JURNAL BISNIS MAHASISWA
Journal homepage: https://jurnalbisnismahasiswa.com
E-ISSN: 2807-2219

Audit transformation in the era of artificial intelligence: an integrative literature review of AI's impact on audit quality, professional skepticism, and auditor competence

Angel II P. Esmeralda*, Nur Hidayah K. Fadhilah, Dea Arme Tiara Harahap, Meutia Riany
Nusa Putra University, Sukabumi, Indonesia

Abstract

Purpose – This study examines how artificial intelligence (AI) is reshaping the external audit, focusing on three linked outcomes: audit quality, auditors' professional skepticism, and the competences auditors need.

Design/methodology/approach – An integrative literature review of 18 peer-reviewed studies in accounting, auditing and information systems published between 2016 and 2026, complemented by recent standard-setting documents from the IAASB and the PCAOB. Studies are coded by AI application, audit phase, research method and outcome, and synthesised thematically.

Findings – AI extends audit coverage from samples to full populations and improves anomaly detection, fraud prediction, the evaluation of estimates and the efficiency of routine procedures. Archival evidence links AI investment by audit firms to fewer restatements, lower fees and more accurate going-concern and internal control opinions. However, the benefits depend on the human–machine relationship: auditors may discount AI evidence (algorithm aversion) or accept it without sufficient challenge (automation bias), and both can impair judgment. Model opacity, data quality, accountability and limited guidance in auditing standards remain unresolved risks, although standard setters have begun to respond.

Research limitations – The review is integrative rather than systematic, covers English-language studies only and relies mainly on evidence from the United States, Europe and large audit firms. Evidence on generative AI in auditing is still at an early stage.

Implications – Audit firms should treat AI output as evidence to be evaluated, design workflows that prompt challenge and protect the development of junior staff. Standard setters should clarify how much assurance AI-based procedures provide, and educators should combine data analytics with judgment training.

Originality – The review integrates technical, behavioural and institutional strands into a single framework in which AI is proposed to affect audit quality mainly through calibrated professional skepticism and auditor competence. It derives five testable propositions and a research agenda relevant to both developed and emerging audit markets.

Keywords: Artificial Intelligence, Audit Quality, Professional Skepticism, Automation Bias, Audit Data Analytics, Auditor Competence

Article History:
Received: September 15, 2026; Revised: October 22, 2026; Accepted: October 23, 2026; Published: October 30, 2026

***Corresponding Author:**
aesmeraldaii@gmail.com

DOI:
https://doi.org/10.60036/jbm.1477

Copyright © 2026 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution-ShareAlike 4.0 International License (http://creativecommons.org/licences/by-sa/4.0/)

INTRODUCTION

The external audit gives users of financial statements independent assurance that management's reports can be relied on. Its value rests on the auditor's ability to obtain sufficient appropriate evidence and to exercise independent judgment. For most of the profession's history, the cost of evidence forced auditors to rely on sampling, manual testing and periodic, after-the-fact assurance.

Artificial intelligence changes that cost structure. Machine learning, natural language processing (NLP) and, more recently, generative AI allow auditors to analyse entire populations of transactions, read contracts and board minutes at scale, and flag anomalies continuously (Issa et al., 2016; Kokina & Davenport, 2017). The largest audit networks have invested heavily in AI-enabled platforms (Fedyk et al., 2022; Law & Shen, 2025), and standard setters have begun to revise their requirements. The Public Company Accounting Oversight Board (PCAOB, 2024) has amended its standards on audit evidence and on responses to risk to address technology-assisted analysis, and the International Auditing and Assurance Standards Board (IAASB, 2023) has proposed a revised ISA 500 that is intended to accommodate the use of technology in obtaining audit evidence.

These developments raise a question that is more than technical. Audit quality is usually understood as the likelihood that the auditor both detects and reports a material misstatement. AI may raise the probability of detection. Yet it may also alter the second element, judgment and reporting, by changing how auditors weigh evidence, question management and take responsibility for conclusions. A tool that produces a confident risk score can sharpen skepticism or replace it.

Research on AI in auditing has grown rapidly but remains fragmented across three strands: technical studies of algorithms and use cases, behavioural experiments on auditor judgment, and institutional work on standards, ethics and the profession. Existing reviews tend to stay within one strand. Barr-Pulliam et al. (2024) review research on audit evidence, technology and judgment in response to the IAASB's proposed ISA 500, Zhang et al. (2022) focus on the explainability of AI models, and Munoko et al. (2020) concentrate on ethical implications. Few studies connect the technical, behavioural and institutional evidence in one framework. This review addresses that gap by asking three questions:

1. RQ1: How, and under what conditions, does AI affect audit quality?
2. RQ2: How does AI interact with auditors' professional skepticism and judgment?
3. RQ3: What competences, governance arrangements and standards are required for AI to improve rather than erode audit quality?

The paper contributes in three ways. First, it synthesises evidence across the three strands. Second, it proposes an integrative framework in which professional skepticism and auditor competence mediate the relationship between AI adoption and audit quality. Third, it sets out implications for audit firms, standard setters and educators, including those in emerging economies such as Indonesia, where survey evidence suggests that the use of AI and big data analytics by public accounting firms is still at an early stage (Hariyani & Muluk, 2026).

The remainder of the paper is organised as follows. The Literature Review section presents the theoretical background, the Method section describes the review method, the Results and Discussion section reports the findings by theme and develops the integrative framework, and the Conclusion section closes with limitations, directions for future research and implications.

LITERATURE REVIEW

Audit Quality

Audit quality is commonly understood as the joint likelihood that an auditor discovers a material misstatement and reports it. Because the construct cannot be observed directly,

research relies on proxies such as restatements, going-concern opinions, fee ratios and deficiencies identified in enforcement actions, and the usefulness of each proxy depends on the research setting (Rajgopal et al., 2021). This matters for the present review because most archival studies of AI infer quality from such proxies (Fedyk et al., 2022; Law & Shen, 2025). AI also touches several levels of the audit at once: it is an input, it reshapes the audit process, it is concentrated in large firms, and it challenges standards written for manual audits. If AI makes assurance cheaper and more complete, the audit should become more valuable to users, but only if they can trust that the auditor, not the tool, remains accountable for the opinion.

Professional Skepticism

Auditing standards require auditors to plan and perform the audit with professional skepticism, an attitude that includes a questioning mind and a critical assessment of audit evidence (ISA 200, in IAASB, 2024). Nolder and Kadous (2018) argue that skepticism should be understood both as a mindset, a way of processing information that can be triggered by the task environment, and as an attitude that guides how auditors evaluate evidence and act on it. This distinction matters for AI: a tool may improve the evidence available, but skeptical action still depends on the auditor deciding to investigate.

Human–Automation Interaction

Two opposite biases describe how people respond to automated advice. Automation bias is the tendency to accept automated output and reduce one's own verification, a tendency that is reported to increase under workload and time pressure (Romeo & Conti, 2025). Algorithm aversion is the tendency to discount algorithmic advice, particularly after seeing an algorithm err, even when it outperforms human judgment (Burton et al., 2020). Both are relevant to auditors, who are trained to be skeptical of evidence but work under tight deadlines.

METHOD

The study uses an integrative literature review. Integrative reviews synthesise representative literature on an emerging topic in order to develop new frameworks and perspectives, rather than to estimate an aggregate effect (Torraco, 2016; Snyder, 2019). This design suits the present aim, which is to connect technical, behavioural and institutional evidence that has developed in separate streams. The review is therefore purposive rather than exhaustive, and it does not follow the full screening and quality-appraisal protocol of a systematic review.

Sources and Search Strategy

The core search covers Scopus, Web of Science, and the American Accounting Association digital library, supplemented by backward and forward citation tracking. The search string combines technology and audit terms:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "generative AI" OR "audit data analytics") AND (audit* OR assurance)AND ("audit quality" OR skepticism OR scepticism OR judgment OR competenc* OR ethic*)

Standard-setting documents from the IAASB and the PCAOB were used to describe current requirements, but not as evidence of effects. Practitioner and vendor publications were not used.

Inclusion and Exclusion Criteria

Applying these criteria, 18 studies were retained for the synthesis: six conceptual or review studies, four archival studies, two experiments, three interview studies and three survey or mixed-method studies. All are listed in Appendix Table A1 with their coding. Theoretical sources

on audit quality, professional skepticism, human–automation interaction and review methodology were used to build the analytical lens but are not counted as included studies.

Table 1. Inclusion and exclusion criteria

Criterion	Included	Excluded
Topic	AI or advanced analytics applied to external or internal audit, or to accounting tasks with a direct audit use (e.g., fraud prediction, accounting estimates)	General IT audit; AI in accounting without an assurance link
Source type	Peer-reviewed journal articles; current IAASB and PCAOB standard-setting documents	Opinion pieces, vendor and practitioner publications, non-academic blogs
Language	English	Other languages
Period	2016–2026	Studies published before 2016
Evidence	Conceptual, archival, experimental, survey and case studies	Studies without an audit outcome or mechanism

Source: Compiled by the author

Coding and Synthesis

Each included study was coded on four dimensions: AI application, audit phase (planning, risk assessment, testing, reporting), research method and outcome theme (applications, quality and efficiency, judgment, competence, ethics and governance). Codes were grouped into themes through iterative thematic synthesis. Where studies disagreed, the conditions behind the disagreement were recorded, because these conditions form the basis of the integrative framework in the Discussion.

Rigour and Transparency

To make the review transparent, the search string, the inclusion criteria and the full list of included studies with their codes are reported (Table 1 and Appendix Table A1). Because the review is integrative, screening counts and a formal quality appraisal are not reported; this is acknowledged as a limitation in the Conclusion. Researchers who wish to extend the review into a systematic review can run the same search string and apply a formal screening and appraisal procedure.

RESULTS AND DISCUSSION

Results

The literature converges on five themes. AI applications now span every audit phase; their effect on quality is positive on average but conditional; the human–AI relationship is the main source of that conditionality; competence requirements are shifting; and governance and standards are only starting to catch up. The number of included studies contributing to each theme is as follows: applications (10 studies), audit quality and efficiency (5), professional skepticism and judgment (4), auditor competences (5), and ethics, governance and standards (6). Table 2 summarises the applications by audit phase, and Appendix Table A1 shows which studies support each theme.

AI Applications across the Audit Process

The shift from sampling to full-population analysis is the most consistent theme. Appelbaum et al. (2017) note that analytics can be applied across all audit phases, but that

standards still describe evidence in sampling terms, leaving auditors unsure how much assurance an analytic procedure provides. Machine-learning models also perform specific audit-relevant tasks better than traditional methods. Bao et al. (2020) show that a model using raw financial data detects accounting fraud more accurately than ratio-based benchmarks, and Ding et al. (2020) find that machine-learning estimates of insurance loss reserves are more accurate than managers' own estimates in most business lines, which suggests a role for AI in benchmarking complex estimates. Generative AI adds a further layer: Eulerich et al. (2024) show that recent versions of ChatGPT can pass major accounting and auditing certification exams when supported by suitable prompting, which points to potential uses in documentation and research tasks.

Table 2. AI applications across the audit process

Audit phase	AI application	Example techniques	Key sources
Client acceptance and planning	Client risk scoring; going-concern and fraud prediction	Supervised classification, text mining of filings and news	Issa et al. (2016); Bao et al. (2020)
Risk assessment	Identifying unusual accounts, entities and periods	Clustering, anomaly detection	Appelbaum et al. (2017)
Substantive testing	Full-population journal-entry testing; contract and invoice reading	Machine learning, NLP, optical character recognition	Kokina & Davenport (2017); Eilifsen et al. (2020)
Estimates and judgments	Benchmarking complex estimates such as impairments and fair values	Predictive models	Ding et al. (2020); Commerford et al. (2022)
Reporting and continuous assurance	Real-time monitoring; drafting and summarising documentation	Continuous auditing, generative AI	Issa et al. (2016); Eulerich et al. (2024)

Source: Compiled by the author from the reviewed literature

Actual use, however, lags behind the technical potential. Eilifsen et al. (2020) find that Norwegian engagement teams regard audit data analytics as useful, but that actual use is limited, advanced techniques are rare, and use is higher for clients with integrated ERP systems. Krieger et al. (2021) show, on the basis of expert interviews, that adoption depends on technological, organisational and environmental factors, and that technological capabilities within audit teams help to generate use cases and spread them into practice. Interviews by Austin et al. (2021) show that auditors' use of analytics is also shaped by their interactions with client managers and regulators. In Indonesia, auditors still rely mainly on computer-assisted audit techniques, while the use of AI and big data analytics is at an early stage (Hariyani & Muluk, 2026).

Effects on Audit Quality and Efficiency

The strongest archival evidence comes from Fedyk et al. (2022), who measure AI investment through the skills of audit firm employees. They find that greater AI investment is associated with fewer restatements, including material ones, together with lower audit fees and reduced reliance on junior staff over time. Law and Shen (2025) reach a similar conclusion on quality using the staggered hiring of AI staff by U.S. audit offices: offices that adopt AI issue more accurate going-concern and internal control opinions. Both studies suggest that AI can raise quality and efficiency at once, rather than trading one for the other.

Other studies are more cautious. The detection gains reported by Bao et al. (2020) and Ding et al. (2020) are obtained with large, well-structured datasets, and the value of full-population testing depends on the quality and completeness of client data; an algorithm applied to incomplete ledgers produces precise but misleading results, which is why data quality is a recurring concern in the literature (Appelbaum et al., 2017). Survey evidence from Indonesia also finds that, of the technologies examined, only computer-assisted audit techniques have a significant effect on audit process effectiveness (Hariyani & Muluk, 2026). Gains therefore accrue mainly to firms and clients with mature data infrastructure.

Professional Skepticism and Judgment

Behavioural studies show that the human–AI relationship decides whether better evidence leads to better conclusions. Commerford et al. (2022) find that auditors who receive contradictory evidence from an AI system propose smaller adjustments to management's complex estimates than those receiving the same evidence from a human specialist. This is consistent with algorithm aversion (Burton et al., 2020) and implies that AI evidence may be under-used precisely where it is most valuable. The client side matters as well: Estep et al. (2024) show that managers record larger adjustments to a complex estimate when both the company and its auditor use AI, whereas the auditor's use of AI alone has no effect.

The opposite risk is automation bias. Where AI output aligns with management's position, or where workloads are high, auditors may accept it without sufficient challenge (Romeo & Conti, 2025). Large volumes of exceptions and false positives can also strain judgment unless auditors are supported in prioritising them, and Barr-Pulliam et al. (2024) note that technology creates threats to professional skepticism that the proposed ISA 500 does not yet fully address. Opaque models make the problem harder, because auditors cannot easily evaluate output they cannot explain (Zhang et al., 2022).

The common finding is that skepticism must be calibrated. Auditors should neither defer to AI nor dismiss it; they should treat its output as evidence whose reliability is itself subject to evaluation, as with any other source.

Auditor Competences

AI shifts work from performing procedures to designing, supervising and interpreting them (Kokina & Davenport, 2017). Labour-market evidence is consistent with this view: audit offices that adopt AI show stronger demand for soft skills, and AI adoption is associated with more, not fewer, auditor positions (Law & Shen, 2025). The competences emphasised in the literature fall into three groups:

- Technical: data literacy, understanding of model logic and limitations, and basic programming or analytics skills.
- Judgmental: the ability to evaluate model output, interpret exceptions and link findings to assertions and materiality.
- Ethical and communicative: explaining AI-based conclusions to audit committees and challenging both clients and tools.

Salijeni et al. (2019) find that the change is uneven: audit firms present analytics as transformative, while much daily practice remains incremental. The evidence on the role of junior staff is mixed. Fedyk et al. (2022) report reduced reliance on junior staff over time, whereas Law and Shen (2025) find that AI adoption is associated with more junior and mid-level positions. If junior auditors nonetheless perform fewer routine tests, they may not develop the tacit knowledge on which later judgment depends, a risk that has not yet been tested empirically. Generative AI may sharpen this concern, since models that perform well on professional examinations (Eulerich et al., 2024) can take over tasks that once served as training.

Ethics, Accountability and Governance

Munoko et al. (2020) identify ethical issues across AI's development stages, including bias in training data, lack of transparency, privacy, and unclear responsibility when an algorithm errs. Opaque "black-box" models are especially problematic because the auditor must be able to explain and document the basis for conclusions; Zhang et al. (2022) argue that explainable AI techniques are needed before AI output can be relied on as audit evidence. Regulators have also raised concerns that auditors' use of data analytics to provide business insights to clients could impair independence and audit quality (Austin et al., 2021).

Standard setters have started to respond, but guidance remains limited. The PCAOB (2024) amended AS 1105 and AS 2301 to clarify the auditor's responsibilities when designing and performing procedures that involve technology-assisted analysis; the amendments apply to audits of fiscal years beginning after 15 December 2025. The IAASB (2023) proposed a revised ISA 500 on audit evidence that is more principles-based and is intended to accommodate the use of technology. Neither change provides detailed guidance on validating AI models or on how much assurance AI-based procedures provide. Interviews in Norway reveal considerable uncertainty about how regulators will treat evidence from data analytics (Eilifsen et al., 2020), and auditors and managers report confusion caused by the lack of specific guidance (Austin et al., 2021). The literature therefore calls for clearer guidance, firm-level AI governance and documentation of model testing (Appelbaum et al., 2017; Munoko et al., 2020).

Discussion

An Integrative Framework

The findings suggest that AI does not improve audit quality directly. It improves the evidence available, and that evidence becomes better audit conclusions only through human judgment. The framework therefore runs from AI adoption to evidence capability (coverage, timeliness, pattern detection), then through two mediators, calibrated professional skepticism and auditor competence, to audit quality. Three moderators shape each link: data quality and infrastructure, firm governance of AI, and regulatory and standards clarity (Figure 1).

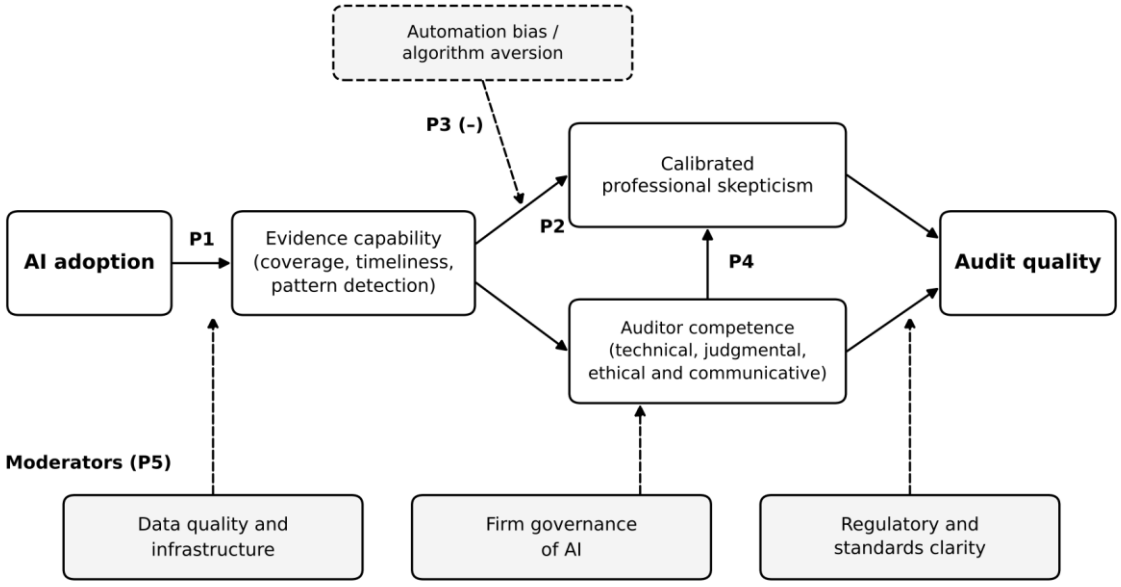


Figure 1. Integrative framework linking AI adoption, professional skepticism, auditor competence and audit quality
Source: Developed by the author

The framework yields five propositions for future testing. Table 3 summarises the evidence on which each proposition rests.

P1: AI adoption increases audit evidence capability, with larger effects where client data quality is high.

P2: The effect of evidence capability on audit quality is mediated by calibrated professional skepticism.

P3: Both automation bias and algorithm aversion weaken the link between AI evidence and audit quality.

P4: Auditor competence in data and model evaluation strengthens calibrated skepticism.

P5: Firm AI governance and clear standards strengthen all of the above relationships.

Table 3. Propositions and their basis in the reviewed literature

Proposition	Basis in the reviewed literature
P1	Full-population analysis and machine learning improve detection and estimates (Appelbaum et al., 2017; Bao et al., 2020; Ding et al., 2020); use of analytics is higher where clients have integrated ERP systems (Eilifsen et al., 2020).
P2	AI investment is associated with better audit quality proxies (Fedyk et al., 2022; Law & Shen, 2025), but whether AI evidence changes conclusions depends on how auditors and managers respond to it (Commerford et al., 2022; Estep et al., 2024).
P3	Auditors give less weight to contradictory AI evidence than to the same evidence from a human specialist (Commerford et al., 2022), consistent with algorithm aversion (Burton et al., 2020); automation bias reduces verification (Romeo & Conti, 2025), and opaque models are harder to evaluate (Zhang et al., 2022).
P4	AI shifts audit work toward designing and interpreting procedures (Kokina & Davenport, 2017); AI-adopting offices demand new skills (Law & Shen, 2025); the use of technology requires technical skills to sustain skepticism (Barr-Pulliam et al., 2024).
P5	AI raises ethical and accountability risks that call for governance (Munoko et al., 2020); regulatory uncertainty shapes auditors' use of technology (Austin et al., 2021; Eilifsen et al., 2020); standards are being revised (IAASB, 2023; PCAOB, 2024).

Source: Compiled by the author from the reviewed literature

Together, the framework answers the research questions. AI affects audit quality conditionally (RQ1). The condition is the auditor's calibrated stance toward AI evidence (RQ2). That stance depends on competences, governance and standards that are currently underdeveloped (RQ3).

CONCLUSION

AI is changing what an audit can examine, but not what an audit is for. The evidence reviewed shows that AI can improve audit quality and efficiency, chiefly by extending coverage and detecting anomalies. These gains are conditional. They depend on data quality, on auditors who neither over-trust nor dismiss AI output, and on competences and governance that many firms and standards have yet to develop. Professional skepticism is therefore not made obsolete by AI; it becomes the mechanism through which AI's value is realised.

Limitations

The review is integrative rather than systematic. It is purposive rather than exhaustive, does not report screening counts or a formal quality appraisal, and is limited to English-language sources published from 2016 onward. Much of the empirical evidence comes from the United States, Europe and large audit firms, which limits generalisation to smaller firms and emerging markets; the only Indonesian evidence included is a single regional survey. Research on generative AI in auditing is still early, so conclusions about it are tentative.

Future Research

Five directions stand out:

1. Empirical tests of the propositions in Section 4.2, using archival data on AI investment combined with inspection findings.
2. Experiments on workflow designs that reduce automation bias and algorithm aversion.
3. Studies of generative AI in documentation, evidence evaluation and client communication.
4. Research on AI adoption by small and medium-sized audit firms, particularly in Southeast Asia.
5. Longitudinal work on how reduced exposure to routine tasks affects the judgment of future audit seniors and partners.

Implications

Implications for Audit Firms

1. Treat AI output as audit evidence that must itself be evaluated, with documented validation of models, inputs and thresholds.
2. Design workflows that prompt challenge, such as requiring the auditor to record an independent expectation before viewing the AI result.
3. Protect learning: rotate junior staff through manual and AI-supported procedures so that tacit knowledge still develops.
4. Establish AI governance covering model ownership, change control, bias testing and independence reviews.

Implications for Regulators and Standard Setters

Standard setters should clarify how much assurance AI-based procedures provide, how full-population analysis relates to sampling requirements, and what documentation is expected for model validation. Inspection programmes should examine not only whether firms use AI but how engagement teams evaluate its output.

Implications for Education and Emerging Markets

Accounting curricula should combine data analytics with judgment training, using cases in which AI output is wrong or incomplete. In emerging economies such as Indonesia, where many public accounting firms still rely mainly on computer-assisted audit techniques (Hariyani & Muluk, 2026), smaller firms are likely to face cost and skills barriers to adopting AI. Professional bodies can narrow this gap through shared tools, training and proportionate guidance, so that AI does not widen quality differences across the audit market.

REFERENCES

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. https://doi.org/10.2308/ajpt-51684

Austin, A. A., Carpenter, T. D., Christ, M. H., & Nielson, C. S. (2021). The data analytics journey: Interactions among auditors, managers, regulation, and technology. *Contemporary Accounting Research, 38*(3), 1888–1924. https://doi.org/10.1111/1911-3846.12680

Bao, Y., Ke, B., Li, B., Yu, Y. J., & 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. https://doi.org/10.1111/1475-679X.12292

Barr-Pulliam, D., Calvin, C. G., Eulerich, M., & Maghakyan, A. (2024). Audit evidence, technology, and judgement: A review of the literature in response to ED-500. *Journal of International Financial Management & Accounting, 35*(1), 36–67. https://doi.org/10.1111/jifm.12192

Burton, J. W., Stein, M.-K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making, 33*(2), 220–239. https://doi.org/10.1002/bdm.2155

Commerford, B. P., Dennis, S. A., Joe, J. R., & Ulla, J. W. (2022). Man versus machine: Complex estimates and auditor reliance on artificial intelligence. *Journal of Accounting Research, 60*(1), 171–201. https://doi.org/10.1111/1475-679X.12407

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. https://doi.org/10.1007/s11142-020-09546-9

Eilifsen, A., Kinserdal, F., Messier, W. F., Jr., & McKee, T. E. (2020). An exploratory study into the use of audit data analytics on audit engagements. *Accounting Horizons, 34*(4), 75–103. https://doi.org/10.2308/HORIZONS-19-121

Estep, C., Griffith, E. E., & MacKenzie, N. L. (2024). How do financial executives respond to the use of artificial intelligence in financial reporting and auditing? *Review of Accounting Studies, 29*(3), 2798–2831. https://doi.org/10.1007/s11142-023-09771-y

Eulerich, M., Sanatizadeh, A., Vakilzadeh, H., & Wood, D. A. (2024). Is it all hype? ChatGPT's performance and disruptive potential in the accounting and auditing industries. *Review of Accounting Studies, 29*(3), 2318–2349. https://doi.org/10.1007/s11142-024-09833-9

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies, 27*(3), 938–985. https://doi.org/10.1007/s11142-022-09697-x

Hariyani, A., & Muluk, M. A. (2026). Artificial intelligence, big data, and audit process effectiveness under UTAUT in public accounting firms. *CURRENT: Jurnal Kajian Akuntansi dan Bisnis Terkini, 7*(1), 62–76.

International Auditing and Assurance Standards Board. (2023). *Proposed International Standard on Auditing 500 (Revised), Audit evidence* [Exposure draft]. International Federation of Accountants.

International Auditing and Assurance Standards Board. (2024). *Handbook of international quality management, auditing, review, other assurance, and related services pronouncements* (2023–2024 ed.). International Federation of Accountants.

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*(2), 1–20. https://doi.org/10.2308/jeta-10511

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

Krieger, F., Drews, P., & Velte, P. (2021). Explaining the (non-) adoption of advanced data analytics in auditing: A process theory. *International Journal of Accounting Information Systems, 41*, 100511. https://doi.org/10.1016/j.accinf.2021.100511

Law, K. K. F., & Shen, M. (2025). How does artificial intelligence shape audit firms? *Management Science, 71*(5), 3641–3666. https://doi.org/10.1287/mnsc.2022.04040

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. https://doi.org/10.1007/s10551-019-04407-1

Nolder, C. J., & Kadous, K. (2018). Grounding the professional skepticism construct in mindset and attitude theory: A way forward. *Accounting, Organizations and Society, 67*, 1–14. https://doi.org/10.1016/j.aos.2018.03.010

Public Company Accounting Oversight Board. (2024). *Amendments related to aspects of designing and performing audit procedures that involve technology-assisted analysis of information in electronic form* (PCAOB Release No. 2024-007).

Rajgopal, S., Srinivasan, S., & Zheng, X. (2021). Measuring audit quality. *Review of Accounting Studies, 26*(2), 559–619. https://doi.org/10.1007/s11142-020-09570-9

Romeo, G., & Conti, D. (2025). Exploring automation bias in human–AI collaboration: A review and implications for explainable AI. *AI & Society*. Advance online publication. https://doi.org/10.1007/s00146-025-02422-7

Salijeni, G., Samsonova-Taddei, A., & Turley, S. (2019). Big data and changes in audit technology: Contemplating a research agenda. *Accounting and Business Research, 49*(1), 95–119. https://doi.org/10.1080/00014788.2018.1459458

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Torraco, R. J. (2016). Writing integrative literature reviews: Using the past and present to explore the future. *Human Resource Development Review, 15*(4), 404–428. https://doi.org/10.1177/1534484316671606

Zhang, C. A., Cho, S., & Vasarhelyi, M. (2022). Explainable artificial intelligence (XAI) in auditing. *International Journal of Accounting Information Systems, 46*, 100572. https://doi.org/10.1016/j.accinf.2022.100572

APPENDIX

Table A1. Studies included in the review and their coding

Study	AI application	Audit phase	Method	Themes
Appelbaum et al. (2017)	Big data and analytics	All phases	Conceptual / research agenda	1, 5
Austin et al. (2021)	Data analytics	All phases	Interviews	1, 5
Bao et al. (2020)	Machine learning (fraud prediction)	Planning, risk assessment	Archival	1, 2
Barr-Pulliam et al. (2024)	Technology-based audit evidence	Testing, evaluation of evidence	Literature review	3, 5
Commerford et al. (2022)	AI-based evidence on estimates	Estimates	Experiment	3
Ding et al. (2020)	Machine learning (loss reserve estimates)	Estimates	Archival	1, 2
Eilifsen et al. (2020)	Audit data analytics	Risk assessment, testing	Interviews and questionnaire	1, 5
Estep et al. (2024)	AI used by companies and auditors	Estimates	Survey and experiment	3

Study	AI application	Audit phase	Method	Themes
Eulerich et al. (2024)	Generative AI (ChatGPT)	Documentation, research	Experimental test of model performance	1, 4
Fedyk et al. (2022)	AI investment by audit firms	Firm level	Archival	2, 4
Hariyani & Muluk (2026)	AI, big data and CAATs (Indonesia)	Audit process	Survey	1, 2
Issa et al. (2016)	AI across the audit	All phases	Conceptual	1
Kokina & Davenport (2017)	AI and automation	All phases	Conceptual	1, 4
Krieger et al. (2021)	Advanced data analytics	Firm level	Expert interviews	1
Law & Shen (2025)	AI adoption by audit offices	Firm level, reporting	Archival and interviews	2, 4
Munoko et al. (2020)	AI in general	All phases	Conceptual	5
Salijeni et al. (2019)	Big data analytics	All phases	Interviews	4
Zhang et al. (2022)	Explainable AI	Risk assessment, testing	Conceptual with illustration	3, 5

Note. Themes: 1 = AI applications; 2 = audit quality and efficiency; 3 = professional skepticism and judgment; 4 = auditor competences; 5 = ethics, governance and standards.