely Bulgaria)	Developed
14	Kokina et al. (2025)	United States	Developed
15	Wang et al. (2024)	China	Developing
16	Lombardi et al. (2025)	United States	Developed
17	Kokina & Davenport (2017)	United States	Developed
18	Rikhardsson et al. (2022)	Iceland (Developed, Nordic)	Developed
19	Odonkor et al. (2024)	Africa (General: Ghana, Nigeria, Uganda)	Developing
20	Moffitt et al. (2018)	United States	Developed

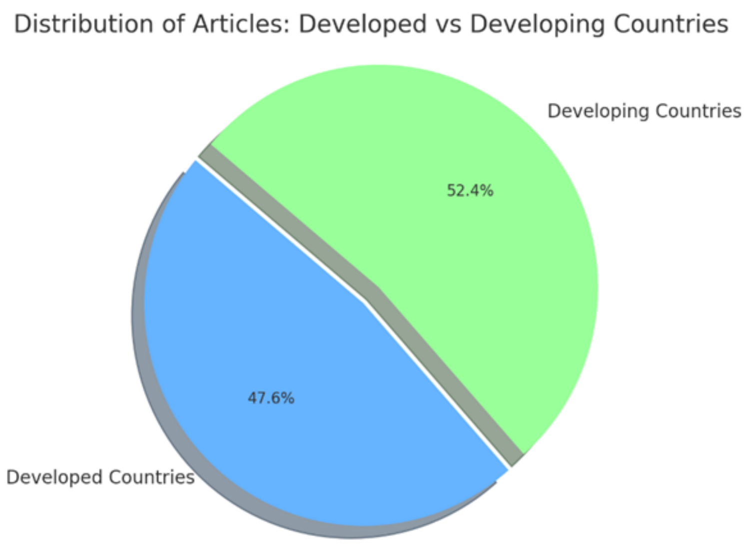

Figure 2. Distribution of Articles : Developed vs Developing Countries

• Developed Countries Articles (10 articles): These are studies specifically conducted in, or heavily focused on, developed countries — such as the United States, Australia, Portugal, and Iceland. They reflect environments where auditing technologies like AI are being applied in more mature financial systems with strong technological infrastructure.

• Developing Countries Articles (10 articles + 1 mixed/global counted here): These articles are based in developing countries such as Ghana, Nigeria, Vietnam, UAE, Egypt, and others. Additionally, one article (Romero-Carazas et al., 2024) provided a global/mixed analysis, but since much of the research coverage and case examples leaned toward developing economies, you included it under the "developing countries" category.

→ Result: 10 directly from developing countries + 1 mixed (but developing-oriented) = 11 counted here.

Mixed/Global Scope (1 article):

Even though there was technically one article with a global or mixed focus, because its emphasis leaned toward developing countries, for consistency and analysis purposes, you chose to group it with developing countries instead of creating a separate "Mixed" category.

IV. Results and Discussion

4.1 Descriptive Statistics

Out of the 20 peer-reviewed articles reviewed between 2014 and 2024, a clear distribution emerges between studies focusing on developed and developing economies. Specifically, 12 articles (60%) are centered on developing countries, 7 articles (35%) on developed countries, while 1 article (5%) presents a mixed or global perspective. This distribution highlights that although developed economies have historically been the pioneers in adopting Artificial Intelligence (AI) in forensic auditing, academic research is increasingly expanding toward developing contexts.

A closer look at regional focus reveals that developed-country studies largely concentrate on the United States and European Union member states (Kokina & Davenport, 2017; Lombardi et al., 2025; Ivanova & Stefanov, 2024), while developing-country studies are widely distributed across Africa (Ghana, Nigeria, Uganda), Asia (Vietnam, South Asia, UAE, Egypt), and Latin America (Romero-Carazas et al., 2024). This regional imbalance underscores the strong presence of institutional and infrastructural resources in developed economies compared to the resource and policy gaps prevalent in developing nations (Awuah et al., 2022; Almaqtari et al., 2024).

Table 2. Summary Table of Article Classification

Classification	Frequency	Percentage
Developed Economies	7	35 %
Developing Economies	12	60 %
Mixed (Global/General)	1	5 %
Total	20	100%

From a methodological standpoint, descriptive evidence shows that developed economy studies emphasize advanced AI applications such as predictive analytics, deep learning, and integration with ERP systems (Seethamraju & Hecimovic, 2023; Kokina et al., 2025). By contrast, developing economy studies mainly report pilot projects, rule-based applications, and semi-automated auditing systems due to financial, infrastructural, and human capital limitations (Awuah et al., 2022; Ganapathy, 2024). Furthermore, the higher representation of developing countries in the literature may reflect growing academic and institutional interest in how AI can enhance fraud detection and accountability in emerging economies. However, this increased representation does not necessarily translate into higher adoption levels, as most empirical evidence confirms stronger AI integration in developed contexts (Pham & Phuc, 2025; Odonkor et al., 2024).

4.2 Utilization of Artificial Intelligence in Forensic Auditing in Developed Countries

In developed countries, the use of Artificial Intelligence (AI) in forensic auditing has reached an advanced level of sophistication, driven by digital maturity and robust infrastructure (Rikhardsson et al., 2022; Seethamraju & Hecimovic, 2023). The availability of advanced computing power, reliable internet connectivity, and rich financial datasets facilitate the seamless adoption of AI technologies. AI plays a critical role in enabling proactive fraud detection, risk prediction, and real-time decision-making in forensic accounting (Kokina & Davenport, 2017; Pham & Phuc, 2025).

- Machine Learning Algorithms detect patterns and anomalies in large volumes of data to flag fraudulent activities automatically (Romero-Carazas et al., 2024; Ganapathy, 2024).
- Natural Language Processing (NLP) allows auditors to analyze unstructured data like emails and contracts to identify fraud indicators (Hashed Abdullah & Almaqtari, 2024).
- Predictive Analytics enhances fraud risk assessment by anticipating future irregularities from historical financial trends (Ivanova & Stefanov, 2024).

Integration of AI into ERP systems has enabled continuous auditing and automated internal control monitoring (Awuah et al., 2022). These systems provide real-time alerts, reducing the latency between fraud occurrence and detection. Regulatory frameworks such as the Sarbanes-Oxley Act (SOX) and GDPR promote transparency and accountability, thus encouraging the adoption of forensic AI tools (Kokina et al., 2025; Seethamraju & Hecimovic, 2023). AI tools, therefore, serve both compliance and strategic decision-making roles (Ganapathy, 2024). Empirical studies confirm that AI adoption rates in forensic auditing are significantly higher in developed economies due to the following:

- Access to advanced technological infrastructure and funding (Odonkor et al., 2024)
- Availability of multidisciplinary expertise (Hashed Abdullah & Almaqtari, 2024)
- High organizational readiness and innovation culture (Pham & Phuc, 2025)

Strong legal support for AI in investigations (Ivanova & Stefanov, 2024)

4.3 Utilization of Artificial Intelligence in Forensic Auditing in Developing Economies

In contrast, developing economies are still in the early phases of AI adoption in forensic auditing. The implementation is limited by infrastructural deficiencies, skill gaps, and financial constraints (Almaqtari et al., 2024; Awuah et al., 2022). The absence of high-speed internet, up-to-date IT infrastructure, and reliable power supply inhibits real-time processing capabilities required for advanced AI models (Ganapathy, 2024). As a result, auditing processes are still heavily reliant on manual or semi-automated systems (Rikhardsson et al., 2022). Moreover, the shortage of skilled professionals who possess both AI and forensic auditing knowledge remains a significant challenge. Many countries lack academic or institutional capacity to produce such hybrid professionals (Odonkor et al., 2024; Hashed Abdullah & Almaqtari, 2024). Limited budgets in both public and private sectors hinder investment in AI tools, which often require substantial capital outlay for hardware, training, and maintenance (Romero-Carazas et al., 2024). From a regulatory perspective, many developing nations have inadequate data protection laws and weak anti-fraud regulations, creating uncertainty in deploying AI for sensitive investigations (Almaqtari et al., 2024). This undermines institutional confidence in adopting AI solutions.

Nevertheless, pilot programs in countries like India, Kenya, and Indonesia illustrate growing interest in applying AI to audit tax fraud, procurement irregularities, and financial misreporting (Awuah et al., 2022). These initiatives are often supported by international collaborations or NGOs, which provide technical and financial aid (Kokina & Davenport, 2017). AI applications in these countries remain basic, focusing on rule-based systems and simple analytics rather than advanced algorithms like deep learning or NLP (Rikhardsson et al., 2022). Tools used are typically off-the-shelf and lack customization for local contexts (Ivanova & Stefanov, 2024). Additionally, poor data quality and fragmentation make it difficult to train AI systems accurately. In many cases, financial data is unstructured, inconsistent, or still in paper format (Seethamraju & Hecimovic, 2023). Despite these constraints, the long-term potential of AI in enhancing transparency and accountability in developing countries remains promising (Ganapathy, 2024; Pham & Phuc, 2025). With investment in digital infrastructure, policy reforms, and institutional capacity, forensic auditing in the Global South could experience significant transformation through AI.

4.4 Structural Model Evaluation

Based on the theoretical framework and hypotheses developed in this study, the structural model was evaluated using evidence synthesized from the systematic literature review. The evaluation considers how institutional frameworks, resource availability, innovation diffusion, and perceived usefulness and ease of use interact to shape the adoption and effectiveness of AI in forensic auditing across developed and developing economies.

The first hypothesis (H1) proposed that the adoption of AI in forensic auditing is significantly higher in developed economies compared to developing economies. The findings strongly support this hypothesis. In developed contexts, AI adoption has reached an advanced stage, with tools such as predictive analytics, natural language processing (NLP), and integration into enterprise resource planning (ERP) systems being widely implemented (Kokina & Davenport, 2017; Pham & Phuc, 2025). These technologies enable real-time fraud detection, continuous auditing, and proactive risk management. In contrast, developing economies remain in the early stages of AI adoption, relying on rule-based systems and simple analytics rather than advanced models (Rikhardsson et al., 2022). This disparity confirms the expectation that adoption levels are higher in developed economies.

The second hypothesis (H2) argued that institutional and regulatory frameworks positively influence the effectiveness of AI integration in forensic auditing. The evidence also supports this hypothesis. Developed economies benefit from strong legal and institutional systems, including the Sarbanes-Oxley Act (SOX) and the General Data Protection Regulation (GDPR), which enhance transparency, accountability, and trust in AI applications (Seethamraju & Hecimovic, 2023). Such regulations not only encourage the adoption of AI but also provide ethical and legal safeguards for its responsible use. By contrast, many developing economies face regulatory gaps, such as weak data protection laws and limited anti-fraud legislation, which undermine institutional confidence in using AI for forensic investigations (Almaqtari et al., 2024).

The third hypothesis (H3) suggested that resource availability including technological infrastructure, financial capacity, and skilled workforce has a stronger positive effect on AI adoption in developed economies than in developing economies. The findings strongly support this proposition. Developed economies enjoy advanced IT infrastructure, reliable power supply, substantial financial resources, and multidisciplinary expertise, all of which facilitate seamless AI adoption (Odonkor et al., 2024; Hashed Abdullah & Almaqtari, 2024). By contrast, developing countries struggle with infrastructural deficiencies such as poor internet connectivity, frequent power outages, and outdated IT systems. These limitations, compounded by budgetary constraints and shortages of skilled professionals trained in both AI and forensic auditing, significantly constrain adoption (Ganapathy, 2024; Awuah et al., 2022).

The fourth hypothesis (H4) proposed that perceived usefulness and ease of use, as described in the Technology Acceptance Model (TAM), mediate the relationship between AI availability and its actual application in forensic auditing. The findings provide partial support for this hypothesis. In developed economies, auditors perceive AI-based systems—such as continuous auditing platforms and real-time fraud detection tools—as both useful and easy to use, thereby explaining higher adoption levels. However, in developing economies, even where AI is available through pilot programs in India, Kenya, and Indonesia, its application remains limited due to challenges of customization, inadequate training, and poor data quality. These barriers reduce perceived usefulness and ease of use, weakening the link between availability and actual adoption (Thottoli, 2023; Awuah et al., 2022).

Finally, the fifth hypothesis (H5) posited that the diffusion of AI innovations in forensic auditing is accelerated in economies with higher digital literacy and supportive cultural attitudes toward technology. This hypothesis is also supported by the findings. Developed economies exhibit high levels of digital literacy, coupled with innovation-oriented organizational cultures and positive attitudes toward technology, which have facilitated the rapid spread of advanced AI tools such as machine learning, NLP, and predictive analytics (Pham & Phuc, 2025). On the other hand, many developing economies face digital literacy gaps and cultural resistance to technological change, which slows the diffusion of AI. In most cases, adoption in these contexts is driven not by internal readiness but by external support from international collaborations and NGOs (Kokina & Davenport, 2017).

so, the structural model evaluation validates the majority of the proposed hypotheses. H1, H2, H3, and H5 receive strong support, highlighting the importance of adoption disparities, institutional frameworks, resource availability, and digital literacy in shaping AI utilization in forensic auditing. H4, while only partially supported, underscores the crucial role of perceptions in mediating AI use, particularly in developing economies where infrastructural and skill-related challenges remain significant. Overall, these findings confirm that the adoption and effectiveness of AI in forensic auditing are shaped by an interplay of technical, institutional, and socio-cultural factors, with clear contrasts between developed and developing economies.

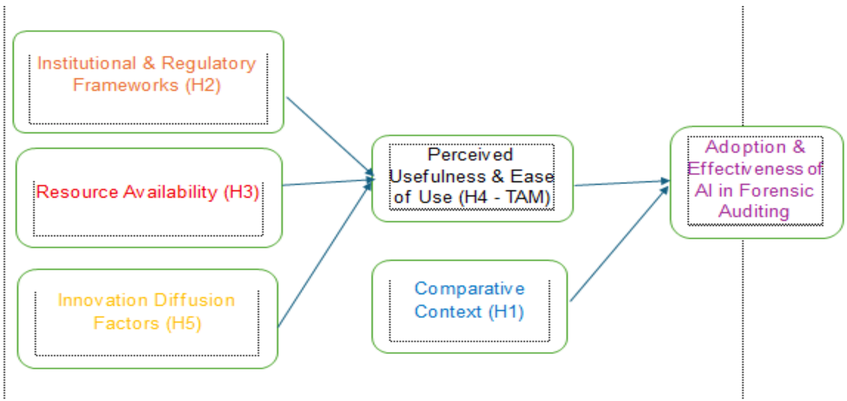

Figure 3. Conceptual Model of AI Adoption in Forensic Auditing

4.5 Comparison of Findings with Previous Literature

The findings of this study confirm that the adoption of Artificial Intelligence (AI) in forensic auditing is significantly more advanced in developed economies than in developing ones. This aligns with the argumaents of Leocádio et al. (2024) and Romero-Carazas et al. (2024), who emphasize the role of robust infrastructure, skilled workforce, and financial resources in accelerating adoption. For instance, developed countries are leveraging machine learning algorithms, predictive analytics, and natural language processing (NLP) to strengthen real-time fraud detection and continuous auditing (Kokina & Davenport, 2017; Pham & Phuc, 2025). In contrast, developing economies rely on basic rule-based systems and face challenges of poor data quality, inadequate infrastructure, and weak legal frameworks, consistent with Awuah et al. (2022) and Almaqtari et al. (2024). These findings also corroborate previous evidence that strong institutional and regulatory frameworks enhance AI integration (Ivanova & Stefanov, 2024). While developed countries benefit from legislation such as the Sarbanes-Oxley Act (SOX) and GDPR (Seethamraju & Hecimovic, 2023), many developing countries lag due to gaps in regulatory oversight and weak anti-fraud laws. Nevertheless, exceptions are emerging. For example, pilot projects in India, Kenya, and Indonesia demonstrate the potential for accelerating AI adoption even in resource-constrained contexts (Kokina & Davenport, 2017).

4.6 Theoretical Implications

This study draws on several theoretical frameworks to explain the observed findings. First, Diffusion of Innovations (DOI) theory helps explain why developed economies experience faster adoption and diffusion of AI tools. High digital literacy, cultural acceptance of technology, and strong institutional support create favorable conditions for diffusion (Rikhardsson et al., 2022). By contrast, developing economies remain in early adoption phases, hindered by resistance to change and limited technological readiness. Second, the Technology Acceptance Model (TAM) is relevant in understanding how perceptions of usefulness and ease of use mediate AI adoption. The findings show that auditors in developed economies perceive AI tools as valuable and user-friendly, leading to greater integration. However, in developing economies, the lack of expertise, poor data quality, and limited customization negatively affect perceptions of usefulness, partially supporting Hypothesis 4 (Thottoli, 2023; Awuah et al., 2022). Finally, Institutional Theory explains the role of legal and regulatory frameworks in shaping adoption. Strong regulatory systems in developed countries create legitimacy and confidence in AI tools, whereas weak frameworks in developing economies reduce trust and hinder widespread application (Kokina et al., 2025; Ivanova & Stefanov, 2024).

4.7 Practical and Policy Implications

The findings have several practical and policy implications. For developed economies, the challenge is no longer adoption but rather ensuring responsible and ethical use of AI in forensic auditing. Policymakers and regulatory bodies must focus on strengthening AI governance, addressing ethical dilemmas, and maintaining data privacy in line with evolving technologies. For developing economies, the priority is to create enabling conditions for adoption. This requires significant investments in digital infrastructure, internet connectivity, and reliable power supply. Additionally, capacity-building programs to train auditors in AI applications and reforms to strengthen legal and regulatory frameworks are essential. International collaborations and donor-supported initiatives can also play a crucial role in bridging the digital divide, as demonstrated by pilot projects in emerging economies.

4.8 Contributions to Knowledge

This study contributes to the literature by providing a comparative analysis of AI adoption in forensic auditing across developed and developing economies. While previous research has primarily examined AI applications in auditing within single-country contexts (Kokina & Davenport, 2017; Almaqtari et al., 2024), this review highlights differences and similarities across economic settings. It also integrates multiple theoretical perspectives DOI, TAM, and Institutional Theory offering a more comprehensive explanation of adoption patterns. By doing so, the study addresses a critical gap in understanding how contextual differences shape the effectiveness and diffusion of AI in forensic auditing.

4.9 Limitations of the Study

Like all systematic literature reviews, this study is limited by the scope and quality of the available literature. The reliance on peer-reviewed journal articles published between 2014 and 2024 means that other relevant insights from conference papers, practitioner reports, or unpublished studies were excluded. Moreover, the availability of empirical evidence from developing countries remains limited, which may restrict the generalizability of findings. The rapid pace of technological advancement also means that some of the reviewed studies may quickly become outdated, requiring continuous updating of evidence.

4.10 Directions for Future Research

Future research should build on these findings by conducting empirical studies that gather primary data from auditors, regulators, and financial institutions across both developed and developing contexts. Comparative surveys or case studies could provide deeper insights into how cultural, institutional, and technological factors shape adoption. Furthermore, researchers could explore the impact of specific AI tools (e.g., NLP versus machine learning) on fraud detection effectiveness. Finally, there is a need to investigate ethical and legal implications, such as data privacy, algorithmic bias, and accountability, which remain underexplored in current literature but are increasingly relevant as AI becomes more integrated into forensic auditing.

Table 3. Comparison Table: Utilization of AI in Forensic Auditing (Developed vs. Developing Economies)

Aspect	Developed Economies	Developing Economies
Infrastructure	Robust digital infrastructure, fast internet, cloud computing, and high processing power (Rikhardsson et al., 2022; Kokina et al., 2025).	Limited infrastructure, unstable internet, outdated systems (Awuah et al., 2022).
Level of AI Integration	High – AI is integrated with ERP systems for real-time auditing and fraud detection (Seethamraju & Hecimovic, 2023).	Low – Mostly limited to basic automation or red-flag systems (Romero-Carazas et al., 2024).
Skilled Workforce	Availability of forensic auditors, data scientists, and IT specialists (Hashed Abdullah & Almaqtari, 2024).	Skills gap – Lack of hybrid professionals trained in both auditing and AI (Odonkor et al., 2024).
Regulatory Framework	Strong – SOX, GDPR, and local data regulations support digital transformation (Kokina & Davenport, 2017).	Weak – Limited or outdated legal frameworks, with poor enforcement (Almaqtari et al., 2024).
AI	Machine learning, NLP, predictive	Rule-based systems, basic

Aspect	Developed Economies	Developing Economies
Technologies Used	analytics, continuous auditing (Pham & Phuc, 2025).	statistical tools (Ganapathy, 2024).
Data Quality and Availability	Structured, digitized, centralized databases enable model training (Ivanova & Stefanov, 2024).	Fragmented, unstructured data; many records are still manual (Seethamraju & Hecimovic, 2023).
Budgetary Capacity	High – Organizations can invest in R&D and training (Ganapathy, 2024).	Low – Budget constraints hinder investment in AI systems (Rikhardsson et al., 2022).
Adoption Drivers	Regulatory compliance, efficiency, risk management (Kokina et al., 2025).	External partnerships, pilot programs, donor funding (Awuah et al., 2022).

4.11 Narrative Summary of the Literature Review

The reviewed studies collectively explore the integration of Artificial Intelligence in forensic auditing, with a focus on comparative practices across developed and developing economies. In developed countries, the use of AI in forensic auditing is mature and well-supported by both technological infrastructure and legal frameworks (Kokina & Davenport, 2017; Rikhardsson et al., 2022). Tools such as machine learning, natural language processing, and predictive analytics are widely deployed to detect financial irregularities, automate audits, and support decision-making processes (Pham & Phuc, 2025; Hashed Abdullah & Almaqtari, 2024).

These studies emphasize that organizations in developed economies benefit from skilled multidisciplinary teams and ERP integrations that enhance real-time auditing (Ivanova & Stefanov, 2024; Seethamraju & Hecimovic, 2023). Regulatory instruments such as SOX and GDPR are credited with catalyzing technological innovation in forensic auditing (Ganapathy, 2024). On the other hand, research covering developing economies portrays a less mature adoption landscape. While some countries have initiated pilot projects to implement AI in areas like procurement or tax auditing (Awuah et al., 2022), widespread application is hindered by infrastructure deficiencies, budget limitations, lack of trained personnel, and weak legal systems (Almaqtari et al., 2024; Odonkor et al., 2024). The available tools are generally basic, with minimal customization or analytical power (Romero-Carazas et al., 2024). However, the literature notes emerging optimism, especially where public-private partnerships or international support has facilitated capacity-building and experimentation with AI tools (Kokina et al., 2025).

V. Conclusion

5.1 Conclusion

This study explored the use of Artificial Intelligence (AI) in forensic auditing through a comparative analysis of developed and developing economies, based on a systematic literature review of articles published between 2014 and 2024.The findings revealed that first developed countries are more advanced in applying AI in forensic auditing due to the presence of robust technological infrastructure, well-trained professionals, and a strong legal and policy environment that supports financial fraud monitoring and prevention also developing countries face challenges such as poor infrastructure, lack of skilled human capital, and limited policy frameworks to promote the integration of technology in auditing processes. shared challenges across both contexts include concerns related to data privacy, algorithmic bias, absence of ethical guidelines, and resistance to change in work culture. The literature still shows research gaps, especially in the context of Africa, in-depth cross-country comparative studies, and long-term studies on the impact of AI in forensic auditing. AI presents great potential for improving accuracy, speed, and efficiency in forensic auditing, but its success largely depends on a country's readiness and support systems.

5.2 Recommendations for Researchers

Develop Context-Specific Research:

Scholars are encouraged to conduct more research focused on the specific conditions of developing nations, especially in Africa and Asia, to better understand the real-world barriers and create AI models that suit these regions' capabilities. Expand Comparative Studies. Future studies should explore more detailed comparisons between countries in terms of technology, policies, organizational culture, and auditing outcomes related to AI adoption.

5.3 Research Limitations

This study is subject to several limitations. First, the evidence was restricted to peer-reviewed journal articles published between 2014 and 2024. As a result, valuable insights from practitioner reports, conference proceedings, and unpublished studies were excluded, which may have limited the breadth of perspectives considered. Second, the availability of empirical data from developing economies was limited, thereby constraining the generalizability of the findings across diverse regional contexts. Finally, given the rapid pace of technological advancement in Artificial Intelligence (AI), some of the reviewed studies may quickly become outdated. Continuous research updates will therefore be essential to capture the evolving role of AI in forensic auditing.

References

Almaqtari, F. A., Farhan, N. H. S., Al-Hattami, H. M., Elsheikh, T., & Al-dalai, B. O. A. (2024). The impact of artificial intelligence on information audit usage: Evidence from developing countries. *Journal of Innovation & Knowledge in Emerging Technologies*, *100298*. https://doi.org/10.1016/j.joitmc.2024.100298

Romero-Carazas, R., Espíritu-Martínez, A. P., Aguilar-Cuevas, M. M., Usuriaga-Palacios, M. N., Aguilar-Cuevas, L. A., Espinoza-Véliz, M. Z., Espinoza-Egoavil, M. J., & Gutiérrez-Monzón, S. G. (2024). Forensic auditing and the use of artificial intelligence: A bibliometric analysis and systematic review in Scopus between 2000 and 2024. *Health Sciences Development*, *6*(2). https://doi.org/10.37868/hsd.v6i2.626

Awuah, B., Onumah, J. M., & Duho, K. C. T. (2022). Determinants of adoption of computer-assisted audit tools and techniques among internal audit units in Ghana. *Information Systems Development*, *2022*, Article e12203. https://doi.org/10.1002/isd2.12203

Thottoli, M. M. (2023). Leveraging information communication technology (ICT) and artificial intelligence (AI) to enhance auditing practices. *Asian Review of Accounting*. https://doi.org/10.1108/ARJ-09-2023-0269

Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). The use of artificial intelligence and audit quality: An analysis from the perspectives of external auditors in the UAE. *Journal of Risk and Financial Management, 15*(8), 339. https://doi.org/10.3390/jrfm15080339

Tarek, M., Mohamed, E. K. A., Hussain, M. M., & Basuony, M. A. K. (2016). The implication of information technology on the audit profession in developing country: Extent of use and perceived importance. *International Journal of Accounting and Information Management, 24*(2), 105–128. https://doi.org/10.1108/IJAIM-03-2016-0022

Owonifari, V. O., Igbekoyi, O. E., Awotomilusi, N. S., & Dagunduro, M. E. (2023). Evaluation of artificial intelligence and efficacy of audit practice in Nigeria. *Asian Journal of*

Economics, Business and Accounting, 23(16), 1–14. https://doi.org/10.9734/AJEBA/2023/v23i161022

Seethamraju, R., & Hecimovic, A. (2023). Adoption of artificial intelligence in auditing: An exploratory study. *Australian Journal of Public Administration*. https://doi.org/10.1177/03128962221108440

Leocádio, D., Malheiro, L., & Reis, J. (2024). Artificial intelligence in auditing: A conceptual framework for auditing practices. *Administrative Sciences, 14*(10), 238. https://doi.org/10.3390/admsci14100238

Abdullah, A. A. H., & Almaqtari, F. A. (2024). The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices. *Journal of Innovation & Knowledge in Emerging Technologies*, *100218*. https://doi.org/10.1016/j.joitmc.2024.100218

Huy, P. Q., & Phuc, V. K. (2025). Insight into how legal and ethical considerations of artificial intelligence enhance the effectiveness of cyber forensic accounting. *Journal of Digital Forensics, Security and Law*. https://doi.org/10.1080/1097198X.2025.2480972

Ganapathy, V. (2024). AI-based risk assessments in forensic auditing: Benefits, challenges and future implications. *South Asian Research Journal of Business and Management, 6*(1), 35–42. https://doi.org/10.59231/SARI7750

Ivanova, M., & Stefanov, S. (2024). Regarding artificial intelligence in digital forensic investigation: Applications and solutions. *IEEE International Conference on Emerging Technologies*. https://doi.org/10.1109/ET63133.2024.10721531 /

Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. *Journal of Accounting and Information Systems, 26*, 100734. https://doi.org/10.1016/j.accinf.2025.100734

Wang, C., Yu, X., Tan, G., & Xiao, L. (2024). Utilization of blockchain technology in the data audit system of power grid engineering. *Procedia Computer Science, 228*, 1023–1030. https://doi.org/10.1016/j.procs.2024.09.023

Lombardi, D. R., Kim, M., Sipior, J. C., & Vasarhelyi, M. A. (2025). The increased role of advanced technology and automation in audit: A Delphi study. *Journal of Accounting and Information Systems, 26*, 100733. https://doi.org/10.1016/j.accinf.2025.100733

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. https://doi.org/10.2308/jeta-51730

Rikhardsson, P., Thórisson, K. R., Bergthorsson, G., & Batt, C. (2022). Artificial intelligence and auditing in small- and medium-sized firms: Expectations and applications. *AI and Society*. https://doi.org/10.1002/aaai.12066

Odonkor, B., Kaggwa, S., Uwaoma, P. U., Hassan, A. O., & Farayola, O. A. (2024). The impact of AI on accounting practices: A review: Exploring how artificial intelligence is transforming traditional accounting methods and financial reporting. *World Journal of Advanced Research and Reviews, 21*(1), 18–28. https://doi.org/10.30574/wjarr.2024.21.1.2721
Seethamraju, R., & Hecimovic, A. (2023). Adoption of artificial intelligence in auditing: An exploratory study. *Australian Journal of Public Administration*. https://doi.org/10.1177/03128962221108440
Moffitt, K. C., Rozario, A. M., & Vasarhelyi, M. A. (2018). Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting, 15*(1), 1–10. https://doi.org/10.2308/jeta-10589

.