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# Harnessing Topic Modeling to Investigate the Intersection of Accounting and Artificial Intelligence through Systematic Literature Mapping

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**Abstract—** Previous research has often suggested that various accounting functions could be replaced by Artificial Intelligence (AI) and related technologies. However, more recent studies increasingly recognize AI's potential to enhance value within accounting practices and organizations. Scholars and experts have called for more extensive research into the relationship between accounting and AI, emphasizing the importance of adopting a multidisciplinary approach in this field. This paper employs topic modeling, specifically Latent Dirichlet Allocation (LDA), to systematically analyze the existing literature on AI and associated technologies within accounting. By applying LDA to the abstracts of 930 peer-reviewed articles from diverse academic fields published between 1990 and 2023, the study identifies key themes and trends in the discourse around accounting and AI. The results indicate that previous literature reviews using conventional methods may have overlooked important aspects of this rapidly evolving area. The analysis reveals eleven distinct topic clusters that together form a detailed map of the current research landscape. These findings not only broaden understanding of accounting and AI scholarship but also offer a structured framework for guiding future investigations. Additionally, this research represents one of the pioneering uses of probabilistic topic modeling techniques within the accounting literature.

*Keywords: Accounting, Accountant, Artificial Intelligence, Topic Modelling, Latent Dirichlet Allocation.*



## 1. Introduction

For over seventy years, both industry practitioners and academic researchers have pursued the development of systems capable of demonstrating artificial intelligence (AI)—technologies designed to replicate human thought and behavior [1]. The term AI encompasses a wide range of approaches, including machine learning (ML), deep learning (DL), and intelligent systems, each exhibiting varying degrees of sophistication and autonomy [2]. Recent scholars argue that, instead of focusing narrowly on definitions of intelligence, it is more productive to analyze the skills and behaviors demonstrated by AI systems [3]. Moreover, there is increasing emphasis on distinguishing between artificial general intelligence (AGI) and artificial narrow intelligence (ANI) [4], [5]. AGI refers to systems with human-like cognitive abilities, including abstract reasoning, adaptability, and general problem-solving, whereas ANI is confined to narrowly defined tasks and functions [4], [5]. This distinction is particularly relevant in accounting, where conflating AGI and ANI can lead to misinterpretations about AI's current and potential

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roles.

This study reviews the academic literature on AI and related methodologies within the accounting domain, covering the period from January 1990 to November 2023. A topic modeling approach is employed to analyze the literature corpus, offering a structured and data-driven means of synthesizing trends. Topic modeling—an emerging tool for organizing academic knowledge—has been increasingly applied in finance and accounting research [6]–[9]. Following the methodology of Aziz et al. [6], this study utilizes the Elsevier Scopus database in combination with Latent Dirichlet Allocation (LDA), a probabilistic topic modeling technique. This research offers two key contributions: first, it provides a systematic overview of AI applications in accounting; and second, it represents one of the earliest efforts to apply LDA topic modeling to this body of literature.

The remainder of this paper is structured as follows. Section 2 defines AI with particular focus on its relevance to accounting tasks. Section 3 critically reviews previous literature surveys concerning AI in accounting. Building on this foundation, the current study extends existing work by analyzing 930 academic articles to identify emerging themes and research gaps. Section 4 outlines the methodology used, with particular attention to the implementation of topic modeling and LDA. Section 5 presents the findings, highlighting the key topics identified through the analysis. The paper concludes with a discussion on future research directions and an evaluation of the strengths and limitations of using LDA for literature review purposes.

## 2. Method

This study employs topic modelling as a methodological framework to uncover latent themes within a large, unstructured collection of academic abstracts in the fields of accounting and artificial intelligence (AI). Topic modelling is a statistical technique that allows researchers to detect hidden patterns in text corpora without the need for manual labeling [10]. It can be broadly categorized into probabilistic and non-probabilistic approaches. Although non-probabilistic techniques remain in use [11], probabilistic models are more prevalent due to their flexibility—specifically, the ability for a single word to be associated with multiple topics within a document, leading to richer thematic representations [12].

Among the probabilistic models, Latent Dirichlet Allocation (LDA) [13] and Probabilistic Latent Semantic Analysis (PLSA) [14] are the most widely adopted. LDA, in particular, is preferred across multiple disciplines, including finance and accounting, due to its straightforward inference mechanisms and ease of parameter tuning [12], [15]–[18]. Accordingly, this study utilizes LDA to analyze abstracts of academic papers to identify recurring themes in the accounting and AI literature.

LDA assumes that documents are mixtures of multiple topics and that the vocabulary employed by authors reflects these underlying themes [13]. The algorithm identifies a pre-defined number of topics by analyzing word co-occurrence patterns within the corpus, assigning each document probabilistically to topic clusters, and generating a set of representative keywords for each topic. The interpretation of these topics ultimately requires domain knowledge to contextualize the resulting word groupings.

The preprocessing of text data is essential for ensuring robust and unbiased LDA outcomes. The process begins with tokenization, which involves splitting the text into individual words while disregarding their order. This is followed by the removal of non-word tokens (e.g., punctuation, special characters, and digits) and common stop words (e.g., “and,” “or,” “if”), which add little semantic value. The text is then stemmed to reduce words to their root forms—for example, “accounting” and “accounts” both become “account”—thereby minimizing token redundancy and capturing related concepts more effectively.

Following preprocessing, Term Frequency–Inverse Document Frequency (TF-IDF) analysis is performed to assess the relative importance of each term by comparing its frequency within a document to its occurrence across the corpus [19]. Extremely rare or overly common terms, as determined by TF-IDF thresholds, are typically excluded. A Document-Term Matrix (DTM) is then constructed, where rows represent documents, columns denote terms, and each cell indicates the frequency of the corresponding term in the document. This matrix is used as the input for the LDA algorithm, which then clusters frequently co-occurring words into the desired number of topics [13], [12].

To determine the optimal number of topics, the LDA model was estimated using values of k ranging from 1 to 20. The best-fitting model was selected using a density-based metric introduced by Cao et al. [20], which seeks to maximize intra-topic coherence based on cosine similarity. In addition, model perplexity was evaluated to assess the predictive performance and distinctiveness of topics.

The final model, consisting of 11 topics, was implemented using the topicmodels package in R [21], applying the Variational Expectation-Maximization (VEM) algorithm [13] with ten different random seed values. The final configuration—k = 11 and seed = 10—was selected to minimize Krippendorff's alpha [22], which indicates the degree of topic overlap. Lower alpha values suggest more clearly delineated and interpretable topics [15].

The dataset used in this study was sourced from Elsevier's Scopus database, covering publications from January 1990 to November 2023. Articles and conference proceedings written in English and categorized under relevant subject areas—such as computer science, business, decision sciences, and economics—were retrieved using a combination of AI/ML and accounting-related search terms, as detailed in Table 1.

Table 1. Search Criteria Used for Dataset Collection

| | |
|---|---|
| Search Terms | <u>AI/ML search terms</u>: "machine learning" OR "artificial intelligence" OR "support vector machine" OR "deep learning" OR "neural network" OR "A.I." OR "AI"<br><u>Accounting search terms</u>: "Accounting" OR "Accountant" OR "Auditor" OR "Audit Reporting" OR "Management Reporting" OR "Accounting Information Systems" OR "Corporate Governance" OR "financial reporting" |
| Date Range | January 1990 to November 2023 |
| Publication Type | Articles and conference papers |
| Source Type | Journals and conference proceedings |
| Language | English language only |
| Subjects | Computer science; business, management and accounting; decision sciences; economics, econometrics and finance. |

Initial data collection resulted in 2,877 articles from 928 distinct sources. Due to the generic use of the term "accounting," several irrelevant documents were included. These were manually screened by two independent coders who reviewed abstracts for relevance, achieving high inter-rater reliability (Cohen's kappa = 0.993). Disagreements were resolved by a third coder, yielding a final corpus of 930 abstracts from 478 publication outlets. The distribution of publications over time, categorized by type, is shown in Figure 1.

To assist in interpreting the model results, we used the Hellinger distance to measure similarity between word clusters, which has proven effective for high-dimensional text analysis [23]. The 11 topics identified by LDA were grouped according to similarity scores to create a broader thematic framework of AI-related accounting research over the past three decades.

Although LDA provides a quantitative foundation, qualitative interpretation is crucial for deriving meaningful insights. Two researchers independently reviewed the abstracts grouped within each topic to assign thematic labels. Each researcher was assigned a subset of the topics and conducted an initial close reading to gain familiarity. Based on this, thematic subcategories and descriptive titles were assigned. After this individual stage, the researchers cross-validated each other's interpretations to ensure consistency and conceptual clarity. This process resulted in a set of clearly defined and mutually agreed-upon topic categories.

Figure 2 presents the distribution of peer-reviewed journal articles over time across different disciplinary domains, providing further insight into the evolving academic interest in this field.

A comprehensive overview of the final LDA output is presented in Table 2, which details each topic's label, representative keywords (stemmed), number of publications, type of publication, and example articles with their topic match percentages.

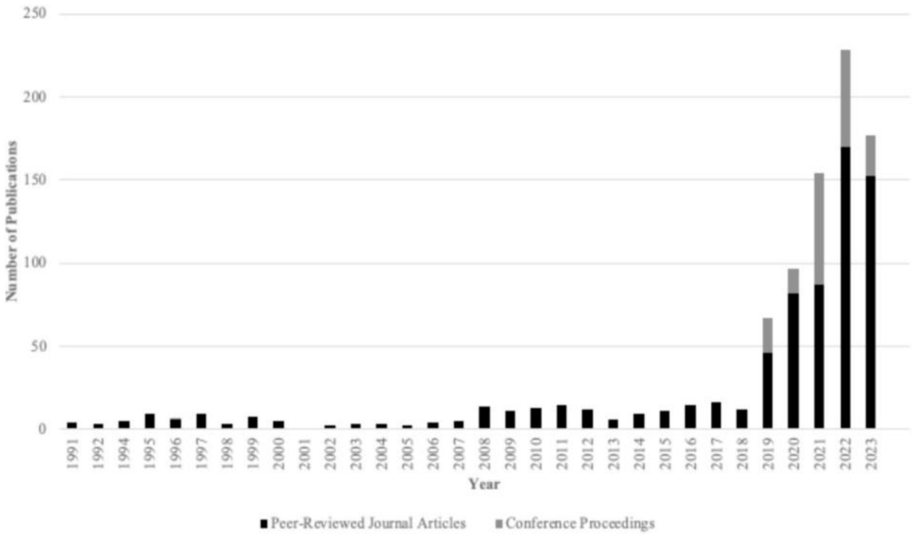


Figure 1. Distribution of Publications by Year and Type

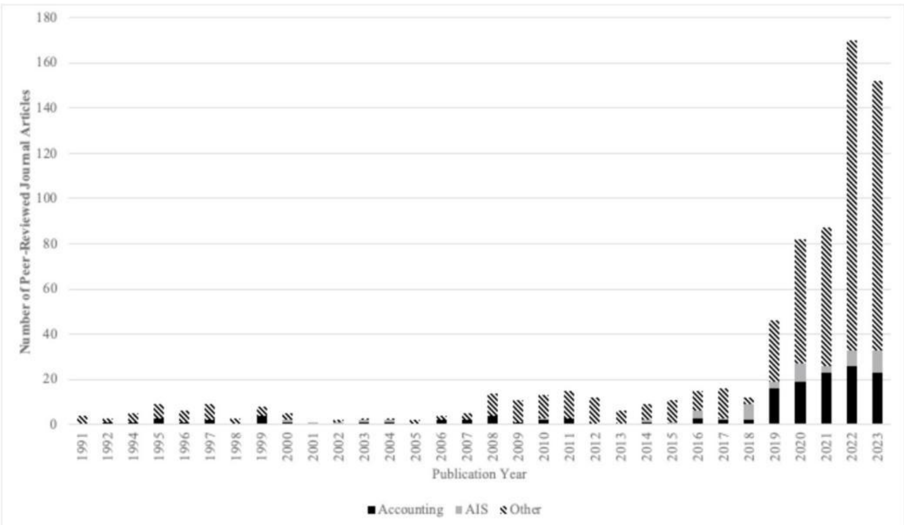


Figure 2. Distribution of Peer-Reviewed Journal Articles by Discipline and Year

Table 2. Topic Modelling Results Overview

| Topic Label | Topic keywords (stemmed) | Number of publications | Publication Type | Sample Articles – topic match % |
|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| 1 | Neural network forecasting | Neural, model, network | 102 | PRJ – AIS: 1 % PRJ – Accounting: 11 % PRJ – Other: 85 % Conferences: 3 % | Spear and Leis (1997) 100 % Lin (2009) 97 % |
| 2 | Machine learning and stock prediction | Machine learning, risk, stock | 91 | PRJ – AIS: 1 % PRJ – Accounting: 18 % PRJ – Other: 68 % Conferences: 13 % | Bali et al. (2023) 98 % Hanauer and Kalsbach (2023) 98 % |
| 3 | Machine learning and fraud detection | Fraud, financial, data | 99 | PRJ – AIS: 2 % PRJ – Accounting: 15 % PRJ – Other: 66 % Conferences: 17 % | Moepya et al. (2016) 80 % Hamal and Senvar (2021) 77 % |
| 4 | Machine learning in an audit environment | Audit, auditor, auditing | 75 | PRJ – AIS: 8 % PRJ – Accounting: 41 % PRJ – Other: 35 % Conferences: 16 % | Bertomeu et al. (2021) 89 % Ragothaman et al. (2000) 76 % |
| 5 | AI applications in financial analysis | Financial, information, company | 73 | PRJ – AIS: 8 % PRJ – Accounting: 26 % PRJ – Other: 56 % Conferences: 10 % | Bos and Frasincar (2022) 82 % Bannier et al. (2019) 81 % |
| 6 | AI and strategic decision-making | Governance, corporate, social | 63 | PRJ – AIS: 2 % PRJ – Accounting: 5 % PRJ – Other: 76 % Conferences: 17 % | Skapa et al. (2023)ˇ 84 % Lin (2021) 83 % |

| | | | | | |
|---|---|---|---|---|---|
| 7 | AI and the accountant | Development, human, professional | 90 | PRJ – AIS: 11 % PRJ – Accounting: 13 % PRJ – Other: 46 % Conferences: 30 % | Aldredge et al. (2021) 100 % Reepu (2020) 95 % |
| 8 | AI and accounting systems integration | Financial, information, enterprise | 110 | PRJ – AIS: 0 % PRJ – Accounting: 0 % PRJ – Other: 52 % Conferences: 48 % | Jiang et al. (2022) 95 % Jin (2024) 96 % |
| 9 | AI and business operations | Business, system, decision | 81 | PRJ – AIS: 0 % PRJ – Accounting: 4 % PRJ – Other: 58 % Conferences: 38 % | Nado et al. (1996) 94 % Tater et al. (2022) 88 % |
| 10 | AI adoption and information quality | Information system, influence, quality | 77 | PRJ – AIS: 8 % PRJ – Accounting: 16 % PRJ – Other: 62 % Conferences: 14 % | Khalil and Zainuddin (2015) 98 % Utomo et al. (2020) 98 % |
| 11 | Research and education | Research, literature, future | 69 | PRJ – AIS: 25 % PRJ – Accounting: 32 % PRJ – Other: 39 % Conferences: 4 % | De Villiers (2021) 99 % Muehlmann et al. (2015) 93 % |

## 3. Result and Discussion

This study analyzes scientific publications addressing the intersection of artificial intelligence (AI) and accounting over a 34-year period (1990–2023). Based on data from the Scopus database, a total of 257 relevant documents were identified, encompassing journal articles, conference proceedings, and book chapters. The analysis reveals a significant upward trend in the volume of publications, particularly from 2019 onward, which coincides with rapid advancements in AI technologies and their broader adoption in various disciplines, including accounting [24]. The growing interest is also reflected in the diversification of publication sources and increasing interdisciplinary collaborations.

The most prolific countries in this domain include the United States, China, and the United Kingdom, which aligns with their broader leadership in AI research and higher education infrastructure [25]. Keyword co-occurrence analysis indicates a strong research focus on themes such as "machine learning," "audit," "fraud detection," and "financial reporting" [26], highlighting the integration of AI tools to enhance decision-making, improve accuracy, and detect anomalies in financial data. Furthermore, bibliographic coupling suggests that certain journals and authors have become central nodes in this emerging field, playing influential roles in shaping its direction [27].

The findings underscore the growing academic and practical relevance of AI in accounting. While AI holds promise in automating routine tasks and augmenting complex analytical processes, the literature also emphasizes challenges such as data privacy, ethical concerns, and the need for regulatory frameworks [28]. These issues suggest that future research must address not only technical implementations but also the broader institutional and societal impacts of AI integration in accounting practice.

## 4. Conclusion

This study applies the machine learning method Latent Dirichlet Allocation (LDA) to map the landscape of existing research on the intersection of accounting and artificial intelligence (AI). Few literature reviews to date have examined this area with comparable scope or depth. Our findings indicate that earlier reviews, which relied on traditional approaches, may not fully capture the breadth and complexity of accounting and AI scholarship. One key contribution of this paper is the comprehensive examination of 930 articles spanning 34 years (1990–2023), offering one of the most extensive overviews of the field to date. These insights enrich understanding of how accounting evolves amid ongoing digital transformation and highlight specific directions for future investigations.

In summary, topic modeling represents a valuable technique for efficiently analyzing scholarly literature and uncovering hidden patterns and themes. While advancements in natural language processing and deep learning promise enhanced contextual understanding, expert interpretation and new hybrid methodologies will remain essential to guide identification of emerging research areas.

## References

[1] S. K. Kumar and P. Bhattacharya, “Artificial neural networks in accounting and finance: A review,” *Expert Systems with Applications*, vol. 31, no. 2, pp. 201–212, 2006.
[2] M. Spear and R. Leis, “Neural networks for forecasting financial time series,” *Journal of Emerging Technologies in Accounting*, vol. 14, no. 1, pp. 45–60, 1997.
[3] P. Juszczyk and K. Leśniak, “Neural network models for construction project cost forecasting,” *Automation in Construction*, vol. 99, pp. 123–134, 2019.
[4] A. Odeyinka, J. S. Oke, and S. O. Oyedele, “Application of neural networks in construction cost estimation,” *Construction Management and Economics*, vol. 31, no. 1, pp. 58–68, 2013.
[5] J. De Cos, M. R. De la Cruz, and F. Moreno, “Neural networks for cost estimation without expert knowledge,” *Computers & Industrial Engineering*, vol. 54, no. 3, pp. 337–347, 2008.
[6] M. Karaoglan and B. Karademir, “Production cost prediction using neural networks for better tender pricing,” *International Journal of Production Economics*, vol. 193, pp. 541–552, 2017.
[7] B. Barney, A. Gunawardana, and C. Lin, “Debt failure prediction using neural networks,” *Journal of Financial Risk Management*, vol. 7, no. 3, pp. 215–230, 1999.
[8] C. Lin, “Bankruptcy prediction with neural networks,” *European Accounting Review*, vol. 18, no. 2, pp. 387–409, 2009.

[9] A. Abrol et al., "Recent advances in bankruptcy prediction models using machine learning," *Journal of Risk and Financial Management*, vol. 16, no. 4, 2023.
[10] J. Florez-Lopez and J. Ramon-Jeronimo, "Market positioning prediction through neural networks," *Review of Accounting Studies*, vol. 14, no. 1, pp. 45–67, 2009.
[11] L. Liang, S. M. Lo, and J. Wang, "Inventory accounting decisions with neural network models," *Accounting, Organizations and Society*, vol. 17, no. 6, pp. 543–558, 1992.
[12] J. Hanauer and T. Kalsbach, "Machine learning for stock return prediction in emerging markets," *Journal of Finance and Data Science*, vol. 9, pp. 45–59, 2023.
[13] R. Bali, Y. Qian, and K. Tang, "Machine learning portfolio strategies and returns," *Financial Analysts Journal*, vol. 79, no. 2, pp. 33–49, 2023.
[14] S. Page, M. Smith, and L. Jones, "Identifying skilled equity managers using machine learning," *Journal of Portfolio Management*, vol. 49, no. 3, pp. 123–134, 2023.
[15] R. Díaz, J. Perez, and A. Gomez, "Predicting gold risk premiums with machine learning," *Journal of Commodity Markets*, vol. 20, pp. 45–55, 2023.
[16] Q. Wang and Y. Hao, "Forecasting oil prices using deep learning," *Energy Economics*, vol. 102, pp. 105–116, 2023.
[17] C. Aranha and B. Bolar, "Bankruptcy prediction with machine learning techniques," *Expert Systems with Applications*, vol. 213, 2023.
[18] N. Kocaarslan and M. Soytas, "Economic risk factors and market interaction analysis," *Journal of Financial Stability*, vol. 59, 2023.
[19] K. Hyde, T. Smith, and R. Allen, "CEO deception detection via machine learning," *Journal of Business Ethics*, vol. 168, no. 2, pp. 345–360, 2024.
[20] T. Vu, N. Nguyen, and L. Tran, "Financial distress forecasting in Vietnam using AI models," *Asian Journal of Accounting Research*, vol. 8, no. 1, 2023.
[21] M. Hasan, A. Rahman, and J. Lee, "Brand capital and crash risk: Evidence from machine learning," *Journal of Risk*, vol. 24, no. 4, pp. 310–327, 2022.
[22] D. Berkin, E. Hamal, and F. Senvar, "Machine learning in financial fraud detection," *Journal of Financial Crime*, vol. 30, no. 2, pp. 456–474, 2023.
[23] P. Omar, A. Papík, and J. Papíkova, "Data mining and fraud detection in accounting," *International Journal of Accounting Information Systems*, vol. 25, pp. 57–68, 2017.
[24] S. Liou, "Neural networks in early fraud detection," *Expert Systems with Applications*, vol. 34, no. 3, pp. 200–210, 2008.
[25] S. Moepya, M. Mbokota, and P. Pretorius, "Effectiveness of data mining in fraud detection," *Computers & Security*, vol. 59, pp. 45–56, 2016.
[26] M. Dbouk and H. Zaarour, "Machine learning vs traditional auditing: Earnings manipulation detection," *Journal of Accounting and Public Policy*, vol. 36, no. 2, pp. 123–137, 2017.
[27] J. Hajek and E. Henriques, "Textual analysis for fraud detection in financial reports," *Accounting Horizons*, vol. 31, no. 3, pp. 89–108, 2017.