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Research on the Theoretical Logic and Development Path of Artificial Intelligence Audit

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Abstract: With the deep integration of digital technology and the real economy, AI auditing has emerged as a core paradigm that breaks through the pain points of traditional auditing, such as "sampling limitations, post-event lag, and reliance on manual labor". This paper systematically reviews the theoretical connotations of AI auditing, reveals its current practical status, deeply analyzes four core challenges: data quality, ethical compliance, talent adaptation, and institutional synergy, and proposes feasible development paths from four dimensions: technological optimization, institutional construction, talent cultivation, and industry synergy. The research indicates that AI auditing needs to be "based on data elements, driven by technological innovation, with institutional guarantees as the bottom line, and talent adaptation as the core", and achieve an upgrade from "tool assistance" to "governance synergy" under the promotion of new productive forces.

Keywords: Artificial intelligence audit; Audit quality; Digital transformation; New-quality productivity

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1. Introduction

1.1. Research background

1.1.1. Digital transformation drives the transformation of audit paradigm

The global digital economy has grown from \$22.5 trillion in 2016 to \$53.3 trillion in 2024. While digital technology reshapes business models, it also expands the scope of audit from "structured financial data" to "structured + unstructured + real-time streaming data". Liang et al. pointed out that new-quality productivity reconstructs audit production relations through "data elements + technological innovation", driving the transformation of auditing from "sample verification" to "full-scale intelligent analysis" - traditional manual auditing of annual reports of listed companies, which requires 30 people per week, can be completed by an AI audit system within 48 hours for full data verification [1].

1.1.2. Industry demand drives the implementation of AI auditing

From the perspective of enterprises, Xu's research shows that 85% of listed companies prioritize "improving audit quality and reducing compliance risks" as their core needs [2]. The "real-time monitoring" feature of AI auditing can solve the pain point of "irreversible discovery after the fact" in traditional auditing. From the perspective of audit institutions, Li pointed out that small and medium-sized accounting firms are facing the dual pressure of "30% increase in labor costs and low audit efficiency", and AI has become the key to reducing costs [3].

1.1.3. Policy support to guide the development of AI auditing

The "14th Five Year Plan for the Development of Digital Economy in China" clearly proposes to promote the digital transformation of auditing and enhance intelligent auditing capabilities. The EU's Digital Services Act (DSA) requires platform enterprises to conduct compliance audits using AI technology; The Public Company Accounting Oversight Board (PCAOB) of the United States will release the "AI Audit Guidelines" in 2024 to standardize the application of AI in auditing. The policy dividend provides institutional guarantees for AI auditing.

1.2. Research significance

1.2.1. Theoretical significance

This study aims to fill the theoretical gap of "integration of new quality productivity and auditing". Existing audit research mostly focuses on the application of a single technology, and there is insufficient exploration of systematic changes in audit models under new quality productivity. This article introduces the theory of new quality productivity into the field of auditing, constructs a four-dimensional framework of "data technology system talent", and explains the impact of new quality productivity on the form of audit data, technological logic, institutional system, and talent demand, providing a new perspective for the cross integration of the two theories.

Additionally, this study serves to enrich the theoretical foundation of auditing. Although the current responsible innovation perspective supports audit risk management, there are gaps in subject behavior and governance boundaries. This study also introduces the theory of holistic governance, clarifies the positioning of auditing in organizational governance, clarifies the collaborative boundaries with other management functions, and improves the theoretical system of auditing.

1.2.2. Practical significance

The practical significance are as follows:

(1) Provide industry standard references for policy-makers;

(2) Regarding the lack of digital standards for auditing, it is suggested to clarify the data quality threshold;

(3) Require audit firms to publicly disclose method logic and data compliance proof to avoid "black boxes method";

(4) Establish a digital tool filing system, clarify the scope of application and risk control measures, and promote standardization in the auditing industry.

1.3. Research innovation points

One of the innovation points of this research is its theoretical innovation, where we are constructing a four-dimensional framework for auditing driven by new quality productivity and breaking through the limitations of traditional audit theory's single dimension, guided by the theory of new quality productivity, and starting from the core elements.

Under the new quality productivity in the "data" dimension, it emphasizes the clarification of data collection and governance standards. In the "technology dimension", the focus lies on sorting out the path, such as process automation to enhance audit efficiency. The "system" dimension aims to refine the definition of audit responsibilities and to optimize the design of quality control mechanisms, thereby reinforcing accountability and consistency across the audit process. Conversely, the "talent" dimension defines the digital capability needs of auditors, proposes a training system approach, and achieves deep integration of the two theories.

The second is its practical innovation, through proposing a "low-cost transformation path" for small and medium-sized audit institutions. In response to the difficulty of transformation for small and medium-sized institutions, it is recommended to prioritize the introduction of low threshold process automation tools (such as voucher verification systems) to replace manual labor and improve efficiency. After resource accumulation, upgrade data analysis technology and transform in stages to reduce costs and risks.

2. Literature review

2.1. Theoretical connotation research

Cui et al. defined AI auditing as a "new model based on big data to achieve process automation, risk intelligence, and clear accountability" from the perspective of responsible innovation, and proposed a three-level accountability boundary of "AI model developers auditors enterprise management" [4]. Fang et al. constructed an "AI audit boundary recognition model" based on the theory of holistic governance, clarifying the criteria for dividing the "manual review process" and the "AI autonomous decision-making process" [5].

2.2. Technical application research

Li et al. used DeepSeek as an example and confirmed that its accuracy in identifying abnormal transactions reached 92%, which is 35% higher than traditional models [6]. Xu et al. added that DeepSeek can parse the Enterprise Accounting Standards through natural language processing to generate a "revenue recognition compliance report" [7]. Yun proposed the "RPA + AI combination model", which, after being applied by a manufacturing enterprise, improved the efficiency of "procurement approval verification" by 85% and reduced the error rate from 5% to 0.3% [8]. Xu pointed out that this model can cover 70% of repetitive audit tasks [9].

According to a survey conducted by Ni et al., 38% of manufacturing companies identified issues such as "abnormal equipment shutdown" and "energy waste" through "IoT device collection of production data + AI analysis", resulting in an 18% increase in production efficiency in a certain automobile factory [10].

2.3. Review of domestic and foreign research

From the current research status in the field of auditing at home and abroad, there are several research consensuses in academia:

(1) At the technical level, it is widely recognized that digital technology has a positive effect on improving audit efficiency and optimizing risk identification accuracy. It is believed that the application of automation tools and data analysis technology can effectively break through the efficiency bottlenecks and risk blind spots of traditional manual auditing;

(2) At the challenge level, uneven data quality, blurred ethical and compliance boundaries, and mismatched talent capabilities and technological applications have become common problems that constrain the digital development of auditing. It is necessary to focus on data governance, compliance control, and talent

cultivation;

(3) At the institutional level, it is proposed to improve the regulatory system and industry standards in the field of auditing, providing clear institutional guidance for digital auditing practices. However, there are still three shortcomings in existing research: at the theoretical level, there is insufficient exploration of the deep integration of cutting-edge theories such as new quality productivity and holistic governance with audit practice, making it difficult to fully explain the systematic changes in audit models under the new development background;

(4) At the practical level, there is a lack of differentiated research on the audit characteristics of different industries, and customized audit plans that are suitable for the needs of various industries have not been formed, resulting in limited guidance value of general research conclusions for specific industry practices;

(5) At the empirical level, domestic research mainly focuses on single case analysis, lacking large-scale questionnaire surveys and statistical tests covering multiple industries and institutions. The universality and persuasiveness of research conclusions need to be improved.

Based on this, the research positioning of this article focuses on the integration of new quality productivity and audit theory, and the coordinated development of system technology talent, aiming to fill the existing research gap.

3. Theoretical basis and definition of connotation

3.1. Theoretical basis

3.1.1. Theory of new quality productivity

The core of new quality productivity is "led by technological innovation, promoting the reconstruction of production factors and the transformation of production relations". This theory is reflected in three aspects in auditing: at the level of production factor reconstruction, data becomes the core audit element, gradually replacing the traditional audit model of "labor + sampling data", achieving full coverage and deep mining of audit data sources, and providing data support for accurate identification of audit risks.

At the level of production relations transformation, the audit subject has expanded from a "single audit institution" to a diverse collaborative entity of "audit institution + technical model developer + regulatory agency". Each entity needs to clarify their rights and responsibilities, such as technical model developers being responsible for ensuring the reliability of tools, audit institutions being responsible for standardizing the use process, regulatory agencies being responsible for supervising overall compliance, and jointly ensuring the standardized promotion of audit processes.

At the level of productivity improvement, the application of digital technology breaks through the "upper limit of manual efficiency" and realizes the audit mode of "full data + real-time analysis", significantly shortening the audit cycle and improving the timeliness and accuracy of risk identification.

3.1.2. Responsible innovation theory

The theory of responsible innovation emphasizes that "technological innovation needs to take into account ethical, legal, and social values." Its specific application in audit practice includes: the dimension of ethical responsibility, which requires the use of technical models in audits to avoid algorithmic discrimination. For example, in credit audit scenarios, it is necessary to prevent unreasonable evaluation bias towards small and micro enterprises by optimizing evaluation indicators, balancing data samples, and other methods to ensure fair and impartial audit results.

In terms of legal responsibility, it is necessary to clarify the responsible parties for “technical model errors”. For example, model developers should bear 30%–50% of the responsibility, and audit institutions should be responsible for the compliance of the model application process to avoid audit risks that cannot be traced due to unclear responsibility definitions.

In terms of social responsibility, audit work needs to serve the dual goals of “corporate compliance + social governance”, and accurately identify illegal activities such as “money laundering” and “tax evasion” through technological empowerment, providing audit support for maintaining market order and social fairness.

3.1.3. Holistic governance theory

The theory of holistic governance emphasizes “cross departmental and cross level collaboration to solve fragmentation problems”, and its application in auditing is mainly reflected in three aspects of collaboration:

(1) Cross-departmental collaboration: Audit institutions need to work with the internal finance IT, establish a collaborative mechanism among business departments, break down departmental data barriers, obtain comprehensive data covering the entire process of enterprise operations, and ensure the integrity and relevance of audit data;

(2) Cross-level collaboration: National, provincial, and municipal audit institutions need to establish a technical tool and data sharing mechanism. For example, a province needs to build a “provincial digital audit platform” to integrate audit resources across the province, covering audit services in 16 cities, and achieve efficient sharing of experience in technology application, data analysis, and risk identification between upper and lower level audit institutions;

(3) Cross-subject collaboration: Audit institutions need to establish a collaborative linkage mechanism with regulatory agencies (such as the China Securities Regulatory Commission and the China Banking and Insurance Regulatory Commission) to timely synchronize the clues of corporate violations discovered during the audit process to regulatory departments, and receive key regulatory direction guidance from regulatory departments, forming a “audit supervision” linkage force and enhancing the overall efficiency of market supervision and audit supervision.

3.2. Definition of connotation

3.2.1. Definition of refactoring

Based on the above theory, this study defines AI auditing as a new auditing model driven by new quality productivity, based on big data, and utilizing technologies such as machine learning, RPA, and the Internet of Things (IoT) to achieve automated auditing processes, intelligent risk identification, and collaborative governance. It needs to consider both ethical compliance and accountability, and serve the creation of enterprise value and social governance.

3.2.2. Comparison with traditional auditing

Table 1. Comparison of traditional auditing and artificial intelligence audit

Comparative dimension	Traditional auditing	Artificial intelligence audit	Increase margin
Scope of data processing	Sampling data (1%–5%)	Full data (100%)	Risk identification omission rate reduced from 15% to 2%
Audit efficiency	30 people per week	48 hours (AI system)	Efficiency increased by 95%
Risk identification type	Explicit risk (such as incorrect amount)	Explicit and implicit risks (such as concealment of related party transactions)	Hidden risk identification rate increased by 80%
Audit timeline	Post audit (such as annual audit)	Real-time + post audit	Risk response time reduced from 3 months to 1 hour
Personnel skill requirements	Auditing standards + financial Knowledge	Auditing standards + finance + AI technology + business knowledge	The demand for composite talents has increased by 120%
Cost structure	The main cost is labor (accounting for 80%)	Technical cost + labor cost (technology accounts for 40%)	Long-term cost reduction of 30% (after economies of scale)

4. The current practice status of artificial intelligence auditing

4.1. Industry application penetration rate

The AI application rate in the national audit industry is expected to reach 58% by 2025, an increase of 42 percentage points compared to 2020. The financial industry has the highest penetration rate (85%), followed by government auditing (72%), manufacturing (55%), retail (48%), and small and medium-sized accounting firms (32%). The penetration rate in the eastern region is 75%, significantly higher than the 45% in the central and western regions. The core reason is the difference between "technology investment capability" and "talent reserve".

4.2. Technical application preferences

The application rate of basic technologies such as simple machine learning reaches 80%, mainly used for "repetitive task automation". The application rate of advanced technologies such as deep learning and big models reaches 45%, mainly concentrated in the fields of finance and government auditing. The application rate of AI + blockchain and other integrated technologies reaches 25%, mainly used in "high-risk scenarios" such as credit audits and tax audits.

4.3. Preliminary feedback on implementation effect

Table 2. Satisfactory feedback upon the implementation of artificial intelligence auditing

Effect dimension	Very satisfied (%)	Satisfaction (%)	General (%)	Dissatisfied (%)	Average satisfaction
Audit efficiency improvement	45	40	13	2	4.2
Risk identification accuracy	38	42	18	2	4.0
Cost reduction	25	35	35	5	3.6
Operational convenience	20	40	35	5	3.4
Interpretability of results	15	30	45	10	3.0

5. Core challenges faced by artificial intelligence auditing

5.1. Data level challenges

The data level is a fundamental obstacle for artificial intelligence auditing, manifested in four major problems:

(1) Low data quality, including the problem of original vouchers not being digitized in enterprises, inconsistent data formats across multiple systems, a certain error rate in manual input, and lagging updates to enterprise data;

(2) Data security risks, such as unencrypted storage of sensitive data by audit institutions, lack of encrypted channels for enterprise audit data transmission, and lax control over enterprise data access permissions. A certain institution was fined 2 million Chinese Yuan for violating the Personal Information Protection Law due to data leakage (2024 case);

(3) Difficulties in data sharing, such as internal data silos within enterprises, lack of sharing mechanisms between audit institutions and banking, taxation and other departments, and cross-border data restrictions on international audit projects;

(4) High cost of data, with an average annual cost of 500000 to 2 million Chinese Yuan for enterprise digital transformation, 100000 to 500000 Chinese Yuan for professional data cleaning tools, and 50000 to 200000 Chinese Yuan for massive data storage, which small and medium-sized institutions find difficult to afford.

5.2. Technical challenges

The technological constraints on the large-scale application of AI auditing are reflected in four aspects:

(1) The problem of "black box" models, where deep learning models (such as DeepSeek and GPT) have difficulty tracing the decision-making process and lack a complete evidence chain in their output, which conflicts with auditing standards;

(2) Poor technical adaptability, as generic models cannot meet industry needs (such as financial anti-money laundering and manufacturing production efficiency auditing), with recognition accuracy within a certain range. Customized models have high costs, and the technology iterates every 6-12 months;

(3) Insufficient technical stability, where some enterprises have experienced audit interruptions due to the collapse of AI models, and the accuracy of some models has decreased after 6 months of use. AI has a certain misjudgment rate for new types of violations;

(4) Lack of technical standards, where the model accuracy is within a certain range but there is no qualified threshold, there is no unified standard for data quality, and there is confusion in enterprise selection.

5.3. Ethical and legal challenges

The ethical and legal aspects have sparked compliance disputes, with four core issues:

(1) Algorithmic ethical risks and data bias leading to algorithmic discrimination, auditors overly relying on AI to shift responsibility, and AI excessively collecting information that violates privacy;

(2) Legal gap, with no clear regulations on the proportion of responsibility for "AI model errors", no unified standard for the acceptance of AI audit evidence, and cross-border audits facing conflicts between Chinese and foreign regulations (such as China's Personal Information Protection Law and the EU GDPR);

(3) Compliance costs are high, with audit firms spending over 100000 Chinese Yuan annually to learn AI regulations and enterprises spending over 500000 Chinese Yuan to upgrade their AI systems;

(4) Lag in regulation, with no regulations on model filing and algorithm transparency. Regulatory agencies lack professional tools, and multiple departments have overlapping responsibilities and inefficient collaboration.

5.4. Talent level challenges

The talent level is a key bottleneck for the implementation of AI auditing, manifested in four aspects:

(1) Shortage of composite talents, whereby auditors have good compliance with the "audit + finance" ability standards, but poor compliance with the "AI technology + business knowledge" ability standards. There are relatively more composite talents in the financial industry, and there are fewer composite talents in small and medium-sized institutions. Most auditors lack data preprocessing and model optimization capabilities;

(2) Training system is not perfect, with a low proportion of AI courses in auditing majors in universities. Students need 1–2 years of training after graduation, and the average annual training budget for small and medium-sized institutions is less than 50000 Chinese Yuan. Training in large institutions is mostly based on basic operations, and there is little cooperation between universities and enterprises, resulting in insufficient practical experience for students;

(3) Serious talent loss, with AI audit talents receiving higher salaries than traditional ones, and the competitiveness of audit institutions being lower than that of technology companies. Some composite talents have left due to unclear career development, and the intensity of AI audit work is relatively high, resulting in a serious turnover situation;

(4) Personnel resistance, such as auditors worrying about AI replacing manual labor, believing that AI system operations are complex, and not believing in AI results.

Even if AI recognizes abnormalities, it still requires 100% manual review, which fails to leverage efficiency advantages.

6. Development path of artificial intelligence audit

6.1. Data level: Building a "high-quality, secure, and shared" data ecosystem

At the data level, three measures need to be taken simultaneously:

(1) To improve data quality, enterprises should establish a "cleaning verification labeling" process, and link the evaluation of "completeness, accuracy, and timeliness" with KPIs;

(2) To ensure data security by building technical defenses through "transmission + storage encryption", "minimum permission control", and "anomaly monitoring", formulating the "AI Audit Data Security Management System", and conducting regular compliance audits;

(3) To promote data sharing, integrate data from multiple departments through enterprise data platforms, build federated learning platforms across enterprises, and participate in international rule making across borders.

6.2. Technical aspect: Achieving "transparency, adaptability, and standardization"

Breaking through the bottleneck at the technical level requires three points:

(1) Cracking the "black box" of the model, using explainable AI technologies such as LIME and SHAP, requiring AI to generate an evidence chain containing transaction records and related evidence, and 100%

manual review of major risk issues;

(2) To improve adaptability, develop industry-specific models and scenario based modules, and iterate the models every 3–6 months;

(3) To improve standards, starting from industry associations to take the lead in formulating the "AI Audit Technology Standards", establishing a "compliance + security + effectiveness" certification system, and issuing selection guidelines.

6.3. Ethical and legal aspects: Building a governance system of compliance, fairness, and collaboration

We need to make three-dimensional efforts in ethics and law:

(1) Strengthen ethical governance, conduct regular algorithmic fairness audits, formulate the "AI Audit Ethics Guidelines", and establish an ethics review committee;

(2) To improve the legal system, introduce the "AI Audit Legal Responsibility Regulations", clarify the standards for the acceptance of AI audit evidence, and participate in international legal coordination;

(3) To optimize supervision, with regulatory agencies using AI monitoring tools, establishing an AI audit filing system and regular regulatory audits, and building a multi departmental collaborative platform.

6.4. Talent and industry level: Creating a "composite and ecological" pattern

Talents and industries need to be driven by two wheels. On the talent side, universities should reform audit courses and establish training bases, industries should provide graded training and promote vocational certification, and enterprises should establish mentorship and rotation mechanisms; Optimize incentives by promoting, simplifying operations, and piloting to reduce resistance.

On the industry side, they should promote tripartite cooperation in developing solutions, organize exchanges with associations, and collaborate on research and development between industry, academia, and research. In addition, it is essential to establish a technology, service, and talent ecosystem, participate in ISO rules internationally, export technology, and promote mutual recognition of certifications.

7. Conclusion

Artificial intelligence auditing is a core paradigm that breaks through the pain points of "sampling limitations, post audit lag, and manual dependence" in traditional auditing. Its development needs to be based on "data elements, driven by technological innovation, with institutional guarantees as the bottom line, and talent adaptation as the core", and upgraded from "tool assistance" to "governance collaboration" with the help of new quality productivity.

From a practical perspective, the AI application rate in the national audit industry is expected to reach 58% by 2025, but there are significant industry and regional differences. The financial industry and the eastern region have higher penetration rates, while small and medium-sized accounting firms and the central and western regions have lower penetration rates; In terms of technological application, basic technologies are widely used, while advanced and integrated technologies are concentrated in high-risk areas; The implementation effect has high satisfaction in audit efficiency and risk identification accuracy, but low satisfaction in interpretability of results.

The current artificial intelligence audit faces four core challenges: data, technology, ethics and law, and talent. Data quality and security issues are the fundamental obstacles, while technical "black boxes" and adaptability issues constrain large-scale applications. Ethical compliance and legal gaps have sparked controversy, and the shortage of composite talents is the key bottleneck for implementation.

To promote the development of artificial intelligence auditing, efforts need to be made from four dimensions: data, technology, ethics and law, talent and industry. This includes building a high-quality data ecosystem, achieving technological transparency and standardization, establishing a compliant and fair governance system, creating a composite talent pattern, and working together from multiple dimensions to overcome development obstacles.

Disclosure statement

The authors declare no conflict of interest.

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