International Journal of Accounting Information Systems 55 (2024) 100709

Contents lists available at ScienceDirect

International Journal of Accounting Information Systems

journal homepage: www.elsevier.com/locate/accinf

Exploring accounting and AI using topic modelling

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ARTICLE INFO

Keywords:
Accounting
Accountant
Artificial intelligence
Topic modelling
Latent Dirichlet Allocation

ABSTRACT

Historically, literature suggests that a variety of accounting roles will be replaced by Artificial Intelligence (AI) and related technologies; however, in recent years there is a growing recognition that accounting can in fact harness AI's potential to add value to organisations. Commentators have highlighted the need for increased research exploring accounting and AI and for accounting scholars to consider multi-disciplinary research in this area. This study uses a form of topic modelling to analyse literature exploring AI and related techniques in an accounting context. Latent Dirichlet Allocation (LDA) has been used to enable probabilistic, machine-based interrogation of large volumes of literature. This study applies LDA to the abstracts of 930 peer-reviewed academic publications from a variety of disciplines to identify the most significant accounting and AI topics discussed in the literature during the period 1990 to 2023. Our findings suggest that prior literature reviews based on more traditional methodologies do not capture a comprehensive picture of accounting and AI research. Eleven topic clusters are identified which provide a comprehensive topology of the extant literature discussing accounting and AI and set out an agenda for future research designed to foster academic progress in the area. It also represents one of the first applications of probabilistic topic modelling to accounting literature.

1. Introduction

For over seventy years, industry and academia have attempted to construct systems that exhibit artificial intelligence (AI) – systems that think and act like humans (Russell and Norvig, 2010). AI can refer to many things, from analytical techniques (including machine learning (ML) and deep learning (DL)) to intelligent systems, all exhibiting varying degrees of 'intelligence' (Lynn et al., 2019). Recent commentators have suggested that instead of focussing on a particular definition of intelligence, it may be more useful to explore the competencies and behaviours demonstrated by AI systems (Kotseruba and Tsotsos, 2016). Others have emphasised the need to distinguish between artificial general intelligence (AGI) and artificial narrow intelligence (ANI) (Fjelland, 2020; Jiang et al., 2022). While AGI may exhibit capabilities similar to a human in that it can think abstractly, adapt to change in the environment and new situations, and perform a wide range of tasks, ANI can only perform a limited range of predefined tasks (Fjelland, 2020, Jiang et al., 2022). This distinction is important as AGI and ANI are often conflated and may adversely impact our understanding of the role and impact of AI in accounting.

Initially prevalent in more process-oriented activities, AI is increasingly applied within the knowledge sector, creating an

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https://doi.org/10.1016/j.accinf.2024.100709
Received 6 July 2023; Received in revised form 3 May 2024; Accepted 12 September 2024
Available online 21 September 2024
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opportunity for accountants to rethink how they engage with their role in an organisational context (Chui et al., 2016). Long held normative assertions that accounting roles will ultimately be replaced by AI-related technologies (e.g. Frey and Osborne, 2017) are giving way to a recognition that the accounting function can in fact embrace the growing potential of AI to add value to organisations (Issa et al., 2016; Issa and Kogan, 2014) i.e. it is now believed that AI can transform the occupational field of accounting as well as accounting-related tasks (Bauer and Hofmann, 2018; Diller et al., 2020; Lehner et al., 2019; Marrone and Hazelton, 2019; Moll and Yigitbasioglu, 2019; Murphy and Feeney, 2023). Notwithstanding AI's potential in this regard, it is important to note that the accounting profession historically lags business adoption of emerging technologies (Dai and Vasarhelyi, 2016).

AI techniques and the nature and use of ML and DL have been the subject of academic focus in a variety of disciplines, notably computer science, management information systems (MIS) and finance. In their review of accounting research, Sutton et al. (2018) suggest that, in contrast to Gray et al. (2014), while AI research in accounting did suffer a lull in the early noughties, it has steadily increased in recent years. There is now a growing volume of research based on a wide range of accounting-related topics including audit support systems (Sun, 2019), fraud detection (Bao et al., 2020, Papík and Papíková, 2022; Perols, 2011), business intelligence (Rikhardsson and Yigitbasioglu, 2018), explainable AI (XAI) (Zhang et al., 2022), and accounting service automation (Bavaresco et al., 2023), amongst others. Given the renewed interest in, as well as reasonable concerns regarding, how AI might change accounting work and the role of the accountant (ACCA and EY, 2019; AICPA, 2020), it is worthwhile to revisit the literature to evaluate the extant research on AI in accounting and, based on this review, highlight research gaps and opportunities for future research.

This paper presents an analysis of extant literature exploring AI and related techniques in an accounting context from January 1990 to November 2023 using a topic modelling approach. Topic modelling for structuring literature is a relatively novel innovation in scholarly research, however it is growing in use in finance, accounting and related fields (Aziz et al., 2022; Dyer et al., 2017; Garanina et al., 2022; Moro et al., 2015). We follow the approach adopted by Aziz et al. (2022), using the Elsevier Scopus database as the corpus, and LDA as the topic modelling technique. As such, our study makes two primary contributions. Firstly, it is the first attempt to structure the topology of the AI and accounting literature and secondly, it is one of the first applications of probabilistic topic modelling to the accounting literature.

The remainder of this paper is structured as follows. Section 2 defines AI, specifically in an accounting context. Section 3 examines prior literature reviews on accounting and AI. Our study contributes to this literature by providing an up-to-date typology of research in accounting and AI, based on an analysis of 930 articles, which identifies emerging trends and an agenda for future research. Section 4 describes the methodological approach and in particular topic modelling and LDA. Section 5 presents the results which set out the key areas addressed within each topic. The paper concludes with a discussion of potential future avenues for accounting research on AI as well as the benefits and limitations of LDA as a literature review technique.

2. Defining AI

AI technologies leverage computers and machines to mimic the problem-solving capabilities of the human mind. AI systemises activities traditionally associated with human intelligence such as planning, learning, reasoning, problem solving, knowledge representation, perception, manipulation, even social intelligence, and creativity (Autor and Dorn, 2013; Autor et al., 2003; Frey and Osborne, 2017). The key difference between an AI and a non-AI application is that AI tools learn to do their job and advance based on experience without the need to be explicitly programmed (Bolton et al., 2018). Russell and Norvig (2010) distill the various definitions of AI into two distinctions i.e., human vs rational and think vs act, but their typology has faced criticism for being too simplistic and imprecise. For example, Wang (2008) suggests that AI should be categorised in five ways – structure, behaviour, capability, function and principle. In contrast, Kaplan and Haenlein (2019) categorise AI systems by types of competencies i.e., cognitive intelligence, emotional intelligence, social intelligence, and artistic creativity.

More recently, there has been an increased focus on differentiating between different types of AI. As discussed, ANI (Artificial Narrow Intelligence) can only perform a limited range of defined tasks and is sometimes referred to as 'weak AI' (Fjelland, 2020; Jiang et al., 2022). ANI represents most AI applications in use today. AGI (Artificial General Intelligence) or 'strong AI' is AI that exhibits or mimics the intelligence capabilities of a human, meaning it can reason, plan, learn from experience, and solve problems autonomously for tasks that it was never even designed for (Kaplan and Haenlein, 2019). In turn, ASI (Artificial Super Intelligence) is an AI significantly more intelligent than humans in all respects (Barrett and Baum, 2017).

AI is not an entirely new phenomenon in an accounting context. First generation AI in the form of expert systems, knowledge-based systems and intelligent systems has existed for decades. Expert systems developed in the 1980s attempted to replicate human expertise and transform it into rules to perform accounting tasks (Gregor and Benbasat, 1999). It is fair to say that they didn't live up to their potential (O'Leary, 1991), probably because they were based on 'if-then' rules and decision-trees which frequently codified flawed logic facilitating the same mistakes to be made over and over (Makridakis, 2017). However, with AI supporting these knowledge-based systems, together with more emphasis on data analytics and the associated use of ML techniques, increased use of AI in accounting is not only more likely, but is inevitable (Sutton et al., 2016). As AI-based systems learn to do their jobs and advance based on experience, much like a human professional, their use will progress from supporting repetitive, routine accounting tasks (Cooper et al., 2019) to more complex and novel situations requiring flexibility and reasoning (Autor and Dorn, 2013; Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017; Skrbiš and Laughland-Booÿ, 2019).

What is still unknown at this stage is exactly what human work in accounting will be transferred to AI software and services. Prior research focused on accounting and the automation of data processing and transaction-based activities (Ghasemi et al., 2011; Taipaleenmäki and Ikäheimo, 2013). However, the digital transformation of the accounting function using AI and Big Data analytics increases the network of people and software, both within and outside the organisation, creating more data pools and decision points than ever before (Marrone and Hazelton, 2019). Arguably, the real value of AI and Big Data analytics generally, and AI specifically, will be in enhanced planning, control, forecasting, and decision-making using exponentially larger data pools within a significantly broader information ecosystem (Brynjolfsson et al., 2011; Feeney, 2022; Vial, 2019). Sutton et al.'s (2016, p.70) suggestion that accounting researchers 'have a responsibility to step back and consider the ramifications (of AI) for the future of accounting professionals' led to several studies which sought to understand the changing nature of roles in accounting in light of the digital transformation of society (Leitner-Hanetseder et al., 2021; Moll and Yigitbasioglu, 2019; Oesterreich and Teuteberg, 2019). Our paper contributes to this literature stream.

3. Prior literature reviews in accounting and AI

Several authors have previously examined literature on accounting and AI, using a variety of approaches. In so doing, they provide some understanding of the evolution of this topic, its theoretical underpinnings, and some insights into potential new directions. Mardini and Alkurdi (2021) employed the qualitative panel dimensions approach, which comprised detailed discussion of prior studies through panels and narrative review, with each panel listing most of the critical prior studies that discuss the uses of AI in accounting fields. Mardini and Alkurdi (2021) structured the literature into five fields – AI and financial accounting, AI and auditing, AI and cost and managerial accounting, AI and tax accounting, and AI and public accounting. Hasan (2021) adopted a semi-systematic or narrative review approach to examine how AI fits into the accounting and audit profession/discipline, as well as benefits and risks associated with AI implementation for the period 1992–2020. Hasan (2021) identified 10 focus areas – expert systems, continuous auditing, decision support systems, neural networks, DL and ML, natural language processing (NLP), fuzzy logic, genetic algorithms, robotic process automation, and hybrid systems. A significant weakness in these focus areas is the overlap between them e.g. one might reasonably argue that a number of these areas are sub-categories of ML and DL e.g. neural networks, NLP etc. Berdiyeva et al. (2021) provided a qualitative review of research papers published between the years 1989–2020. While this review is largely descriptive, it attempts to classify whether extant research suggests a positive, negative, or neutral impact of AI in the accounting and finance process; they find that the research suggests a strongly positive impact. Ranta et al. (2023) adopted a qualitative approach to provide a comprehensive synopsis of different ML techniques that might be used to conduct research in management accounting. They note that there has been progress in the accounting literature in relation to ML and AI in three fields: (1) how AI will change the field of accounting and the development of the accounting profession, (2) textual analysis related to accounting data/reports, and (3) prediction methods.

Other authors have completed literature reviews on specific sub-themes of accounting and AI literature. For example, Kroon et al. (2021) undertook a systematic literature review on the impact of emerging technologies (including AI, Big Data analytics, Blockchain etc.) on accountants' role and skills, using nVivo to analyse 40 articles published between 2015 and 2020. They adopted the Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) Statement approach. Lehner et al. (2022) conducted a theoretically-informed, narrative, semi-systematic literature review spanning 2015–2020, using ATLAS.TI qualitative coding software, and based on Rest's (1986) four-component model of antecedents for ethical decision-making. Lehner et al. (2022) identified five categories of ethical challenges – objectivity, privacy and data protection, transparency, accountability, and trustworthiness. Kureljusic and Karger's (2023) systematic literature review of 47 articles resulted in three key themes centred on AI-based forecasting in financial accounting – bankruptcy, financial analysis, and frauds and errors. Agustí and Orta-Pérez (2023) generated an overview of the AI (and blockchain) literature in the fields of accounting and auditing using a bibliometric co-word analysis on 247 research papers published between the years 1986–2020 using VOSviewer software. They extracted the bibliometric network based on the co-occurrences of keywords by calculating similarity relations, generating five clusters of words and creating a graphic mapping of the co-word network. The five clusters emphasise auditing including Big Data analytics and issues related to fraud, risk, and disclosures (Cluster 1), Big Data and social media, blockchain, or audit evidence (Cluster 2), accounting and AI including applications and accountant training (Cluster 3), ratio prediction and analysis for bankruptcy predictions (Cluster 4), and information technology and decision-making processes (Cluster 5). Belfiore et al. (2022) analysed a dataset of 3,836 articles published from 2010 to 2021 based on the co-occurrence of key terms describing the content of documents in a dataset, using the Bibliometrix R package. Their thematic network is drawn on a two-dimensional matrix, where the axes are functions of relevance (centrality) and density (Callon et al., 1991). This facilitates the generation of motor themes, basic themes, emerging or declining themes, and niche themes. They identify three basic themes – quality, impact, and management – and one emerging or declining theme, information. It is important to note that this review is very high level, thereby limiting utility for future research.

Recent commentators have noted that the use of ML and related methods for accounting research remains in its infancy (Ranta et al., 2023). Ranta et al. (2023) specifically discuss the use and value of ML techniques for literature reviews and note that LDA has been used to identify and analyse latent themes in extant literature. However, they do not cite any such reviews related to accounting and AI. To address this gap and in contrast to extant literature reviews on accounting and AI, this paper uses LDA to structure a topology of the accounting and AI literature and in so doing uncovers latent themes within the research base.

4. Methodology

Topic Modelling is a statistical 'modelling approach' which enables the unsupervised discovery of abstract topics that occur in an unstructured collection or corpus of documents (Blei, 2012). Topic modelling can be non-probabilistic and probabilistic. While non-probabilistic approaches are still in use (see, for example, Anandkumar et al., 2012; Arora et al., 2013), probabilistic topic modelling approaches are increasingly the norm as such approaches allow documents and terms belonging to different topics i.e., 'the same word might be assigned to *different* topics in the *same* document' (Boyd-Graber et al., 2017, p.14). As such, they provide more nuanced and realistic results than non-probabilistic approaches. The two main probabilistic topic modelling approaches are LDA (Blei et al., 2003) and Probabilistic Latent Semantic Analysis (PLSA) (Hofmann, 1999). LDA is more widely used due to easier inference and simpler model fine-tuning (Boyd-Graber et al., 2017) and has been used in several studies for structuring research literature in finance, accounting and related fields (Aziz et al., 2022; Dyer et al., 2017; Garanina et al., 2022; Moro et al., 2015). In this paper, we apply LDA to the abstracts of academic publications to identify topics discussed in the literature.

LDA assumes that a document reflects a collection of topics, and the words used by authors are representative of these topics (Blei et al., 2003; Blei, 2012). In other words, text documents using a similar combination of words relate to the same 'topic'. In fact, the LDA algorithm looks for a predefined number of topics in a corpus of documents, determines these topics based on word co-occurrence, allocates each document to the topic with the highest probability, and provides a list of the most prominent words for each topic. At this point, the domain knowledge of the researcher is required to interpret the results by working backwards from the list of observed words to the latent topics.

Documents pre-processing is a multi-step process that is of primary importance for the successful implementation of LDA and to avoid biased results. To prepare the corpus of documents for the analysis, documents are 'tokenized' meaning that each document is broken down into a collection of each individual word it contains regardless of the order they appear in. In the following step, tokens that do not represent words (e.g. special characters, punctuation marks, numbers etc.) and so-called 'stop words' (i.e., words that connect different parts of a sentence or that do not carry a meaning *per se*) are removed (e.g. 'and', 'or', 'if' etc.). The remaining words are then 'stemmed', meaning that suffixes are removed based on the assumption that words with the same stem would recall the same concept (e.g. "accounting" and "accounts" would both be reduced to "account"); this is an important step as it reduces the word count (and therefore the complexity of the model) and improves the identification of unique terms within documents (and therefore the detection of topics). The next step consists of a Term Frequency-Inverse Document Frequency (TF-IDF) analysis which assesses the importance of a word to a document in a corpus (Salton and Buckley, 1988). This is measured by calculating the percentage of occurrences of any term in a given document compared to all other terms in that document and multiplying it by the logarithm of the number of documents in the corpus divided by the number of documents in the corpus that contain the term. Terms with a higher TF-IDF measure are more important in the corpus than terms with a lower TF-IDF measure. At this step, terms with very low or very high TF-IDF are typically removed as they are too uncommon or occur too often in the corpus to describe individual topics. The final step of this process consists of the construction of a document-term matrix (DTM) where each row represents a document, each column represents a term in a document, each term and the values reported in the matrix are the frequency of occurrence of a term in a document. The LDA will then take the DTM as an input and will reduce the number of columns to the predefined number of topics by grouping together frequently co-occurring terms into a topic. This last phase of the analysis is described in more detail in Blei et al. (2003) and Boyd-Graber et al. (2017).

In this study, 11 clusters of words were extracted using the LDA model. These clusters were based on text similarity to facilitate the interpretation and presentation of the results. More specifically, text similarity between clusters was measured using the Hellinger distance as it has been proven to perform better than other measures in high-dimensionality applications like the one presented in this study (Sohangir and Wang, 2017). Clusters with higher text similarity (and lower distance) were grouped together to structure the topography of a corpus of documents spanning multiple disciplines and over 34 years from 1990 to 2023. The source of the corpus was the Elsevier Scopus database. We used this database to identify studies related to AI or ML and accounting by applying the search criteria presented in Table 1.

Retrieved articles had to feature any of the AI/ML search terms and any of accounting search terms within the title, abstract, or indexing keywords. The initial list included 2,877 articles published in 928 different outlets. Due to the frequent use of the word "accounting" as a verb, a number of non-relevant papers were included in this original list. Two independent coders manually classified the abstracts as relevant or not (Cohen's kappa = 0.993); disagreements were reviewed by a third independent coder to agree on the final classification. The final list included 930 abstracts published in 478 discrete outlets. Fig. 1 provides an overview of the time distribution of the number of publications in our final list by type (peer reviewed journals and conference proceedings).

When running an LDA algorithm, the number of topics is not known to the researchers *a priori*. To identify the optimal number of topics in the corpus of documents, we estimated separate models with the number of topics (k) ranging from 1 to 20 in increments of one. The optimal number of topics was then selected using the density-based approach presented in Cao et al. (2009) according to which the best model for a given corpora is the one that maximises the similarity within each topic (measured using cosine similarity)

Table 1
Search criteria.

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" <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.

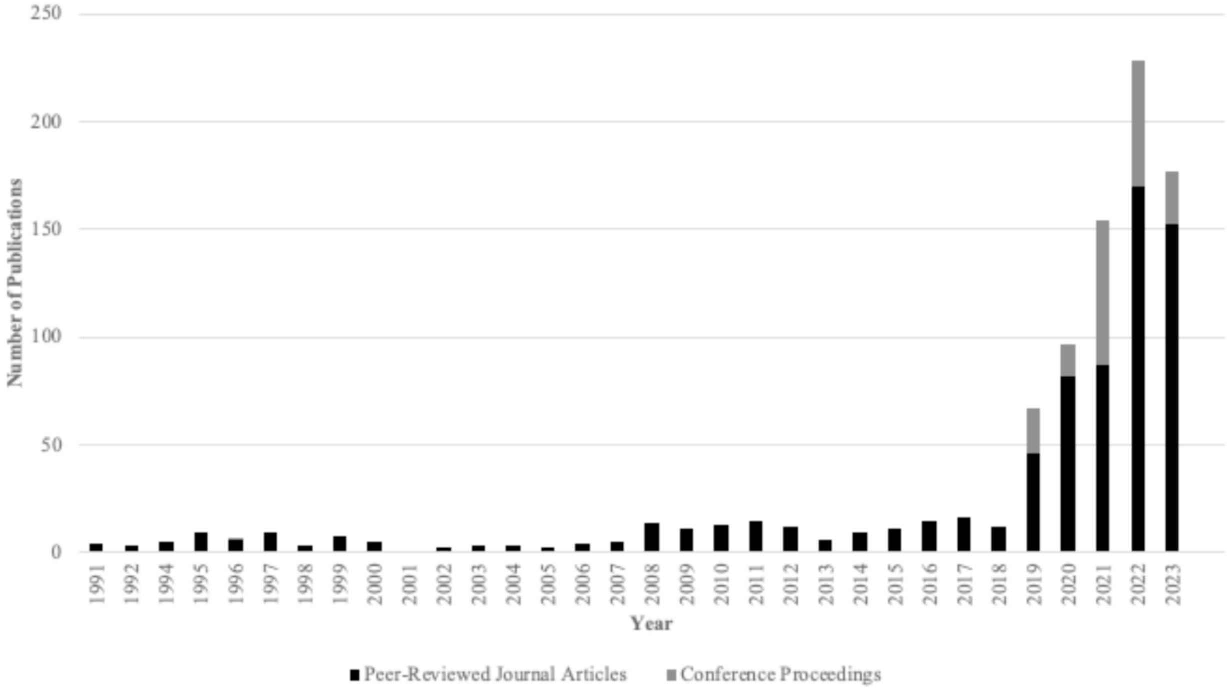

Fig. 1. Publication Distribution by Year and Publication Type.

while minimising similarity across topics (measured using a perplexity score). The results of this analysis suggest that 11 different topics could be identified in the corpus of documents. Finally, we ran the LDA algorithm using the 'topicmodels' package in R (Grün and Hornik, 2011). We implemented variational expectation–maximization inference (VEM) (Blei et al., 2003) with 10 different starting points (seeds) to minimise the Krippendorff's α (Krippendorff, 1970); lower values of α identify topic models with sharper topic distributions (Aziz et al., 2022) meaning that while topics may occasionally overlap, they are less likely to do so and therefore easier to logically separate when interpreting the results. As a result, the final parameters were k = 11 and seed = 10.

While the LDA technique uses quantitative methods to organise the content of a large dataset into topics, a qualitative approach is needed post-LDA in order to interpret and validate results and align with previous or well-established human-defined categories. This qualitative phase required the authors to first identify the themes generated by the LDA. This involved scrutinizing the abstracts within the topics, contextualising them within the broader research context and linking the key themes within the different papers so as to understand each topic. Two of the authors carried this out independently, taking half of the topics each, first familiarizing themselves

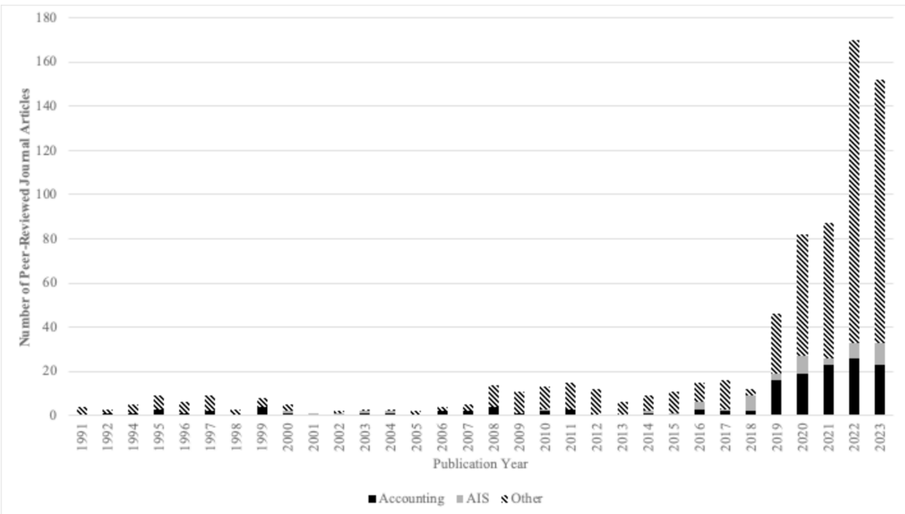

Fig. 2. Distribution of Peer-Reviewed Journal Articles by Discipline and Year.

with the data by reading the abstracts within the topics, labelling the abstracts with potential themes within the topics and grouping papers into patterns and subcategories within those topics. The two authors then validated each other's analyses before bringing all the analyses together in order to set out clear definitions and descriptive names that captured the 11 topics. This final phase involved a lengthy and iterative process of fine tuning which necessitated a degree of domain expertise on the part of the researchers conducting the analysis. Topics are described and discussed in the next section.

Table 2
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 %	Škapa et al. (2023) 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 %

5. Results

The results present an analysis of papers focusing on AI and accounting which span 34 years (1990–2023) and published in a wide range of disciplinary journals. It is worth noting that the number of publications has increased significantly in the last four years covered by our analysis (2020–2023), suggesting a dramatic growth in academic interest in the area of accounting and AI (See Fig. 1 above).

We categorise the peer-reviewed journal articles which emerged from the model across three categories: (1) articles published in AIS journals (e.g. International Journal of Accounting Information Systems, International Journal of Digital Accounting Research, Journal of Emerging Technologies in Accounting); (2) articles published in accounting journals (e.g. European Accounting Review, Journal of Accounting Research; Review of Accounting Studies); (3) articles published in other journals (e.g. Expert Systems with Applications, Journal of Risk and Financial Management, Sustainability). Fig. 2 presents an overview of the distribution of peer-reviewed journal articles by journal category and publication year.

Eleven topics pertaining to accounting and AI were extracted. Table 2 provides an overview of the topics, corresponding keywords and some exemplar papers. It also includes a column titled "Publication Type" that provides a breakdown of the relative frequency of the number of publications across the three highlighted journal categories.

Topic 1 – Neural Network Forecasting

Topic 1 deals with the use of neural networks for cost estimation, forecasting and prediction. The 102 papers in this topic span the broadest time frame, with the first published in 1994 and the most recent in late 2023, and include some early seminal papers in the area. Exemplar keywords include '*neural', 'model'* and *'network'*. The purpose of many of the earlier papers was to introduce the technology and explain how it can be applied. As a result, the majority of papers appear in engineering, technology and computing journals and so are categorized in 'Other Journals' in Table 2 above. Conventional statistical methods assume linearity, normality and independence among input variables. These assumptions rarely apply to actual financial data, which limits their validity. 'Soft' computing techniques such as probabilistic neural networks and back-propagation neural networks replicate the way the human brain works. This means that instead of 'hard' coding results into a computer using restrictive models or 'if-then' coding, an ANN is set-up with weights, initially random numbers. As it is trained (i.e. engages with actual data) the network learns by adjusting the weights in positive ways when it achieves a correct outcome, and in negative ways when it achieves an incorrect outcome (Kumar and Bhattacharya, 2006). Such learning is particularly useful when a model or 'if then' relationship is unknown. Spear and Leis (1997) was one of the earliest papers to explore how neural network models can be fine-tuned based on the error rates obtained in prior iterations, leading to more reliable modelling and enhanced capacity for generalisation. In most cases, these articles report on studies which compare the accuracy of cost prediction over a project's life using neural networks with actual results or predicted results attained through non-AI applications, and emphasis is on the technology as much as the accounting application.

Prominent application domains include construction, project and engineering contexts (Juszczyk and Leśniak, 2019; Odeyinka et al., 2013). Other studies in this topic conduct similar analyses of the efficacy of neural networks in day-to-day cost estimation, e.g. De Cos et al. (2008) explore the use of an ANN technique for the rapid cost estimation of turbine components eliminating the need for expert intervention, while Karaoglan and Karademir (2017) examine the predictive capability of neural networks in determining the production cost of orders with a view to generating more accurate price offers at the tender stage. Several studies also discuss the application of neural networks in financial analysis in a more general context, e.g. Barney et al. (1999) and Gunawardana (2021) for debt failure prediction, Lin (2009) and Abrol et al. (2023) for bankruptcy prediction and Florez-Lopez and Ramon-Jeronimo (2009) for market positioning, while Liang et al. (1992) examine the use of neural networks to make inventory accounting decisions (i.e. LIFO/FIFO).

Topic 2 – Machine Learning and Stock Prediction

Exemplar keywords in Topic 2 include '*machine learning*', '*risk*' and '*stock*'. Papers are focused largely on the potential for neural networks to make accurate stock market predictions. The topic comprises 91 papers, 72 of which were published since 2020, highlighting a proliferation of these types of studies in the last four years of the study. In early AI applications it was difficult to train neural networks to outperform more traditional linear approaches, so it was limited to use in only a handful of specialised problems. But as the field advanced, techniques for learning through 'deep neural networks' were developed and continue to develop today. Deep Learning (DL) allows more abstracted learning where there is no known relationship within the input data (Hastie et al., 2009). A more abstract level of analysis and pattern recognition is required in order to develop a more meaningful and reliable algorithm. These neural networks are usually based on nonlinear models that can learn complex patterns in high-dimensional data. These models are more powerful than non-AI, linear-based models because they can capture more complex relationships between variables. They require more training data, more computational power, and more tuning in order to obtain good results, but they are better suited to real-world problems and reveal trends that would otherwise be almost impossible to detect. Again, the papers in this topic are, in the main, technical examinations of potential applications of DL and a large number of these papers are published in 'Other Journals' as categorised in Table 2.

Most of the studies are concerned with predicting stock price movements. In the main, they compare the accuracy of predicted stock market returns using neural networks with actual returns or predicted returns attained through non-AI applications. Hanauer and Kalsbach (2023) compare various ML models to predict emerging stock market returns and find that nonlinear models lead to economically and statistically superior returns over traditional linear models. Bali et al. (2023) drew on more than 12 million observations over a 25-year period and also report that nonlinear ML models generated statistically and economically sizable profits in the long-short portfolios of equity options. Page et al. (2023) use ML to identify skilled equity asset managers, Díaz et al. (2023) to predict gold risk premium performance and Wang and Hao (2023) to forecast oil prices. A key issue addressed in papers in this topic is risk. ML is used to predict bankruptcy (Aranha and Bolar, 2023), examine interactions between major equity markets and economic risk factors (Kocaarslan and Soytas, 2023) as well as operationalize the likelihood of CEO deception (Hyde et al., 2024). Vu et al. (2023) use ML to identify financial distress predictors for Vietnamese listed firms while Hasan et al. (2022) use advanced ML approaches to examine the relationship between brand capital and stock price crash risk.

Topic 3 – Machine Learning and Fraud Detection

Exemplar keywords associated with Topic 3 include '*fraud*', '*financial*' and '*data*'. Again, most of the 99 papers in this topic apply ML to historical data and compare predictions with actual results (e.g., Berkin et al., 2023; Hamal and Senvar, 2021; Omar et al. 2017; Papík and Papíková, 2023). The majority of the papers appear in 'Other Journals' in Table 2. In the early 2000s, neural networks became increasingly important tools for data mining, and the papers on this theme have grown significantly from 2010 onwards. Data mining predicts future outcomes by identifying patterns in clusters of data and building models of what is happening in that data. Liou (2008) and Moepya et al. (2016) were seminal papers which examined the efficacy of data mining techniques for early fraud detection. Dbouk and Zaarour's (2017) paper was designed to provide guidance to regulators and practitioners on how AI technologies can be used to detect accounting manipulations. It presents the results of a ML application which detects and then predicts earnings manipulation. Their application was applied to the financial statements of 53 companies over three years, the first year provided the 'training data' feeding the model which was applied to years two and three. The ML approach outperformed a manual auditing approach. Papers in this topic also explore the use of AI in examining textual content from financial statements to detect corporate fraud. For example, Hajek and Henriques (2017) apply ML to identify fraudulent misrepresentation in the financial comments section of financial statements. Dong et al. (2018) builds on such work, but instead of relying on data from financial statements uses systemic functional linguistics (SFL) theory to tap into unstructured data from financial social media platforms to assess the risk of corporate fraud.

Within ML, a support vector machine (SVM) is a computer algorithm that 'learns', using examples, to assign labels to objects. For example, a SVM can learn to recognize fraudulent credit card activity by examining a large volume of fraudulent and non-fraudulent credit card activity reports, or to recognize handwritten digits by examining a large collection of scanned images of handwritten digits. SVMs are particularly useful for numerical prediction, classification and pattern recognition tasks (Noble, 2006). They are amongst the most robust prediction models and many of the papers in Topic 3 set out to examine their predictive power when compared with other approaches such as rough set theory (RST), decision trees, and logistic regression (e.g. Trustorff et al., 2011). A further technique, particle swarm optimization (PSO), can be used to address some of the limitations of SVMs. A PSO model was first presented by Eberhart and Kennedy (1995) and loosely modelled on group behaviour, such as birds flocking and fish schooling. It optimizes a problem by iteratively trying to improve a solution in terms of a given measure of quality. PSO is metaheuristic in that it makes no assumptions about the problem being optimized and can deal with huge volumes of candidate solutions. However, there is no guarantee that a solution can ever be found. A key aspect of PSO is its flexibility in terms of solving problems that have different mathematical constraints and is applied as a parameter to SVM models. Chen (2011) examines how AI can be used in bankruptcy prediction and applies PSO to obtain a suitable parameter setting for a SVM model which can predict financial distress. Chen (2014) builds on the same study, using PSO in combination with SVMs to establish a model to better forecast financial failure in Taiwanese listed companies.

Topic 4 – Machine Learning in an Audit Environment

Articles pertaining to Topic 4 focus on how ML can support a variety of audit activities. Of the 75 papers in this topic, 50 were published since 2020 indicating a real growth in this research context. It is not surprising that the majority of these papers are published in 'Accounting Journals' as illustrated in Table 2. Many of these papers reflect how audit activities are evolving in response to AI. Exemplar keywords include *'audit', 'auditor'* and *'auditing'*. Early articles explore the initial application of AI-type technology in an audit sustainability context, such as expert systems and rules-based decision trees (Ragothaman et al., 2000).

In a conventional approach to programming, programmers 'tell' the computer what to do, breaking big problems down into many smaller clearly defined tasks that a computer can easily perform. As noted above (topic 1), humans do not 'tell' the computer how to solve the problem in a neural network. Instead, it learns from observational data, figuring out its own solution to the problem. This approach has been found to be particularly effective for fraud detection where there are essentially no clues as to where fraud might be, i.e., a program can't be instructed specifically as to what to look for or what to do (Bertomeu et al., 2021; Huang et al., 2022; Lokanan, 2019). Sun and Vasarhelyi (2018) introduces the notion of using data analytics combined with DL in an auditing context in order to identify business insights from massive volumes of text documents. Sun (2019) further illustrates the value of incorporating DL into the audit environment using text understanding, speech recognition, visual recognition and structured data analysis.

There is also some discussion on the need for enhanced auditor skills (Brazel and Agoglia, 2007), as well as calls for an increased culture of innovation within audit firms and the profession more broadly (Manita et al., 2020). However, early fears that auditors would be replaced by ML and AI more broadly are refuted (Chase and Shim, 1991); instead, the evolving nature of audit practices, thanks to the supporting role of AI, is acknowledged (Alles and Gray, 2020). Auditors deal with large volumes of information and evidence and AI can greatly aid audit efficiency by enabling the analysis of large populations of data that heretofore could only have been audited on a sample basis. AI can also play a role in managing audit risk by focusing on areas that require increased attention, reducing over-auditing, and achieving audit conclusions more quickly (e.g., Davis, 1996). This facilitates more continuous, real-time auditing with increased forward-looking information (Zhao et al., 2004). Use of ML can also lead to greater audit effectiveness, with improved audit quality and enhanced accuracy of audit judgments (Rodrigues et al., 2023). Davis (1996) suggests that while more experienced auditors might use AI models more selectively, these models are also pertinent to training. The use of a multitude of client examples can supplement experience from real audits to help audit trainees develop the ability to select more relevant information and make more efficient and effective judgements. Given the potential social impact of accounting/auditing judgements and decisions, a need for some caution concerning broader ethical and societal impacts is also reported (Sánchez-Medina et al., 2019).

Topic 5 – AI Applications in Financial Analysis

Exemplar keywords associated with Topic 5 include '*financial', 'information'* and '*company'*. All but 14 of the 73 papers in this corpus were published since 2019. As illustrated in Table 2, just over half are published in 'Other Journals', with approximately a quarter appearing in 'Accounting Journals', reflecting the technical nature of a number of the studies. The primary focus is on textual analysis and papers largely fall into two categories: content analysis of companies' financial reports (e.g. Ding et al., 2019; Holowczak et al., 2019; Mushtaq et al., 2022) and sentiment analysis of publicly available company information (e.g. Bannier et al., 2019; Eachempati and Srivastava, 2022). With reference to the former, AI programs can interrogate financial statements, providing accurate and valuable insights in a fraction of the time it would take a team of finance professionals to complete. For example, Minhas and Hussain (2016) use data mining and linguistic analysis on the narrative sections of 10-K forms to establish a means to identify falsification in financial text while Back et al. (2001) apply neural networks in the form of self-organising maps to analyse text information in annual reports and compare it with numerical information.

AI applications can also be used to analyse large volumes of text data in publicly available information and determine the sentiment or overall emotion expressed in the text, offering more accurate, nuanced, and context-aware insights. In several papers, AI is used to forecast stock prices and influence stock market decisions based on public sentiment as ascertained from news and social media. For example, Bos and Frasincar (2022) use ML to extract market sentiment from microblogs, Bannier et al. (2019) measure textual sentiment from business communications and Eachempati and Srivastava (2022) examine the effect of changing market sentiments associated with news cycles on asset pricing.

Topic 6 – AI and Strategic Decision-Making

Topic 6 focuses on strategic decision-making and comprises 63 papers. The first paper in this topic was published in 2009, with 57 papers published since 2020, 23 in 2023 alone, reflecting a current and future-oriented focus. The significant keywords are '*corporate*', *'governance',* and *'social'*. With huge volumes of information flowing around organisations, a variety of advanced AI techniques and capabilities, including ANN, neuro fuzzy logics and SVM modelling, may help to structure both internally generated and wider industry financial information and lead to more strategic and better-quality decision making at high/senior levels in organisations. The articles examine how senior management in large organisations typically operates within a global context, involving a complex ecology of legislation and regulations, both impacting and impacted by a variety of externalities. A predominant focus is on how AI can lead to improved management reporting and decision making by bringing a scientific rigour to both quantitative and qualitative information analysis. Key decisions where AI modelling can support accounting decision making are in the strategic areas of investment (Creamer and Freund, 2010), tax evasion (Warner et al., 2015) and corporate culture (Chindasombatcharoen et al., 2023). There is a call for those involved in strategic decision making, both management in organisations and regulators, to take an active role in understanding and shaping policies and processes concerning AI (Hilb, 2020), particularly with reference to fintech contexts (Burton, 2020).

The vast majority of papers in this topic appear in the 'Other Journals' category in Table 2, driven largely by the emergence of sustainability as a key focus, with studies falling into two groups. The first demonstrates how environmental applications for AI are broadening as it looks set to be used as a tool within organisations to enhance their economic growth while also improving their sustainability outcomes (Antoncic, 2020; Giannarakis et al., 2023; Koh et al., 2013). The second recognises that AI can be used to identify companies' sustainability efforts, which may not easily be distinguished from financial statements. AI provides investors with a tool to comprehensively interrogate vast datasets including social media, news and satellite imaging in order to capture sentiment and provide insights into a company's true sustainability efforts (Gupta et al., 2021; Lin, 2021; Škapa, et al., 2023). While research appears to be at an early stage in this arena, AI looks set to complement traditional analyses in order to improve sustainable decision making and/or drive more sustainable investment (D'Amato et al., 2022; Liu et al., 2023).

Topic 7 – AI and the accountant

Topic 7 comprises 90 articles and focuses on increased AI innovations within the accounting profession and their impact on accounting professionals. All but eight of the 90 articles were published from 2019 onwards, highlighting a very strong current and future-oriented focus. As illustrated in Table 2, almost half are published in 'Other Journals', reflecting the need for accountant roles to continue to transform and to interact with broader innovations. Exemplar keywords associated with this topic include *'development', 'human'* and *'professional'*.

The accelerated automation of accounting tasks is examined. Early articles discuss technologies such as expert systems (Baldwin-Morgan, 1995; Meservy et al., 1992) while more recent articles explore AI as a more disruptive technology (Faulconbridge et al., 2023; Moll and Yigitbasioglu 2019; Moore and Felo, 2022; Reepu, 2020). The continuing digital transformation, increased innovations to structure systems within organisations, and the potential for further learning innovation and collaboration between humans and machines are articulated (Chang et al., 2021; Krishna et al., 2022; Leitner-Hanetseder et al., 2021; Marshall and Lambert, 2018; Petkov, 2020). Some core contexts are specifically examined, including audit (Henage, 2020; Puthukulam et al., 2021; Zemankova, 2019; Zhu, 2021), management accounting (Andreassen, 2020; Marques et al., 2023; Vărzaru, 2022a,b; Zhang et al., 2023b) and Small and Medium Enterprises (SMEs) (Gonçalves et al., 2022; Nóbrega et al., 2023; Ulrich and Kratt, 2021).

The overriding consensus is that new technologies such as AI will not replace human accountants, but, rather, will provide an important collaborative opportunity where machines augment accounting professionals' work (Andreassen, 2020; Goto, 2021). While AI may replace lower-end and mid-level personnel who were previously engaged in more basic accounting work, studies reveal it will lead to increased demand for higher-end professionals (Li, 2019; Tiberius and Hirth, 2019). Korhonen et al. (2021) however urge caution and suggest that when processes are assessed from a distance, non-programmable tasks and expertise may be misinterpreted as programmable which may result in unsuccessful outcomes, highlighting that humans are critical to future endeavours. In a similar vein, Li (2019) highlights the importance of making moral judgements and urges caution in relation to addressing the ethical dilemmas associated with replacing the human element with machines. On a practical level, accounting professionals will need to intensify their engagement with rapidly developing AI technologies in order to update skills and competencies, keep pace with innovations, remain relevant and competitive, add value and ultimately facilitate the more strategic transformation of the accounting profession (Aldredge et al., 2021; Handoko et al., 2019; Holmes and Douglass, 2022; Moll and Yigitbasioglu, 2019; Yang, 2021).

Topic 8 – AI and Accounting Systems Integration

Topic 8 comprises 110 articles, and all but two were published from 2019 onwards, highlighting a very current emphasis. Interestingly, no articles have been published in mainstream Accounting or AIS journals. Table 2 illustrates that a little more than half of the articles to date are published in 'Other Journals' while the remainder are conference presentations. The articles focus largely on the increasing use of AI to enhance financial information systems within organisations. Exemplar key words include *'financial', 'information'* and *'enterprise'*. A number of different AI techniques may be used to improve the accuracy of and enhance the quality of an individual enterprise's accounting information system(s). These include neural networks for large data sets, specifically back-propagation neural networks used as a training process to feed error rates back through a neural network (e.g. Chen, 2022; Cao, 2023; Li and Liu, 2022; Zeng, 2022b); SVM, used largely for data classification in smaller data sets (e.g. Jiang et al., 2022; Shao et al., 2022; Shen et al., 2021; Wang et al., 2021; Zhang, 2023; Zhou, 2021); and PSO, to deal with more complex items and their interactions (e.g. Malhotra, 2023). Cai (2022) acknowledges the challenges AI brings to the workplace but also in terms of education and training to prepare for the changes associated with accelerating technological advancements.

By incorporating data from a variety of both internal and external sources e.g., accounting software, business plans, ratio analysis, comparative analysis, AI can help to enhance accounting and financial information systems and outputs (Feng, 2024; Li, 2022a). Such optimised information can help organisations to manage risks associated with such accounting informatization (Han, 2022) by identifying and monitoring key risks, including early warning of financial risks (Chen and Zhang, 2022; Hou, 2022; Li, 2022b; Yang, 2022; Zeng, 2022a), fraud risk (Zhang et al., 2021) and broader security risks (Jin, 2024). Other areas of potential application are also highlighted e.g. environmental accounting (Zhang and Zhu, 2022), accounting for cross-border trading (Zhou, 2023), and accounting in SMEs (Wu, 2021; Zhao et al., 2022).

Topic 9 – AI and Business Operations

Topic 9 comprises 81 articles, 62 of which were published since 2019. The remaining 19 articles range from 1991 to 2017 i.e., publications illustrate a sustained but increasing examination of this topic since the 1990s (with the exception of some years in the early 2000s). The vast majority of papers appear in the 'Other Journals' in Table 2, highlighting the interdisciplinary nature of the topic. The articles focus on the use of AI tools and techniques to support businesses. Exemplar topic keywords are *'business', 'system'* and *'decision'*. Technology is a key focus: recent articles report how hybrid decision support systems and frameworks can expand information processing ability beyond that facilitated by single layer modelling tools. These hybrid systems can effectively cater for more complex problems and more dynamic contexts. They can also incorporate interdependencies among key constituents and thereby generate more useful information for decision-making. The integration of AI with other technologies is also examined, e.g., blockchain (Zand et al., 2020; Zhang et al., 2022) and big data (González-Carrasco et al., 2019) which combine the security, immutability and traceability of data with the possibilities AI offers.

In terms of accounting and reporting, ML may be used to combine fragmented information across companies, sectors and jurisdictions and in multiple languages to generate an accounting topology or chart-of-account (Jørgensen and Igel, 2021; Lesner et al., 2020; Munoz et al., 2022; Zhang and Liang, 2023), and to also aid detection of journal entry anomalies (Zupan et al., 2020). More broadly, AI may be used to support a wide range of salient accounting-related business applications, including accounts payable (Tater et al., 2022), costing (Lee and Leung, 2012), order management (Khataie et al., 2011), resource management (Hilmola and Gupta, 2015; Hsu and Hsu, 2008), capital structuring (Östermark, 2015), corporate valuation (Yang et al., 2023), inventory classification (Kaabi, 2022), expense management (Lecue and Wu, 2017), project management (Al-Tabtabai et al., 1997) and process engineering (Arif et al., 2020). Prominent application domains include construction, project and engineering contexts (Al-Tabtabai et al., 1997; Baalousha and Çelik, 2011), advertising (Fan and Delage, 2022) insurance (Zuin et al., 2023), banking (González-Carrasco et al., 2019), and audit (Nado et al., 1996).

Topics 8 and 9 are closely related, each focusing on the use of AI tools and techniques to enhance financial information systems (Topic 8) and support business decisions (Topic 9). As noted earlier in the paper, occasionally there is some overlap between topics. Such overlaps can be caused by words or phrases shared amongst different topics, or papers examining AI technologies in diverse contexts. For example, there also appears to be some overlap between topics 8 and 9 and topic 1 above, though topic 1 is dominated by older more seminal papers which introduce the technology and its potential while topics 8 and 9 are more current empirical examinations of AI applications.

Topic 10 – AI Adoption and Information Quality

Comprising 77 articles, Topic 10 examines factors influencing AI adoption and the impacts of AI adoption on information quality. It demonstrates a significant focus in more recent years – all but 10 of the 77 articles were published from 2019 onwards. As illustrated in Table 2, the majority are published in 'Other Journals', indicating that information quality is impacted by a wide variety of factors. The significant keywords are *'information system', 'influence'* and *'quality'*. Data were predominantly gathered using survey instruments and quantitatively analysed using regression and structural equation modelling (e.g. Bonsu et al., 2023).

Effective AI adoption is linked to a number of elements in relation to the wider information system, including firm size, organisational culture, regulatory policies, appropriate planning/implementation activities, intrinsic motivations of key personnel, technology readiness (e.g. existing accounting automation), top management support, user capability, knowledge readiness, perceived ease of use, perceived usefulness, trust, and system security (Alathamneh, 2020; Al-Dmour et al., 2019; Khalil and Zainuddin, 2015; Siew et al., 2020; Sumaryati et al., 2020; Ta and Nguyen, 2020; Utomo et al., 2020). Specific contexts are also examined, including adoption by SMEs (Abdi et al., 2021), banks (Salameh and Lutfi, 2021), auditors (Handoko and Liusman, 2021), public sector entities (Solikin and Darmawan, 2023), corporate governance functions (Abdou et al., 2021), and accounting and auditing students (Damerji and Salimi, 2021).

Reported impacts of AI adoption focus largely on improvements in the quality of information and control systems (Alrjoub et al., 2023; Qasaimeh et al., 2022; Solikin and Darmawan, 2023) Studies reveal greater efficiencies result from replacement of human roles by ML-based automation (Bavaresco et al., 2023). Impacts are also examined in relation to other technologies and findings suggest that the impact of AI adoption is greater than that of big data (Bonsu et al., 2023).

Topic 11 – Research and Education

Comprising 69 articles, Topic 11 focuses on literature reviews charting the emergence of AI as a research strand, as well as developments within educational settings. All but 10 of the 69 articles were published since 2018, illustrating an exponential growth pattern since the early 2000s (Apostolou et al., 2014; Barrick et al., 2019; Chiu et al., 2019; Kocsis, 2019; Sutton et al., 2016). Almost one third of these papers are published in 'Accounting Journals' and one quarter in 'AIS Journals', reflecting the discipline's responsiveness to developments in research and education. Exemplar keywords include *'research', 'literature'* and *'future'*. The articles predominantly appraise prior literature, comprise largely quantitative methodologies, and discuss the transformative force of technology on accounting research and accounting education.

The evolution of Accounting Information Systems (AIS) from information to knowledge systems, the interdisciplinary nature of research, the range of research designs and methodologies and metrics such as citations, citation impact and downloads, are described (Jones and Alam, 2019; Muehlmann et al., 2015; O'Leary, 2010; Vasarhelyi and Greenstein, 2003). In many cases, bibliometric analysis is used to examine evolving research themes (Agustí and Orta-Pérez, 2023; Aspiranti et al., 2023; Atayah and Alshater, 2021; Hutchison et al., 2004; Muehlmann et al., 2015; Sun et al., 2022). The growth in unstructured data accelerates the need for new and more specific tools and techniques to facilitate research on these unstructured data (Ciampi et al., 2021; Ranta et al., 2023), e.g., computational linguistics (El-Haj et al., 2019). Such applications have been used to mine documents to obtain insights, make inferences and to create additional methodologies and artefacts to advance knowledge in accounting, auditing and finance. Optimum results may be achieved when a combination of tools and techniques are employed (Cai et al., 2019; Mahlendorf et al., 2023). Researchers therefore need to continue to update skills and identify potential future research directions (Bertomeu et al., 2021; Gray et al., 2014; Mancini et al., 2021; Rikhardsson and Yigitbasioglu, 2018; Sutton et al., 2016).

The need to integrate more innovative AI technology for learners in the accounting curriculum within higher education is also explored as the disconnect between education and practice widens (Coyne et al., 2016; De Villiers, 2021). The manner in which various technologies have been and/or should be incorporated into accounting education settings, both conceptually and empirically in various accounting teaching and learning systems, is explored in both a general context (Coyne et al., 2016; Yang and Zhu, 2023) but also specifically in relation to management accounting (Jayasinghe, 2021; Nielsen, 2022; Samanthi and Gooneratne, 2023) and audit (Tiron-Tudor and Deliu, 2022).

6. Discussion and conclusion

The paper uses a ML technique, LDA, to structure the topology of the extant literature discussing accounting and AI. There are a limited number of literature reviews of similar scope or detail on this theme. Our analysis suggests that prior literature reviews, using more traditional methodologies, do not capture a comprehensive picture of the accounting and AI literature. Our first contribution is an analysis of 930 articles over a 34-year period from 1990 to 2023 that presents the most holistic view of the accounting and AI literature to date. These findings contribute to literature exploring the changing role of accounting in light of the digital transformation of society and provide some focused avenues for future research.

The volume of Accounting and AI research is growing, particularly in the last four years examined (2020–2023) where exponential growth was revealed. Over the 34-year period of analysis, the two topics drawing the most attention, i.e. with the most published articles in peer reviewed journals and conference proceedings, are topic 1 '*Neural Network Forecasting*' and topic 8 '*AI and Accounting Systems Integration*'. Over time, the trends of publications reveal some interesting insights. In the 1990s and early 2000s, almost half of articles published focused on topic 1 '*Neural Network Forecasting*'. This first topic continued to dominate in the 2010–2019 period but an increasing focus on topic 3 '*Machine Learning and Fraud Detection*' was also observed. The 2020–2023 period revealed an explosion of articles, representing over 70 % of the total articles published over the full 34-year period of the study. Analysis of this recent period reveals that the dominant topic was topic 8 '*AI and Accounting Systems Integration*', followed by topic 2 '*Machine Learning and Stock Prediction*', and topic 7 '*AI and the Accountant*'. Despite its earlier dominance, topic 1 '*Neural Network Forecasting*' generated the least papers within this recent time period. Neural networks still garner significant academic attention, but are overshadowed somewhat by newer foci which have emerged in recent years.

The intersection of accounting and AI has opened up new frontiers of research in the areas of financial analysis, auditing and decision-making. Our results help to identify specific needs for future research in this rapidly evolving landscape. Within Topics 1 and 2, i.e. '*Neural Network Forecasting*' and '*Machine Learning and Stock Prediction*' respectively, we have seen a wealth of research examining the use of advanced algorithms in the areas of cost estimation, financial distress prediction and stock market forecasting. Future research in this domain would benefit from increasing datasets to include additional geographies and emerging markets (e.g. Page et al., 2023, Vu et al., 2023). There is also a need to enhance the interpretability and explainability of AI models in these contexts, which would help to increase trust amongst practitioners, regulatory bodies and wider stakeholders, which is crucial for a more widespread adoption of AI.

Topics 3 '*Machine Learning and Fraud Detection*' and 4 '*Machine Learning and Auditing*' revealed sustained focus over the period of the study and increasing growth in associated publications from 2019 onwards. Future research is likely to focus on enhancing anomaly detection algorithms to better identify irregularities in financial data (e.g. Hamal and Senvar, 2021). Additionally, exploring the integration of a variety of AI and other techniques for analysing data in financial reports will provide deeper insights (e.g. Sun, 2019). As professionals charged with providing assurance over financial data, auditors will need to adapt by gaining proficiency in data analytics, programming and ML in order to leverage technological advancements effectively. This is likely to drive a research agenda. In addition, ethical considerations pertaining to AI-augmented auditing processes will require greater scrutiny from both practitioners and researchers to ensure responsible implementation and execution (Sánchez-Medina et al., 2019).

In Topic 5 '*AI Applications in Financial Analysis*' and Topic 6 '*AI and Strategic Decision-making*', we present empirical evidence of AI supporting financial analysis and consequent decisions in a variety of accounting contexts. A key strength of AI in this domain is its ability to analyse the sentiment of large volumes of varied text data. Future efforts will develop more complex models capable of discerning context, sarcasm and subtle nuance to provide a more comprehensive understanding of the data (e.g., Bannier et al., 2019), and enable researchers to better interpret such data. In turn, managers will likely make more optimum decisions which will also provide a catalyst for further research endeavours. Sustainability emerged as a key research area within Topic 6 in the last four years of the study. Future research is likely to focus further on the use of AI to help businesses align their economic goals with their environmental responsibilities (e.g., Giannarakis et al., 2023) and identify more sustainable investment opportunities (e.g., D'Amato et al., 2022).

Topic 7 *'AI and the Accountant'* reveals the transformative effect of AI on accounting as a discipline. As AI accelerates the automation of routine accounting tasks, the evolving role of accountants remains at the forefront of the accounting agenda. Future studies should explore not only the skills and competencies required of accountants in an increasing AI-driven era but also how professionals in an accounting context should work together and negotiate going forward (e.g., Faulconbridge et al., 2023). Again, a primary focus must be on developing trust mechanisms that enhance the transparency and interpretability of AI-driven accounting information.

Topic 8 '*AI and Accounting Systems Integration*' and Topic 9 '*AI and Business Operations*' report on the use of AI within accounting information systems and wider decision-making systems. Studies suggest that evolving AI techniques have more potential than traditional techniques to support more complex problems and more dynamic contexts (Feng, 2024). Future research is likely to focus on an expanding array of AI techniques, both individually and in tandem with other technologies e.g. blockchain (Zhang et al., 2022) and big data (González-Carrasco et al., 2019), to analyse vast datasets.

Topic 10 '*AI Adoption and Information Quality*' reports that a wide array of factors have influenced AI adoption to date (e.g. Utomo et al., 2020). As AI becomes more of an imperative for adoption, future research will need to study contexts that have not yet been subject to such examination e.g. nonprofit organisations, additional sectors and jurisdictions. With regard to reported impacts of AI adoption, existing research has focused largely on information quality, efficiencies and control systems (Alrjoub et al., 2023; Bavaresco et al., 2023). Future research might also consider additional variables and impacts e.g. transparency, fairness, integrity. In addition, research to date has largely focused on quantitative data analysis: future research could incorporate more qualitative methodologies and generate a deeper but richer understanding of both AI adoption and impacts in varied settings.

Topic 11 '*Research and Education*' suggests that research scholars must continuously update skills in order to research more effectively. Cross-disciplinary research will remain crucial to advancing this research agenda and it is hoped that more qualitative and mixed method approaches will be embraced so as to develop greater depth of insight. This topic also highlights that the future of accounting education lies in preparing students to navigate a technologically advanced landscape, ensuring that they possess the skills to utilise AI while upholding ethical and professional standards i.e. AI literacy must also be integrated into various accounting curricula (De Villiers, 2021). This will present additional fields for research as students navigate unprecedented evolution.

A topology of research on accounting and AI aids researchers and journal editors by providing a tool for identifying emerging trends and gaps in the field or a specific journal(s) and enhancing research quality through informed and targeted literature reviews. As such, it facilitates interdisciplinary collaboration, informs editorial policies, and guides the design of educational curricula. This topology is also valuable for strategic planning in research, aiding in grant applications, and fostering community building among researchers with interests in specific topics. Moreover, it promotes transparency, reproducibility, and the effective allocation of resources, ultimately contributing to the advancement and impact of research at the intersection of accounting and AI.

While more comprehensive than extant literature reviews, there are limitations in our study. Firstly, we limited our analysis to journal and conference publications in the Elsevier Scopus database. Increasing the corpus to include more publication types (e.g., books and book chapters), other databases, and a wider number of research fields, may present even greater insights. Secondly, our analysis presents a comprehensive overview of what has been studied and provides an agenda for future research addressing the 11 topics in our typology, but structuring corpora into different disciplines (e.g., accounting, banking and finance, economics, IS, computer science) or fields of accounting (similar to Mardini and Alkurdi (2021)) may provide greater comparison or insight. Thirdly, all literature reviews are a snapshot in time. Even in the last four years of the study, there has been an upsurge in interest with respect to topic modelling, fuelled by the release and widespread adoption and use of generative AI such as ChatGPT. It is likely the significant increase in the volume of research in the latter years of our review will continue to accelerate.

Our second contribution relates to our use of probabilistic topic modelling and addressing a gap in the general accounting literature with respect to the use of LDA for scholarly literature reviews. As discussed, LDA has been used for such purpose in related fields including banking and finance (Aziz et al., 2022; Moro et al., 2015), economics and management (Elmsili and Outtaj, 2018), and blockchain in accounting (Garanina et al., 2022). However, it has not been applied widely in accounting, and not specifically to accounting and AI. Our experience with LDA is similar to others in that it has substantial advantages over traditional literature review methodologies including more efficient topic extraction, organisation and categorization, and exploration. However, it is not without limitations. This technique involves significant interpretation challenges and therefore LDA still requires domain expertise and careful analysis to interpret and validate results and align with previous or well-established human-defined categories. Similarly, as LDA is sensitive to the number of topics chosen and other hyperparameters, there is still a degree of manual fine-tuning and cross-validation for results. Researchers seeking to use LDA should be aware that LDA ignores word order and contextual information, thereby hindering the understanding of relationships and contextual nuances a human or other techniques may identify. A typical challenge with LDA is the quality of input data. In the case of scholarly publications, the quality and consistency of input data is typically higher than other input sources and so this was not a significant issue in our study. Notwithstanding, care should still be taken that appropriate inclusion/exclusion criteria are chosen, and pre-processing undertaken.

Recent advancements in neural topic models based on advanced NLP architectures using transformers (e.g., BERT, GPT and LLaMA) overcome some of the limitations of classic topic models such as LDA (Churchill and Singh, 2022; Egger and Yu, 2022). These transformer-based models have greater capacity for contextual understanding, interpretability, topic hierarchy, and modelling large and very large corpora (Egger and Yu, 2022). However, it is important to note that these models may bring their own challenges, such as increased computational requirements, the need for large amounts of training data, and the costs of labelling such data (Churchill and Singh, 2022; Egger and Yu, 2022; Zengul et al., 2023). Furthermore, they may generate large numbers of topics and outliers, which may ultimately result in greater time and effort (Egger and Yu, 2022). There is increasing evidence that transformer-based models may also result in hallucinations i.e., output that conflicts with the source or cannot be verified by factual knowledge, which raises concerns regarding the accuracy of results (Huang et al. 2023; Zhang et al., 2023a). LDA and transformer-based large language models (LLMs) may be used as part of a wider pipeline. In this scenario, LDA might be used for broader topic modelling and transformer-based LLMs used for deeper analysis within each topic. Given the novelty of neural topic modelling, there are relatively few applications to literature reviews in the business research domain. Echoing Eickhoff and Neuss (2017), more implementations and comparative evaluation studies are required to benchmark and validate these techniques and their suitability in different literature review contexts, both separately and as part of a wider NLP pipeline.

In conclusion, topic modelling is a useful tool for the efficient analysis of scholarly literature and the identification of latent patterns and themes. While advancements in natural language modelling and DL promise even greater contextual understanding and analytical power, such models still require domain expertise for interpretation and new specialised ensemble or hybrid methodologies for identifying under-researched areas for future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.accinf.2024.100709.

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