DOI: 10.53469/jssh.2025.7(10).12

Application and Exploration of Artificial Intelligence Technology in Audit Risk Identification

Weicheng Pan

School of Computer Science, Nanjing Audit University, Nanjing 211815, Jiangsu, China

Abstract: ***Audit risk identification is a core task in the audit planning stage, and its results directly affect the accuracy and reliability of audit conclusions. Under the traditional audit model, constrained by tight timelines and limited technical means, auditors often have difficulty mining and verifying massive volumes of raw data in a timely and comprehensive manner. However, with the powerful natural language processing capabilities of large language models (LLMs) and the automated execution features of intelligent agents (Agents), auditors are now able to quickly filter and deeply analyze various structured and unstructured data, accurately identify key audit risks, and further improve and systematically construct the audit evidence chain. This paper focuses on analyzing the collaborative working mechanism of LLM and Agent technologies in audit risk identification, designs an intelligent audit risk identification methodology that integrates LLM and Agent, and discusses its application value in multi-source data analysis, evidence chain construction, and other aspects.***

Keywords: Audit, Artificial Intelligence, Large Language Models, Agents.

1. Introduction

President Xi Jinping emphasized at the 2025 National Audit Work Conference that auditing must deepen reform and innovation, build a centralized, unified, fully covered, authoritative, and efficient audit supervision system, and continuously improve the quality and effectiveness of audit oversight to safeguard high-quality economic and social development. In recent years, audit institutions have achieved remarkable results by focusing on the central tasks of the Party and the state and fully leveraging the role of auditing in ensuring national economic security, revealing risks and hidden dangers, and promoting anti-corruption efforts. However, with economic globalization and technological progress—especially the rapid development of information technology—audit work is facing unprecedented challenges and transformations. Specifically, **first**, the volume of data has exploded, transaction structures are increasingly complex, and financial products are continuously innovating. Traditional methods are inefficient at handling large-scale data, making it difficult to promptly and accurately pinpoint audit risks, thereby placing enormous pressure on modern auditing. **Second**, audit data sources are becoming increasingly diverse: they include not only traditional financial data but also massive unstructured data such as emails, documents, images, etc. Traditional auditing methods struggle to effectively extract and analyze this unstructured information, which means important clues may be overlooked [2,3].

Currently, the rapid development of new-generation artificial intelligence technology is driving a revolutionary change in audit risk identification paradigms. Many scholars such as Zhu Yi [4] and Huang Jiajia [5] are exploring how AI can reconstruct the pathways for identifying and validating audit risks, thereby improving the quality and efficiency of audit work. Advanced AI technologies represented by large language models (LLMs) are profoundly reshaping the methodology of audit risk identification. With their outstanding semantic understanding and text generation capabilities, LLMs can efficiently process massive audit data and provide powerful technical support for auditing. At the same time, the deep integration of LLMs with intelligent agents (Agents) further expands the technological boundaries of audit risk identification, offering new possibilities for intelligent auditing.

This study aims to theoretically explore how current AI technologies (especially LLMs and intelligent agents) can enhance the efficiency and accuracy of audit risk identification. Centered on the core question of "the technological coupling of LLMs and Agents, exploring how intelligent audit risk identification can achieve dual improvements in quality and efficiency under the assistance of new-generation AI," this paper proposes the following approach:

1) **LLM-driven data extraction and cross-verification:** Combine the multimodal data processing capability of LLMs with the automated workflow of Agents to automatically extract unstructured data and perform cross-verification.

2) **Semantic reasoning and intelligent rule engine:** Leverage the semantic reasoning ability of LLMs to construct a potential intelligent rule engine, enabling the Agent to conduct associative data analysis in complex contexts.

3) **Closed-loop feedback mechanism:** Explore the possibility of establishing a closed-loop feedback mechanism between LLMs and Agents to dynamically optimize risk identification strategies and reduce human intervention.

This technical integration concept breaks through the linear work pattern of traditional audit risk identification and theoretically demonstrates the potential value of combining cognitive intelligence with behavioral intelligence. Consequently, an AI-driven audit risk identification solution can provide the auditing industry with an exploratory intelligent infrastructure and offer insights for updating and upgrading audit methodologies.

2. Literature Review

2.1 Artificial Intelligence Development and the Rise of

Large Models

Early research in artificial intelligence (AI) focused mainly on symbolic logic reasoning and rule-based expert systems, but due to limitations in computing power and data resources, the application scenarios were very restricted. Entering the 21st century, the rise of deep learning and leaps in computing capacity have propelled the rapid development of AI. The proposal of the Transformer architecture [6] and the widespread use of GPUs in deep learning [7] provided breakthrough progress for large-scale natural language processing. Building on these advances, large language models (LLMs) gradually became central to AI research. In 2022, OpenAI launched ChatGPT, demonstrating powerful capabilities in language understanding, reasoning, and multimodal processing [8], and ushering in a wave of generative AI. Since then, Google, Meta, and domestic companies such as Baidu, Alibaba, and iFlytek have released their own large models, bringing LLMs into professional fields like finance, medicine, and auditing [9].

2.2 Progress in AI Applications for Audit Risk Identification

AI's initial applications in auditing were embodied in tools like natural language processing (NLP), optical character recognition (OCR), and robotic process automation (RPA), for example in contract review, invoice authenticity verification, and working paper generation. However, these methods have limitations when processing unstructured data and complex contexts. With the advent of LLMs, researchers found that these models can process massive text and other unstructured data in a short time, quickly identify risk points and generate preliminary audit clues, thereby significantly improving evidence collection efficiency and accuracy [10]. Further, by combining retrieval-augmented generation (RAG), knowledge graphs, and domain-specific fine-tuning, some scholars have proposed building audit-focused large models, i.e., "audit expert models," to enhance a model's adaptability and reliability in professional audit scenarios.

In recent years, the fusion of intelligent Agent technology with LLMs has been regarded as a new pathway for upgrading audit risk identification models. Zhang Li et al. [11] pointed out that audit intelligent agents can achieve process automation and risk identification through tool invocation and multi-Agent collaboration. Wang Yueyun, Ding Mei et al. [12] proposed a framework based on RAG and Agents that improved the accuracy of judgments in key tasks by over 20% compared to baseline models, and, by incorporating differential privacy and federated learning methods, also ensured data security and compliance. These explorations provide a theoretical basis and methodological reference for constructing an intelligent risk identification system that is self-optimizing and evolves in a closed loop.

2.3 Review and Limitations

Overall, the application of AI in audit risk identification has shifted from rule-driven to data-driven approaches, and is gradually entering a new stage of "large model + Agent" collaborative driving. Existing research shows that AI has clear advantages in processing unstructured data, identifying risks, and automating processes, offering new ideas for improving audit quality and efficiency. However, most current studies remain at the stage of theoretical conception or prototype validation, lacking systematic experiments and empirical analysis in real audit scenarios [13]. In terms of robustness in complex audit tasks, multi-Agent collaboration mechanism design, and cost-benefit evaluation, further in-depth research and practical exploration are needed. Going forward, stronger collaboration among industry, academia, and research institutions is required to advance intelligent auditing technology from concept to mature application.

3. Technical Framework for Intelligent Audit Risk Identification

With the rapid development of AI technology, the deep combination of LLMs and Agents provides a brand-new paradigm for audit risk identification. As illustrated in **Figure 1**, the intelligent audit risk identification system can be divided into four core modules: **Multi-modal Data Integration**, **Logic Iteration**, **Data Evaluation**, and **Rationality Verification**. This framework not only achieves unified integration and processing of different types of data, but also constructs a closed-loop risk identification logic through reasoning, verification, and feedback mechanisms, thereby providing more systematic and intelligent technical support for audit work.

3.1 Multi-modal Data Integration: Comprehensive Ingestion and Unified Preprocessing

In traditional auditing, clues primarily come from structured data such as financial statements and accounting vouchers. However, as business activities grow more complex, audit clues have become increasingly diverse, including contract text, emails, scanned images, voice recordings, and external transaction logs, among other unstructured data. The multi-modal data integration module is designed to address this challenge.

Specifically, this module adopts a pluggable approach to ingest different data sources, including spreadsheet processing plugins, image processing plugins, text processing plugins, and other data handling plugins. Each plugin operates under a unified task list, enabling synchronous parsing and preprocessing of heterogeneous data. On this basis, structured data enters a data modeling and cross-check stage, while unstructured data is subjected to natural language processing and feature extraction before proceeding to subsequent semantic analysis stages. This design ensures that audit clues from multi-source inputs can be represented in a unified manner, thereby avoiding information silos.

Multi-modal integration offers several advantages. On one hand, it significantly broadens the range of sources for clues in audit risk identification, allowing more potential clue data to be brought into the analysis. On the other hand, it lays the data foundation for subsequent logical reasoning and semantic analysis, providing auditors with a "panoramic" perspective of evidence.

3.2 Logic Iteration and Semantic Reasoning: Intelligent Understanding and Progressive Optimization

In the process of identifying and handling risk clues, relying solely on data parsing is not sufficient to support complex audit judgments. The logic iteration module achieves multi-round reasoning and stepwise optimization through a division of labor between a coordinating "host" LLM and several specialized "reasoning" LLMs. The host LLM serves as the core coordinator, responsible for task decomposition and results integration, whereas the reasoning LLMs each undertake specific sub-tasks (for example, analyzing contract clauses, performing numerical logic checks, identifying anomalous risk patterns, etc.).

The key to this mechanism lies in iterative feedback. Each round of reasoning results is fed back to the host LLM, which then triggers new task decompositions and pathway adjustments. Through multiple iterations, the system can gradually converge on a reasonable conclusion, avoiding the biases or errors that a one-shot output might produce. Meanwhile, a semantic reasoning component introduces audit domain knowledge and industry standards, ensuring that the final output is not only logically sound but also compliant with professional auditing standards.

This progressive reasoning approach not only mitigates the "hallucination" problem of a single-pass model generation, but also allows the system to remain stable and reliable in complex audit scenarios. For example, in performing a cross-year revenue recognition check, the host LLM can integrate multi-angle analyses from the reasoning LLMs—including contract execution status, invoice flows, and fund receipt information—thereby producing an audit judgment that more closely aligns with the actual business context.

3.3 Data Evaluation and Dual Filtering: Multi-layer Assurance and Risk Control

During auditing, validating data is critical to ensure the credibility of conclusions. The data evaluation module introduces a "dual filtering" mechanism, combining the strengths of rule-based engines and LLM-based reasoning to provide multi-layered gatekeeping.

The first layer of filtering comes from a preset rule engine, which typically includes cross-verification checks, trend analyses, range validations, and other quantitative criteria. This mechanism can quickly screen out obviously abnormal or non-compliant data, thus improving efficiency. The second layer of filtering is performed by an LLM, which makes a holistic judgment based on context and semantic logic, compensating for the rigidity of hard-coded rules. For example, in analyzing expense reimbursement documents, the rule engine might only flag amounts that exceed preset limits, whereas the LLM could further identify cases where "the amount is within limits but inconsistent with the business context."

With these dual safeguards, the data evaluation module not only prevents false risk data from creeping in, but also avoids the false positives and negatives that overly mechanical audits might cause. This achieves a multidimensional improvement in the quality of audit clues.

3.4 Rationality Verification and Result Output: Closed-loop Feedback and Evidence Chain Generation

Finally, the rationality verification module employs a parallel multi-channel validation mechanism to ensure the reliability of audit results. Different reasoning LLMs re-examine the findings from the perspectives of numerical logic, business context, and semantic consistency. If any inconsistency or anomaly is detected, the system automatically returns to the logic iteration module for reanalysis and regeneration of results.

After completing multiple rounds of verification, the LLM-based summary component consolidates all results and produces a well-organized, logically coherent list of risks. This list is not the final audit report itself, but—given its traceable and reviewable nature—it can serve as an important basis and supporting material for drafting the audit report.

In summary, the intelligent audit risk identification framework uses multi-modal integration, iterative reasoning, dual filtering, and rationality verification to establish a closed-loop and dynamically optimized evidence-gathering mechanism. This system breaks away from the traditional audit approach that relies heavily on manual experience and linear procedures, providing a systematic technological solution for audit practice.

4. Practical Implications and Challenges

4.1 Implications for Audit Practice

The introduction of an intelligent framework makes it possible for audit risk identification to move from the traditional practice of sampling checks toward comprehensive coverage. Through multi-modal integration, auditors can rapidly draw upon a richer set of data sources, reducing the chance of missing key evidence. Through logic iteration and semantic reasoning, the system can achieve deep understanding of complex business scenarios, thereby improving the accuracy of audit judgments. This shift signifies that audit methodology is transforming from "experience-driven" to "intelligence-driven," and the role of auditors is evolving from that of data processors to overseers of decision-making—focusing more on high-level judgment and reasoning.

4.2 Need for Institutional and Regulatory Adaptation

While the intelligent audit framework provides technological support, it also raises new challenges for the institutional environment. First, the legal validity of AI-generated evidence has yet to be fully established; regulators urgently need to clarify how such evidence should be treated in audit reports. Second, the question of responsibility allocation must be resolved: if a model's misjudgment leads to a distorted audit conclusion, should the accountability lie with the auditor, the technology provider, or the oversight authorities? In addition, current auditing standards still largely presume manual evidence collection as the norm. It will be necessary to develop dedicated guidelines for AI-assisted auditing in the future to ensure that technological applications are aligned with legal and regulatory frameworks.

4.3 Data Security and Privacy Protection

Auditing involves a large amount of sensitive information, and the introduction of AI inevitably brings risks to data security and privacy. How to ensure that client data is not misused when using LLMs and Agents, and how to prevent data leakage during cross-system or cross-platform operations, are issues that must be addressed. Emerging technologies such as differential privacy, federated learning, and blockchain-based recordkeeping offer possible solutions, but they still require tailored practice and validation in audit scenarios.

4.4 Talent Development and Organizational Transformation

The implementation of an intelligent audit framework depends on building a team of professionals with diverse skill sets. Future auditors will need not only to master auditing standards and professional judgment, but also to possess basic literacy in data science and artificial intelligence. Universities and professional associations should incorporate courses on AI, data governance, and related subjects into audit education, in order to cultivate auditors capable of understanding and harnessing new technologies. At the same time, audit firms should establish new roles such as “AI Audit Supervisor” or “Data Analysis Specialist” to drive the organization’s shift from traditional hierarchies toward human-machine collaboration.

5. Conclusion

In the long run, the intelligent audit risk identification framework represents not only a technological innovation but also a strategic transformation of the audit supervision model. By utilizing closed-loop feedback mechanisms and traceable evidence chains, audit authorities can discover risks and uncover problems in a much shorter time, thereby enhancing the role of auditing in the national governance system. In the future, with the maturation of multimodal large models, explainable AI, and adaptive Agent orchestration technologies, intelligent auditing is expected to achieve “three transformations”: from sampling-based audits to full coverage, from reactive (ex-post) audits to real-time and proactive (ex-ante) audits, and from experience-driven decision making to intelligence-driven processes. This will not only improve the quality and authority of audit conclusions, but also expand the function of auditing in risk early-warning and governance oversight.

References

[1] Yang Jing. Research on audit technology and methods under the big data environment [J]. Modern Auditing and Economy, 2016(06).

[2] Guo Hongjian, Zhuang Mingju, Li Jiahao. Research on the application of unstructured data processing technology in investment big data audit [J]. Chinese Certified Public Accountant, 2025(02): 73–77.

[3] Zhu Yi, Hua Guiqi, Lou Jinwen. The impact of artificial intelligence on the development of audit profession under the background of new quality productivity - an empirical study based on auditor perception [J]. Friends of Accounting, 2025(06): 147–153.

[4] Huang Jiajia, Li Pengwei, Xu Chao. Research on thinking transformation and audit platform construction for smart auditing [J]. Audit Research, 2023(05): 11–20.

[5] Vaswani A, Shazeer N, Parmar N, et al. Attention is All You Need [J/OL]. arXiv, 2017. DOI:10.48550/arXiv.1706.03762.

[6] Krizhevsky A, Sutskever I, Hinton G. ImageNet Classification with Deep Convolutional Neural Networks [C] // Advances in Neural Information Processing Systems. Red Hook: Curran Associates Inc., 2012. DOI:10.1145/3065386.

[7] OpenAI. *Introducing ChatGPT* [EB/OL]. (2022-11-30) [2025-09-17]. https://openai.com/blog/chatgpt.

[8] Nie X, Zhang Z, Wang Z, et al. CFinBench: A Comprehensive Chinese Financial Benchmark for Large Language Models [EB/OL]. (2024-07-03) [2025-09-17]. https://arxiv.org/abs/2407.02301.

[9] Huang J, Wang L, Li Y, et al. AuditWen: An Open-Source Large Language Model for Audit [EB/OL]. (2024-10-15) [2025-09-17]. https://arxiv.org/abs/2410.10873.

[10] Zhang Li, Li Ming, Zhou Kai. Potential application and technical path of large language model in auditing [J]. Accounting Research, 2023(07): 85–94.

[11] Wang Yueyun, Ding Mei, Chen Hao. Research on intelligent audit framework driven by intelligent agents [J]. Finance and Accounting Monthly, 2024(12): 102–110.

[12] Rahman M, Zhu J, Li Y, et al. Does the Adoption of Artificial Intelligence by Audit Firms and Their Clients Affect Audit Quality and Efficiency? Evidence from China [EB/OL]. (2024-08-01) [2025-09-17]. https://www.researchgate.net/publication/383039276.