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ARTIFICIAL INTELLIGENCE AND ACCOUNTANTS' WORK EFFICIENCY: A GLOBAL BIBLIOMETRIC AND SCIENCE-MAPPING ANALYSIS OF ACCOUNTING RESEARCH

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Abstract: *This study maps the intellectual, conceptual, and temporal structure of research on artificial intelligence (AI) and accountants' work efficiency. Design/methodology/approach — A Scopus search identified 1,418 English-language, open-access journal articles published from 2020 to 2026. Because the term "account" generated finance- and banking-related noise, title and author-keyword screening retained 185 accounting- and audit-relevant articles. Performance analysis was combined with keyword co-occurrence, network, overlay, and density mapping using VOSviewer-compatible files. Findings — Annual output increased from 3 articles in 2020 to 67 in 2025, with 39 additional articles indexed during the partial 2026 period. The corpus comprised 91 sources and 520 authors, with a mean of 14.0 citations per article and a median of 3. The keyword network contained 35 terms, 70 links, and five clusters covering audit and risk analytics; professional automation and ethics; generative AI, financial reporting, and governance; digital infrastructure; and education and technology acceptance. The thematic focus shifted from RPA, blockchain, and IoT toward generative AI, large language models, explainable AI, corporate governance, and financial reporting. Originality/value — This study provides an outcome-centered and reproducible map of AI-enabled accounting efficiency, distinguishes established automation themes from emerging generative-AI and governance research, and documents the screening required to address query contamination.*

Keywords: *artificial intelligence; accounting; work efficiency; bibliometric analysis; science mapping.*

Abstrak: Studi ini memetakan struktur intelektual, konseptual, dan temporal dari penelitian mengenai kecerdasan buatan (AI) dan efisiensi kerja akuntan. Desain/metodologi/pendekatan — Pencarian di Scopus mengidentifikasi 1.418 artikel jurnal akses terbuka berbahasa Inggris yang diterbitkan antara tahun 2020 dan 2026. Karena istilah "account" menghasilkan data yang tidak relevan (noise) terkait keuangan dan perbankan, penyaringan berdasarkan judul dan kata kunci penulis menyisakan 185 artikel yang relevan dengan bidang akuntansi dan audit. Analisis kinerja digabungkan dengan pemetaan ko-okurensi kata kunci, jaringan, overlay, dan kepadatan menggunakan berkas yang kompatibel dengan VOSviewer. Temuan — Jumlah publikasi tahunan meningkat dari 3 artikel pada tahun 2020 menjadi 67 artikel pada tahun 2025, dengan tambahan 39 artikel terindeks selama periode parsial tahun 2026. Korpus data mencakup 91 sumber dan 520 penulis, dengan rata-rata 14,0 sitasi per artikel dan nilai tengah (median) sebesar 3. Jaringan kata kunci memuat 35 istilah, 70 tautan, dan lima klaster yang mencakup analitik audit dan risiko; otomatisasi profesional dan etika; AI generatif, pelaporan keuangan, dan tata kelola; infrastruktur digital; serta pendidikan dan penerimaan teknologi. Fokus tematik bergeser dari RPA, blockchain, dan IoT menuju AI generatif, model bahasa besar (LLM), AI yang dapat dijelaskan (explainable AI), tata kelola perusahaan, dan pelaporan keuangan. Orisinalitas/nilai — Studi ini menyajikan peta efisiensi akuntansi berbasis AI yang berorientasi pada hasil dan dapat direplikasi, membedakan tema otomatisasi yang sudah mapan dari penelitian baru mengenai AI

generatif dan tata kelola, serta mendokumentasikan proses penyaringan yang diperlukan untuk mengatasi kontaminasi hasil pencarian.

Kata kunci: kecerdasan buatan; akuntansi; efisiensi kerja; analisis bibliometrik; pemetaan sains.

INTRODUCTION

Artificial intelligence (AI) has moved from a specialized expert-systems agenda to a broad family of technologies that includes machine learning, deep learning, natural language processing, robotic process automation (RPA), intelligent process automation, computer vision, and generative AI. Early accounting scholarship argued that AI research remained strategically important even when expert-systems research appeared to be declining, while audit-focused studies anticipated the formalization and supplementation of professional work through intelligent systems (Sutton et al., 2016; Issa et al., 2016). Subsequent research linked cognitive technologies and RPA to changes in audit workflows, evidence collection, and repetitive process execution (Kokina & Davenport, 2017; Moffitt et al., 2018; Zhang, 2019). More recently, textual analysis and contextual language models have expanded the field from structured automation toward interpretation of narrative disclosures, risk signals, and accounting documents (Bochkay et al., 2023; Bhattacharya & Mickovic, 2024; Küster et al., 2025).

This technological broadening is accompanied by a reconfiguration of accountants' tasks and professional roles. AI-based accounting is increasingly described as a transition from data preparation and routine control toward analysis, exception management, communication, and advisory work (Leitner-Hanetseder et al., 2021; Mohammad et al., 2020). Interventionist and field-oriented studies show that automation potential depends on the programmability of work, the standardization of process steps, and the ability to redesign rather than merely digitize existing routines (Korhonen et al., 2021; Perdana et al., 2023). Machine-learning applications also extend beyond transaction processing to fraud detection, executive-risk assessment, and audit evidence evaluation (Hrazdil et al., 2020; Rahman & Zhu, 2023). Accordingly, accountants' work efficiency should not be reduced to faster processing; it also concerns coverage, error prevention, quality-adjusted output, and capacity released for judgment-intensive activities.

Empirical studies generally report favorable expectations or associations between AI use and audit quality, reporting accuracy, process efficiency, and decision support. External auditors perceive AI as capable of enhancing audit quality, while accounting and auditing firms report that AI readiness, organizational support, and data governance shape whether these benefits are realized (Noordin et al., 2022; Anh et al., 2024; Abdullah & Almaqtari, 2024). Research on RPA similarly documents potential improvements in repetitive accounting and internal-audit processes, including small-firm and emerging-economy settings (Hsiung & Wang, 2022; Razak & Ismail, 2022; Alassuli, 2025). Evidence from accounting and auditing firms further suggests that AI adoption can improve financial-reporting accuracy and auditing efficiency when supported by effective big-data governance (Bin-Nashwan et al., 2025). Nevertheless, much of this evidence remains based on perceptions, adoption intentions, or broad performance constructs rather than direct measurements of elapsed time, rework, exception handling, or cost per completed accounting task.

The efficiency argument is also constrained by ethical, professional, and governance risks. AI-assisted accounting decisions raise questions about moral responsibility, explainability, bias, privacy, and the preservation of professional skepticism (Lehner et al., 2022; Puthukulam et al., 2021). Studies of controlling and audit governance warn that algorithmic capability does not eliminate the need for human interpretation, control design, and accountability (Losbichler & Lehner, 2021; Hu et al., 2023; Almaqtari, 2024). A socio-technical perspective is therefore essential because RPA and AI implementations can generate new coordination demands, control dependencies, and user-resistance problems even when the underlying technology functions as intended (Dahabiyeh & Mowafi, 2023; Jackson & Allen, 2024). Field evidence from large audit firms similarly indicates that simple extraction and automation tools are more widely deployed than complex AI, partly because transparency, reliability, privacy, and overreliance remain unresolved concerns (Kokina et al., 2025). Generative AI intensifies these issues because fluent output can conceal factual or accounting errors, making verification and provenance central to net productivity (Zhao & Wang, 2024; Blankespoor et al., 2026).

Despite the rapid expansion of this literature, the knowledge base remains fragmented across auditing, financial reporting, management accounting, tax, education, governance, and information-systems outlets. Existing reviews have mapped emerging technologies in audit and tax, examined AI's implications for accounting education, and proposed broad research frameworks for AI in accounting (Atayah & Alshater, 2021; Ballantine et al., 2024; Stratopoulos & Wang, 2025). Recent bibliometric work confirms accelerating interest in AI and auditing, but broad maps do not necessarily isolate studies that address accountants' work efficiency as an outcome (Epelbaum & Farrell, 2026). Reviews of management accounting likewise emphasize role transformation, privacy, security, reskilling, and professional boundaries, demonstrating that productivity effects are intertwined with organizational change (Abbas, 2026; Kerr et al., 2025). This study responds by constructing an outcome-centered bibliometric map that links technologies, accounting tasks, and efficiency-related consequences.

The central research gap lies not in the absence of studies on AI in accounting, but in the lack of a focused bibliometric map explaining how the field conceptualizes and measures accountants' work efficiency. Broad technology-oriented searches may conflate accounting-related research with unrelated studies retrieved through the term "account," while broader thematic reviews often combine adoption, education, ethics, and technical applications without distinguishing realized productivity gains from anticipated benefits (Atayah & Alshater, 2021; Epelbaum & Farrell, 2026). To address these limitations, the present study develops an explicitly screened corpus, integrates performance analysis with network, overlay, and density visualizations, and interprets the resulting clusters through the dimensions of operational efficiency, quality-enabled efficiency, and strategic capacity. The study's novelty lies in combining bibliometric analysis with a task–technology–outcome perspective and in treating verification, correction, integration, and governance requirements as realization costs that may influence net productivity rather than as peripheral implementation concerns (Goodhue & Thompson, 1995; Stratopoulos & Wang, 2025). These research gaps and the corresponding responses adopted in this study are summarized in Table 1.

Table 1. Identified Research Gaps and the Study's Responses

Gap	Response in this study
Outcome-definition gap	Interprets clusters through operational, quality-enabled, and strategic efficiency rather than technology adoption alone.
Query-validity gap	Reports that the original broad query retrieved 1,418 records and transparently screens out 1,233 non-accounting records.
Structural-integration gap	Combines performance indicators with keyword network, temporal overlay, density, and corpus-level article documentation.
Task-level gap	Separates audit, financial reporting, management accounting, bookkeeping, governance, and education themes.
Temporal gap	Uses average publication year to distinguish established RPA/blockchain themes from emerging GenAI/LLM/XAI themes.
Reproducibility gap	Supplies screened metadata and VOSviewer-compatible map, network, and thesaurus files.

The study addresses five related questions. First, it examines how scientific production on AI and accounting or audit work evolved between 2020 and 2026. Second, it identifies the sources, documents, authors, and countries that are most prominent in the screened corpus.

Third, the analysis investigates the conceptual clusters that structure the keyword co-occurrence network. Fourth, it distinguishes established and emerging topics through average publication year. Fifth, it derives a research agenda from the combined network, overlay, and density patterns.

METHOD

Data Source and Search Strategy

The primary dataset was the Scopus CSV export supplied by the researcher. The exact search syntax was:

TITLE-ABS-KEY ("artificial intelligence" OR "generative AI" OR "large language model" OR "machine learning" OR "natural language processing" OR "robotic process automation" OR rpa OR "intelligent automation" OR "computer vision") AND (account OR audit OR bookkeeping OR "financial reporting" OR "management accounting" OR tax) AND (efficient OR productive OR "time saving" OR "cycle time" OR "cost reduction" OR accuracy OR "error reduction" OR throughput OR "audit lag" OR "reporting lag" OR performance) AND PUBYEAR > 2019 AND PUBYEAR < 2027 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (OA, "all")) AND (LIMIT-TO (SUBJAREA, "ECON"))

Eligibility Screening and Data Integrity

The initial Scopus export contained 1,418 records. Preliminary inspection revealed that the broad search term "account" generated a substantial number of false-positive results related to bank accounts, robo-advisory services, investment management, credit scoring, and other financial-service topics that did not examine accounting or auditing work. To improve the topical precision of the dataset, records were screened using their titles and author keywords. This process retained 185 articles directly relevant to accounting or auditing and excluded 1,233 records that fell outside the study's scope. The screening flow is reported to enhance transparency and reproducibility and follows PRISMA-informed reporting principles. However, the study remains a bibliometric analysis rather than a systematic review of intervention effects (Page et al., 2021). The screening results are summarized in Table 2.

Table 2. Record Screening and Final Bibliometric Corpus

Stage	Records
Scopus records retrieved	1,418
Duplicate removal	0 (single Scopus export; EID/DOI retained for auditing)
Excluded by topical title/author-keyword screen	1,233
Final bibliometric corpus	185

Bibliometric Procedures

Performance analysis covered annual output, citations, sources, documents, authors, and country affiliations. Keyword mapping combined author and index keywords, harmonized major synonyms through a thesaurus, and created co-occurrence networks using association-strength normalization. Network, overlay, and density visualizations were produced in a VOSviewer-compatible format, while bibliometric interpretation followed established guidance on performance analysis, science mapping, threshold sensitivity, and cluster inspection (van Eck & Waltman, 2010; Aria & Cuccurullo, 2017; Donthu et al., 2021; Zupic & Čater, 2015).

Interpretive Caution

The year 2026 is incomplete because the export was generated on 3 July 2026. Citation counts are Scopus values at export time and favor older publications. The maps represent scholarly attention and conceptual proximity; they do not by themselves establish causal productivity effects.

RESULTS AND DISCUSSION

Results

Corpus Profile and Publication Growth

The final bibliometric corpus comprised 185 articles published across 91 journals and authored by 520 distinct researchers. The articles received an average of 14.0 citations, while the median citation count was 3, indicating a strongly right-skewed citation distribution in which a relatively small number of publications accounted for a substantial proportion of the total citations. Annual scientific production increased markedly, from 3 articles in 2020 to 67 articles in 2025. An additional 39 articles were indexed during the partial 2026 publication year, indicating continued research activity. However, the 2026 figure should be interpreted cautiously because it does not represent a complete calendar year. The annual publication output is presented in Table 3.

Table 3. Annual Scientific Production in the Final Bibliometric Corpus

Year	Documents
2020	3
2021	9
2022	11
2023	22
2024	34
2025	67
2026	39

Leading Sources, Documents, Authors, and Countries

The Journal of Risk and Financial Management was the most productive publication outlet, contributing 23 articles and accumulating 278 citations. Several other journals published considerably fewer articles but demonstrated substantial citation influence. For example, Contemporary Accounting Research published only four articles but received 218 citations, while Critical Perspectives on Accounting published four articles and accumulated 140 citations. These results indicate that publication productivity and citation impact were not necessarily aligned, as some journals with relatively

low output hosted highly influential studies. The leading publication sources and their citation performance are presented in Table 4.

Table 4. Leading Publication Sources and Citation Performance

Source	Documents	Citations
Journal of Risk and Financial Management	23	278
Journal of Open Innovation: Technology, Market, and Complexity	6	193
International Journal of Accounting Information Systems	6	188
Financial and Credit Activity: Problems of Theory and Practice	6	61
Intelligent Systems in Accounting, Finance and Management	6	15
International Journal of Accounting and Economics Studies	6	4
WSEAS Transactions on Business and Economics	5	47
Journal of Accounting Research	5	39
Contemporary Accounting Research	4	218
Critical Perspectives on Accounting	4	140

The most-cited publications encompass a broad range of themes, including textual analytics, professional-role transformation, ethical decision-making, audit quality, accounting education, and process automation. The highest citation count was recorded by Textual Analysis in Accounting: What's Next?, with 184 citations, followed by A Profession in Transition: Actors, Tasks and Roles in AI-Based Accounting, with 168 citations, and Artificial Intelligence-Based Decision-Making in Accounting and Auditing: Ethical Challenges and Normative Thinking, with 149 citations. Overall, the citation profile indicates that scholarly influence in this field is distributed across both technical applications of AI and its broader sociotechnical, ethical, educational, and professional implications. The ten most-cited publications are presented in Table 5.

Table 5. Most-Cited Publications in the Final Bibliometric Corpus

Document	Year	Source	Cited by
Textual Analysis in Accounting: What's Next?	2023	Contemporary Accounting Research	184
A profession in transition: actors, tasks and roles in AI-based accounting	2021	Journal of Applied Accounting Research	168
Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking	2022	Accounting, Auditing and Accountability Journal	149
The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices	2024	Journal of Open Innovation: Technology, Market, and Complexity	126
A critical review of AI in accounting education: Threat and opportunity	2024	Critical Perspectives on Accounting	100

Document	Year	Source	Cited by
Exploring the programmability of management accounting work for increasing automation: an interventionist case study	2021	Accounting, Auditing and Accountability Journal	84
The Use of Artificial Intelligence and Audit Quality: An Analysis from the Perspectives of External Auditors in the UAE	2022	Journal of Risk and Financial Management	82
The Effect of Technology Readiness on Adopting Artificial Intelligence in Accounting and Auditing in Vietnam	2024	Journal of Risk and Financial Management	76
How artificial intelligence changes the future of accounting industry	2020	International Journal of Economics and Business Administration	70
Enablers, barriers and strategies for adopting new technology in accounting	2024	International Journal of Accounting Information Systems	68

Author productivity was relatively dispersed, with no individual researcher contributing more than four articles to the final corpus. Lehner O. M. and Almaqtari F. A. were the most productive authors, each publishing four articles, followed by Li Y. and Alnor N. H. A., with three articles each. The remaining leading contributors published two articles each. This distribution indicates that the field is characterized by broad participation rather than a high concentration of publications among a small group of scholars. The most productive authors are presented in Table 6.

Table 6. Most Productive Authors in the Final Bibliometric Corpus

Author	Documents
Lehner O.M.	4
Almaqtari F.A.	4
Li Y.	3
Alnor N.H.A.	3
Benyasrisawat P.	2
Faccia A.	2
van Zijl W.	2
Alaskar M.Z.	2
Bonelli M.I.	2
Islam S.M.N.	2

Country-level participation was led by the United States, which was associated with 26 articles, followed by Saudi Arabia with 15 articles. Jordan and Ukraine each contributed to 13 articles, while the United Kingdom and China were represented in 11 and 10 articles, respectively. Portugal and Australia each accounted for nine affiliation-linked articles, followed by Finland with seven and Canada with six. These findings indicate broad international participation, although research output was concentrated in a relatively small group of countries. The leading countries based on authors' institutional affiliations are presented in Table 7.

Table 7. Leading Countries by Affiliation-Linked Publications

Country	Affiliation-linked documents
United States	26

Country	Affiliation-linked documents
Saudi Arabia	15
Jordan	13
Ukraine	13
United Kingdom	11
China	10
Portugal	9
Australia	9
Finland	7
Canada	6

Keyword Network Visualization

Thirty-five cleaned keywords met the predefined occurrence and linkage thresholds, generating a network of 70 co-occurrence links and five thematic clusters. Artificial intelligence emerged as the dominant network hub, with 77 occurrences, followed by machine learning with 33 occurrences, accounting with 25, audit with 24, and financial reporting with 13. The central position of audit-related terms indicates that audit analytics serves as the primary integrating domain within the literature. At the same time, themes related to the accounting profession, generative AI and financial reporting, digital infrastructure, and accounting education occupy distinct but interconnected positions. The keyword co-occurrence network is presented in Figure 1, while the thematic composition and interpretation of each cluster are summarized in Table 8.

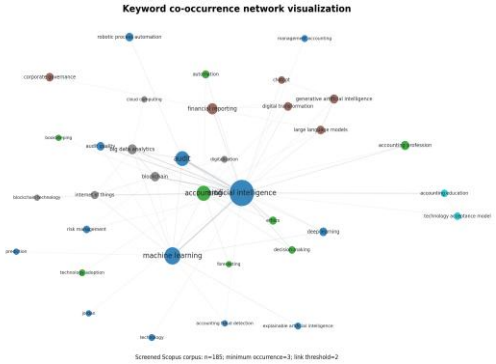

Figure 1. VOSviewer-compatible keyword co-occurrence network. Node size represents occurrence; colors represent detected clusters; links represent keyword co-occurrence.

Table 8. Thematic Clusters in the Keyword Co-occurrence Network

Cluster	Dominant keywords	Interpretation
1. AI-enabled audit and risk analytics	Artificial intelligence, machine learning, audit, audit quality, deep learning, RPA, risk management, XAI	Automation and augmentation of assurance, anomaly detection, fraud detection, and risk assessment.
2. Profession, automation, and ethics	Accounting, accounting profession, automation, ethics, decision-making, technology adoption, bookkeeping	Work redesign, professional roles, ethical accountability, and adoption conditions.
3. GenAI, reporting, and governance	Financial reporting, generative AI, large language models, ChatGPT, corporate governance, digital transformation	Emerging content generation, disclosure, reporting, governance, and verification challenges.
4. Digital infrastructure	Big-data analytics, blockchain, IoT, digitalization, cloud computing	Data architecture and interoperable infrastructure enabling automated accounting processes.

Cluster	Dominant keywords	Interpretation
5. Education and acceptance	Accounting education, technology acceptance model	Skills, curriculum, readiness, and user acceptance.

Overlay Visualization

The overlay map reveals a temporal transition. Robotic process automation, blockchain, IoT, and technology-acceptance themes have earlier average publication years. More recent terms include generative artificial intelligence (2025.38), large language models (2025.29), ChatGPT (2025.00), deep learning (2025.00), corporate governance (2025.14), risk management (2025.20), and explainable AI (2025.50). The movement is therefore not simply from automation to more automation; it is toward generative, explainable, and governance-intensive systems whose outputs require professional verification.

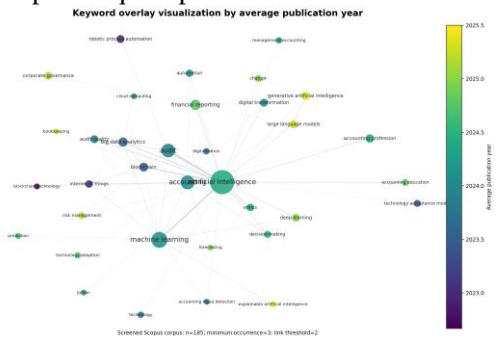

Figure 2. VOSviewer-compatible overlay visualization. Color represents average publication year, from earlier themes to more recent themes

Density Visualization

The density map confirms that the conceptual core remains concentrated around artificial intelligence, machine learning, accounting, and audit. Financial reporting and generative-AI terms form a newer but less dense zone, while education, acceptance, bookkeeping, and management-accounting themes remain peripheral. This pattern suggests that research volume is growing faster around technology labels than around standardized measurements of accountant-level efficiency.

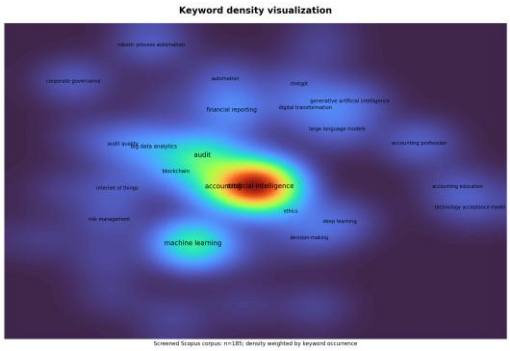

Figure 3. VOSviewer-compatible keyword density visualization. Warmer areas indicate a higher concentration of frequently occurring, closely positioned keywords.

Discussion

From Automation Efficiency to Verification-Intensive Augmentation

The mapping indicates two overlapping phases in the development of AI-enabled accounting work. The established phase is organized around machine learning, RPA, audit quality, big-data analytics, and digital infrastructure. This pattern is consistent with research that conceptualizes RPA as a mechanism for executing rule-based audit activities, extracting data, and reducing repetitive manual effort (Moffitt et al., 2018; Zhang, 2019; Perdana et al., 2023). Studies in small accounting firms, internal audit, and professional adoption settings similarly emphasize process standardization, ease of use, implementation resources, and perceived performance benefits (Hsiung & Wang, 2022; Razak & Ismail, 2022; Alassuli, 2025). These applications are closest to conventional automation because the expected output and validation rules can generally be specified before execution.

The emerging phase is centered on generative AI, large language models, ChatGPT, explainability, corporate governance, and financial reporting. In

contrast to deterministic RPA, generative systems produce probabilistic text and analysis whose surface fluency may exceed their evidential reliability. Research on ChatGPT in accounting highlights gains in drafting, summarization, and analytical access but also identifies hallucination, confidentiality, and professional-responsibility risks (Zhao & Wang, 2024). Recent work on generative AI in financial reporting and accounting research agendas similarly suggests that the technology can reshape disclosure production and research practice while increasing the importance of validation, provenance, and human review (Blankespoor et al., 2026; Stratopoulos & Wang, 2025). The temporal overlay therefore signals more than a change in technology labels: it represents a movement from automation efficiency toward verification-intensive augmentation.

This interpretation is reinforced by field evidence showing that audit firms widely use simpler AI applications such as optical character recognition and information extraction, whereas more complex systems face barriers related to explainability, bias, robustness, privacy, and auditor overreliance (Kokina et al., 2025). Textual-analysis research also demonstrates that sophisticated models can extract decision-relevant information from accounting narratives, but their usefulness depends on construct validity, domain adaptation, and transparent evaluation (Bochkay et al., 2023; Küster et al., 2025). Consequently, the correct productivity question is not whether GenAI produces a first draft faster, but whether the entire process—including review, correction, evidence tracing, authorization, and downstream use—is more efficient and reliable.

Efficiency is Under-Measured

Although the search explicitly included efficiency, productivity, time saving, cost reduction, accuracy, error reduction, throughput, audit lag, reporting lag, and performance, these outcome terms do not dominate the keyword map. This discrepancy suggests that a substantial part of the literature treats performance benefits as motivations for adoption rather than as directly observed dependent variables. Survey-based studies report positive relationships between AI readiness or use and audit quality, accounting transformation, and reporting performance (Noordin et al., 2022; Abdullah & Almaqtari, 2024; Anh et al., 2024). Firm-level evidence also indicates that AI adoption can enhance financial-reporting accuracy and auditing efficiency, particularly when big-data governance is strong (Bin-Nashwan et al., 2025). However, these constructs do not automatically reveal how many staff hours, process steps, corrections, or exception cases were eliminated.

The field therefore requires a clearer distinction between gross and net productivity. Gross productivity captures the immediate reduction in drafting, extraction, classification, or testing time. Net productivity deducts the time and cost of prompt preparation, review, correction, data integration, model monitoring, training, control redesign, and error remediation. Studies of digital accounting and AI integration frequently emphasize improved accuracy, competitiveness, and workflow efficiency, but measurement is often based on perceptions or aggregate organizational assessments (Gnatiuk et al., 2023; Alruwaili & Mgammal, 2025; Sampaio & Silva, 2025). Future research should combine system logs, time-and-motion data, error-severity measures, and quality indicators to establish whether reported benefits survive after realization costs are included.

Adoption research remains valuable because it identifies conditions under which objective efficiency might emerge. Technology readiness, organizational support, perceived usefulness, vendor ecosystems, and process compatibility influence whether accountants use AI consistently and appropriately (Hu et al., 2021; Jackson & Allen, 2024). Nevertheless, adoption intention,

frequency of use, and perceived benefit should not be used as substitutes for actual productivity. A mature evidence base should link adoption conditions to objective process outcomes and should report heterogeneous effects by task complexity, professional experience, firm size, and regulatory environment.

Audit Dominance and Neglected Accounting Tasks

Audit is more central in the mapped literature than management accounting, bookkeeping, taxation, or internal decision support. This concentration reflects the long-standing positioning of AI as a tool for formalizing audit procedures, expanding population coverage, and detecting anomalies or fraud (Issa et al., 2016; Kokina & Davenport, 2017). It is also consistent with the visible growth of research on audit automation, audit quality, professional judgment, and AI-enabled risk assessment (Dahiyat, 2022; Puthukulam et al., 2021; Epelbaum & Farrell, 2026). Audit offers relatively observable outputs—such as flagged exceptions, risk classifications, or evidence coverage—which may make it easier to operationalize AI applications than in less structured advisory work.

The dominance of audit nevertheless narrows the field's understanding of accountants' overall productivity. Management accounting research shows that automation depends on the programmability of planning, reporting, and control activities, while AI may also alter the relationship between management accountants and other organizational functions (Korhonen et al., 2021; Abbas, 2026). Research on controlling cautions that complex managerial judgments cannot be reduced to algorithmic optimization without considering context and organizational interpretation (Losbichler & Lehner, 2021). Reviews of AI and management accounting similarly call for attention to decision support, professional identity, and societal consequences rather than only transaction automation (Kerr et al., 2025).

Tax, bookkeeping, close management, forecasting, and advisory services remain comparatively peripheral. The review of emerging technologies in audit and tax indicates that these domains share infrastructure and governance challenges but have developed unevenly (Atayah & Alshater, 2021). Accounting education is another peripheral yet strategically important theme because workforce productivity depends on whether curricula develop data, model-evaluation, ethical, and communication capabilities (Ballantine et al., 2024). Future studies should therefore examine close-cycle duration, management-report preparation, tax-workflow throughput, exception handling, forecast revision, and the amount of professional capacity redirected toward advisory work.

Sociotechnical and Governance Implications

The coexistence of ethics, technology adoption, corporate governance, accounting profession, explainable AI, and audit quality supports a sociotechnical interpretation. AI efficiency is not produced by algorithmic capability alone; it depends on task fit, data quality, standardized workflows, user competence, professional skepticism, review design, access controls, and accountability. Ethical analyses show that AI-based accounting decisions redistribute responsibility across developers, managers, accountants, and system users, while the opacity of complex models can weaken the ability to justify professional conclusions (Lehner et al., 2022). Governance studies likewise emphasize strategic alignment, risk management, resource control, compliance, and value delivery as conditions for integrating AI into accounting and auditing operations (Almaqtari, 2024; Hu et al., 2023).

The socio-technical evidence also explains why technically successful automation may fail to generate organizational efficiency. RPA implementation can create dependencies on process owners, IT specialists,

exception-management routines, and maintenance resources; these dependencies are particularly visible when workflows cross legacy systems or contain unstable rules (Dahabiyeh & Mowafi, 2023). Professional skepticism and judgment remain essential because auditors must evaluate whether AI-generated evidence is relevant, reliable, and sufficient rather than treating system output as authoritative (Puthukulam et al., 2021). Studies of the profession's digital transformation further connect AI adoption with ethics, quality of working life, and reskilling, implying that productivity gains should not be evaluated separately from human sustainability (Fülöp et al., 2025).

These findings shift the managerial question from "Can AI automate this task?" to "Can the organization integrate, verify, and govern the output at a lower total cost and risk than the previous process?" The answer is likely to vary by task structure and risk. High-volume reconciliations may permit automated validation, whereas narrative reporting, estimates, and advisory recommendations require stronger human review and evidence tracing. Governance maturity therefore functions not only as a control variable but as a productivity complement: effective controls can reduce correction, dispute, and rework costs, while weak controls can transform initial speed gains into downstream inefficiency.

Theoretical Contribution

The results support an integrated task–technology–verification framework. Task–Technology Fit theory proposes that performance improves when technological capabilities correspond to task requirements (Goodhue & Thompson, 1995). The mapped literature extends this logic in two ways. First, it shows that different AI families fit different accounting tasks: RPA is most compatible with stable and rule-based processes, machine learning is well suited to prediction and classification, and language models are increasingly applied to unstructured reporting, interpretation, and communication. Second, it demonstrates that apparent fit at the output-generation stage may be offset by verification, accountability, and integration requirements.

The framework therefore treats verification burden as an endogenous realization cost rather than an external implementation detail. This extension is consistent with studies showing that professional roles evolve toward supervision, interpretation, and exception handling as routine work is automated (Leitner-Hanetseder et al., 2021). It is also consistent with adoption research demonstrating that organizational enablers and barriers determine whether technological potential becomes usable practice (Jackson & Allen, 2024). Theoretical models of AI-enabled accounting efficiency should consequently include task structure, AI capability, governance maturity, human expertise, and verification cost as interacting determinants of quality-adjusted productivity.

A further contribution is the separation of operational, quality-enabled, and strategic efficiency. Operational efficiency concerns time, cost, throughput, and cycle time. Quality-enabled efficiency concerns error reduction, audit coverage, reporting accuracy, and lower rework. Strategic efficiency concerns capacity released for analysis, communication, and advice. The bibliometric clusters show that the literature discusses all three, but often without a common measurement architecture. Bringing them together provides a more defensible basis for comparing technologies and prevents a narrow speed metric from being interpreted as comprehensive professional productivity.

Research Agenda

The combined findings from the performance analysis, keyword network, overlay visualization, and density mapping reveal several priorities for future research on AI-enabled accounting efficiency. The most important need is to move beyond

perceived benefits and examine whether technological gains remain after accounting for review, correction, integration, governance, and exception-handling costs. Future studies should also evaluate quality-adjusted efficiency, verification burdens associated with generative AI, applications in underexplored accounting domains, differences across worker and organizational characteristics, and the role of governance maturity. These priorities, together with the corresponding research questions and recommended empirical approaches, are summarized in Table 9.

Table 9. Recommended Future Research Agenda

Priority	Research question	Recommended evidence
Net productivity	Do AI tools reduce total elapsed time after review, correction, integration, and exception handling?	System logs, time-and-motion data, field experiments.
Quality-adjusted efficiency	How do speed gains interact with error severity, rework, audit quality, and decision usefulness?	Multi-outcome designs and cost-of-error measures.
Generative AI verification	When do LLM verification costs offset drafting and analysis gains?	Randomized tasks plus workplace deployment.
Management accounting and tax	How do AI tools affect forecasting, planning, close, tax preparation, and advisory work?	Domain-specific longitudinal studies.
Skills and inequality	Do gains differ by expertise, prompt skill, seniority, language, and firm resources?	Multilevel and cross-country designs.
Governance maturity	Which controls, explainability practices, and accountability structures convert technical capability into reliable efficiency?	Comparative case studies and governance indices.

Limitations

The analysis is based on one Scopus export and inherits its source coverage, indexing, open-access, subject-area, and citation-count limitations. The subject-area filter ECON may exclude relevant accounting-information-systems or computer-science studies, while the open-access filter may bias the source distribution. The title-and-author-keyword eligibility rule improves precision but may omit relevant articles whose accounting context appears only in the abstract. Country counts are affiliation mentions rather than fractionalized contributions. Keyword maps are sensitive to thesaurus choices and thresholds. Finally, bibliometric proximity measures scholarly attention, not causal efficiency.

CONCLUSION

This study transforms a broad 1.418-record Scopus export into a focused corpus of 185 accounting- and audit-relevant journal articles and integrates the verified results into a complete bibliometric manuscript. The field expanded rapidly through 2025 and is organized around five conceptual communities. Audit-oriented AI and machine learning remain the central core, while generative AI, large language models, explainable AI, financial reporting, and governance form the most recent research front.

The principal substantive conclusion is that the literature is moving from structured automation toward verification-intensive augmentation. Yet efficiency outcomes remain less visible than

technology and adoption concepts, leaving a major measurement gap. Future research should report net, quality-adjusted productivity and explicitly account for verification, correction, integration, governance, and learning costs. These measures are necessary before publication growth can be interpreted as evidence that AI has improved accountants' work efficiency.

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