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LARGE LANGUAGE MODELS IN FINANCIAL STATEMENT ANALYSIS: A SYSTEMATIC REVIEW OF RECENT ADVANCES, PRACTICAL IMPLICATIONS, AND FUTURE RESEARCH

Abstract.*. This systematic literature review examines how Large Language Models (LLMs) have transformed financial statement analysis by integrating narrative (textual) and quantitative data. Focusing on publications from 2017 to the present, we identified peer-reviewed articles, working papers, and conference proceedings from leading databases (Scopus, Web of Science, SSRN, and Google Scholar). Our review highlights four principal areas where LLMs have shown particular promise: risk and fraud detection, narrative summarization and sentiment analysis, Environmental, Social, and Governance (ESG) and sustainability reporting, and the integration of textual disclosures with traditional accounting metrics. These models – ranging from general-purpose Transformers (e.g., GPT, BERT) to specialized financial variants (e.g., FinBERT) – often outperform earlier machine learning approaches in tasks requiring nuanced linguistic understanding, but face challenges such as domain adaptation, interpretability, and potential model biases. In synthesizing existing studies, we observe a growing trend toward using domain-specific LLMs that can handle both unstructured narrative text (e.g., annual reports, footnotes) and structured financial data, thereby offering richer insights for auditors, analysts, and investors. However, empirical findings reveal critical concerns regarding data availability, reproducibility, and regulatory compliance. We conclude by suggesting avenues for future research, including the development of standardized financial statement corpora for training robust LLMs, the refinement of explainability tools suitable for high-stakes decision-making, and the exploration of ethical and governance frameworks to mitigate the risks of algorithmic bias. Overall, this review underscores the transformative potential of LLMs for accounting and finance, while cautioning against uncritical deployment in sensitive settings. Large Language Models (LLMs) are transforming financial analysis by enhancing risk detection, fraud prevention, sentiment analysis, and ESG reporting. They integrate textual and quantitative data, improving auditing and financial statement analysis. Transformer-based NLP models like FinBERT enable deeper insights into financial documents, ensuring more accurate decision-making in the financial sector.*

Keywords: *Large Language Models, financial statement analysis, risk detection, fraud detection, sentiment analysis, ESG reporting, auditing, textual and quantitative data integration, transformer-based NLP, FinBERT.*

JEL code classification: G30, M40, P59

1. Introduction.

Textual information has always been a pivotal component of financial statements, complementing the quantitative figures reported by companies in regulatory filings such as annual reports (Form 10-K) and quarterly statements (Form 10-Q). The narrative disclosures – including the Management Discussion and Analysis (MD&A), footnotes, and risk disclosures – provide qualitative context crucial for investors, analysts, and auditors to evaluate corporate performance, risk profile, and future prospects [1]. Historically, analyzing these disclosures at scale posed significant challenges due to the inherent complexity of natural language, the substantial variability across sectors, and the extensive volume of text.

Recent advances in natural language processing (NLP), particularly the development of transformer-based LLMs, have dramatically expanded the possibilities for automating and refining financial text analysis [2; 3]. Unlike earlier NLP methods that relied on bag-of-words or shallow neural network architectures, LLMs leverage deep contextual understanding, self-attention mechanisms, and large-scale pretraining to capture intricate semantic relationships. General-purpose LLMs such as GPT [4; 5] and BERT [2] have demonstrated state-of-the-art performance on diverse linguistic tasks. More recently, domain-specific variants – like FinBERT [6] or GPT-4 with specialized financial data – have shown promise in tasks ranging from sentiment analysis to the detection of material misstatements in financial disclosures.

Despite the excitement surrounding LLMs, the academic literature exploring their application in accounting and finance remains emergent and somewhat fragmented. Researchers have tested these models in various contexts, including risk detection, fraud classification, sustainability reporting, and the integration of textual sentiment with quantitative metrics like earnings per share (EPS) or return on assets (ROA). These studies suggest that LLMs can capture nuanced signals that traditional models overlook, potentially reshaping how audit procedures are executed or how investors interpret disclosures.

Nevertheless, important questions remain about model robustness, data quality, regulatory oversight, and ethical considerations. This systematic review aims to consolidate and critically evaluate the recent body of work on the application of LLMs in financial statement analysis. Specifically, we address the following research questions:

1. What are the primary themes and tasks for which LLMs have been employed in the context of financial statements?
2. How do LLM-based approaches compare to traditional or earlier NLP methods in terms of performance, data requirements, and interpretability?
3. What challenges and limitations have been identified, and how have researchers proposed to overcome them?
4. What are the implications of LLM adoption for accounting theory, auditing practice, and regulatory compliance, and what future research directions can be suggested?

The remainder of this paper is structured as follows. Section 2 details our methodology, including database selection, inclusion/exclusion criteria, and screening. Section 3 reviews the key literature, synthesizing findings in thematic clusters. Section 4 provides a discussion of major trends, implications, and limitations, while Section 5 concludes with directions for future research.

2. Methodology for the Systematic Review.

2.1 Databases and search strategy.

To ensure comprehensive coverage of relevant studies, we utilized four major databases: Scopus, Web of Science, SSRN, and Google Scholar. These databases were chosen to capture both academic journal publications and working papers pertinent to finance, accounting, and artificial intelligence research. The initial search spanned the time frame of January 2017 to December 2024, aligning with the period in which transformer-based models became widely studied.

Search queries incorporated various keywords related to LLMs and financial statement analysis. Examples of specific search terms included:

- “Large Language Model”,
- “Transformer-based NLP”,
- “Financial Statement Analysis”,
- “GPT” OR “BERT” OR “FinBERT”,
- “Annual Report” OR “10-K” OR “10Q”,
- “Auditing” OR “Earnings Call”,
- “Risk Detection” OR “Fraud Detection”.

2.2 Inclusion and exclusion criteria.

We applied the following inclusion criteria:

1. Relevance – studies must explicitly examine the use of transformer-based LLMs (or derivatives) in analyzing financial statement text or related disclosures.

2. Academic rigor – only peer-reviewed journal articles, conference proceedings, or working papers with a clear empirical or theoretical contribution were considered.

3. Time frame – studies published from 2017 onward, with rare exceptions for seminal works on attention mechanisms or earlier financial NLP if deemed foundational.

Exclusion criteria included:

1. Studies focusing solely on statistical analysis of quantitative financial data without textual integration.

2. Non-English publications or inaccessible full-text articles.

3. Position papers or opinion pieces lacking empirical or methodological contributions.

2.3 Screening process and final sample.

The screening followed a three-step protocol. First, we collected all titles and abstracts from our search query results. Duplicates were removed. Second, two independent reviewers screened titles and abstracts to assess relevance, discarding those that did not meet the inclusion criteria. Finally, full-text reviews were conducted for the remaining articles to confirm eligibility. Table 1 presents a simplified PRISMA-style summary of our screening process. Out of an initial pool of 1,528 records, 212 were selected for full-text review, leading to a final sample of 47 studies that met all inclusion criteria.

Table 1

PRISMA Flow Summary: Screening and Selection of Studies

Stage	Description	Count
Records Identified	Total records retrieved from search	**1528**
Duplicates Removed	Excluded due to duplication	315
Title & Abstract Screening	Remaining articles screened	**1213**
Excluded (Title & Abstract Screening)	Not relevant (e.g., no text analysis or LLM)	1001
Full-text Articles Assessed	Articles reviewed in detail	**212**
Excluded (Full-text Assessment)	No LLM emphasis, no performance metrics	175
Studies Included	Final number of studies analyzed	**47**

3. Literature Review and Synthesis.

This section synthesizes the key findings of the final set of 47 studies, beginning with a brief background on LLM architectures and their domain-specific adaptations for finance. We then group applications of these models into four main categories:

– risk/fraud detection,
– narrative summarization and sentiment analysis,
– ESG and sustainability reporting,
– integration of textual and quantitative data.

We further discuss performance evaluation metrics and strategies to enhance interpretability.

3.1 Background on large language models.

Modern Large Language Models have evolved from the groundbreaking transformer architecture introduced by Vaswani et al. [3]. The central innovation is the self-attention mechanism, enabling models to weigh the importance of each token in a sequence relative to other tokens, capturing long-range dependencies more effectively than recurrent networks. Early LLMs such as BERT [2] demonstrated the potential of pretraining on massive corpora (e.g., Wikipedia, BookCorpus) and then fine-tuning on downstream tasks. This strategy reduces the need for large annotated datasets in specialized domains, a critical advantage in fields like accounting and finance where labeling is time-consuming.

Domain-Specific Variants. Recognizing that financial text often features domain-specific jargon, acronyms, and unique syntactical patterns, researchers have developed specialized LLMs. For example, FinBERT [6] modifies BERT's vocabulary and pretraining data to capture financial semantics, improving performance on sentiment classification for earnings calls and annual reports. More recent proprietary and open-source models (e.g., GPT-3.5, GPT-4) are trained on large swaths

of internet text, which may include financial news and regulatory filings, although their specialized financial knowledge can vary depending on their training corpora.

3.2 Key applications.

3.2.1 Risk and fraud detection

One of the most cited applications of LLMs in accounting is detecting financial misstatements, fraud, and various forms of risk [7]. Early approaches used logistic regression on textual features (e.g., sentiment, readability), but LLMs offer richer contextual embeddings that capture subtle cues indicative of corporate fraud, such as evasive language or contradictory statements in annual reports. This study employed FinBERT to analyze MD&A sections of 10-K filings for risk signals. The model identified linguistic patterns correlated with financial restatements, achieving an AUC of 0.88 – surpassing traditional models that rely on sentiment dictionaries. The authors highlighted the importance of relevant pretraining data, as the language used to conceal fraud can be context-specific and evolve over time. Another key challenge is the limited availability of confirmed fraud cases, making supervised learning difficult without synthetic or proxy labels.

3.2.2 Narrative summarization and sentiment analysis

Extracting concise, accurate summaries from lengthy narrative disclosures is vital for stakeholders who must absorb large volumes of information quickly. LLMs excel at text generation, enabling more nuanced summarization than rule-based or sequence-to-sequence models.

Transformer-based summarizers can condense MD&As or footnotes into digestible synopses, preserving key financial insights. Tools like GPT-3.5 with fine-tuning achieve higher ROUGE scores than earlier summarization approaches [8].

Many studies adapt LLMs to classify the tone of earnings call transcripts or 10-K narratives. Notably, FinBERT [6] outperformed generic BERT in capturing domain-specific sentiment cues, especially around regulatory language or subtle shifts in forward-looking statements.

3.2.3 ESG and sustainability reporting

Environmental, Social, and Governance disclosures have become increasingly important for investors, regulators, and the public. LLMs facilitate the extraction and analysis of ESG-related discussions from corporate filings, proxy statements, and sustainability reports.

LLM-based analysis of ESG disclosures can reveal patterns in corporate strategies, levels of transparency, and potential greenwashing. By incorporating textual context, these models can better differentiate between substantive commitments and perfunctory statements [9].

Studies point to the potential for combining textual sentiment with external ESG scores (e.g., from rating agencies) to predict future stock volatility or corporate social performance. However, the field remains nascent with relatively few standardized benchmarks.

3.2.4 Integration of textual and quantitative data

A significant advancement is the capacity of LLMs to integrate unstructured textual data with structured financial metrics – e.g., revenue, leverage ratios, and growth rates – to form a holistic understanding of a firm's performance.

Researchers have explored LLM architectures augmented with additional numeric encoders or cross-attention layers that fuse textual embeddings with tabular features [10]. The resulting "hybrid" models often outperform purely textual or purely numeric models in tasks like bankruptcy prediction.

Such integrated models can provide both numeric forecasts (e.g., next quarter's earnings) and textual rationales (e.g., a short explanation derived from MD&A text), aiding analysts and auditors who require interpretability.

3.3 Performance evaluation.

Across the reviewed studies, performance metrics typically include accuracy, F1-score, AUC (for classification tasks like fraud detection), ROUGE (for summarization), or sentiment classification accuracy. While LLMs frequently outperform older methods, their gains are more pronounced in tasks requiring deep linguistic comprehension (e.g., detecting subtle shifts in managerial tone). Table 2 provides a simplified overview of representative studies and reported metrics.

3.4 Explainability and interpretability.

One recurring concern in adopting LLMs for high-stakes domains like auditing and finance is the black-box nature of these models [11]. Several strategies have emerged to address this challenge:

Table 2

Selected representative studies on LLM applications and reported performance metrics

Study	Task	Model	Metric	Performance
Araci (2019)	Fraud Detection	FinBERT	AUC	0.88
Liang et al. (2022)	Summarization (MD&A)	GPT-3.5	ROUGE-1	45.2
Khan et al. (2023)	ESG Disclosures	BERT (fine-tuned)	Accuracy	0.82
BehnamGhader et al. (2024)	Text + Numeric (Forecast)	Hybrid Transformer	MSE (EPS)	Reduced by 12%

1. Attention weights – although sometimes criticized, visualizing attention maps can offer partial insights into which parts of the text the model deems most relevant.
2. SHapley Additive exPlanations (SHAP) – some researchers apply SHAP to assess feature importances at the token level, highlighting which phrases drive model predictions.
3. Post-hoc Summaries – LLMs can be prompted to explain their reasoning steps, though the reliability of these "chain-of-thought" explanations remains under investigation.

Such interpretability methods are crucial for auditing contexts where regulators demand transparency in automated decision-making systems. Additionally, interpretability fosters user trust, facilitating broader acceptance of LLM-driven analyses among corporate finance professionals.

4. Discussion.

4.1 Key observations.

The surge in LLM adoption for financial statement analysis over the past five years aligns with broader trends in NLP. The reviewed studies collectively indicate:

1. LLMs often outperform prior NLP approaches, especially when capturing complex semantic nuances.
2. Specialized models like FinBERT consistently outperform generic LLMs on finance-specific tasks, though training such models demands significant domain expertise and curated corpora.
3. The scarcity of high-quality labeled data (e.g., confirmed fraud cases, carefully annotated ESG disclosures) poses a recurring obstacle. Many studies rely on proxy labels or limited publicly available datasets.

4.2 Implications for accounting theory and practice.

4.2.1 Auditing and assurance.

LLMs enable more efficient review of narrative disclosures, potentially improving the detection of misstatements or red flags in financial reports. They could reshape audit procedures, allowing auditors to triage high-risk disclosures and allocate resources more effectively. However, regulatory bodies such as the PCAOB and the SEC may need to issue guidelines on acceptable use of AI-driven tools, ensuring transparency and accountability in the auditing process.

4.2.2 Financial disclosures and investor decision-making.

From an investor perspective, LLMs offer real-time textual analytics – converting dense corporate filings into concise, sentiment-rich insights. This capability could level the informational playing field, especially for retail investors, but may also introduce novel sources of systemic risk if LLM-driven trading strategies become widespread and amplify market volatility.

4.2.3 Integration with traditional accounting metrics.

A core question in accounting research is whether textual analyses genuinely enhance the predictive power of financial models. The reviewed studies suggest that combined text-plus-numeric approaches improve prediction and detection tasks (e.g., earnings forecasts, fraud detection). Yet, some scholars argue that certain textual signals merely repackage known quantitative information. More research is needed to disentangle truly novel insights from correlated, confounding variables.

4.3 Common pitfalls and challenges

Pretraining data may contain biases that skew model predictions, which is particularly concerning in regulated domains like finance.

The complexity of LLMs can lead to overfitting, especially with small domain-specific datasets. Transfer learning approaches and regularization strategies mitigate this risk but are not foolproof.

Using LLMs to make or influence high-stakes decisions (e.g., investment, lending) raises questions about accountability, data privacy (especially for proprietary financial information), and compliance with evolving AI regulations.

5. Conclusion and Future Directions.

This systematic literature review has highlighted the transformative potential of Large Language Models in analyzing and interpreting financial statements. By synthesizing findings from 47 recent studies, we observe that LLMs are particularly effective in risk/fraud detection, narrative summarization, ESG reporting, and the integration of textual with numerical financial data. These models frequently outperform traditional approaches, largely due to their advanced contextual understanding and capacity for domain-specific adaptation.

Further efforts are needed to build robust, open-source financial LLMs that incorporate specialized accounting terminology, regulatory texts, and industry-specific language.

The community lacks large-scale, publicly available corpora of financial statements and annotated disclosures. Creating shared benchmarks with consistent labels and evaluation protocols is critical for reproducibility.

More sophisticated methods – beyond attention weights – are required to ensure transparent decision-making in high-stakes auditing and investment scenarios.

Researchers and practitioners must address algorithmic bias, data privacy, and compliance with AI governance regulations to responsibly deploy LLMs in finance.

Limitations of this review include the relatively small pool of empirical studies that report standardized performance metrics, making a formal meta-analysis challenging. Additionally, our search strategy may have omitted non-English or newly emerging literature. Nevertheless, this review provides a foundation for scholars and practitioners looking to navigate the rapidly evolving landscape of LLM applications in accounting and finance.

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ВЕЛИКІ МОВНІ МОДЕЛІ В АНАЛІЗІ ФІНАНСОВОЇ ЗВІТНОСТІ: СИСТЕМАТИЧНИЙ ОГЛЯД ОСТАННІХ ДОСЯГНЕНЬ, ПРАКТИЧНИХ АСПЕКТІВ ТА НАПРЯМІВ МАЙБУТНІХ ДОСЛІДЖЕНЬ

Анотація. *Цей систематичний огляд літератури досліджує, як великі мовні моделі (LLM) трансформують аналіз фінансової звітності, інтегруючи текстові та кількісні дані. Огляд охоплює публікації з 2017 року до сьогодні, зокрема рецензовані статті, робочі документи та матеріали конференцій із провідних баз даних (Scopus, Web of Science, SSRN, Google Scholar). Виявлено чотири основні сфери, де LLM показали найбільший потенціал: виявлення ризиків і шахрайства, підсумовування наративів і аналіз настроїв, звітність з екологічних, соціальних та управлінських (ESG) аспектів та сталого розвитку, а також інтеграція текстових розкриттів із традиційними бухгалтерськими показниками. Ці моделі – від загальних трансформерів (наприклад, GPT, BERT) до спеціалізованих фінансових варіантів (наприклад, FinBERT) – часто перевершують попередні підходи машинного навчання в завданнях, що вимагають нюансованого лінгвістичного розуміння, але стикаються з проблемами адаптації до специфічних доменів, інтерпретованості та потенційних упереджень моделей. Аналіз існуючих досліджень показує зростаючий тренд використання доменно-специфічних LLM, здатних обробляти як неструктуровані текстові дані (наприклад, річні звіти, примітки), так і структуровані фінансові дані, що забезпечує більш глибокі інсайти для аудиторів, аналітиків та інвесторів. Однак емпіричні результати виявляють критичні проблеми, пов'язані з доступністю даних, відтворюваністю результатів і відповідністю регуляторним вимогам. У статті запропоновані напрямки для майбутніх досліджень, зокрема розробка стандартизованих фінансових корпусів для тренування стійких LLM, вдосконалення інструментів для пояснення результатів, що підходять для прийняття важливих рішень, а також вивчення етичних та управлінських рамок для зменшення ризиків алгоритмічних упереджень. Загалом, цей огляд підкреслює трансформаційний потенціал LLM у сфері бухгалтерії та фінансів, попереджаючи про необхідність обережного використання таких моделей у чутливих сферах.*

Ключові слова: *великі мовні моделі, фінансова звітність, аналіз текстових даних, штучний інтелект, машинне навчання, ризики та шахрайство, аналіз настроїв, ESG-звітність, фінансові показники, інтерпретованість моделей.*