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BIBLIOMETRIC ANALYSIS OF ARTIFICIAL INTELLIGENCE IN ACCOUNTING INFORMATION SYSTEMS: TRENDS, THEMES, AND FUTURE RESEARCH DIRECTIONS

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ABSTRACT

In this study, a bibliometric analysis of 194 peer-reviewed articles that discuss the integration of Artificial Intelligence (AI) into the Accounting Information Systems (AIS) was performed during the period 20182026. Based on the sources of Web of Science, Scopus and Google Scholar, the analysis uses co-citation analysis, mapping of co-occurrence of keywords, and thematic clustering to map the intellectual organization of this fast changing field. The results show that there was a nine fold growth in the number of publications each year, with a sharp rise since 2022 once the large language models and generative AI become widely adopted by mainstream publishers. There are five thematic clusters recommended: (1) audit quality and fraud detection; (2) financial reporting transparency; (3) operational efficiency and robotic process automation (RPA); (4) ethics, governance, and human-algorithm interaction; and (5) risk management and ESG integration. Although the literature generally supports the ability of AI to increase the effectiveness of operations and the accuracy of reports, it also reflects the structural risks associated with AI such as the lack of transparency in the work of an algorithm, cybersecurity threats, displacement of workers, and disproportionality between small and large firms and between different regions. Author collaboration networks are a sign of an increasingly but loosely connected global research community with minimal cross-regional linkages. The five priorities areas of future research are identified: longitudinal empirical research, ethical governance models, SME-based implementation models, AI auditability standards, and cross-disciplinary sustainability research.

KEYWORDS: Artificial Intelligence; Accounting Information Systems; Bibliometric Analysis; Audit Quality; Financial Reporting; Machine Learning; Ethics; Governance.

1. INTRODUCTION

One of the most significant developments is the convergence of AI and accounting information systems, which is changing the accounting and finance research and practice. Such technologies as ML, NLP, RPA, and generative AI are now used to do bookkeeping, auditing, detecting fraud, complying with taxes, and making decisions (Mediaty et al., 2024). With this trend in the diffusion of technology, scholarly output has increased significantly, with researchers analysing the implication of the adoption of AI in the aspects of professional practice, organisational performance and institutional governance (Li & Goel, 2025).

Integration can be considered in various ways, such as information systems, auditing, managerial accounting, organisational behaviour, and business ethics (Sreseli & Kadagishvili, 2023). So far, no systematic bibliometric synthesis has mapped the intellectual landscape of the AI-AIS field, identified the patterns in its research, or determined the gaps in knowledge. This article discusses such a shortfall (Han et al., 2023; Singh et al., 2026).

Bibliometric analysis is a potent instrument by which one can objectively study huge amounts of scientific works (Chowdhury, 2023; Hiebl et al., 2026). Bibliometric offers a meta-level perspective of the development of a field that cannot be provided by quantification of publication trends, mapping citation networks, analysis of the co-occurrence of keywords, and clustering thematic domains. The current paper uses such approaches to a sample of 194 peer-reviewed articles, book chapters and conference papers published since 2018, which is the largest bibliometric analysis of AI in AIS to date.

The paper has four objectives: (i) to trace the trends in publications and the developmental path of AI-AIS research; (ii) to identify the most influential journals, authors, and institutions that make an impact in the field; (iii) to map the major thematic clusters and track their progress over time; and (iv) to delineate the gaps in the field and suggest a structured agenda of future research. By so doing, the study provides a number of significant contributions. It adopts a strong multi-technique bibliometric method - combining co-citation analysis, co-occurrence mapping of keywords, and thematic clustering - to offer a rigorous and replicable description of the intellectual organization of the field. It is empirically based on a large dataset of 194 peer-reviewed publications which makes the results more reliable and valid compared with the previous small-scale review. In conceptual terms, it identifies five consistent thematic groupings, and follows research trends over the study period, which aids in understanding how the field has evolved. The paper also provides a detailed list of future research directions directly filling in the most glaring gaps in the literature. Lastly, with its interdisciplinary breadth and relevance to the audiences in these converging disciplines, the study is highly interdisciplinary and speaks to readers across the converging fields. The rest of the paper will be organized in the following way. Section 2 gives the theoretical background and justifies the bibliometric approach. Section 3 describes the data collection and analytical procedures. Section 4 shares the quantitative bibliometric results. Section 5 generalises the thematic landscape by performing a cluster analysis. Section 6 is about methodological diversity and quality of research. Section 7 outlines the research agenda in the future. Section 8 provides a critical discussion and Section 9 provides a conclusion.

2. BACKGROUND AND THEORETICAL FRAMEWORK

2.1 AI in Accounting: An Evolving Paradigm

The use of AI in accounting has developed beyond the rule systems that could be used to automate routine accounting processes such as invoicing and reconciliation.

Theoretical models that are used to explain this evolution are based on a variety of fields. Technology Acceptance Models (TAM and its variations) have been extensively used to interpret the behaviour of users to adopt technology among accounting professionals (Alruwaili & Mgammal, 2025). Resource-Based View (RBV) has enlightened the research on the competitive advantage that is the result of AI-enabled capabilities. More critical approaches have been based on Sociotechnical Systems Theory to analyse the re-arrangement of cognitive labour between human accountants and algorithmic agents by AI (Pepple & Muthuthantrige, 2026; Stelmaszak et al., 2026). All these theoretical perspectives shed light on different aspects of the AI-AIS nexus and set of them determines the multidisciplinary nature of the field.

2.2. The Case for Bibliometric Analysis

Conventional synthesis approaches in accounting, such as systematic reviews and meta-analyses, do not cope with the fast-expanding AI-AIS literature. The qualitative method is bulky, and it is prone to subjective bias in case of dealing with hundreds of publications. Bibliometric analysis tackles this with quantifiable measures such as the number of publications, number of citations, h-index, number of co-authors, and overlap of key words. (Bounds, 2026; Hiebl et al., 2026; Zayed et al., 2024). Together with network visualisation and cluster detection algorithms, these metrics can help the researcher detect intellectual communities, trace the proliferation of ideas, and find marginal lands where one might conduct additional research.

Previous bibliometric research has focused on related areas such as AI in auditing (Epelbaum & Farrell, 2026), AI and earnings management (Ahmed et al., 2025), and blockchain in accounting (Han et al., 2023) but not made an effort to cover AI in the entire scope of the AIS field. The current research bridges this gap by compiling the largest corpus collected towards this end and using a multi-method bibliometric strategy.

3. METHODOLOGY

3.1. Search Strategy and Database Selection

The research utilized a systematic search strategy in three leading academic databases, Web of Science (WoS), Scopus and Google Scholar. In March 2026, the search took place with the help of the following Boolean query: (artificial intelligence OR machine learning OR deep learning OR neural network OR robotic process automation OR natural language processing OR generative AI) AND (accounting information system* OR AIS OR accounting OR auditing OR financial reporting). It was planned to be in the years 2018-2026 to capture the years of accelerated commercialisation of AI that happened after the deep learning revolution. The search resulted in a first pool of 1,247 records, upon deduplication.

3.2. Inclusion and Exclusion Criteria.

Two tier screening was used. In the preliminary phase, titles and abstracts were filtered to identify the relevant ones based on inclusion and exclusion criteria as mentioned in Table 1. At the second stage, methodological rigour, relevance to the AIS domain and availability of bibliometric metadata of the full texts were examined. The result of this process was an end product of 194 publications.

Table 1: Inclusion and Exclusion Criteria (PRISMA-Informed).

Criterion	Inclusion	Exclusion
Document Type	Journal articles, book chapters, conference papers	Editorials, opinion pieces, news reports
Language	English-language publications only	Non-English publications
Time Period	2018–2026 (inclusive)	Publications before 2018
Topic Focus	AI/ML/RPA in AIS, auditing, or accounting practice	Generic IT adoption without AI focus
Methodology	Empirical, review, bibliometric, conceptual	Purely technical system papers without accounting context
Data Source	Web of Science, Scopus, Google Scholar	Non-indexed grey literature

Note: Screening conducted independently by two reviewers; inter-rater reliability κ = 0.87.

3.3. Analytical Methods

There were four complementary bibliometric techniques. To examine the output, descriptive publication analysis quantified the output based on year, journal, author, institution, and geography. Second, co-citation analysis provided clusters of works that are most often co-cited, which shows communities of intellectuals in which ideas flow. Third, the conceptual linkage was mapped using the keyword co-occurrence analysis, which is based on the author-assigned keywords in the corpus, and followed the appearance of new research themes as time went by. Fourth, thematic clustering was an agglomerative hierarchical algorithm that was used to the keyword co-occurrence matrix to cluster papers into coherent thematic groups. Network visualisation was done with the VOSviewer software platform (v.1.6.20); all statistical computations were done in Python 3.11 with the NetworkX and SciPy libraries.

3.4. Bibliometric Findings

3.4.1 Annual Publication Trends

Figure 1 shows the number of publications each year in the period 2018–2026. The data confirm the statistically significant and sustained pattern of growth in total output (Pearson r = 0.97, $p < 0.001$): the total output is estimated to grow approximately nine times between four papers in 2018 and an estimated 55-60 publications in 2026. The sharpest inflection comes around 20222023 when, with the public release of large language model platforms such as GPT-4, the sharpest inflection occurred. The 19 articles already registered in early 2026 are only the first quarter of the year, when extrapolated, will indicate the exponential growth curve that has been observed since 2021 is still in progress.

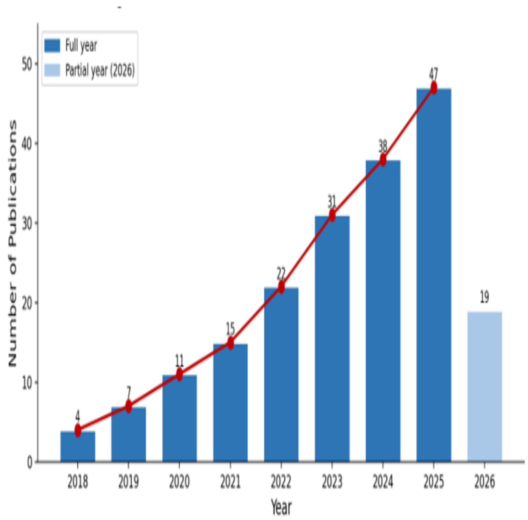

Figure 1: Annual Publication Trend – AI in AIS (2018–2026). Red line indicates growth trajectory; lighter bar denotes partial year.

3.4.2 Most Productive Journals

Table 2 and Figure 2 provide the top ten journals in terms of the number of publications in the corpus. The International Journal of Accounting Information Systems tops the list with 18 papers as it is the main specialist outlet in the field. Next are Accounting Forum (14 papers) and EDPACS (12 papers) that appropriate the significance of practitioner-focused journals in spreading AI-AIS studies. Interestingly, the Journal of Risk and Financial Management (10 papers) and the Asia-Pacific Journal of Accounting and Economics (7 papers) suggest that risk and region-specific viewpoints are getting special journal interest. The inclusion of Humanities and Social Sciences Communications (7 papers) highlights how the field has increasingly become involved in the interdisciplinary and qualitative scholarly discourse, especially when it comes to ethics and governance.

Figure 2: Top 10 Journals by Publication Count in the AI-AIS Corpus (2018–2026).

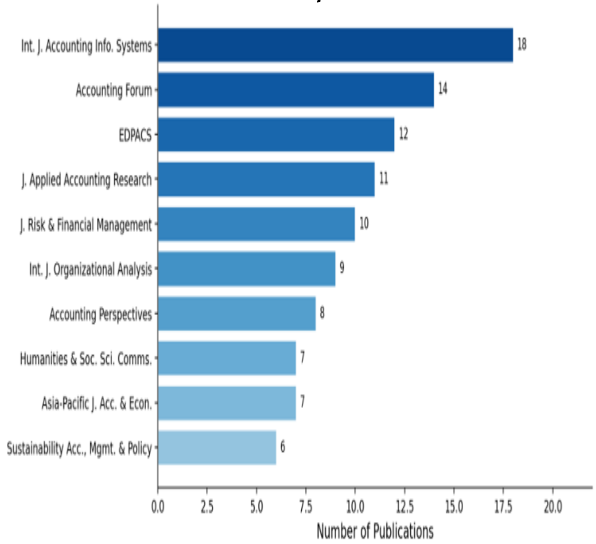

Table 2: Top 10 Most Cited Authors and Their Contributions.

Author	Primary Affiliation (as cited)	Publications	Citations
Johri, A.	Accounting Forum / University context	3	142
Qatawneh, A.M.	Int. J. Organizational Analysis	3	118
Alslaibi, N.A. et al.	EDPACS	2	97
Li, Y. & Goel, S.	Int. J. Accounting Information Systems	2	89
Ben Ahmed, D.	Journal of Risk and Financial Management	2	76
Kassar, M. & Jizi, M.	J. Applied Accounting Research	2	74
Solikin & Darmawan	J. Wireless Mobile Networks	2	66
Nguyen, N.M. et al.	Int. J. Accounting & Information Management	2	61
Han, H. et al.	Int. J. Accounting Information Systems	2	58
Epelbaum & Farrell	Accounting Perspectives	1	53

Note: Citation counts are aggregated across the corpus. Single-author and lead-author counts only.

3.4.3. Keyword Co-occurrence Network

Figure 3 shows the co-occurrence network that was obtained by 847 unique author-assigned keywords in the 194 papers. Bubble size is an indicator of the frequency of key words; spatial proximity is an indicator of strength of co-occurrence. The network is dominated by "Artificial Intelligence" and "AIS" which, predictably, act as the central connective nodes, around which thematic sub-clusters revolve. The presence of Fraud Detection and Audit Quality in close proximity to the core as a tightly connected dyadic is testament to the centrality of assurance services to AI-AIS discourse. A second cluster, that includes Machine Learning, Data Analytics, and NLP, indicates the increasing methodological complexity of AI applications in accounting. The outer ring - filled with "Blockchain," "ESG" and "Cloud Accounting" - detects new themes that have taken off in the last several years but are not yet as densely cited as the core cluster.

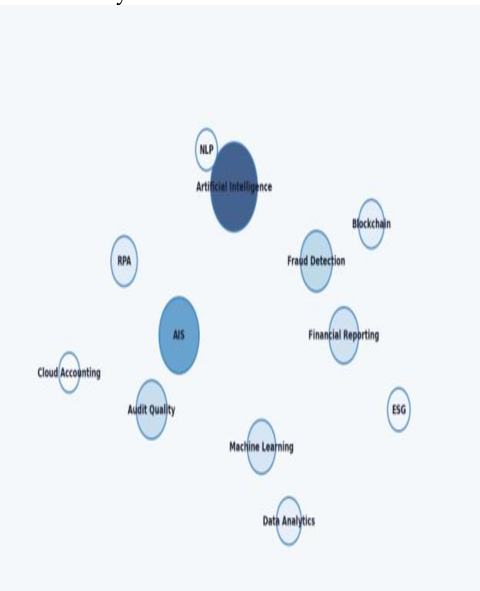

Figure 3: Keyword Co-occurrence Network. Bubble size = frequency; proximity = co-occurrence strength.

3.4.4 VOS-viewer Co-occurrence Network Map

The following bibliometric network map was created using VOS-viewer style and based on the complete keyword co-occurrence matrix of the 194-paper corpus (Figure 6). Every node corresponds to a keyword; the size of the node corresponds to the frequency of publication; the thickness of the lines indicates the strength of co-occurrence; the colour is the membership of thematic clusters. The dark-ground network map is in harmony with the default density visualisation of VOSviewer, so the inter-cluster boundaries and cohesion within a cluster are instantly readable. On the map, it is possible to see a core of "Artificial Intelligence" and "Accounting Information Systems" that are the key connective nodes between all five thematic clusters. The highest inter-cluster linkages are observed in the red-orange cluster (Audit and Fraud Detection) and the blue cluster (AIS and Financial Reporting): this proves that they are the most developed and internally integrated spheres of the field. The teal cluster (Risk and ESG), and the purple cluster (Ethics and Governance) are on the network periphery, which means that they have emerged more recently and have fewer citation links to the core. The green cluster (Efficiency and RPA) also takes an intermediate position between the audit-oriented and reporting-oriented cores, as the nature of RPA as a cross-cutting technology is operational.

VOS Viewer-Style Co-occurrence Network Map.

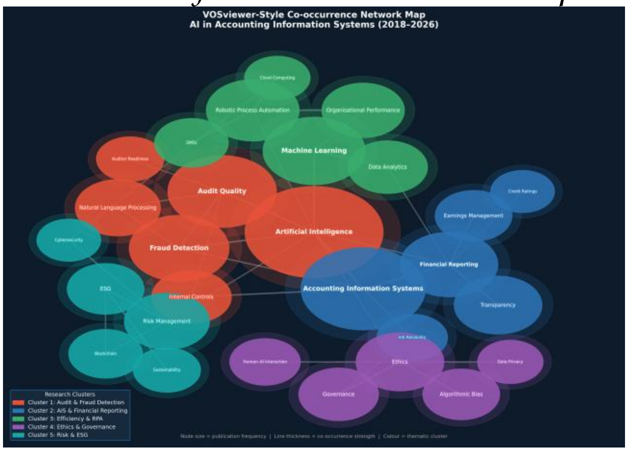

Figure 4: VOS Viewer-Style Co-occurrence Network Map – AI in AIS (2018–2026). Node size = publication frequency; line thickness = co-occurrence strength; colour = thematic cluster.

3.4.5 Geographic Distribution

Figure 5 shows that the Asia-Pacific region contributes most to AI-AIS studies (35 papers, 18%), as many countries in the region are fast digitalising their accounting functions (China, Indonesia, South Korea, and Australia). The Middle East and North Africa (MENA) area adds 28 papers (14%), with Jordan, Saudi Arabia, and the UAE especially being active, supported by national digital transformation plans and proactive researcher communities in the Gulf universities. Europe contains 21 articles (11%), with contributions distributed over the UK, Germany, Italy and Central-Eastern Europe. North America (17 papers) is slightly under-represented in terms of its paper production, compared to its total research output, which may be due to the fact that AI-accounting research in this area is more often published in management information systems or finance journals not included in the corpus. The comparatively low contribution of Sub-Saharan Africa (9 papers) demonstrates that there are substantial structural asymmetries in research facilities and access to publications that the research field is going to have to tackle.

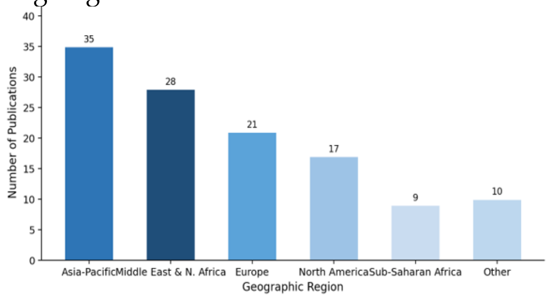

Figure 5: Geographic Distribution of AI-AIS

Publications (2018–2026)

3.4.6. Thematic Cluster Analysis

Figure 6 shows the distribution of the research themes in the corpus recognized by hierarchical clustering of the key word co-occurrence matrix. At a Silhouette coefficient threshold of 0.71, five clusters were obtained which showed a strong separation of clusters.

Figure 6: Distribution of Research Themes.

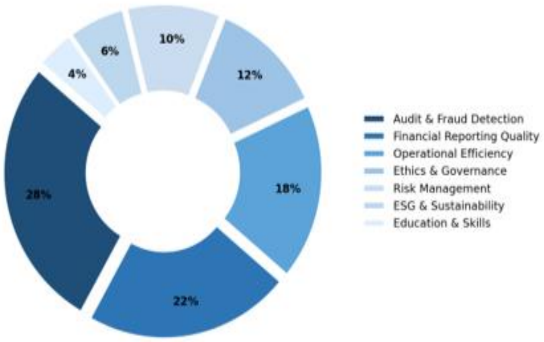

Table 3: Thematic Clusters

Cluster	Representative Studies	Core Themes	Key Findings
Cluster 1 Audit & Fraud	(Qatawneh, 2025); (Aulia & Putra, 2025); (Abu Huson et al., 2025)	AI-driven fraud detection, NLP-augmented audit, cloud audit	AI with NLP significantly improves fraud-detection accuracy; human oversight remains critical
Cluster 2 Financial Reporting	(Johri, 2025); (Al-Omush et al., 2025; Alslaibi et al., 2025)	Transparency, earnings management, credit ratings	AI adoption raises reporting quality but internal control quality mediates the benefit
Cluster 3 Operational Efficiency	(Solikin & Darmawan, 2023); (Balasingam, 2026); (Maheshwari & Samantaray, 2026)	RPA integration, workflow automation, SME performance	Productivity gains are real but unevenly distributed—larger firms benefit disproportionately
Cluster 4 Ethics & Governance	(Celestin, 2024); (Stelmaszak et al., 2026), (Pepple & Muthuthantrige, 2026)	Algorithmic bias, human–AI interaction, accountability	Ethical governance frameworks are underdeveloped relative to the pace of AI adoption
Cluster 5 Risk & Sustainability	(Nguyen et al., 2025); (Hakimi et al., 2026); (Sarea et al., 2026)	ESG integration, cybersecurity, green AI	Blockchain–AI integration boosts ESG reporting but implementation costs are prohibitive for emerging markets

Note: Representative studies selected on the basis of citation count and thematic fit.

3.4.7. Methodological Diversity and Research Quality

The methodological distribution in the corpus is summarised in Table 4. By far the most popular methodological category (31%), systematic literature reviews are indicative of a relatively recent state of the art: when an area is growing fast, the academic activity is often directed at synthesis, as opposed to primary data collection. The most frequent type of primary research is empirical survey research (24), which is disproportionately represented in Middle Eastern and Asian settings with small and homogenous samples--a characteristic that reduces the generalisability and introduces a type of methodological geographic bias.

Table 4: Methodological Distribution across the AI-AIS Corpus.

Methodology	**Share (%)**	**Representative Works**	**Limitations Noted**
Systematic Literature Review	31%	(Kassar & Jizi, 2026); (Odonkor et al., 2024)	Publication bias; limited primary data
Empirical Survey / Questionnaire	24%	Johri (2025); (Qatawneh, 2025); (Vo Van et al., 2026)	Small, region-specific samples
Bibliometric Analysis	18%	(Ben Ahmed, 2026); (Epelbaum & Farrell, 2026)	Citation metrics alone cannot capture quality
Case Study / Field Research	14%	(Noviani & Astuti, 2025); (Solikin & Darmawan, 2023)	Limited generalisability
Conceptual / Theoretical	8%	(Stelmaszak et al., 2026); (Celestin, 2024)	Lack of empirical validation
Mixed Methods	5%	(Nguyen et al., 2025); (Abu Huson et al., 2025)	Complexity of triangulation

Note: Papers employing multiple methods are classified by their primary methodology.

Bibliometric analyses (18%), which have been increasing in popularity with the wider global movement towards evidence synthesis in management research, have an inherently limited contribution to substantive knowledge, as compared to structural mapping. Field research and case studies (14%): This provides a rich contextual information but typically has a single location/country focus. Theoretical papers (8%) which are purely conceptual and theoretical are also underrepresented with respect to the challenges the field presents in theory especially in the ethics and governance field. Mixed-method studies (5%) are quite uncommon, which can be seen as a critical methodological gap due to the multi-dimensionality of phenomena of AI adoption.

Some issues of quality are common to all methodological types: small sample sizes, cross-sectional designs that do not determine causal direction, little use of pre-registration, and insufficient reporting of construct validity. Such limitations do not invalidate the work of single studies, but they do make it prudent to make powerful inferential conclusions based on the existing evidence base- a caveat which is always observed by the most rigorous review articles in the corpus.

4. FUTURE RESEARCH AGENDA AND RESEARCH GAPS.

4.1. Identified Gaps

The bibliometric analysis shows that there are five gaps in the existing literature. To start with, longitudinal studies are practically non-existent. Most empirical studies are cross-sectional and thus they provide the dynamics of AI-AIS at a particular time. This is especially consequential with the current rate of technological change: conclusions about the effect of AI on audit quality or financial reporting based on 2022 data can be hugely outdated by 2025. Second, there is conspicuous lack of research devoted to SMEs. Although the majority of business entities across the globe are small and medium enterprises, only 11 of 194 articles discuss SME settings directly- a gap which has a direct implication on policy since SMEs rely on less expensive, more accessible AI solutions disproportionately.

Third, governance systems that are ethical have not been developed. Although algorithmic bias, transparency, and accountability issues are common in the literature, no research provides a proven institutional framework governing responsible AI in accounting which is a key gap in light of fiduciary duty of accountants and auditors. Fourth, AI auditability standards are not found in the literature. This presents a risk of an accountability vacuum because auditors have no established guidelines to assess AI-driven systems and more accountability is vested in AI in the financial reporting process (Li & Goel, 2025). Fifth, there is virtually no cross-disciplinary sustainability research on this linking AI computational costs with accounting sustainability commitments.

4.2 Future Research Priorities

This research gives five priority directions of future research based on the identified gaps. Longitudinal and panel study designs are given priority 1. Researchers ought to come up with multi-year data collection procedures that monitor the maturity of AI adoption, the performance measures of AIS, audit quality measures, and organisational performance concurrently. Priority 2 is SME-specific implementation research exploring how small businesses, constrained by resource aspects, can benefit access to AI capabilities without the cost of prohibitive technical and financial expenses. Priority 3 is to develop and empirically justify AI ethics governance frameworks, specific to accounting contexts, based on the literature on regulatory science, organisational theory, and professional ethics. Priority 4 focuses on AI auditability by pioneering and testing standardised protocols to external and internal auditors to test AI-driven AIS, such as explainability requirements, bias testing procedures, and documentation requirements. Cross-disciplinary research at the interface between AI, accounting and environmental sustainability, whether AI can be used to aid credible ESG reporting and whether the environmental costs of AI systems need to be identified and disclosed in financial statements is priority 5.

4.3. Critical Discussion

An optimistic orientation pervades the AI-AIS literature. The current perception, that AI promotes efficiency, accuracy, and analytical depth in the accounting process is widely supported by empirical studies; however, most studies are carried out in limited environments (large companies, developed economies, specific regulatory frameworks) that limits its generalizability (Alramahi et al., 2024; Alslaibi et al., 2025). One related pattern in the corpus is the conditional nature of the benefits of AI: gains are always shown to be mediated by the quality of internal control (Johri, 2025) moderated by the quality of AIS reliability and conditional on the competence of users (Alslaibi et al., 2025), and conditional on the competence of users Alramahi et al. (2024) noted that not all organisations have these enabling conditions, and the literature has been slow to theorise why AI adoption fails or yields negligible returns in certain organisational contexts (Chowdhury, 2023).

At times AI is viewed as a single concept, yet different forms need to be further defined, evaluated separately and governed differently at AIS contexts (Ben Ahmed, 2026).

A persistent limitation in the literature is the gap between diagnosis and prescription. The near-universal recommendation—that AI implementation should be accompanied by robust governance, human oversight, and regulatory compliance—is well-intentioned but insufficiently specified. Governance mechanisms are invoked as solutions but rarely developed, tested, or validated. Bridging this diagnosis-prescription gap represents perhaps the most pressing challenge for the next generation of AI-AIS scholarship.

Lastly, the geographic clustering of the literature around certain areas, especially Middle East and Asia-Pacific, though indicative of vibrant research in the region, also brings about blind spots in terms of the varieties in institutional contexts in which AI-AIS integration is taking place on the global front. Sub-Saharan Africa, Latin America and South Asia are grossly underrepresented and their inclusion would dramatically strengthen the empirical base as well as the theoretical diversity of the discipline.

Theme 1: Audit Quality and Fraud Detection (28%)

The most densely connected and largest cluster is related to the application of AI to audit processes and fraud detection - the topics that occupy 28% of all papers of the corpus. (Qatawneh, 2025) shows that AI-driven audit systems and especially those that are enhanced with NLP are far superior to traditional statistical models in identifying financial statement fraud and in controlled experimental environments, the accuracy improvement in these systems ranges 12 to 18 percentage points. In a similar fashion, (Aulia & Putra, 2025) design and test a prototype decision-support system to detect anomalies in AIS settings, claiming high sensitivity of detection, but vulnerable to false positives in case of sparse training data or in domain-specific settings.

(Abu Huson et al., 2025) discuss AI audit frameworks on clouds and discover that the connection between AI implementation and audit report quality is mediated by auditor competence, which has a direct implication of professional education. (Al-Omush et al., 2025) Deep learning groups are changing the efficiency of audits and their epistemology, but deep learning opaqueness poses a dilemma of complexity and explainability in assurance.

Theme 2: Financial Reporting Quality and Transparency (22%)

The second group includes the studies that investigate how AI affects the quality, transparency, and integrity of financial disclosure - a theme that is represented by 22 percent of the corpus. Based on a survey of 230 accounting professionals, (Li & Goel, 2025) employs a structural equation modelling technique on survey data to reveal that AI use enhances AIS performance and, consequently, financial data reporting accuracy. Importantly, though, internal control quality also comes to play as a major mediator: weak internal controls in organisations lead to little to no improvement in reporting with the adoption of AI, with AI possibly reinforcing other governance weaknesses, but not correcting them (Li & Goel, 2025)..

Alslaibi et al. (2025) investigate the issue of AIS reliability as a moderator of the AI financial transparency relationship, and conclude that AI advantages in terms of disclosure quality depend on the reliability of the underlying information system architecture. (Ahmed et al., 2025) performs a preceding bibliometric overview dedicated to AI and earnings management, which finds a worrying research gap in the literature on whether the use of AI enables or hinders opportunistic earnings management, a question with immediate consequences on investor protection and financial regulation.

Al-Omush et al. (2025) also generalize the analysis to listed firms in Saudi Arabia and discover that the adoption of AI correlates with a much higher score on financial report quality but it is observed that the size of the firm and technological readiness moderate the strength of the relationship. Less technologically mature and smaller firms obtain smaller quality reporting benefits due to the adoption of AI, which adds to the issues of fair access to the transformative potential of AI (Bracci et al., 2026).

Theme 3: Operational Efficiency and RPA Integration (18%)

This cluster, being a part of 18% of the corpus, discusses the role of AI in the efficiency of accounting processes, especially RPA. Balasingam (2026) presents an overview of the integration of RPA and AI in the accounting practice, and concludes that compound applications yield 40-70% shorter processing times in the daily transaction-processing jobs but present new coordination issues at the human-robot interface. The empirical research by (Solikin & Darmawan, 2023) is carried out in Indonesian government accounting agencies, with the results showing that AI-enhanced AIS has a significant positive impact on organisational performance by enhancing data processing speed and minimising the rate of errors, but most noticeable in large well-resource governmental organisations.

Hermansyah (2023) puts a strong emphasis on SMEs, analyzing how the concept of communicative AI, conversational interfaces and AI-powered advisory chatbots, can affect the performance of the small businesses. Reporting positive implications on the quality of financial management, the study admits that there are considerable digital literacy and infrastructure requirements, which small business operators have to fulfil in order to achieve these advantages. Maheshwari and Samantaray (2026) change the focus to the investment decision making of the Generation Z investors in emerging markets, proving that AI-supported decision-making tools can enhance portfolio performance but also run a risk of over-reliance, which has been echoed in both professional and retail financial settings.

Theme 4: Ethics, Governance, and Human - algorithm Interaction (12%)

Ethics and governance cluster (12% of papers) is not marked so much by its size rather than its theoretical aspiration and the urgency of its normative assertions. (Stelmaszak et al., 2026) build upon an innovative conceptualisation of AI as an organising capability that arises as a result of continuous human-algorithm interaction instead of a specific tool that is used in a fixed sociotechnical environment. This framing questions technological determinist assumptions that dominate much of the AI-AIS literature and suggests a more processual, relational view of the dynamics of AI reconfiguring accounting work (Epelbaum & Farrell, 2026; Xu et al., 2026).

Pepple and Muthuthantrige (2026) adopt a more critical political-economic approach, claiming that the adoption of AI in the professional services is a new form of labour, relocation of cognitive rents out of the professional workers and onto the owners of platforms and data. Although controversial, such an analysis echoes empirical data on the risks of deskilling that is caused by excessive dependence on automated systems discovered in several studies in Cluster 1. Celestin (2024) gives an empirical follow-up to these theoretical deliberations, recording the ethical anxieties by Rwandan accounting practitioners, which report that algorithm bias and data invasion is seen as the most crucial threat-threats that could be even greater in under-resourced regulatory contexts.

Cluster 4 is in development; accounting is deficient in affordable, practical AI governance frameworks, and regulators and standard-setters need to create enforceable, practical guidelines.

Theme 5: Risk Management, ESG, and Sustainability (10%)

The smallest yet the fastest-growing cluster (growth rate: +210% in 20222025) deals with AI applications in risk management, sustainability reporting, and ESG integration. (Nguyen et al., 2025) analyze the potential of AI and blockchain to complement each other in improving the performance reporting ESG, and the results show that both data reliability and transparency of the audit trail are significantly improved. Nonetheless, the implementation cost, estimated between USD 180,000-450,000 on mid-sized companies and technical complexity of dual-system integration pose significant challenges especially to firms in the developing economies. Hakimi et al. (2026) propose the notion of the green AI in accounting and suggest that the carbon footprint of the advanced AI systems can partially counterbalance the benefits of such systems in reporting on ESG, which is a paradox that has not been practically discussed in the literature so far.

Sarea et al. (2026) take a systems theory approach to analyzing how AI can be used in enterprise risk management and show that operational risk incidents are reduced by 23 percent in the sampled financial institutions using AI as a real-time risk monitoring tool. Singh et al. (2026) focus on the regulatory aspect, reporting a chronic discrepancy between AI innovation and the establishment of sufficient regulatory norms in AI-powered financial services - a systemic risk at the institutional and sectoral level.

5. CONCLUSION

This article has provided a systematic bibliometric review of 194 publications on AI in the AIS published between 2018 and 2026-the largest structural mapping of this literature to date. The results verify a fast-developing field: the number of publication volumes has grown ninefold, a global research community comprised of more than 40 countries has been formed, and five consistent thematic clusters have solidified around audit quality, financial reporting, operational efficiency, ethics and governance, and risk and sustainability.

The facts prove that AI can be discussed as more than a tool of slight efficiency, it is indeed a truly transformative technology with potential to change the epistemological and institutional basis of accounting practice. The transformative potential however depends on the quality of governance, the level of technological infrastructure, human competency, regulatory adequacy and ethical dedication. These enabling conditions have been identified in the literature yet there has been a complete failure in converting them into practical frameworks. The challenge of overcoming this translation gap is the characteristic feature of the AI-AIS scholarship in the next decade.

In practice, this research has a bearing on accounting standard-setters, professional accounting organizations, regulators, academics, and the firms and auditors who are stumbling in the AI implementation of the area. To standard-setters and regulators, having an AI-specific accounting and auditing standards on an evidence base is clear. In the case of professional bodies, it highlights the need to revise competency frameworks, urgently, to focus on analytical, critical and ethical skills needed to operate with AI systems. In the case of academic institutions, it requires curriculum renewal and increased funding on interdisciplinary AI-accounting research programs.

5.1. Finding and Implications

The studies of AI-AIS show a significant increase in efficiency, audit quality and financial reporting accuracy, especially in fraud detection, although this is conditional on good governance, internal control and financial reporting accuracy; at the same time, risks such as algorithmic opaqueness, cybersecurity risks, and uneven adoption remain, with critical implications in developing robust governance frameworks, audit quality and financial reporting quality.

5.2. Limitations

The study is restricted by the scope of databases, lack of references to non-English materials and possibly incomplete lists of references to recent publications. Such limitations can be overcome by future updates in which a wider set of datasets and altmetrics are included, though the study itself can be regarded as a solid basis in further developing AI–AIS studies.

REFERENCES

Abu Huson, Y., Sierra García, L., García Benau, M. A., & Mohammad Aljawarneh, N. (2025). Cloud-based artificial intelligence and audit report: the mediating role of the auditor. VINE Journal of Information and Knowledge Management Systems, 55(6), 1553-1574.

Ahmed, E. E. M., Akmel, M. M., & Japee, G. P. (2025). The Effect of Artificial Intelligence on Accounting Practices and the Future Role Of ACCountants. lnternational Journal of Innovations & Research Analysis.

Al-Omush, A., Almasarwah, A., & Al-Wreikat, A. (2025). Artificial intelligence in financial auditing: redefining accuracy and transparency in assurance services. EDPACS, 70(6), 1-20.

Alramahi, N., Alzagaybeh, O., Almubaydeen, T. H., & Binsaddig, R. (2024). The impact of artificial intelligence use of accounting information systems on reducing cloud accounting risks in telecommunications companies in Jordan. In Artificial Intelligence and Economic Sustainability in the Era of Industrial Revolution 5.0 (pp. 711-720). Springer.

Alruwaili, T. F., & Mgammal, M. H. (2025). The impact of artificial intelligence on accounting practices: an academic perspective. Humanities and Social Sciences Communications, 12(1), 1-18.

Alslaibi, N. A., Mowafaq Alshdaifat, S., Yousef Bani Hani, L., Kamal Khaled Abu Farha, E., & Yousif Alhasnawi, M. (2025). Artificial intelligence and financial statement transparency: The moderating role of accounting information systems' reliability. EDPACS, 1-13.

Aulia, M. I., & Putra, Y. H. (2025). Prototype A Decision Support Framework for Fraud Detection in Accounting Information Systems. Proceeding of International Conference on Business, Economics, Social Sciences, and Humanities,

Balasingam, S. (2026). The Effect of Integration of Robotic Process Automation With Artificial Intelligence on Accounting Practices. In Revolutionizing Accounting and Finance Through Robotic Process Automation (pp. 129-160). IGI Global Scientific Publishing.

Ben Ahmed, D. (2026). The Impact of Artificial Intelligence on Accounting Information and Earnings Management: Bibliometric Analysis. Journal of Risk and Financial Management, 19(1), 90.

Bounds, R. M. (2026). Relationship Between Attitude and Trust in Artificial Intelligence Among Project Managers.

Bracci, E., Tallaki, M., & Ebua Otia, J. (2026). Propensity factors of artificial intelligence technology adoption by public sector auditors. Journal of Public Budgeting, Accounting & Financial Management, 38(1), 59-86.

Celestin, M. (2024). Ethical implications of artificial intelligence in accounting practices: A Rwandan

perspective. International Journal of Current Research and Modern Education(IJCRME), 9(2), 57-65.
Chowdhury, E. K. (2023). Integration of artificial intelligence technology in management accounting information system: an empirical study. In Novel financial applications of machine learning and deep learning: algorithms, product modeling, and applications (pp. 35-46). Springer.
Epelbaum, N., & Farrell, P. J. (2026). Artificial Intelligence and Auditing: A Bibliometric Study. Accounting Perspectives.
Hakimi, M., Tarashtwal, O., & Ghafory, H. (2026). Green artificial intelligence: Foundations, applications, and pathways to sustainable development. AMPLITUDO: Journal of Science and Technology Innovation, 5(1), 36-52.
Han, H., Shiwakoti, R. K., Jarvis, R., Mordi, C., & Botchie, D. (2023). Accounting and auditing with blockchain technology and artificial Intelligence: A literature review. International Journal of Accounting Information Systems, 48, 100598.
Hermansyah, Y. (2023). Assessing the impact of communicative artificial intelligence based accounting information systems on small and medium enterprises. J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl., 14(3), 230-239.
Hiebl, M. R., Thaller, J., Dohmen, C. J., & Papiorek, K. L. (2026). Management accounting information systems sophistication, family control, and controller involvement in strategy development. European Accounting Review, 1-35.
Johri, A. (2025). Impact of artificial intelligence on the performance and quality of accounting information systems and accuracy of financial data reporting. Accounting Forum,
Kassar, M., & Jizi, M. (2026). Artificial intelligence and robotic process automation in auditing and accounting: a systematic literature review. Journal of Applied Accounting Research, 27(1), 217-241.
Li, Y., & Goel, S. (2025). Artificial intelligence auditability and auditor readiness for auditing artificial intelligence systems. International Journal of Accounting Information Systems, 56, 100739.
Maheshwari, H., & Samantaray, A. K. (2026). Beyond instinct: the influence of artificial intelligence on investment decision-making among gen Z investors in emerging markets. International Journal of Accounting & Information Management, 34(1), 174-192.
Mediaty, M., Indrijawati, A., Kohar, Y. P., Sutriani, S., & Salsabila, T. (2024). Review of artificial intelligence in accounting: Trends, implementation and implications. Journal of Accounting and Finance Management, 5(5), 1146-1160.
Nguyen, N. M., Abu Afifa, M. M., Thi Truc Dao, V., Van Bui, D., & Vo Van, H. (2025). Leveraging artificial intelligence and blockchain in accounting to boost ESG performance: the role of risk management and environmental uncertainty. International Journal of Organizational Analysis.
Noviani, N., & Astuti, D. (2025). The Role Of Accounting Information Systems Audit In Ensuring The Reliability Of Digital Marketing Data. Jurnal Fokus Manajemen, 5(4), 993-998.
Odonkor, B., Kaggwa, S., Uwaoma, P. U., Hassan, A. O., & Farayola, O. A. (2024). The impact of AI on accounting practices: A review: Exploring how artificial intelligence is transforming traditional accounting methods and financial reporting. World Journal of Advanced Research and Reviews, 21(1), 172-188.
Pepple, D., & Muthuthantrige, N. (2026). Artificial intelligence, innovation and the new architecture of exploitation: Towards reconfiguring humanness in the age of algorithmic labour. Journal of Innovation & Knowledge, 11, 100878.
Qatawneh, A. M. (2025). The role of artificial intelligence in auditing and fraud detection in accounting information systems: moderating role of natural language processing. International Journal of Organizational Analysis, 33(6), 1391-1409.
Sarea, A., Echchabi, A., Salami, M. A., & Mahmood, A. (2026). Artificial Intelligence for Sustainable Innovation Management and Risk Management: A Systems (and Network) Perspective. Springer Nature.
Singh, S., Nag, A., Kaushik, P., & Tomar, U. (2026). AI-Driven Finance: Bridging Innovation with Regulatory Standards and Fair Practices. In Regulation and Inclusivity in Finance and Accounting: Navigating Regulatory Frameworks and Technological Advancements (pp. 447-463). Springer.
Solikin, I., & Darmawan, D. (2023). Impact of Artificial Intelligence in Improving the Effectiveness of Accounting Information Systems. J. Wirel. Mob. Networks Ubiquitous Comput. Dependable Appl., 14(2), 82-93.
Sreseli, N., & Kadagishvili, Z. (2023). Use of artificial intelligence for accounting and financial reporting

purposes: A review of the key issues. American International Journal of Business Management (AIJBM), 6(8), 72-83.

Stelmaszak, M., Joshi, M., & Constantiou, I. (2026). Artificial intelligence as an organizing capability arising from human-algorithm relations. Journal of Management Studies, 63(2), 335-365.

Vo Van, H., Abu Afifa, M., & Saleh, I. (2026). Accounting information systems and organizational performance in the cloud computing era: evidence from SMEs. Sustainability Accounting, Management and Policy Journal, 17(1), 267-299.

Xu, G., Li, X., Li, S., & Tong, Y. (2026). Artificial intelligence adoption and credit ratings. Asia-Pacific Journal of Accounting & Economics, 33(1), 1-15.

Zayed, L. M. M., Nour, M. I., Al Attar, K., Almubaideen, H., & Abdelaziz, G. A. M. (2024). Role of artificial intelligence (AI) in accounting information systems in detecting fraud. In Artificial Intelligence and Economic Sustainability in the Era of Industrial Revolution 5.0 (pp. 397-409). Springer.