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Audit Automation Process and Realization Path Analysis Based on Financial Technology

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Abstract: Against the backdrop of rapid development of financial technology, traditional audit models are accelerating their transformation towards automation and intelligence. This article conducts research on the basic theory of audit automation, constructs a system architecture with data collection automation, data analysis decision support systematization, and data processing process automation as the framework structure, and deeply explores the problems of data heterogeneity, low algorithm credibility, and weak legal adaptability in the current implementation process. Based on this, solutions are proposed to build a cross system data harmony processing mode, improve the explanatory ability of intelligent audit models, and enhance the matching path of legal and regulatory standards. Thus, it is found that financial technology plays a key leading role in achieving efficient, transparent, and legal audit. Audit automation will be the backbone in leading the digital transformation of the industry in the era of financial technology.

Keywords: financial technology; audit automation; data fusion

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1. Introduction

With the advent of the digital economy era, financial technology continues to integrate into the auditing industry, shifting from traditional manual auditing to intelligent and automated transformation. Introducing big data, AI, and advanced technologies such as blockchain has not only improved the level of audit work and data processing capabilities, but also put forward new requirements for audit methods, technical indicators, and audit standards. Especially in the context of complex financial behavior and huge changes in information volume of enterprises, the use of financial technology to achieve full process and full coverage real-time auditing is an important means to improve audit quality and reduce audit risks. However, there are still significant bottlenecks in data processing, algorithm application, and mechanism adaptation in the current implementation of audit automation. This article focuses on technology empowerment and fully analyzes the basic principles, construction system, existing difficulties, and countermeasures of audit automation, aiming to provide theoretical and methodological guidance for the digitalization reform of the audit industry.

2. Overview of Audit Automation Theory Based on Financial Technology

FinTech, which integrates advanced technologies such as big data, artificial intelligence, blockchain, and cloud computing, is subtly changing the workflow and work path of the auditing industry. Traditional audit work focuses on sampling inspections and

manual operations, which have many drawbacks in terms of work scope, efficiency, decision-making, and fairness [1]. It is difficult to cope with the increasingly complex operations and increasing information volume of current enterprises. Therefore, in order to adapt to such an environment, it is necessary to transform audit automation. The core is to use financial technology to achieve audit standardization, intelligence, and process management, and to systematically manage the process of automatic data collection, identification, analysis, and result feedback.

According to the above theoretical deduction, the audit automation process exhibits two basic logical mechanisms—data-driven logic and model-driven logic. On the one hand, the data processing capability based on big data technology breaks through the limitations of traditional sampling auditing; On the other hand, embedding audit models using machine learning, knowledge graphs, and other patterns can improve the accuracy of risk identification and the standardization of audit judgments. At the same time, the tamper proof nature of blockchain technology can ensure the security of audit data, and the elastic computing power of cloud computing platforms can support large-scale concurrent analysis, thereby promoting the upgrade of audit systems to "real-time, comprehensive, and accurate" goals. Audit automation is not only a tool innovation, but also a systematic change in audit philosophy and audit system design [2].

3. System Construction of Audit Automation Driven by Financial Technology

3.1. Intelligent Framework for Audit Data Collection and Processing

Driven by financial technology, the collection and processing of audit data are developing towards intelligence and automation. The entire process is divided into four stages: data access, multi-source integration, real-time processing, and anomaly recognition. Firstly, data access can automatically retrieve data from the financial system, Internet business platforms, and third-party sources through API, OCR, and the Internet of Things, breaking through the information island problem of the original single data source. Secondly, multi-source integration can use data cleaning, format standardization, and knowledge graph technology to bridge structured and unstructured data processing, and deeply explore the correlation and meaning between data. Thirdly, real-time processing is built on a big data computing platform, utilizing streaming computing engines such as Flink and Spark Streaming to enhance the timely processing of data. Fourthly, anomaly recognition introduces machine learning algorithms and rule engines to automatically identify and discover anomalies in the collected data, enhancing the intelligence level of preliminary audit judgments. In addition to changing the collection and processing of audit data, this framework also provides a reliable foundation for the next steps of analysis, decision-making, and risk assessment (Figure 1).

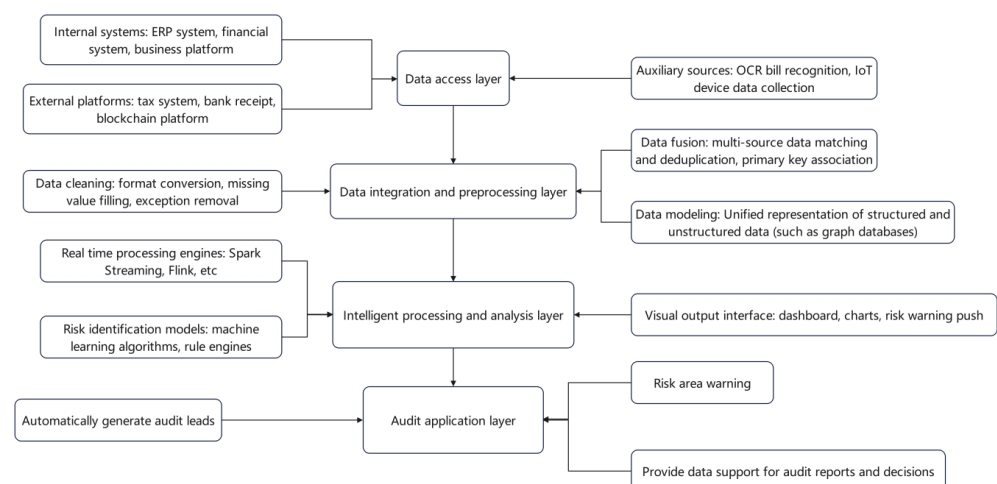


Figure 1. Intelligent Framework for Audit Data Collection and Processing.

3.2. Audit Decision Support and Risk Identification System Architecture

In the audit automation system, decision support and risk identification systems are important components that undertake core functions such as risk assessment, anomaly analysis, and strategy output. The system consists of four parts: a data analysis engine, an intelligent recognition model, a knowledge base module, and an auxiliary decision-making interface. Among them, the data analysis engine is based on multidimensional data input, constructs an indicator system, and performs statistical analysis, clustering analysis, and regression modeling [3]. The intelligent recognition model uses deep learning methods, graph neural networks, and other techniques to perform profiling of enterprise behavior patterns, in order to infer warnings and classification of high-risk behaviors such as malicious activities, repetitive behavior, and violations. The knowledge base module integrates audit criteria, supervision requirements, and historical cases to provide guidance and explanation for the models involved. Finally, the system uses a visual interface to present the analysis results and assist in decision-making for auditors to make decisions based on human-machine collaboration. The above structure can improve the precise positioning and response speed of audit risks, and provide an intelligent decision support interface in complex financial environments.

3.3. Audit Process Automation and Audit Platform Integration Mechanism

The automation of the audit process is the key path to achieving efficient and continuous auditing. The core lies in shifting the audit work from a "manually driven mode" to a "system driven mode", that is, completing the entire business process of task execution, data calling, model application, and result feedback through a unified system. Implement process driven deployment of audit tasks, data verification, risk assessment, initial draft generation, and follow-up on problem rectification, covering business requirements such as audit project planning, data collection and verification, risk assessment, and audit report preparation. Utilize process engines (BPMN flowcharts) and automation software (such as RPA) to achieve task driven execution [4]. Through platform integration strategy, deploy a unified audit platform to connect with the enterprise's ERP system, data warehouse, financial management shared server and other related system resources. This platform achieves data exchange, permission management, log tracing, and data indexing functions between various systems, provides built-in intelligent model library and audit report template library, and realizes intelligent dispatching and automatic text writing according to audit task requirements. It integrates audit work into various process links at the grassroots, middle, and senior levels. By integrating audit services, technology, and systems in three dimensions, the platform not only breaks down audit information silos, but also provides technical support for audit collaboration and regulatory sharing across multiple institutions and scenarios, significantly improving the effective operation of audit automation processes.

4. Issues Faced by the Automation Process of Auditing Based on Financial Technology

4.1. Audit Data Heterogeneity and Insufficient Real-Time Collection

The main obstacles faced in the practice of audit automation are data heterogeneity and real-time issues. One reason is that different audited entities use different financial software, ERP platforms, business recording methods, etc., which makes data aggregation difficult. The second reason is that some data is still processed through manual paper records and other methods, which cannot be received by real-time audit systems. Thirdly, real-time data also depends on the openness of the company's internal information system and the level of interface construction. Many small and medium-sized enterprises or regional units have not yet established effective data transmission channels, often resulting in data lag [5]. This phenomenon not only reduces the accuracy of intelligent analysis

models, but also increases the cost of manual intervention, thereby limiting the realization of automated operation of the entire audit process (Table 1).

Table 1. Comparison of Heterogeneity and Real Time Issues of Audit Data from Different Sources.

Data source type	Existing heterogeneity issues	Real time performance issues
Enterprise ERP system	Inconsistent field naming and differences in encoding rules	There is a data delay that requires scheduled synchronization
Financial Shared Services Platform	The table structure is complex and the cross unit caliber is inconsistent	Audit cycle update, does not support real-time transmission
Banks and third-party receipt systems	Inconsistent interface standards and closed data formats	The access process is complex and the real-time performance is low
Manual receipts and documents	Unstructured and high OCR recognition error rate	Zero timeliness, manual supplementation required

4.2. Low Credibility and Interpretability of Intelligent Algorithms

In audit automation, although intelligent algorithms have powerful data processing and risk identification capabilities, their credibility and interpretability remain the main obstacles to their widespread application. On the one hand, although deep learning, neural networks, and other technologies can accurately identify complex abnormal behavior patterns, they often struggle to explain the reasoning process, leading auditors to be unable to fully trust their audit conclusions. On the other hand, algorithms mainly rely on past case studies for learning. If the learned data is of low quality or lacks representativeness, the model's prediction conclusions may be inaccurate or biased. In addition, due to the significant heterogeneity of data structures between different companies, the general applicability of the model is limited, resulting in the phenomenon of "transfer distortion". These have affected the foundation of trust in the audit model and weakened its legal traceability and accountability in practical operations (Table 2).

Table 2. Comparison of Common Audit Algorithms in Terms of Credibility and Interpretability.

Algorithm type	Advantage performance	Reliability problem	Interpretability issue
Decision tree model	Clear structure and intuitive logic	Sensitive to data noise	Easy to explain, but poor in complex scenes
neural network model	Strong pattern recognition ability	Black box structure, difficult to verify	The reasoning process is opaque, and the conclusion is difficult to trace
Support vector machine	High classification accuracy, suitable for small samples	Sample selection affects stability	Decision boundaries are difficult to visually present
Integrated algorithms (such as XGBoost)	Strong comprehensive ability and strong resistance to overfitting	Complex structure with multiple parameters	Although SHAP and other methods can be used to assist in explanation, it is still not intuitive

4.3. Regulatory Adaptability and Industry Standards Are Not Yet Unified

The development speed of audit automation far exceeds the update of current regulations and standard systems, resulting in an increasingly prominent phenomenon of regulatory lag and disconnection from industry practice. Firstly, there is currently no clear and specific legal guidance on the legal boundaries of intelligent algorithms in audit practice and the standardization of data processing. Therefore, enterprises using intelligent audit technology in practice are prone to the risk of legal non-compliance. Secondly, there is currently no unified standard for market data forms, connection methods, risk assessment methods, etc., and inter institutional systems cannot be connected, which hinders data interconnection and interoperability, resulting in the inability to enhance audit cooperation. The third issue is that a complete intelligent supervision model for auditing has

not yet been formed globally, which has a negative impact on the cross-border development of global auditing services and the construction of audit regulatory consistency. The above factors all constrain the standardized development of audit automation and need to be responded to and unified at the regulatory level (Table 3).

Table 3. List of Legal and Standard Deficiency Issues Faced by Current Audit Automation.

Problem areas	Current missing or conflicting situation	Impact performance
Data processing compliance	Lack of clear regulations on data collection, storage, and cross-border circulation	Facing legal risks of data abuse and privacy breaches
Division of Audit Responsibilities	Unclear definition of responsibility for intelligent decision-making and lack of accountability path	Audit errors are difficult to trace the responsible party
Industry technical standards	Inconsistent evaluation criteria for interfaces, formats, and algorithms	System incompatibility, difficulty in data collaboration, and serious duplication of construction
International regulatory docking	Lack of unified intelligent audit standards and cross-border legal adaptation mechanisms	Difficulty in sharing data and regulatory achievements in overseas business

5. Implementation Path of Audit Automation Based on Financial Technology

5.1. Establish a Cross System Data Fusion and Real-Time Processing Mechanism

To solve the problems of heterogeneous and delayed collection of audit data, it is necessary to establish a data fusion and real-time processing mechanism, break down barriers between various source systems, and enhance the timeliness and accuracy of information. For example, the audit analysis platform of a large-scale state-owned enterprise and public institution group needs to integrate heterogeneous data information from ERP systems, CRM systems, tax control systems, and bank financial interfaces. Through ETL technology and data warehousing, Firstly, the platform can achieve one-to-one correspondence between data items, synchronization of data codes, and primary key registration. Secondly, Spark Streaming, an online computing engine, will be introduced to conduct online analysis of commercial data. The processing delay L can be expressed as:

$$L = \frac{B}{R} \quad (1)$$

Among them, B is the batch size of data (MB), and R is the system processing rate (MB/s). By optimizing system resource allocation, L is controlled within 2 seconds to meet real-time audit requirements. In addition, Kafka is introduced as a message queue to achieve asynchronous data transmission and log traceability across different systems. The platform has achieved a closed-loop system of "data admission cleaning fusion streaming judgment real-time feedback", significantly enhancing the efficiency of data aggregation and audit timeliness, becoming the foundation and prerequisite for intelligent auditing.

5.2. Optimization Algorithm Training and Audit Model Interpretation Mechanism

In order to enhance the credibility and interpretability of the audit model, optimization is carried out from three aspects: algorithm training data, model structure development, and result interpretation tools. Firstly, algorithm training must be conducted using high-quality and multi domain actual audit data as a sample set, such as manufacturing, healthcare, communication, etc. The audit training is conducted in various fields, and the model's universality and robustness are expanded through stratified sampling and reinforcement learning methods. Secondly, the modeling structure should adopt interpretable algorithm combination strategies as much as possible, and the algorithm combination can better express the results, such as integrated trees (such as XGBoost) and rule engine fusion, to improve the traceability of results while ensuring accuracy. Thirdly, using the SHAP (Shapley Additive Explanations) value analysis tool helps display the importance

of various factors in the model results, enabling auditors to better understand audit evidence and processes for forming conclusions. For example, a commercial bank used a SHAP-based audit model to analyze high-risk loan data, which showed a significant improvement in the explanatory power of "abnormal fund flow frequency" and "differences in contract terms", thereby enhancing the interpretability of risk judgments and the rationality of audit conclusions. In summary, after optimization, an intelligent audit model that is understandable, verifiable, and accountable can be constructed.

5.3. Improve the Construction of Regulatory System and Industry Standard Coordination Mechanism

The sustainable development of audit automation relies on the improvement of supporting regulatory systems and the coordinated promotion of industry technical standards. One is to accelerate the legislation of government departments, promulgate relevant laws such as the "Intelligent Audit Data Security Management Measures" and the "Algorithm Audit Responsibility Guidelines", establish the scope of data collection, operational authorization, responsibility intervals, etc., and provide legal protection for the application of audit technology; Secondly, it is necessary to establish and improve unified data format standards, interface interoperability standards, and algorithm rating standards within the industry, promote data interoperability and sharing within the industry, and prevent duplicate construction and data closure. For example, the Chinese Institute of Certified Public Accountants can lead the construction of the "Intelligent Audit Risk Classification Standard V1.0" and cooperate with mainstream ERP service providers to update relevant interface specifications, which is conducive to increasing the compatibility between technology and regulations. The third is to further strengthen the standardization work with international audit regulatory agencies such as IFAC and IAASB, and promote the universal recognition of audit models and data formats in cross-border audit business. Only through a mechanism that integrates legal framework guidance, standard system support, and international rules can we effectively solve the problems of regulatory lag and scattered standards.

6. Conclusion

Fintech has injected strong technological momentum into the auditing industry, driving the transformation of auditing models from traditional manual led to data-driven, model supported intelligent systems. This article conducts specific research from four dimensions: theoretical basis, system architecture, practical difficulties, and optimization strategies. It identifies the main challenges faced by audit automation, such as heterogeneous data, algorithm opacity, and regulatory incompatibility. Furthermore, it provides corresponding effective solution spaces, such as standardizing data architecture, improving algorithm interpretability, and improving legal regulations. Driven by both institutional and technological factors, it is expected that in the future, audit automation will develop a sustainable and easily scalable execution model, greatly improving the quality and compliance level of auditing, and providing a solid foundation for corporate governance and risk control in the digital business world.

References

1. D. H. Feuzeu Djani, A. Mouongue Kelly, et al., "Does Financial Technology Fuel Economic Complexity? Empirical Insights from Africa," *Next Res.*, 2025, Art. no. 100360, doi: 10.1016/j.nexres.2025.100360.
2. X. Chen and N. Metawa, "Enterprise financial management information system based on cloud computing in big data environment," *J. Intell. Fuzzy Syst.*, vol. 39, no. 4, pp. 5223–5232, 2020, doi: 10.3233/JIFS-189007.
3. J. Pešta, et al., "Streamlining Demolition Processes: A Material Cadaster-Based Digitalization and Automation of Predemolition Audit," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1402, no. 1, p. 012041, 2024, doi: 10.1088/1755-1315/1402/1/012041.
4. A. Tiron-Tudor, et al., "Perspectives on how robotic process automation is transforming accounting and auditing services," *Account. Perspect.*, vol. 23, no. 1, pp. 7–38, 2024, doi: 10.1111/1911-3838.12351.

5. X. Fan, et al., "AI-Assisted Urban Flood Prevention Services Decision-Making Framework with Multi-Dimensional Data Fusion via Govern-Intranet," *Int. J. Web Serv. Res.*, vol. 22, no. 1, pp. 1–25, 2025, doi: 10.4018/IJWSR.375425.

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