The Role of Accounting in the Age of Artificial Intelligence: A Systematic Review from 2020 to 2025

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ABSTRACT

Over the last decade, the accounting function has evolved from a role focused on recording and compliance to that of a strategic partner to management. This systematic review of the literature from 2020 to 2025 explores how artificial intelligence (AI) is disrupting accounting by automating processes, generating predictive information, and supporting decision-making. Five objectives are examined: (1) mapping the evolution of accounting within the company, (2) classifying AI applications according to technologies and processes, (3) assessing the impact of AI on the quality and use of accounting information, (4) analyzing the relationship between accounting AI and value creation, and (5) identifying contingent factors and barriers. The results indicate that adopting AI enables accounting to free up time from routine tasks and to collaborate actively in the design of the business model. The technologies used range from machine learning and language processing to intelligent robotics, applied to automation, forecasting, and anomaly detection. AI improves the accuracy and timeliness of information, though it poses challenges in terms of explainability and governance. Value creation depends on the right combination of data, analytical capabilities, and good governance. The review reveals barriers such as data quality, implementation costs, and cultural resistance and proposes a configurational framework linking AI, processes, information, management decisions, and value creation.

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1. Introduction

It is undeniable that the various digital revolutions are transforming traditional business functions (Brynjolfsson & McAfee, 2017; Verhoef, 2021). Accounting, historically relegated to transaction recording and regulatory compliance, is undergoing a transition to a strategic role that contributes to value creation and appropriation. This evolution is underpinned by the adoption of data-driven technologies and the exploration of dynamic business models (Costa-Climent & Haftor, 2021; Möller & Halinen, 2022). The integration of AI into accounting not only automates tasks (Sutton, Holt, & Arnold, 2016) but also reinforces analysis, forecasting (Gutiérrez Nieto & Serrano Cinca, 2019), and the communication of information relevant to management (Vasarhelyi, Kogan, & Tuttle, 2015; Tapia-Marcial & Sánchez-Quinde, 2025).

Recent developments in foundation models and generative AI make this shift more urgent for both practice and research. Beyond automating routine processing, these systems support judgment-intensive tasks such as document interpretation, drafting narratives, and assisting with audit and assurance work. At the same time, they raise new questions about explainability, accountability, and governance that are especially important in accounting settings where trust and traceability are central (Gu, Schreyer, Moffitt, & Vasarhelyi, 2024). Evidence in the accounting information systems literature indicates a rapid growth in research and identifies a need for clearer frameworks that link AI capabilities to accounting outcomes and assurance requirements.

In parallel, recent high-impact work in accounting information systems has begun to formalize how machine learning and advanced AI methods can be analyzed and positioned within accounting research tasks (Booker, Chiu, Groff, & Richardson, 2024). This strengthens the case for a structured synthesis that not only lists applications but also clarifies mechanisms, boundary conditions, and the organisational capabilities required for value creation.

The purpose of this article is to provide a structured synthesis of the literature published between 2020 and 2025 on AI applied to accounting. Five research questions are investigated: How has the role of accounting in business evolved? What AI technologies and applications are used in accounting processes, and for what purposes? To what extent does AI affect the quality and usefulness of accounting information? What is the relationship between accounting AI and the creation of economic value?

Furthermore, what are the contingent factors and barriers that condition the adoption of AI? The analysis focuses on empirical works in English (peer-reviewed articles), with special attention to contributions that include field evidence. This study aligns with other works that have reviewed the impact of AI on accounting and auditing (Odonkor et al., 2024) but differs in its focus on the period 2020–2025 and its explicit attention to business value creation.

The structure of the article is as follows: after the abstract and introduction, a theoretical framework on the evolution of the role of accounting and the main AI technologies is presented. The results section summarizes the findings from the literature in line with the objectives set. The theoretical and practical implications are then discussed, a conceptual model is proposed, and lines for future research are outlined. Finally, the conclusions summarize the main contributions and recommendations for professionals and academics.

2. Methodology

2.1. Review Design

This study uses a systematic literature review to synthesize empirical evidence on how AI affects accounting processes, accounting information quality, and business value creation. A systematic review is appropriate because the field combines heterogeneous empirical designs, technologies, and organizational contexts, and the research questions require mapping, classification, and integration rather than statistical aggregation.

2.2. Search Strategy and Data Sources

We searched academic databases relevant to accounting, information systems, and management research, including the Web of Science (WoS), Scopus, IEEE and Google Scholar databases. The search was conducted in September 2025. The search string combined AI-related terms and accounting-related terms, for example: (artificial intelligence OR machine learning OR deep learning OR natural language processing OR generative AI OR large language model) AND (accounting OR accounting information system OR financial reporting OR auditing OR management accounting). We also performed backward and forward citation checks on key review and **Accounting Information System** AIS articles to identify additional relevant studies.

2.3. Inclusion and Exclusion Criteria

We included peer-reviewed journal articles published in English between 2020 and 2025 that provide empirical evidence on AI applications in accounting, auditing, financial reporting, or closely related accounting information system contexts. We excluded purely conceptual papers without empirical evidence, papers outside the accounting domain, and publications not subject to peer review.

2.4. Screening and Selection Process

All records were collated in a spreadsheet (Microsoft Excel) for manual management. Duplicates were removed. Titles and abstracts were screened against inclusion criteria, followed by full-text assessment for eligibility.

2.5. Data Extraction and Synthesis

For each included study, we extracted: context and setting, AI technology type, accounting process or task, outcome variables related to information quality and decision support, value creation mechanisms, and reported barriers or contingent factors. We then conducted a structured thematic synthesis aligned with the five research questions, producing a taxonomy of applications and a configurational framework linking AI adoption, process changes, information quality, managerial decisions, and value creation.

2.6. Alignment between Objectives and Methods

The method is coherent with the objectives because it allows: (1) a mapping of the role evolution by coding reported changes in accounting tasks and organisational positioning, (2) a classification of AI applications by extracting technologies and use cases, (3) an assessment of information quality impacts by coding outcomes such as accuracy, timeliness, transparency, and decision usefulness, (4) a synthesis of value creation mechanisms by coding cost, revenue, productivity, and innovation links, and (5) the identification of contingent factors by coding barriers, governance conditions, data readiness, and skills.

3. Theoretical Framework

3.1. Evolution of the Role of Accounting

Accounting emerged as a mechanism for financial recording and control, but as markets have become more competitive and information more abundant, its function has expanded to support management and strategy design. Various studies on accounting digitization have highlighted this shift from activities focused on recording and compliance to analytical and advisory tasks (Savić & Pavlović, 2023).

Business model theory provides a helpful framework for understanding this transition. Costa-Climent and Haftor show that value creation depends on four business model themes—novelty, efficiency, complementarity, and lock-in—and that the use of digital technologies, including artificial intelligence, can activate these themes and reinforce value creation and appropriation when integrated into the business model architecture (Costa-Climent & Haftor, 2021a; Costa-Climent & Haftor, 2021b; Haftor & Costa-Climent et al., 2023–2024). In this way, accounting becomes a strategic lever when aligned with these themes, as it provides information to configure value propositions, manage resources, and design revenue-generation mechanisms.

This evolution is reflected in the accountant's role. The literature has documented the shift from the accounting professional as a simple record keeper or bean counter to a profile that acts as a business partner, participates in decision-making, and forms part of the management team. Digitalization is accelerating this transition: integrated resource planning systems, cloud solutions, and process automation free up time from routine tasks and allow more effort to be devoted to analysis and management support activities. Subačienė and Tamulevičienė highlight that artificial intelligence in accounting is reshaping both business processes and accountant training, reinforcing the analytical and decision-support aspects of the professional role (Subačienė & Tamulevičienė, 2024).

In this context, mastery of data analysis tools and the ability to interpret results have become critical skills, while collaboration with other areas such as operations, marketing, and human resources is intensifying, reflecting the growing cross-cutting nature of accounting information within the organization.

3.2. AI Technologies and Accounting Applications

AI encompasses a family of techniques that aim to replicate human intelligence through algorithms that learn from data and are increasingly applied in accounting and auditing (Adeyeri, 2024; Kassar & Jizi, 2025). Several technologies stand out in this area:

1. **Machine learning (ML).** These algorithms identify patterns in structured and unstructured data and are used to classify transactions, estimate accounting parameters, and detect errors or fraud. Recent studies show that ML is applied to automate accounting classification, extract information from invoices, and detect anomalies in accounting records (Krieger, Drews, & Funk, 2023; Koç & Koç, 2024). Predictive AI enables the automation of repetitive tasks, the forecasting of financial variables, and the detection of anomalies in accounting cycles, strengthening decision-making by integrating analytics into financial processes (Wang, Chiu, & Vasarhelyi, 2025; Ramzan & Lokanan, 2024).

2. **Deep learning**. Multi-layered neural networks can process large volumes of heterogeneous data, such as documents, images, or time series. They enable the extraction of information from digitized invoices, the analysis of textual reports, and the detection of complex patterns that are not evident to humans (Krieger et al., 2023; Wang et al., 2025).

3. **Natural language processing (NLP)**. These techniques enable systems to interpret and generate human language. In accounting, they are used to read contracts and extract clauses, analyze financial report narratives, and generate summaries or reports (Du et al., 2025; Oyewole et al., 2024).

4. **Robotic process automation (RPA) with AI**. This technology combines software bots with intelligent algorithms to automate entire processes, such as the accounts payable cycle. AI is responsible for interpreting documents, validating information, and recording transactions in the accounting system (Perdana, Lee, & Kim, 2023; Kassar & Jizi, 2025).

5. **Explainable AI (XAI) and expert systems**. These tools provide traceability and explanations of the reasoning behind complex models, which is particularly relevant in accounting and auditing, where transparency and accountability are essential. Recent work shows how XAI is integrated into fraud detection systems and auditing applications to make algorithmic decisions more understandable and to support auditors' and regulators' confidence (Zhang, Cho, & Vasarhelyi, 2022; Munoko et al., 2020).

6. **Generative AI and language models.** Generative models, such as large language models, enable the generation of coherent and personalized text from data and queries, facilitating the drafting of financial reports, the interpretation of data, and responses to accounting queries. The popularization of this technology intensified following the public launch of ChatGPT in late 2022 has expanded its application repertoire beyond traditional automation (Dong, Stratopoulos, & Wang, 2024). Unlike many machine learning systems focused solely on classification or prediction, generative AI can produce complex responses and adapt to different business contexts, making it an attractive tool for accounting and auditing.

Generative AI is used for tasks ranging from drafting accounting reports and extracting and summarizing documents to supporting accounting queries through conversational assistants. Some firms have developed specialized bots that support auditors and controllers (Tapia-Marcial et al., 2025), integrating generative AI with accounting systems to offer real-time recommendations. This "virtual assistant" capability allows finance teams to quickly obtain contextual information or compare data from previous periods without the need for extensive manual searches.

However, these models have significant limitations. They do not act as search engines and can generate inaccurate or biased responses; furthermore, they are unreliable for precise calculations and pose risks to privacy and may generate false information. The literature reviewed agrees that generative AI should be considered an assistant that suggests content rather than absolute truth, and that its use requires human validation and quality controls (Dong et al., 2024). Therefore, its adoption in accounting requires responsible design, with quality controls, human validation, and ethical protocols to ensure the traceability and accuracy of results (Munoko et al., 2020).

It is recommended that generative AI be incorporated into accounting organizations on a gradual basis, through pilot projects that allow experience to be gained and risks to be assessed. Various industry reports advise starting with limited use cases, ensuring robust data governance, and establishing intellectual property protection policies (Munoko et al., 2020) before scaling up. These requirements are in addition to the need to train staff to use the tools and interpret their outputs critically.

These technologies are applied in different accounting areas for various purposes. The usual classification of applications distinguishes between automation, prediction, anomaly detection, and decision support objectives, and recent evidence shows that data configuration, analytical capabilities, and governance mechanisms determine the outcomes (Kassar & Jizi, 2025). There is no single factor that explains the success of AI; the effects emerge from combinations of resources and alignment with the business model, as illustrated by configurational studies on the use of machine learning and predictive AI for value creation and appropriation (Costa-Climent, Navarrete, Haftor, & Staniewski, 2024; Haftor, Costa-Climent, & Ribeiro-Navarrete, 2024).

4. Theoretical Lenses Linking AI, Accounting Information, and Value Creation

To strengthen this review's explanatory foundation, we interpret the findings through complementary theoretical lenses. First, accounting information systems research highlights that technology effects depend on the tasks being supported, the organizational context, and the cognitive demands placed on professionals, which helps explain why similar AI tools can produce different outcomes across settings. Second, business model and value creation perspectives clarify how improvements in accounting information quality and process efficiency translate into managerial decision improvements and ultimately into economic value (Li & Zhang, 2025). Third, governance and explainability perspectives are essential because accounting and assurance rely on traceability and accountability, and advanced AI systems can introduce opacity and new control risks if not properly governed.

4.1. Results of the Review

The literature review was based on the identification and analysis of empirical academic articles published in English between 2020 and 2025. Studies on the incorporation of AI into accounting and finance were selected to evaluate its impact on processes, information, and business value.

4.2. Evolution of the Role of Accounting in Business

Evidence confirms that AI frees accounting from manual tasks and reorients its role toward strategy. Studies across various fields indicate that automating accounting records and closings reduces errors and processing time. For example, digitization across companies in the Middle East and Europe shows that AI embedded in enterprise resource planning (ERP) systems, integrated software platforms that support core business functions such as finance, procurement, and operations, helps automate workflows, improve accuracy, and provide real-time information, allowing accountants to participate in strategic planning and control.

Empirical research indicates that the adoption of AI drives interaction between the accounting function and other areas. Accounting becomes a central hub of information, integrating financial data with operational and market variables. This facilitates product profitability analysis, cost control, and scenario evaluation. However, some studies point to cultural resistance: accounting professionals may feel threatened by automation or lack analytical skills. Overcoming these barriers depends on continuous training, curriculum updates, and senior management leadership.

4.3. Classification of AI Applications in Accounting

The literature describes a range of applications that can be grouped according to their primary objective:

1. **Transaction and record automation**. Optical recognition and ML algorithms are used to classify invoices and receipts, validate data, and record transactions in accounts. The aim is to reduce errors and improve efficiency. AI-powered RPA tools enable large volumes of transactions to be processed in real time.

2. **Accounting closing and reporting**. Intelligent systems consolidate information from multiple sources, apply accounting rules, and generate draft financial statements. Natural language models enable the creation of explanatory notes and summaries, speeding up report generation. AI also continuously monitors data, detecting inconsistencies and alerting to deviations before closing.

3. **Auditing and control**. AI is used to review 100% of transactions, identifying anomalies that could indicate fraud or error. ML algorithms trained with historical fraud data have been shown to improve the detection of irregularities. Continuous risk systems monitor indicators and issue automatic alerts.

4. **Management analysis and forecasting**. Predictive analytics tools estimate future sales, cash flows, and costs. These forecasts, combined with simulation techniques, allow different strategies to be evaluated and budgets to be optimized.

5. **Tax and regulatory management**. AI applications prepare tax returns, verify deductions, and automatically update applicable regulations, reducing the risk of noncompliance.

The studies reviewed emphasize that AI combines functions: automation, prediction, and anomaly detection. One example is the implementation of predictive AI, which not only automates transaction classification but also anticipates trends and alerts on deviations. Another relevant contribution is configurational evidence: performance does not depend on a single technology, but on packages of capabilities such as data quality, analytical expertise, and appropriate governance.

4.4. Impact of AI on the Quality and Use of Accounting Information

The quality of accounting information is assessed on the basis of its accuracy, timeliness, transparency, and usefulness for decision-making. The literature agrees that AI improves several of these dimensions.

- **Accuracy and consistency**. Several studies have found that automation reduces recording and calculation errors. Companies that have adopted ML for transaction classification report fewer subsequent adjustments and greater rule consistency. AI applies criteria uniformly, avoiding variations derived from human judgment.

- **Timeliness**. AI systems enable real-time information generation. Companies with AI solutions significantly reduce accounting close times and enable rapid reporting for decision-making. The ability to continuously update data is especially valuable in volatile contexts; during the pandemic, for example, financial AI enabled simulations of the impacts of government measures and quick operational adjustments.

- **Transparency and traceability**. AI enhances transaction oversight and provides detailed traceability. Algorithms record every step of data processing, facilitating continuous audits and increasing managers' and investors' confidence. However, the opaque nature of some deep learning models raises questions about interpretability. The literature proposes applying explainable AI principles and combining automation with human supervision (Munoko et al., 2020) to ensure transparency.
- **Usefulness in decision-making**. AI transforms accounting into a proactive tool. In addition to reporting "what happened," predictive analytics can help explain "why it happened" and visualize "what could happen." This increases the relevance of information for planning and control. A study based on business model theory (Costa-Climent & Haftor, 2021) showed that the adoption of digital technologies in finance follows predictable patterns and that their implementation improves the accuracy and timeliness of information. The integration of AI into closing and reporting reduces errors and provides early warning signs, increasing its usefulness for management decision-making.

In short, AI improves information quality, but its use requires the maintaining traceability and the ability to explain recommendations. The challenge is not technological but rather one of governance and ethics: frameworks are needed to regulate algorithm transparency and accountability in the event of failures.

4.5. Accounting AI and Business Value Creation

The impact of AI on value creation is evident on several fronts. First, reducing operating costs: automation decreases the time and effort spent on manual tasks and reduces errors that require corrections. Small and large companies have reported savings in accounts payable and monthly closing processes. Second, improved revenue: by freeing up resources and providing predictive insights, AI enables optimized decision-making and the rapid capture of opportunities. Third, productivity gains: AI enables the same team to manage more transactions and provides richer analytics, driving innovation in products and services.

The ability to capture value depends on internal capability configurations. A fuzzy-set qualitative comparative analysis (fsQCA)-based configurational study showed that it is the combination of data quality, analytical capabilities, and effective governance that enables value capture, not the mere adoption of AI (Costa-Climent et al., 2024). This view underscores equifinality: different combinations of resources can lead to high performance in accounting analytics. Furthermore, leveraging data network effects on financial platforms amplifies AI performance (Haftor et al., 2023); when companies succeed in orchestrating data networks within their financial systems, they can scale value and gain advantages in cost and learning speed.

Although most of the literature focuses on internal improvements, some studies explore stakeholder perceptions. The adoption of AI in accounting increases transparency and can improve investor and customer confidence, reducing the cost of capital. It is also emphasized that AI contributes to a company's reputation as innovative and efficient.

4.6. Adoption and Recent Trends

The publications reviewed show rapid growth in the use of AI, particularly generative AI, in the accounting field. According to a Thomson Reuters survey of tax and accounting professionals, approximately a quarter of tax firms plan to adopt generative AI tools, and 21% already use some form of AI, up from 8% reported the previous year. This acceleration in adoption has been accompanied by widespread use of open solutions: more than half of accounting firm staff acknowledge using tools such as ChatGPT in their personal work. The most frequent use cases include tax research, tax return preparation, advisory services, routine accounting, and document summarization.

Professionals generally see opportunities in these tools: around 68% say they are enthusiastic or hopeful about generative AI. However, perceptions of risk remain: 46% of respondents believe that AI could threaten jobs in accounting, and organizations such as the World Economic Forum anticipate that accounting, bookkeeping, and payroll positions could be among the most affected by automation. The same study reveals that only half of professionals believe that generative AI should be applied to tax, accounting, or auditing work. This level of caution reflects the need to accompany technological adoption with training and professional reflection initiatives.

Corporate reports emphasize that the adoption of generative AI should not be confused with the total replacement of tasks. In reality, many companies are experimenting with pilot projects to understand where the greatest value is created and how to manage the associated risks. Generative tools are used as "junior analysts" that extract data, identify themes, and generate drafts that human experts then review. Audit firms, for example, are developing bots that synthesize current regulations and provide answers to frequently asked questions, while controllers use language models to review the consistency of figures and explanations. This experimentation shows that generative AI complements professionals and frees up time for more strategic analysis.

Qualitative studies also show that AI adoption is associated with the development of new skills. Successful AI integration requires skills in data analytics, critical thinking, and cross-functional collaboration. AI does not replace experience or professional judgment; on the contrary, it amplifies their value by providing richer information. The Institute of Management Accountants (IMA) notes that the AI revolution is driving accountants to develop technology, analytics, and communication skills, and to work closely with information technology (IT) and data teams. In addition, many organizations are experimenting with AI to anticipate questions from analysts and competitors, suggesting that accounting functions will extend to competitive intelligence and strategy.

Finally, recent trends show that the spread of generative AI is driving changes in education and professional training. Management accountants and auditors need to understand the limitations of these tools and apply ethical and technical criteria when reviewing their outputs. As technology matures, regulatory frameworks are likely to incorporate specific guidelines for the use of generative AI in auditing and accounting, and certifications will emerge to accredit mastery of these skills.

4.7. Contingent Factors and Barriers

The implementation of AI in accounting is influenced by contextual conditions and barriers that shape its success. Among the factors identified are:

1. **Data quality and integration**. AI requires reliable, standardized data. Many companies struggle with fragmented systems and poor-quality data. The lack of availability of sufficient data for model training is a common barrier.

2. **Management support and digital strategy**. The success of AI depends on senior management's commitment and its integration with the digital strategy. Isolated projects without executive sponsorship often fail.

3. **Staff capabilities and culture**. Lack of technical skills and resistance to change (Alim, 2025) are obstacles. It is crucial to invest in training, promote a culture of innovation, and explain that AI complements, not replaces, human work.

4. **Initial costs and investments**. Implementing AI involves investments in software, hardware, and talent. Although the benefits can be significant, the return is not immediate. Small and medium-sized enterprises (SMEs) may find it difficult to bear these costs.

5. **Regulatory and legal framework**. Strict rules govern accounting, and the introduction of AI raises questions about compliance. There is a lack of regulatory clarity regarding the responsibility of algorithms and the validity of automatically generated reports.

6. **Data security and privacy**. The intensive use of sensitive financial data requires cybersecurity and privacy protection measures.

7. **Sectoral and geographical differences**. The adoption of AI varies by industry and region. The financial and technology sectors are advancing faster than traditional industries; regions with greater digital development are adopting AI more readily, while others are lagging behind.

These contingencies illustrate that not all organizations are prepared for intelligent transformation. Alignment of technological capabilities with strategy, robust data governance, and financial team training are necessary conditions for sustainable value to emerge. At the same time, configurational evidence suggests that there are multiple paths (equifinality) to achieving high digital performance: different combinations of competencies and systems may be sufficient to achieve results.

The emergence of generative AI accentuates some of these contingencies. Although language models can speed up information extraction and synthesis, their performance depends on data quality and prompt clarity; moreover, they do not verify facts and can generate erroneous or fabricated content, requiring the implementation of validation controls (Munoko et al., 2020) and training of staff in the critical interpretation of their outputs. The cost of training specific models and developing reliable training corpora adds to the initial investment. Many organizations restrict the use of generative AI for reasons of confidentiality and intellectual property protection, underscoring the need for prudent governance and policies.

The human factor is even more decisive. Successful AI adoption requires accounting professionals to develop skills in data analytics, critical thinking, and collaboration with technology teams. Without these skills, resistance to change can block the deployment of tools and cause work-related stress. The Institute of Chartered Accountants emphasizes the importance of continuing education programmes that prepare accountants to collaborate with AI, understand its limitations, and apply it ethically.

4.8. Conceptual Framework and Future Research Agenda

Integrating these findings, we propose a configurational framework that connects AI adoption with value creation. The causal chain is: AI in accounting → changes in processes and information → improvements in management decisions → value creation and appropriation. AI automates and optimizes processes, generating more accurate and timely information, which translates into better-informed decisions that impact costs, revenue, productivity, and innovation. This framework recognizes equifinality: different configurations of data, analytical capabilities, and governance can generate similar results.

This analysis gives rise to lines of future research:

1. **Sectoral and regional studies**. It is necessary to examine how accounting AI is implemented in different sectors and countries, analyzing cultural and regulatory factors.

2. **Mixed methods**. It is recommended to combine qualitative approaches (to understand how humans and machines interact) with quantitative analyses (to measure financial impacts). The use of fsQCA to identify configurations and structural equation modeling (SEM) to examine latent relationships can offer robust results.

3. **AI, ethics, and sustainability**. Future research should address ethical dilemmas and the role of AI in environmental, social, and governance (ESG) reporting, examining how technology can contribute to sustainability reporting and management.

4. **Transformation of the accounting profession**. Studies are needed on the accounting labor market, the evolution of curricula, and the preparation of accountants for hybrid roles involving data analytics.

5. **Regulatory framework**. It is essential to analyze how accounting and auditing standards should be adapted to include automated processes and algorithms, as well as mechanisms for auditing AI systems.

5. Discussion

This review shows that AI is reshaping accounting, but its impact is neither uniform nor automatic. Technology acts as a facilitator, but transformation depends on sociotechnical factors. The evidence supports the thesis that accounting is an information system whose quality determines the effectiveness of decisions; AI improves that quality by increasing accuracy and timeliness. However, automation does not replace professional judgment; instead, collaboration between humans and machines yields the best results.

From a theoretical perspective, this review contributes to the accounting and information systems literature by linking business model theory (Costa-Climent & Haftor, 2021) to AI adoption. The idea that accounting can create and capture value by aligning itself with business model issues (Costa-Climent & Haftor, 2021) is compelling. Furthermore, applying the configurational approach and recognizing that there is no single path to digital transformation, different combinations of capabilities can lead to success. This perspective challenges deterministic views and opens the door to research exploring the diversity of trajectories.

From a practical standpoint, the findings have clear implications. Organizations should view AI as an ally that amplifies the value of accounting information. Prioritizing automation projects for repetitive, low-value processes can yield "quick wins" and increase staff acceptance. Training in analytics and the creation of hybrid roles (accountant–data scientist) are necessary investments. At the same time, a data governance structure must be developed to ensure the quality, security, and transparency of algorithms.

On the other hand, the review shows that the literature is still in its infancy. Exploratory studies focused on large companies in developed countries predominate; research is needed on SMEs, traditional sectors, and emerging contexts. Rapid technological evolution requires continuous updating of conclusions and review of the relevance of theoretical frameworks.

The use of generative AI in accounting is an emerging issue. The evidence consulted shows that these models expand accountants' ability to synthesize information, generate draft reports, and respond quickly to queries, acting as an always-available "junior analyst." However, their optimal use requires close collaboration between humans and machines: accountants must provide clear instructions, assess the plausibility of responses, and contextualize results in business terms. In this way, generative AI does not replace professional judgment, but rather complements it by reducing the time spent on routine tasks and allowing a focus on strategic issues and decision-making. This collaboration also implies that accounting knowledge must be translated into effective prompts and that systems must learn from human feedback.

Another important implication is the need for robust governance frameworks and multidisciplinary skills. Generative AI will introduce greater complexity into the design of internal controls: it will be necessary to verify the accuracy of results, manage bias risks, and protect confidential data. In addition, research highlights the importance of accountants mastering data analytics concepts and maintaining a fluid dialog with AI specialists (Subačienė & Tamulevičienė, 2024). Cross-functional collaboration becomes key: finance, technology, and legal departments must coordinate to adapt generative tools to the company's needs, ensure regulatory compliance, and exploit opportunities. Ultimately, generative AI calls for a redefinition of the accounting role toward hybrid profiles (Alim, 2025) that combine financial, technological, and ethical knowledge, and promotes the creation of new roles such as "algorithm auditor" or "data curator."

6. Conclusions

This study contributes in three ways. First, it synthesizes recent empirical evidence on AI in accounting and clarifies how AI affects processes, accounting information quality, and managerial decision support. Second, it provides a structured classification of AI technologies and accounting applications across core accounting tasks. Third, it proposes a configurational framework that explains why value creation varies across organizations, depending on data readiness, analytical capability, and governance.

This systematic review concludes that AI is transforming accounting into a strategic function focused on value creation. Technology automates processes and provides advanced analytical capabilities that improve the accuracy, timeliness, and usefulness of information. By adopting AI, companies free up human resources for high-level tasks and strengthen their decision-making capacity. However, value creation does not depend solely on technology; it requires a combination of quality data, analytical capabilities, effective governance, and a supportive organizational culture.

The practical implications advise accounting professionals to develop analytical skills and actively participate in the selection and implementation of AI solutions. It is essential to establish governance structures to ensure transparency and ethical use of algorithms. Organizations must assume that AI is a complementary resource that elevates the role of accounting to a strategic level.

In conclusion, AI has the potential to turn accounting into a value generator, but contextual factors mediate its impact. The proposal for a configurational framework invites future studies to examine different adoption trajectories and explore how AI interacts with business models, organizational culture, and regulatory frameworks. This agenda opens up opportunities for interdisciplinary research to ensure an inclusive and responsible transformation of accounting.

7. Limitations

This review is subject to limitations. First, it focuses on peer-reviewed empirical articles published in English between 2020 and 2025, which may exclude relevant evidence published in other languages or formats. Second, the rapid pace of technological change means that empirical findings can become context specific as tools evolve. Third, differences in research designs and measurement choices limit direct comparability across studies, which reinforces the need for careful contextual interpretation.

8. Future Research

On the basis of the findings and limitations, future research should prioritize:

1. **Sector and country comparative evidence.** More studies are needed in SMEs, traditional sectors, and emerging economies to clarify how regulation, culture, and data infrastructure shape outcomes.
2. **Stronger causal designs and mixed methods.** Field studies, experiments, and longitudinal designs should be combined with quantitative modeling to test how AI changes decisions and performance, not only processes.
3. **Governance, explainability, and internal control design.** Research should specify which governance practices make AI outputs auditable, traceable, and defensible, especially when generative systems are used in reporting and assurance tasks.
4. **Skills, roles, and education.** Evidence is needed on how hybrid roles evolve, what skills actually predict successful adoption, and how professional education should respond.
5. **AI in assurance and ESG contexts.** As firms expand AI use in assurance, e.g., for ESG reporting, research should examine reliability, evidence standards, and accountability when external data and automated reasoning are involved.

The emergence of generative AI reinforces these conclusions. Its ability to create text and analyze information in natural language speeds up report preparation and data synthesis, while posing additional demands in terms of verification, privacy, and ethics. The value it brings will depend on how prudently it is implemented, respect for data protection, and the ability of organizations to develop a culture of continuous improvement in the accounting function. Professionals are called upon to assume more consultative and technical roles, while companies will need to review data policies and control mechanisms to leverage these advances without compromising stakeholder trust.

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