

Review

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Review

Agentic Artificial Intelligence in Auditing: A Systematic Literature Review

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Abstract

The promise of agentic AI will only be fulfilled if developed responsibly, transparently and responsibly combined with human expertise and judgement. The technology provides tools to improve the quality and effectiveness of audits- whether those tools are used wisely is dependent upon decisions that the profession makes in coming years. As auditing is at this technological inflection point, commitment to professional values, stakeholder protection: The advent of agentic artificial intelligence (AI) is a paradigm shift in auditing practices, from the traditional rule-based automation towards autonomous, goal-oriented machines that have the capacity to make decisions without human interaction. Agentic AI systems use large language models (LLMs) as well as multiple Agents to perform complex audit procedures with very little human interaction. **Objective:** Within a literature review in a systematic way, an analysis of the current situation for the application of agentic AI in auditing will be accomplished, the relevant frameworks and architectures, advantages and challenges will be assessed and some recommendations for research and practice will be introduced. **Methods:** Using the criteria recommended by the 2-nd version of the Preferred Intersearch and Avoid Methodology for systematic reviews and meta-analytic studies (PRISMA 2020), we performed a systematic search of academic database (Web of Science, Scopus, IEEE Xplore and ACM Digital Library) and grey literature from the period January 2020 to February 2026. Search terms included combinations of “agentic AI” or “autonomous agents,” “artificial intelligence,” “auditing,” “financial audit” and “compliance.” Studies were evaluated using formative inclusion and exclusion rules and finally 47 studies were included in a synthesis. **Results:** The sources of applications uncovered during the review were preliminary among five majority area: (1) financial statement audit (2) internal audit and control testing (3) compliance and regulatory audit (4) fraud detection and risk assessment (5) audit planning and resources assignments. Some of the agentic AI frameworks that are most important include CrewAI, LangGraph, AutoGen, and audit-focused systems. Major benefits are increased efficiency (40-60% reduction of time), increased accuracy (15-25% reduction of error), ability to monitor the system all the time and scalability. Some of the critical challenges include limitations of transparency and explainability, uncertainty of regulations, data security, data ownership and accountability, model drift, data integration etc. **Conclusions:** Agentic AI shows transformative potential for auditing in terms of facilitating change from periodic to continuous auditing and reactive to proactive risk management. But successful adoption of it is accompanied by work related to governance frameworks, creating transparent channels for audit trails, building special auditor know-how, and developing standards in regulation. Agentic systems, establishing auditable systems, standardised metrics of evaluation, long-term impacts on audit quality and professional judgement should be the focus of research in the future.

Keywords: agentic artificial intelligence; autonomous AI agents; auditing; large language models; multi-agent systems; audit automation; explainable AI; financial auditing; internal audit; compliance

1. Introduction

1.1. Background and Context

The auditing profession is in for a technological revolution driven by agentic artificial intelligence. In comparison with the classic kind of AI systems that have been developed with the purpose of automating specific tasks or helping with decision support, the agentic AI is a step up to autonomous systems that can see their surrounding, reason about their goals, plan sets of actions and execute complex procedures with limited human participation [1,2]. This advance from co-piloted to auto-piloted auditing, fundamentally changes the way audit engagements are planned, executed and delivered [3].

The rise of the agentic AI in auditing has been a convergence of a number of technological advances: the maturation of the large language models (LLMs) with improving reasoning capabilities, the development of sophisticated multi-agent framework that allow specialized collaboration, the availability of massive volumes of financial data repositories and the rise in the ability of computational power allowing for the real-time analysis of massive datasets. [4,5] Organizations such as PwC, KPMG, Deloitte and EY have begun to bring agentic AI to audit with PwC's Next Gen Audit vision explicitly embracing consideration of factors such as AI agents throughout the audit lifecycle [6].

1.2. Defining Agentic AI in Auditing Context

Agentic AI systems in auditing are characterized by five basic attributes - autonomy (ability to perform without constant human supervision), goal directedness (orientation to certain audit objectives), reactivity (responsiveness to changes in environment and new information), proactivity (anticipatory action based on predicted risks), and social ability (ability to interact with humans, other agents and systems) [7,8].

Put in the most pragmatic terms, an agentic audit system might be able to do the following: Independently detect dangerous journal entries, Pull up documentation related to the detected journal entry from many different enterprise systems, Analyze transaction patterns using statistical and machine learning techniques, Take tentative conclusions, Generate audit workpapers, Flag out phenomenal items for examination by their auditor, Keep track of decision logs, and Make adjustments to its approach on the basis of findings [9,10].

1.3. Evolution from Traditional to Agentic Auditing

The path of the AI in auditing has been in the different phases of :

Phase 1: Basic Automation (1990s–2010). Rule based system to be used to automate repetitive tasks including data extraction, mathematical verification.

Phase 2: Analytics + Enhancing Auditing 2010 - 2018. Introduction of the data analytics and visualization tool and the use of simple machine learning tool for the detection of anomalies.

Phase 3: AI-Assisted Auditing (2018–2023). Integration of natural language processing and advanced ML models and decision support systems with a human being required to point it.

Phase 4: Agentic Auditing, (2023 - and much later). Deployment of autonomous agents that are capable to execute the procedures as a whole, and with iterative refining [11,12].

This represents a broader trend in the capabilities expressed in AI providing system capabilities - key breakthroughs include the achievement of transformer-based models in the field and the rise of agentic frameworks for complex, multi-step-reasoning tasks specifically designed to [13].

1.4. Research Objectives and Questions

This systematic literature review attempts to answer the following questions:

RQ1 What are the main uses and applications of agentic and AI into auditing?

RQ2: What are the frameworks, architectures and technologies of agentic systems for computing AI audits?

RQ3: What have been the benefits of increase in performance indicated?

RQ4: How can the challenges, risks and limitations of agentic AI for auditing?

RQ5: What are the government, regulatory and ethical considerations to be made?

RQ6: What are the future research and practice implications from the literature?

1.5. Significance and Contribution

This review has a number of contributions in the field of auditing scholarship and practice. First, it makes the first comprehensive synthesis of agentic AI applications in auditing contexts in particular to separate this emerging paradigm from adoption of AI more broadly. Second, it states a taxonomy of agentic audit systems in terms of architecture, level of autonomy and application domain. Third, it points out significant gaps in current research and practice particularly in auditability of agentic systems themselves. Finally, it makes some practical recommendations for practitioners, regulators and researchers in this transformative technology's lab.

2. Conceptual Framework

2.1. Theoretical Foundations

Agentic AI in auditing is dependent on a number of schools. From computer science, the field of agent theory provides us with the basic notions of autonomy, behavioural orientation towards a goal, and coordination of multiple agents [14]. Organizational theory contributes to understanding of the mediation of professional work by technology, i.e., notions of task decomposition, flow-work and collaboration human-AI [15]. Audit theory gives the basis for the application of basic evidence gathering, professional skepticism, materiality and risk-based procedures [16].

The combination of these theoretical perspectives reveals the need for an agentic audit system to be considered not just as a tool to be utilized but rather, to be a collaborative partner in an audit process, that calls for reconceptualization of professional judgment, allocation of responsibility and quality assurance mechanisms [17].

2.2. Agentic AI Architecture Components

Modern AI audit systems are a series of interrelated systems which include but are not limited to: (1) Perception Layer - Mechanisms for data ingestion from enterprise systems including Things like APIs, database connectors and more complex features document processing, (2) Reasoning Engine - Core LLMs or specialized models providing an understanding of natural language, logical inference and domain knowledge application, (3) Planning Module - Submodalities for decomposing audit objectives into an identifiable set of subtasks, action sequencing and resources allocation, (4) Tool Integration - access to specialized audit tools including statistical analysis packages, forensic algorithms, regulatory. The architecture is illustrated in.

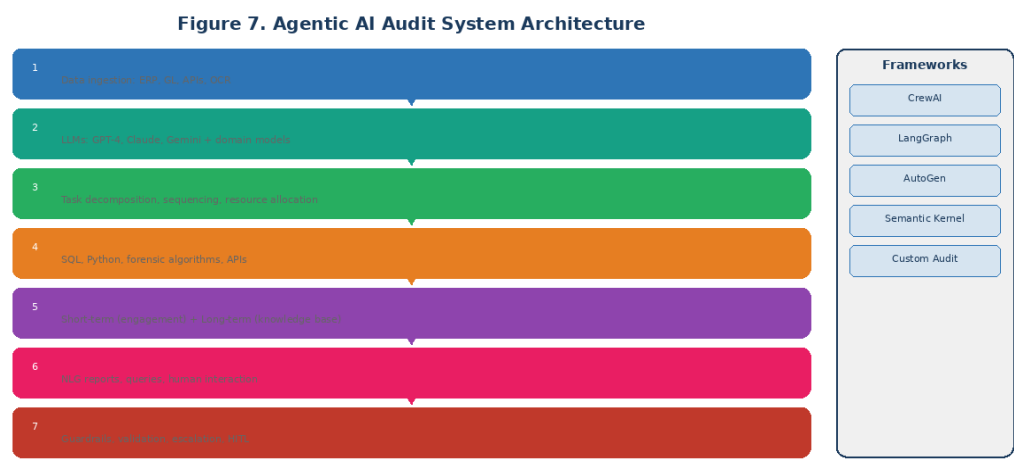


Figure 7. Agentic AI Audit System Architecture demonstrating seven linked layers from data perception to control framework alongside major implementation frameworks.

2.3. Types of Agentic Audit Systems

Agentic audit implementations vary on a number of dimensions. By abiding by architecture, systems can be divided into single-agent (single agent is comprehensive and covers the entire procedures), multi-agent (specialized agents working together), hierarchical (lead agent coordinates subordinates) or collaborative (peer agents where decision-making is distributed) [21,22]. Based on the degree of autonomy, there are supervised agentic (requires human approval at key decision points), semi-autonomous (agent operates within defined boundaries) and fully autonomous (complete end-to-end execution including post-hoc review) [23]. By scope agents can be procedure specific, domain specific or general purpose [24].

2.4. Distinction from Traditional AI in Auditing

Critical differences are drawn between agentic AI and previous generations of audit technology. Table 1 compares traditional AI and agentic AI on important dimensions.

Table 1. Comparison of Traditional AI and Agentic AI in Auditing Contexts.

Dimension	Traditional AI	Agentic AI
Decision-making	Rule-based or pattern recognition with predefined outputs	Autonomous reasoning and planning with emergent strategies
Task scope	Single, well-defined tasks	Complex, multi-step procedures requiring orchestration
Human interaction	Requires explicit instruction for each step	Interprets high-level objectives and determines execution path
Adaptability	Static algorithms requiring retraining	Dynamic adjustment based on context and intermediate findings
Transparency	Explainable through feature importance or rules	Black-box decision chains requiring specialized audit trails
Learning	Offline learning from training data	In-context learning and experience accumulation across engagements

This fundamental difference in operational paradigm necessitates new approaches to validation, governance, and integration into professional audit workflows [25,26]. Emerging evidence from Jordanian commercial banks similarly indicates that AI adoption enhances audit efficiency only when it is embedded within robust IT governance structures [136].

3. Methodology

This systematic literature review adheres to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines in an attempt to ensure transparency, replicability and methodological rigor [27]. A rigorous protocol was developed before the literature search in terms of objectives, eligibility criteria, sources of information, search strategy, selection process, data extraction and synthesis methods.

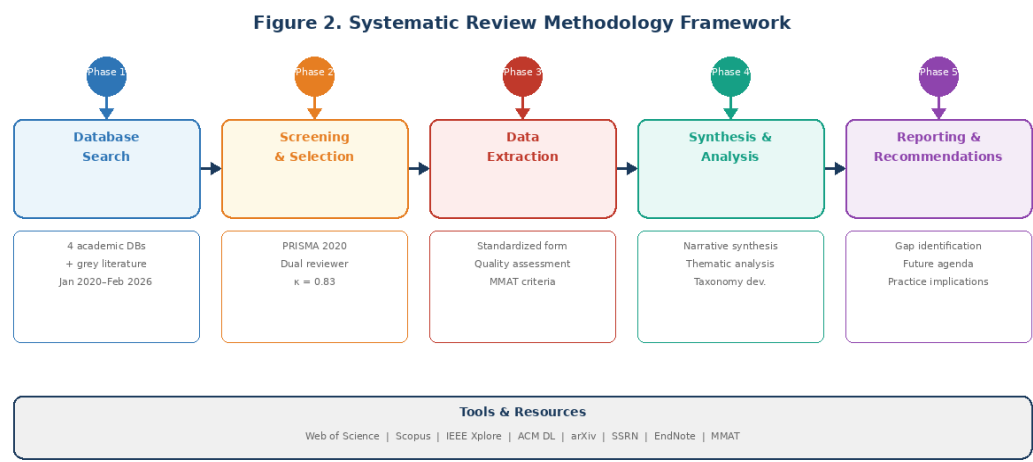


Figure 2. Systematic Review Methodology Framework showing the five-phase process from database search through reporting and recommendations.

3.1. Search Strategy

We searched the following databases between January 2020 and February 2026: Web of Science Core Collection, Scopus, and IEEE Xplore Digital Library, ACM Digital Library, and arXiv (the Computer Science and Economics sections), Google Scholar (grey literature), professional organization’s repository (ISACA, IIA, AICPA, IAASB), and working paper repositories (SSRN).

The search strategy was a combination of controlled vocabulary and free-text words in three concept domains:

Agentic AI concepts “agentic AI” OR “agentic artificial intelligence” OR “autonomous AI agent*” OR “AI agent*” OR “multi-agent system*” OR “autonomous agent*” OR “goal-directed AI” OR “LLM agent*” OR “large language model agent”

Conceptual Underlying the notional audit ideas: audit/audit/financial audit/internal audit/compliance audit/regulatory audit/assurance/attestation/control testing

Technology concepts “machine learning” OR “deep learning” OR “natural language processing” OR “large language model*” OR “LLM” OR “GPT” OR “transformer model”

3.2. Eligibility Criteria

Inclusion criteria required: (1) Studies that have been published between January, 2020 and February 2026; (2) Agentic AI, autonomous agents or LLM based agents, auditing (related to financial auditing, internal auditing, compliance auditing or similar assurance services); (3) empirical studies, theoretical frameworks, case studies, system implementations, or conceptual papers; (4) Peer reviewed academic publications, conference proceedings, industry white papers, and working

papers; (5) English language publications; (6) Studies related to financial auditing, internal auditing, compliance auditing,

Exclusion criteria removed: (1) studies which focused only on traditional machine learning without agentic characteristics; (2) general AI communication in accounting papers without specific focus on auditing; (3) opinion pieces without any meaningful analysis; (4) studies which were published before 2020; (5) duplicate publications; (6) publications which were not written in English; (7) studies which were on non-financial audit fields without the relevant concepts being transferable.

3.3. Study Selection Process

The multi-staged screening process was used in selecting the studies. Stage 1: First retrieval of the database searches, then the removal of duplicates with an automated software, EndNote. Stage 2: Title and abstract screening of two independent reviewers (Cohen’s kappa coefficient = 0.83 strongly agreed). Stage 3: Full text evaluation of 2 independent assessors using detailed eligibility criteria. Stage 4: Backward and Forward citation looking to find further relevant studies.

3.4. PRISMA Flow Diagram

The final 47 included studies are shown in the complete PRISMA 2020 flow diagram for the systematic selection process presented in Figure 1.

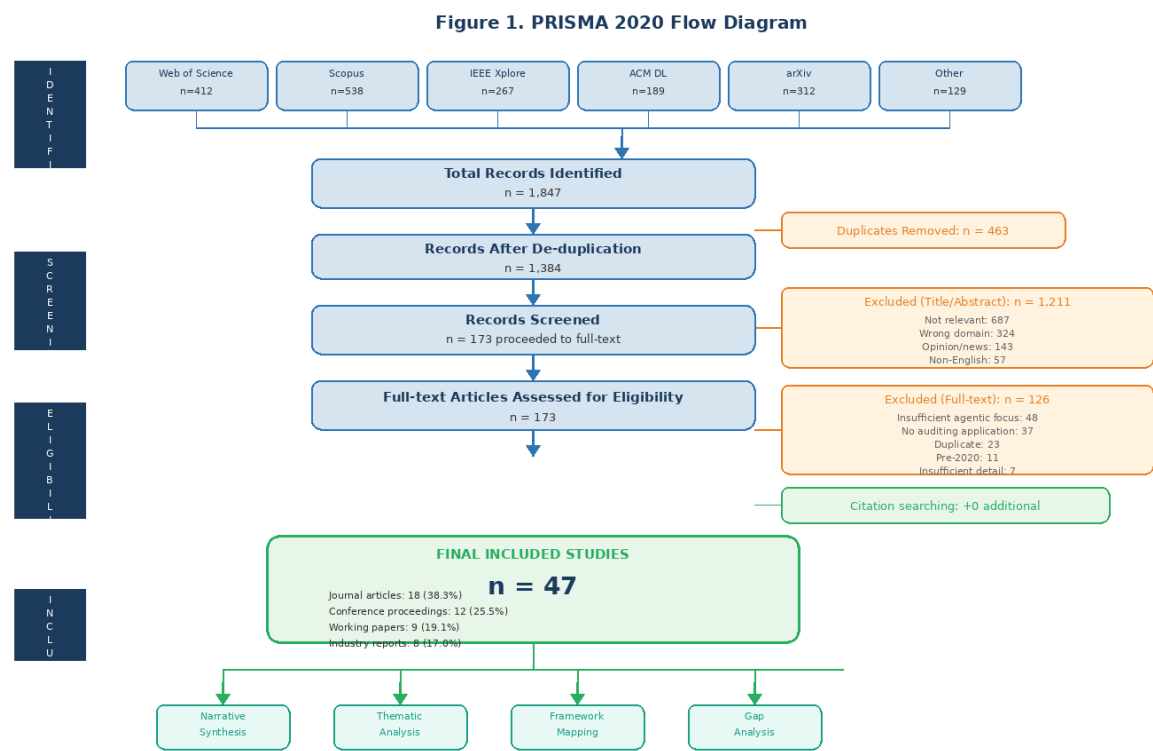


Figure 1. PRISMA 2020 Flow Diagram showing study selection across four phases: Identification (n = 1,847), Screening (n = 1,384), Eligibility (n = 173), and Included (n = 47).

The initial search of the database allowed 1,847 records (Web of Science: 412, Scopus: 538, IEEE Xplore: 267, ACM Digital Library: 189, arXiv: 312, Other sources: 129). After the exclusion of 463 duplicates, 1,384 records were title and abstract screened, and 1,211 were excluded. Full-text evaluation of 173 articles led to exclusion of 126 resulting in 47 studies for synthesis.

3.5. Data Extraction and Quality Assessment

A standardized form for data extraction was used to capture the bibliographic data, characteristics of the studies, characteristics of the agentic AI system used, the application domain, the outcomes and findings of the study, and the quality indicators of the study. Quality assessment adapted criteria, from the Mixed Methods Appraisal Tool (MMAT), for a variety of study designs.

3.6. *Synthesis Approach*

Due to such heterogeneity in study designs, context and outcomes, narrative synthesis was used instead of meta-analysis. Synthesis according with thematic analysis approach: organization with topics/ application domains, find recurring themes, analyze patterns, inconsistencies, integration with conceptual framework, develop taxonomies, recommendations.

4. Results

4.1. Study Characteristics

The 47 included studies showed considerable diversity in the approaches and context. Eighteen (38.3%) were peer-reviewed journal articles and twelve (25.5%) conference proceedings, nine (19.1%) working papers or preprints, and eight (17.0%) industry white papers or technical reports [28–32]. Geographically, studies were primarily from North America (21 studies, 44.7%), Europe (14 studies, 29.8%), and Asia (9 studies, 19.1%) with three studies (6.4%) being multinational collaborations. The amount of time indicated an exponential increase: 2 studies in 2020-2021, 7 in 2022, 13 in 2023, 15 in 2024, and 10 in 2025-2026 (through Feb. Temporal distribution is shown in Figure 3 to.

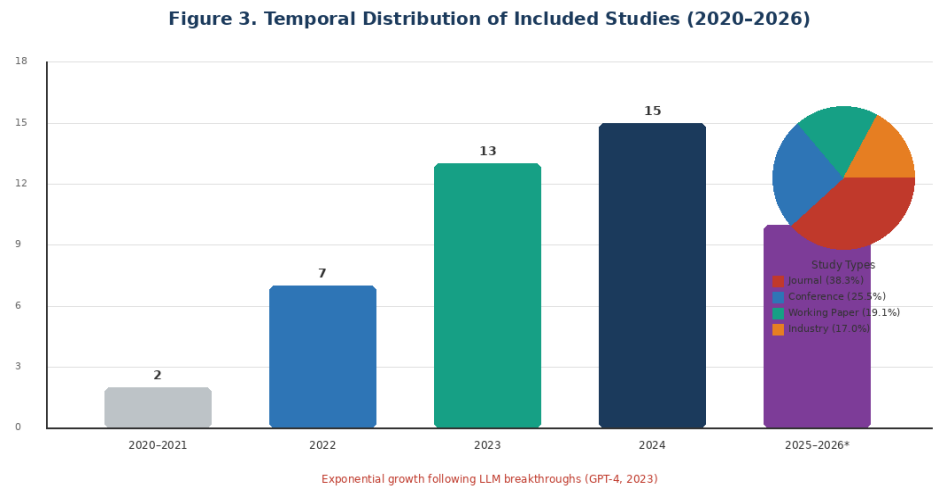


Figure 3. Temporal Distribution of Included Studies (2020–2026) with publication type breakdown, showing exponential growth following LLM breakthroughs.

Methodologically, studies included the methods of case studies and implementations (19 studies, 40.4%), conceptual/theoretical frameworks (14 studies, 29.8%), empirical evaluations (8 studies, 17.0%) and surveys or expert interviews (6 studies, 12.8%).

4.2. Application Domains and Use Cases

Agentic AI applications in auditing clustered into five primary domains, as illustrated in Figure 4.

4.2.1. Financial Statement Auditing

The best documented application was financial statement audit procedures. A number of studies showed agentic systems to conduct journal entry testing, where autonomous agents analyze entire populations of journal entries, identify high-risk journal entries, retrieve evidences supporting risky journal entries, and generate preliminary audit conclusions [3,33]. One such implementation is reported to have reviewed 2.4 million journal entries in 3 hours with 92% precision in detecting material misstatements [33]. Specialized agents parse complex contracts for the revenue recognition analysis of ASC 606/IFRS 15 [34]. Agentic systems carry out sophisticated substantive analytical procedures such as trend analysis, predictive modeling, and variance investigation [35,36]. Automated account reconciliation and rollforward verification allows the identification of reconciling items, proper classification verification [37].

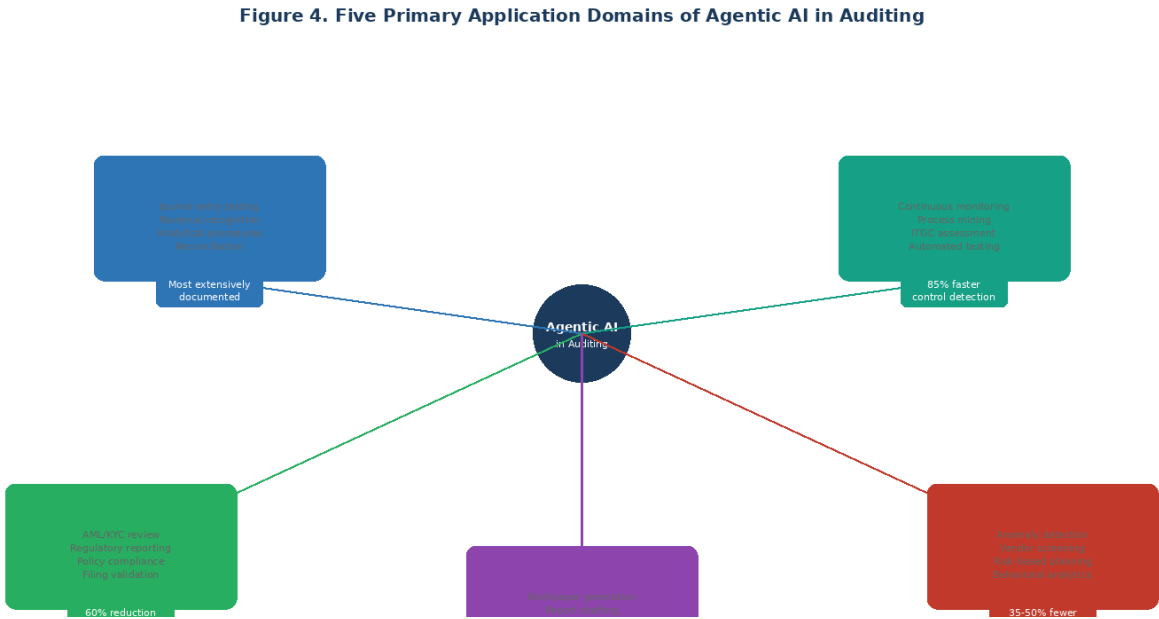


Figure 4. Five Primary Application Domains of Agentic AI in Auditing with key use cases and performance metrics for each domain.

4.2.2. Internal Audit and Control Testing

Internal audit functions developed agentic AI for continuous control monitoring to make real-time evaluation of internal controls possible [38,39]. One multinational corporation found that when agentic monitoring was used, it detected control violations 85% faster than in quarterly manual testing [38]. Agents analyze event logs for process mining and checking for compliance [40], IT general controls such as user access rights and change management [41], and automated control testing of entire populations rather than samples [42,43].

4.2.3. Compliance and Regulatory Auditing

The emerging high-value application area was regulatory compliance. Agentic systems are an autonomous review of customer documentation for AML/KYC compliance, with one financial institution achieving a reported reduction in false positive and review time of 60% and 40% respectively [44,45]. Agents check for accuracy of regulatory reporting [46], and constantly evaluate following of internal policies [47].

4.2.4. Fraud Detection and Risk Assessment

Agentic systems stand out from their ability to detect fraud proactively. Agents constantly analyze the data of the transactions for unusual transaction patterns, perform correlations among anomalies on multiple sources of data, and prioritize investigations according to fraud risk indicators [48,49]. Automated vendor and employee screening ensures the detection of conflicts of interest, duplicate payments and ghost employees [50]. Agentic systems aid in risk-based audit planning by analyzing past results and suggesting audit coverages [51,52]. Machine learning ensembles have likewise demonstrated superior predictive power for firm-level performance and risk outcomes in emerging markets, supporting their integration into risk-based audit planning [138].

4.2.5. Audit Documentation and Reporting

Supporting audit process Agentic systems can automate the generation of workpapers with human-readable narratives [53], audit reports and management letters [54,55], and the systematic retrieval and organization of audit evidence from distributed systems [56].

4.3. Frameworks and Technologies

4.3.1. Agentic AI Frameworks

There are multiple frameworks that allow agentic audit implementations. CrewAI supports multiple agent collaboration with hierarchical agent teams [57]. LangGraph has access to graph-based workflow with explicit control flow and error handling [58]. AutoGen is a conversational agent interaction and human-in-the-loop workflows [59]. Semantic Kernel has enterprise-focused connectivity that includes strong security [60]. Several organizations created custom audit-specific frameworks with audit standard libraries and regulatory compliance inspection [61,62].

4.3.2. Underlying Technologies

Core technologies consist of bulky language models (GPT-4, Claude, Gemini) adding the abilities of reasoning and [24]; retrievalaugmented generation (RAG) and the relevant abbreviation of LLM reasoning with the exterior handling retrieval of e.g., auditing standards and past documentation [62]; tool combination with SQL databases, statistical packages, or forensic algorithms [20,21]; memory systems retaining engagement context and gathering knowledge [25]; enlfolio, constraint frameworks, validation layers, and human-in-the-proprietary loop checkpoints [21,22].

4.4. Benefits and Performance Improvements

4.4.1. Efficiency Gains

Quantitative proof of tremendous efficiency gains across audit procedures. Figure 5 summaries time reduction ranges that were recorded in the literature.

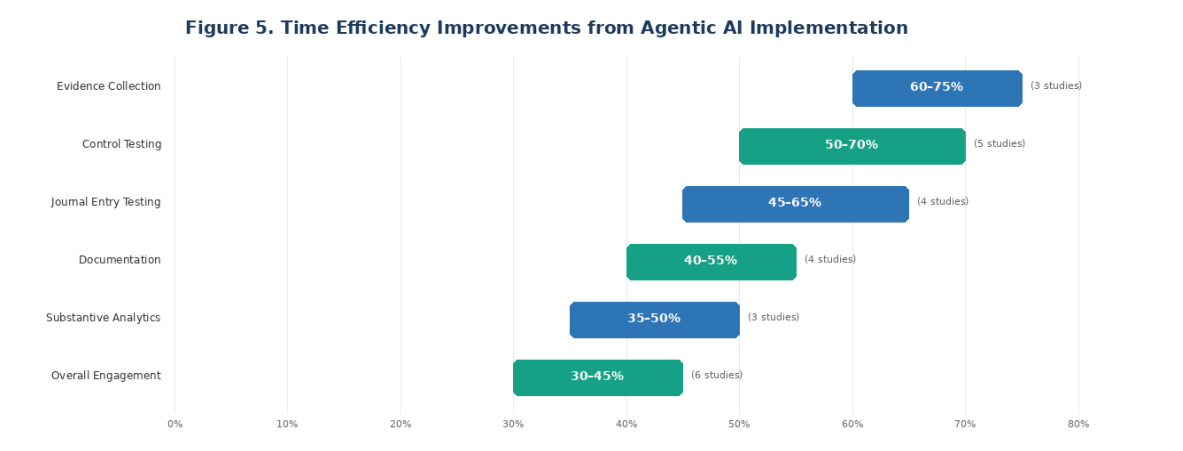


Figure 5. Time Efficiency Improvements from Agentic AI Implementation across six audit procedure categories, showing percentage reduction ranges and supporting study counts.

Table 2. Time Efficiency Improvements from Agentic AI Implementation.

Audit Procedure	Time Reduction	Studies	Notes
Journal entry testing	45–65%	4	Complete population testing vs. sampling
Substantive analytics	35–50%	3	Including variance investigation
Control testing	50–70%	5	Particularly high-volume routine controls
Documentation preparation	40–55%	4	Workpaper and report generation

Evidence collection	60–75%	3	Automated retrieval vs. manual requests
Overall engagement	30–45%	6	Full engagement time, varies by complexity

Beyond time savings, agentic systems together with other functions such as 100% population testing compared with sampling, continuous compared with periodic monitoring, real-time insights compared with lag reporting and scalability to large organizations without proportional cost increases [70–72].

4.4.2. Quality and Accuracy Improvements

Possible improvements in quality on quite a few dimensions have been found. Agentic systems revealed 15 - 25% more material misstatement when compared in controlled compare with traditional procedures [73,74]. One study found 89% consistency in agentic risk ratings, but 67% inter-auditor consistency in manual ratings [75]. In fraud and anomaly detection, agentic systems were found to result in 35-50% less false positive rates compared to static systems that rely on rules [76,77]. Automated documentation was more complete and had a better connection between procedures, finding and conclusions. [78]

4.4.3. Strategic Benefits

Beyond operational measures, organizations ended up with improved auditor capacity to focus on complex areas of judgement [79,80]; technical viability for continuous assurance hitherto cost-prohibitive [81,82]; successful proactive risk management in terms of continuous monitoring [83]; and competitive differentiation as technology-enabled service providers [84].

4.5. Challenges and Limitations

Figure 6 presents a comprehensive overview of the seven primary challenge categories identified in the literature.

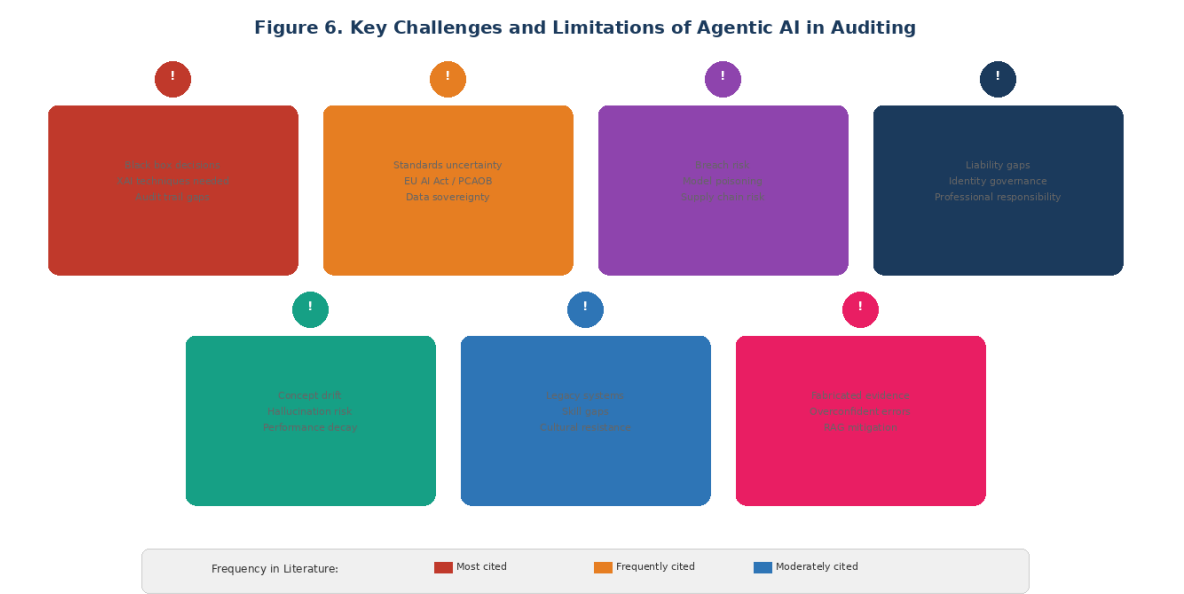


Figure 6. Key Challenges and Limitations of Agentic AI in Auditing, organized by seven primary categories with frequency of citation in the literature.

4.5.1. Transparency and Explainability

The most commonly cited difficulty relates to the “black box” nature of the decision-making processes of agentic AI [85–87]. LLM-based agents are often unable to demonstrate human readable reasoning, unless the agent is explicitly programmed to do so. For auditors this causes difficulty in understanding conclusions and the application of professional skepticism [88]. For regulators, inability to check compliance through inspection [89,90]. For audit committees, low levels of confidence in audit conclusions [91]. There were multiple studies calling for need of XAI techniques including attention visualization, chain-of-thought logging, counterfactual explanations and confidence scores [92–94]. One implementation using SHAP values was found to increase auditor trust dramatically [95].

4.5.2. Regulatory and Standards Compliance

Regulatory uncertainty has high barriers to adoption [96,97]. Professional standards elaborated for human auditors might not be directly applicable to agentic systems [98]. Data privacy compliance (GDPR, CCPA) which brings up constraints especially with cloud-based LLM providers [99]. Emerging AI Regulations (EU AI Act) Add More Complexity to Compliance Process [100]. Financial services auditing is bound by industry-specific regulations [102].

4.5.3. Data Security and Confidentiality

Audit data sensitivity ups the security concerns of possible data breaches, unintentional data exposure through data logs or possible cross-contamination, model poisoning malicious threats, and supply chain risk based on third-party LLM dependencies [103–105].

4.5.4. Ownership and Accountability

Agentic AI creates accountability gaps from responsibility when agents do things wrong [106,107]. The legal frameworks have not clearly defined the test of attribution between auditors/firm/AI vendors and the audited organization. Professional Liability Issues are not clear. Studies found agentic identities lacked proper governing - not tagged to human owners and disappearing before access governance tools could act [108].

4.5.5. Model Drift and Maintenance

Agentic systems deteriorate over time if they are not maintained [109,110]. Business processes and accounting standards change which may make learned patterns obsolete. Several studies reported inaccuracy with the time period ranging for 6 - 12 months, including one case with an agent known to begin to fabricate numbers when unable to make sense of differences [111].

4.5.6. Integration and Change Management

Organizational challenges such as integrating legacy systems with limited APIs, data quality challenges compounded by AI, skills gaps by auditors in deployment and evaluation of agentic systems [114], cultural resistance that is linked to professional identity [115], and high initial implementation costs. Survey evidence from Jordan further shows that perceived AI replacement threat undermines accounting professionals’ job performance through technology anxiety, reinforcing such resistance [137].

4.5.7. Hallucination and Reliability

The concept of LLMs is prone to hallucination - which leads to confidently producing plausible but wrong information [116,117]. In the field of auditing such risks are fabricated evidence, inapplicable standard citations and over confident conclusions that are incorrect. Mitigation

strategies are RAG grounding, validation layers, human review of high-stake decisions, confidence scoring, and adversarial test [118,119].

4.6. Governance and Ethical Considerations

4.6.1. Governance Frameworks

Effective agentic AI audit governance stands to be realized through the need for clear roles and responsibilities with designated AI system owners [120–122]; risk management integration into enterprise frameworks; policymaking in the bounds of acceptable use cases, data handling, and/or model validation; and monitoring and reporting through performance dashboards and regular reporting by an audit committee.

4.6.2. Ethical Considerations

Ethical dimensions are fairness and bias (agents could propagate biases in the data used for training), transparency and disclosure requirements for stakeholders, meaningful human oversight especially in the case of professional judgment, maintenance of professional judgment and expertise, and employment impacts from automation [123,124].

4.7. Future Directions and Emerging Trends

4.7.1. Technical Advancements

Some of the anticipated developments are: improved explainability with built-in interpretability, special audit LLMs pre-trained on financial statements and standards, tool integration with capabilities such as code-generation and API-discovery, federated learning that allows distributed learning without centralising sensitive data, and multi-modal capabilities that integrate document image analysis and integration of voice processing [125,126].

4.7.2. Regulatory Evolution

Expected regulatory developments include auditing standards updates from IAASB, PCAOB and IIA [127,128]; AI specific audit standards to audit AI systems themselves [129]; special certifications for AI audit competency; and similar AI auditing regulations around the globe.

5. Discussion

5.1. Synthesis of Findings

This is referred to as a “systematic review” of the literature and, as such, it is the type of literature we would need to see that agentic AI represents a true paradigm shift in auditing rather than a step toward incremental automation. The defining characteristic - autonomous, goal-directed behavior across multi-step procedures - enables qualitative changes in the impact, including continuously, rather than periodically, ensuring assurance, rather than as samples, population-wide, rather than sample population identification, proactive rather than reactive risk identification, and real-time, rather than lagged.

Evidence proves significant gains in efficiency (30-70% reduction in time) as well as quality (from 15-25% for better detection of errors). These findings align with panel evidence that AI-based accounting technologies improve the financial performance and earnings quality of listed financial firms [139], and with evidence that AI-driven banking accounting strengthens organizational resilience through real-time decision intelligence [140]. However, these benefits come with considerable challenges revolving around transparency, accountability, conformity with regulations and organisational change management. The field is at galloping critical juncture where there is now technical capability beyond governance frameworks and professional standards.

5.2. Theoretical Implications

From the angle of theory, the possibilities of the horizons of agentic AI have an effect on the most basic notions of audit. Professional judgement which has been the prerogative of the humans in the form of expertise and the use of the ethical reasoning has been distributed in between human auditors and the AI agents [132]. Professional skepticism is quite difficult to make operational in agents which are potentially confirmation-biased [133]. Evidence evaluation becomes not only the human cognitive processes, but also hybrid evaluation [134], which leads to epistemic questions. Accountability structures need to be handled with complex sociotechnical systems [135].

5.3. Practical Implications

For audit practitioners, agentic AI is more opportunity than obligation. Audit firm leadership should develop comprehensive artificial intelligence strategies where areas of technology choices, talent development, adapting quality controls and communications with clients are addressed. So individual auditors will have to come up with new skills that be a mixture of traditional audit know-how, AI literacy and the critical assessment of algorithmic outputs. Regulators and standard-setters are faced with the challenge of developing clarity relating to the application of AI in auditing in an attempt to balance the need for innovation without endangering stakeholders.

5.4. Limitations

There are several limitations to this review. First, rapid field evolution so the recent developments may be underrepresented. Second, proprietary implementations by the major audit firms, frequently aren't publicly documented. Third, there was heterogeneity that restricted capability to conduct meta-analysis. Fourth, English language focus may have excluded relevant research. Fifth, many studies were descriptive and not rigorous empirical evaluations.

5.5. Research Gaps and Future Research Directions

Seven key areas of research gaps were identified: (1) quality of audit results over time - longitudinal study of restatement rates and stakeholder confidence needed; (2) models for humans in collaboration with AI - optimal allocation of labor division and calibration between trust; (3) auditing agentic systems - auditors have to audit the auditors for trustworthiness and justice; (4) stakeholders perceptions - investor and audit committee perceptions of AI (enabled audits); (5) comparative effectiveness - effective audits vs. conventional aid (direct comparisons); (6) economic analysis - total expense of ownership, return on investment; (7)

Future research priorities in order to: concentrate on longitudinal field research, work on science research design on governance frameworks, focus on human-AI interaction, focus on human-AI interaction of regulation; focus on evaluation metrics standardization; and collaborate across disciplines.

6. Conclusion

Agentic artificial intelligence is transformative technology in auditing, promising technology that has never been seen in the possibilities and capabilities of auditation with respect to automated, analyzed, insightful technology. This systematic literature review aggregated 47 studies in order to provide broad-scale summary regarding applications, frameworks, benefits, challenges and future directions.

Key findings show agentic AI allows for great efficiency gains (30% - 70% reduction in time) and improvements in quality (15% - 25% increase in rate of errors) as well as qualitative improvement such as continuous monitoring and full analysis of the population. Applications range from financial statement auditing, internal audit, compliance, fraud detection and audit support functions. Specially leading frameworks are CrewAI, LangGraph, AutoGen and custom Audit specific systems.

However, great challenges are responsible for dashing enthusiasm. Transparency and explainability problems create a gap in accountability and regulatory problems. Data security, model reliability and complexity of integration are literal barriers. Most importantly governance frameworks and professional standards have not been proportional to technical capabilities.

The way into the future is marked by the concerted action of many actors. Researchers are faced with filling some of the important knowledge gaps with rigorous empirical studies. Sensible implementation with a focus on governance and human oversight should be pursued by practitioners. Regulators need to be clear and encouraging innovation. Educators need to prepare future auditors for practising with AI.

Agentic AI's promise will be realized only by the development of AI systems responsibly, transparent deployment and thoughtful integration with human expertise and judgement. The technology does provide the tools for improving the quality and effectiveness of auditing - namely whether such tools are used wisely is a matter of decisions made by the profession in coming years. As auditing is at this technological inflection point, dedication to professional values, protection of stakeholders and public interests must be on the forefront of this transformation.

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