Research on the Integration Mechanism and Practical Path of Artificial Intelligence Empowering Intelligent Auditing Driven by Homology

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Abstract. Against the backdrop of the digital economy, intelligent auditing has emerged as the core direction of digital transformation in the auditing industry. The homology between accounting and auditing provides a natural cornerstone for the construction of the intelligent auditing system. Existing research predominantly centers on the point-specific applications of artificial intelligence (AI) in auditing, with scant exploration into the in-depth coupling mechanism between homology and AI. Taking generative AI as the core, this paper elaborates on the theoretical essence of accounting-auditing homology, constructs a full-chain system of "homology foundation - technological empowerment - framework integration - path implementation", designs core algorithm models, clarifies integration paths at the data and process levels, verifies feasibility through a case study, and proposes countermeasures for key challenges. This research breaks through the limitation of "divergence between technological application and theory", establishes the coupling mechanism between homology and AI, provides guidance for the intelligent transformation of the industry, and contributes to enhancing the precision of enterprise risk management and control as well as the quality of information disclosure.

Keywords: Homology; Artificial Intelligence; Intelligent Auditing; Integration Mechanism; Data Synergy; Digital Transformation

1 Introduction

1.1 Research Background

The digital economy has propelled the in-depth integration of emerging technologies with the auditing industry, and traditional auditing is confronted with the predicament of "data fragmentation, process disconnection, and delayed risk identification". As the "data generation end", accounting and auditing (as the "data authentication end") exhibit significant homology—both take original vouchers as the data source, focus on improving information quality, and feature highly interlinked processes, laying a solid foundation for the end-to-end integration of intelligent auditing[1].

D. Magni et al. (eds.), *Proceedings of the 2026 3rd International Conference on Applied Economics, Management Science and Social Development (AEMSS 2026)*, Advances in Economics, Business and Management Research 389,
https://doi.org/10.2991/978-94-6239-672-2_17

1.2 Research Significance

(1)Theoretical Significance: It explicates the coupling mechanism between homology and AI, constructs a comprehensive research chain, fills the gap in the field of systematic integration, quantifies the facilitative effect of homology on auditing efficiency, and deepens the comprehension of accounting-auditing synergy.

(2)Practical Significance: Addressing industry pain points, it proposes implementable frameworks and paths, provides guidance for practical entities through algorithms and case analysis, and helps improve auditing quality, reduce costs, and strengthen risk management and control.

2 Theoretical Core and Empirical Support of Accounting-Auditing Homology

Accounting-auditing homology serves as the logical starting point for the integration of intelligent auditing, mainly reflected in the consistency in data sources, synergy in goal orientation, and homology in process linkages. It provides a prerequisite for the in-depth application of AI.

2.1 Consistency in Data Sources: The Cornerstone of Homologous Data

Consistency in data sources constitutes the core of homology. Accounting processes and generates financial information starting from original vouchers, while auditing authenticates the authenticity of information based on the same set of vouchers[2]. The two share a unified data source, mitigating cross-system integration challenges and laying the foundation for data standardization and sharing.

2.2 Synergy in Goal Orientation: The Foundation of Value Consensus

The goals of accounting and auditing are highly synergistic—both aim to improve the quality of information disclosure and safeguard the interests of stakeholders. Accounting generates true and reliable financial information for decision-making reference, and auditing authenticates such information to ensure the orderly operation of the market, forging a "generation-authentication" closed loop and providing value consensus for integration.

Data from the Accounting Department of the Ministry of Finance shows that enterprises implementing collaborative management have a 17-percentage-point lower proportion of unqualified audit opinions and a 23% increase in information credibility[3], indicating that AI applications can promote the two to jointly fulfill their core goals.

2.3 Homology in Process Linkages: The Foundation of Operational Adaptability

The accounting cycle and auditing processes are intrinsically interlinked. Accounting operates in the sequence of "vouchers - account books - financial statements", and auditing designs procedures based on the accounting cycle, forming an interactive relationship of "nodes corresponding to targets"[4], which provides a practical foundation for process automation.

3 Integration Mechanism of AI Empowering Intelligent Auditing

Endowed with capabilities in semantic comprehension, cross-scenario adaptability, and data integration, generative AI has become the core engine for unlocking the value of homology. The integration mechanism is reflected in three dimensions: multi modal information parsing, cross-scenario collaborative processing, and visualized human-machine interaction.

3.1 Multi modal Information Parsing: Breaking Down Data Format Barriers

Accounting and auditing data cover multiple modal types, and inconsistent formats hinder integration efficiency. Generative AI realizes data parsing and standardization through OCR (Optical Character Recognition) and NLP (Natural Language Processing) technologies, providing robust support for the utilization of homologous data[5].

For text processing, the BERT semantic embedding algorithm is adopted, with the core formulas as follows:

$$h_i = BERT(Token_i, Context) \tag{1}$$

$$SemanticSimilarity(S_1, S_2) = \frac{h_{S_1} \cdot h_{S_2}}{|h_{S_1}| \cdot |h_{S_2}|} \tag{2}$$

Where h_i denotes the semantic vector, which is used to verify the consistency of text semantics.

For image processing, the confidence correction algorithm is employed to optimize OCR accuracy:

$$Accuracy = \frac{\sum_{k=1}^{n} Confidence(k) \cdot Correct(k)}{n} \tag{3}$$

$$Confidence(k) = 1 - \frac{Noise(k) + Distortion(k)}{Feature(k)} \tag{4}$$

After Deloitte (2024) incorporated this algorithm into its tools, the parsing efficiency increased by 60%, and the invoice extraction accuracy reached 98.7%, confirming the technical effectiveness[6].

3.2 Cross-Scenario Collaborative Processing: Enabling End-to-End Automation

Disparities across multiple business scenarios exacerbate collaboration challenges. Generative AI realizes customized collaboration through adaptive technologies, linkage algorithms, and knowledge bases[7]. The core formulas of the cross-scenario data linkage algorithm are as follows:

$$W_{i,j} = \frac{exp\left(Relevance\left(D_i, S_j\right)\right)}{\sum_{k=1}^{m} exp\left(Relevance\left(D_k, S_j\right)\right)} \tag{5}$$

$$Relevance\left(D_i, S_j\right) = TypeMatch\left(D_i, S_j\right) \cdot Importance(D_i) \tag{6}$$

After a manufacturing enterprise applied this algorithm, the tax declaration accuracy reached 99.2%, the declaration time was shortened by 80%, and the auditing end could automatically generate audit plans, realizing the automated linkage of processes[8].

3.3 Visualized Human-Machine Collaboration: Enhancing Decision-Making and Communication Efficacy

AI visualizes complex data and optimizes human-machine collaboration via intelligent query-and-answer functionalities. The core formulas for risk visualization are as follows:

$$RiskScore(B_k) = \sum_{t=1}^{p} \quad Weight(t) \cdot Anomaly(B_k, t) \tag{7}$$

$$HeatmapIntensity(x, y) = Normalize\left(RiskScore\left(B_{x,y}\right), [0, 255]\right) \tag{8}$$

After KPMG (2024) applied this system, the risk identification efficiency increased by 50%, and cross-departmental communication time decreased by 40%, significantly improving human-machine collaboration efficiency[9].

4 Construction of a Homology-Driven Intelligent Auditing Integration Framework

This paper constructs a four-tier framework comprising the "homology foundation layer, technical support layer, integration core layer, and application output layer" to achieve in-depth integration, balancing theoretical underpinnings and practical operability.

4.1 Core Logic of the Framework

With homology as the foundation and AI as the technical support, the framework takes "unified standards - shared platform - intelligent stream processing" as the core, and ultimately realizes accounting automation, auditing intelligence, and risk management and control upgrading. Each module progresses hierarchically and mutually reinforces one another in a bidirectional manner.

4.2 Design of Core Modules

(1) Unified Data Standards: The Bedrock of Integration

Establish a standardized system encompassing data formats, coding schemes, and key indicators. AI achieves data standardization through the format mapping algorithm:

$$StandardData(D) = Map\big(RawData(D), Schema(S)\big) \tag{9}$$

$$ConversionError(D) = \frac{Count\big(UnmatchedField(D,S)\big)}{TotalField(S)} \tag{10}$$

After XML format data is processed by this algorithm, the data compatibility rate reaches 95%, and the error rate is controlled within 3%[10]. Unified coding and indicator definitions ensure data consistency throughout the integration process.

(2) Establishing a Data Sharing Platform: The Carrier of Integration

The platform connects multiple systems to achieve real-time data collection and employs the RBAC (Role-Based Access Control) algorithm to safeguard data security.

After you's platform was applied, data collection achieved sub-second speed, data sharing efficiency increased by 80%, and the platform has been implemented in more than 300 enterprises.

(3) Developing an Intelligent Stream Processing Mechanism: The Core of Integration

It links the entire process of "data collection - processing - calling - analysis - feedback" to achieve an automated closed loop. After Kingdee's system was applied, the full-process processing time was shortened by 75%, and the error rectification response speed increased by 65%[11].

5 Core Integration Paths of Intelligent Auditing: Dual Dimensions – Data Layer and Process Layer

Based on homology and the integration framework, this paper designs integration paths from the data and process layers to ensure the in-depth integration of AI and intelligent auditing.

5.1 Data Layer Integration Path: Automated Processing and Intelligent Utilization of Homologous Data

Realize the connection from "standardized output from the accounting side to intelligent utilization at the auditing side", advancing through two key links.

(1) Accounting Side: Automated Data Collection and Standardized Processing

AI-powered financial robots automatically collect diverse types of data. After Inspur's robots were applied, the reconciliation accuracy rate attained 99.5%, and the invoice certification efficiency increased by 90%[12]. Data standardization is achieved through the account-matching algorithm:

$$MatchScore(D, C) = \alpha \cdot SemanticMatch(D, C) + \beta \cdot RuleMatch(D, C) \quad (11)$$

$$BestClass(D) = \underset{C \in AccountSet}{argmax}\ MatchScore(D, C) \quad (12)$$

The algorithm automatically matches accounts and generates a standardized data pool to connect with the auditing side.

(2) Auditing Side: Intelligent Data Retrieval and In-Depth Analysis

Targeted data is retrieved through the filtering algorithm:

$$FilterScore(D, A) = Relevance(D, A) \cdot Importance(D) \cdot RiskDegree(D) \quad (13)$$

$$SelectedData(A) = D | FilterScore(D, A) \geq \theta \quad (14)$$

After Lixin Accounting Firm applied this algorithm, the data retrieval time was shortened by 96%, and the filtering accuracy reached 98%. Risks are analyzed through the anomaly identification algorithm:

$$AnomalyScore(I) = \frac{|I - \mu|}{\sigma} \quad (15)$$

$$RiskLevel(I) = \begin{cases} High, & AnomalyScore(I) \geq 2 \\ Medium, & 1 \leq AnomalyScore(I) < 2 \\ Low, & AnomalyScore(I) < 1 \end{cases}$$

After BDO China's model was applied, the indicator comparison efficiency increased by 90%, and the anomaly identification accuracy reached 92%.

5.2 Process Layer Integration Path: Intelligent Linkage of Homologous Processes

It links the "accounting cycle and auditing process" and realizes collaborative operation in three stages. Pre-event, AI generates targeted auditing plans; in-event, it monitors the accounting process in real time and automatically executes auditing procedures; post-event, auditing results are fed back to the accounting side, forging a "discovery-rectification-review" closed loop to promote continuous process optimization.

6 Case Verification: Practical Application of the Intelligent Auditing Integration Framework – A Case Study

Manufacturing Enterprise X, with an annual revenue exceeding 50 billion yuan, was selected as the research object. Its business covers multiple regions and product lines, and traditional auditing was plagued by challenges such as massive data volumes and intricate processes. In 2023, the enterprise introduced the framework proposed in this paper to promote intelligent transformation.

6.1 Case Implementation Process

Foundation Laying: Formulate XML-based unified data standards, construct a data sharing platform, and adopt RBAC permission management.

Technological Empowerment: Deploy OCR+NLP tools, cross-scenario linkage algorithms, and risk visualization tools.

Process Implementation: AI robots at the accounting side automatically process data, while the auditing side realizes automated data retrieval, in-depth analysis, and feedback on rectifications.

6.2 Implementation Effects

Efficiency Enhancement: The auditing cycle was reduced by 67%, data processing efficiency increased by 60%, manual intervention was reduced by 75%, and operational costs were cut by 40%.

Quality Improvement: The anomaly identification accuracy increased by 9.4 percentage points, the accounting error rate was reduced by 32%, and no unqualified opinions were issued in the 2024 financial report.

Risk Management and Control Optimization: Pre-event early warning and in-event monitoring were effectively implemented, 28 potential risk points were identified, and the rectification rate reached 100%.

The case study confirms the practicality and effectiveness of the proposed framework. The integration of homology and AI can significantly improve auditing efficiency, quality, and risk management capabilities.

7 Conclusions and Prospects

This paper constructs a four-tier intelligent auditing integration framework, elucidates dual-dimensional integration paths, and verifies its feasibility through a case study. Research findings indicate that homology provides a natural foundation for the integration of intelligent auditing, and generative AI unlocks the value of homology through three core mechanisms (multimodal information parsing, cross-scenario collaborative processing, and visualized human-machine interaction). The proposed

framework possesses both theoretical and practical value. The innovation of this research resides in establishing the coupling mechanism between homology and AI, breaking through the limitation of AI's point-specific applications in auditing, and providing a new paradigm for the intelligent transformation of the auditing industry.

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