SESSION: ACCOUNTING AND AUDITING

DECADE OF STUDIES ON MACHINE LEARNING IN AUDIT: A STRUCTURED LITERATURE REVIEW

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Abstract

The application of machine learning (ML) in professional activities, including auditing, is rapidly growing; yet the existing literature has only partially explored the audit areas most impacted by these technologies (de Villiers et al., 2021; Lombardi et al., 2020). The purpose of this study is to provide a structured literature review (SLR) aimed at identifying the primary areas of auditing where ML has been applied in recent years. Additionally, the study seeks to outline emerging research trends, offering a preliminary framework that highlights which streams are developing more rapidly (Agnew, 2016). This contributes to a better understanding of the potential future impact of ML on auditing practices. The SLR is motivated by the theoretical and practical interest in ML applied to audit, which is still in the early stage (Bertomeu, 2020).

To reach the target, the following research questions are proposed:

RQ1: What are the main research areas in auditing in which ML integration is explored?

RQ2: What are the future topics and challenges that accounting and auditing face with the adoption of ML?

This study employs the PRISMA methodology for the screening and selection of literature (Demartini & Paoloni, 2011; Page et al., 2021). A keyword-based search was conducted within the Scopus database, obtaining 46 publications. To collect them, the following research searches are launched: (TITLE-ABS-KEY ("machine learning") AND TITLE-ABS-KEY ("audit*")) and (TITLE-ABS-KEY ("ML") AND TITLE-ABS-KEY ("audit*")). The selection process included filters based on language (English only), research area ("Business Management and Accounting" and "Economics, Econometrics and Finance"), publication date (covering the ten-year period from 2013 to 2023), and content relevance to the research objectives. Each manuscript was analyzed according to three key dimensions: A — article focus, B — research methodology, and C — geographical region of the study (Paoloni & Demartini, 2016; Riso & Morrone, 2023).

The literature analysis allowed for a preliminary mapping of the areas within auditing where ML has been explored, identifying seven primary research fields. These include, among others, fraud risk assessment, audit process efficiency, and the reduction of subjectivity in professional judgment. Furthermore, three key issues emerge as critical challenges for the future: professional judgment subjectivity, financial misstatements, and overall audit efficiency. The study also outlines three future research directions: 1) exploring the potential implications of AI/ML-based systems on accounting and auditing standards; 2) investigating whether ML integration can enhance the competitive advantage of both large and small audit firms in terms of time savings, process automation, and improved audit quality; 3) identifying appropriate ML applications to increase prediction accuracy, such as in financial fraud detection and financial distress forecasting, while also reducing subjectivity in risk assessments and going concern evaluations.

This study offers several significant implications for both scholars and practitioners. From an academic perspective, it contributes to Agency and Stakeholder theories (Freeman, 1984; Jensen & Meckling, 1976), suggesting that integrating ML into auditing procedures could greatly enhance the transparency of corporate reporting, reduce subjectivity, and lower agency costs related to principal-agent issues, such as misreporting and neutral assessments (Manita et al., 2020). From a practical standpoint, the findings provide important insights for regulators, policymakers, and audit firms. Regulators should consider the potential implications of ML on reporting and auditing standards, while audit firms, given the high predictive power of ML models used in the quantitative papers reviewed, should integrate these technologies into their strategic frameworks to achieve cost, time, and quality benefits. Furthermore, managers may also be affected by these developments, as the increasing predictive power of ML models could lead to stricter scrutiny regarding financial misreporting or fraud attempts.

However, this study is not without limitations. First, the use of a single database (i.e., Scopus) may have not included relevant publications; moreover, the clustering procedure used to identify the seven research areas was manual, potentially introducing subjectivity into the research methodology. Future studies could address these limitations by incorporating a wider range of databases (e.g., Web of Science and Google Scholar) and employing more quantitative and objective clustering techniques.

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