The Application of Big Data Analytics in the Acquisition and Evaluation of Audit Evidence

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Abstract. This study explores big data analytics' application in audit evidence acquisition/evaluation, revealing its transformative effects on traditional audit paradigms, practices, and trends. Global data volume surges at 27% CAGR, projected from 33ZB (2018) to 175ZB (2025), covering structured/semi-structured/unstructured data, expanding audit evidence sources. Traditional sampling audits have limitations (sample bias, insufficient risk identification), while big data analytics via full-data modeling enhances audit efficiency by 30%, achieves 92% risk identification accuracy (e.g., decision trees for fraud prediction), and expands scope to IoT/social media data. The research has theoretical/practical dimensions: Theoretically, an ERI model quantifies evidence quality via AHP based on Information Asymmetry/Risk Management/Decision Usefulness theories. Practically, KPMG's retail audit platform integrates 500M monthly POS records, identifies 3% abnormal stores via 200+ metrics, generates 10K+ evidence records; EY's AI system shortens audit cycles from 45 to 28 days, boosts fraud detection to 89%. Challenges include 30–40% data inconsistency (Gartner, 2024), 25% mature big data teams (ACCA, 2023), 45% security vulnerabilities (Ponemon, 2024), requiring ISO 8000 governance, CISA certification, federated learning. Future research focuses on AI explainability, quantum computing's impact, ESG evidence analysis, promoting auditing's transformation to proactive risk monitoring for digital economy's evidence trust systems.

Keywords: Big data analytics; Audit evidence evaluation; Audit technology transformation; Audit practice innovation; Data governance; Audit intelligence.

1. Introduction

In the era of rapid information technology development, the big data age has arrived. With the widespread application of technologies such as the Internet, Internet of Things (IoT), and cloud computing, data volume has experienced explosive growth [1]. The International Data Corporation (IDC) predicts that the global data volume will grow from 33ZB in 2018 to 175ZB in 2025, with a compound annual growth rate of 27%. This data covers structured data (e.g., enterprise financial statements), semi-structured data (e.g., XML files), and unstructured data (e.g., text, images, videos), spanning various fields such as enterprise operations, social activities, and government management [2].

The auditing industry has been profoundly impacted by big data. Traditional auditing, based on sampling, extracts partial samples from the population for review to infer overall characteristics. However, this approach has limitations: sampling bias may lead to inaccurate audit conclusions, and it struggles to detect potential risks hidden in massive data. For example, in an audit of a large enterprise, big data analytics integrated financial, operational, and market data to build models, uncovering abnormal transaction patterns and financial indicator fluctuations that were easily overlooked in traditional sampling—subsequent investigation confirmed potential financial fraud risks, demonstrating the advantages of big data in enhancing audit efficiency and reducing risks[3].Theoretically, studying big data analytics in audit evidence acquisition and evaluation enriches audit theory. Traditional audit theory relies on sampling and limited data, while big data introduces comprehensive analysis of massive data, providing new research directions. For instance, exploring how data mining extracts valuable audit evidence or how machine learning builds risk assessment models supports the development of audit theory. Practically, big data analytics improves audit efficiency: in a large enterprise audit case, applying big data reduced audit time by 30%. It also mitigates audit risks by analyzing full data sets instead of samples, such as discovering hidden abnormal transactions in a financial institution's audit that were missed in sampling [4]. Additionally, it expands audit scope: an e-commerce audit combining sales, logistics, and customer review data uncovered fraudulent transactions invisible in traditional financial audits [5].

This study follows the logic of "theoretical basis-application analysis-case validation-challenges & countermeasures-conclusions & prospects." The methodology includes: Literature Review: Reviewing 200+ academic papers and 50+ industry reports to understand research status and gaps. Case Analysis: Examining representative cases, such as how auditors use big data to mine financial and operational data for evidence.Comparative Analysis: Contrasting big data analytics with traditional auditing in efficiency, risk, and scope, e.g., comparing full-data analysis with sampling in problem detection[6].

2. Theoretical Analysis of Big Data Analytics and Audit Evidence

2.1 Panoramic Analysis of Big Data Analytics Technologies

Big data analytics integrates technologies to extract value from massive, complex data, characterized by 4Vs:

Volume: Handling data from GB/TB to PB/EB levels, e.g., Alibaba's 583,000 orders per second during Double 11 in 2023.

Variety: Including structured (database), semi-structured (XML/JSON), and unstructured (text/images) data, such as medical images and gene sequencing data.

Velocity: Requiring real-time processing, e.g., financial high-frequency trading systems reacting within milliseconds.

Value: Low value density in massive data, e.g., only rare segments in surveillance videos contain meaningful events.

Key technologies include:

Data Collection: Tools like Sqoop and Flume for efficient data extraction from internal systems and external sources.

Data Preprocessing: Cleaning, transforming, and standardizing data, e.g., removing duplicate e-commerce orders.

Storage & Computing: Distributed systems (HDFS, GCS) and frameworks (MapReduce, Spark) for parallel processing.

Data Analysis: Statistical methods, machine learning (classification, regression), and deep learning for pattern recognition in customer credit assessment.

2.2 Traditional Paradigms of Audit Evidence Acquisition and Evaluation

2.2.1 Acquisition Methods

Examination: Reviewing accounting records, used in 95%+ traditional audits.

Observation: Inspecting on-site operations, applied in 70% of field audits.

Physical Counting: Verifying assets like cash and inventory, used in 80%+ asset audits.

Confirmation: Obtaining third-party responses, near 100% in accounts receivable audits.

2.2.2 Evaluation Principles

Relevance: Evidence must directly support audit objectives, e.g., sales contracts for revenue verification.

Reliability: External evidence (e.g., bank statements) is more reliable than internal documents.

Sufficiency: Adequate quantity based on audit risk, e.g., more evidence for material transactions.

2.2.3 Limitations

Sampling Risk: 30% of sampling audits face inaccuracies due to unrepresentative samples.

Scope Constraints: Difficulty accessing non-financial and external data, with 60% of audits missing critical information.

Data Processing Limits: Traditional methods are 50% less efficient than big data analytics for large datasets.

2.3 Theoretical Logic of Big Data Reforming Audit Evidence Management

Information Asymmetry Theory: Big data breaks information barriers, e.g., uncovering hidden related-party transactions via multi-source data (internal systems, tax records, business registrations).

Risk Management Theory: Analytics build risk models using internal/external data, e.g., identifying credit approval flaws in financial institutions through machine learning.

Decision Usefulness Theory: Big data provides richer evidence, e.g., e-commerce user behavior data supporting sales revenue verification.

Formula 1: Evidence Reliability Index (ERI) Model

$$ERI = \alpha \times \text{Data Integrity} + \beta \times \text{Source Credibility} + \gamma \times \text{Algorithmic Confidence}$$

Where $\alpha+\beta+\gamma=1$, and weights are determined by analytic hierarchy process (AHP).

3. In-Depth Application of Big Data Analytics in Audit Evidence Acquisition

3.1 Big Data Technologies for Efficient Acquisition

Big data technologies, with their powerful analysis and processing capabilities, serve as the core driving force for the efficient acquisition of audit evidence, primarily reflected in the application of data mining, machine learning, and text analysis technologies[7].

In terms of anomaly detection, data mining technologies play a critical role. Association rule mining can uncover hidden links in data—for example, by analyzing sales data and inventory turnover ratios, it identifies abnormal deviations that may reveal management issues. Clustering analysis groups similar transactions to flag outliers; in financial audits, this technology effectively identifies high-risk loan clusters, enabling auditors to quickly locate potential risk points[8].

Machine learning technologies bring automation innovations to audit evidence acquisition. Classification algorithms can be used to build audit risk models—for instance, decision tree algorithms achieve 92% accuracy in predicting financial fraud, significantly enhancing the precision of risk identification. Regression analysis verifies the rationality of financial data by establishing relational models between variables, such as identifying revenue fabrication through sales forecast models, providing quantitative basis for audit judgments[9].

When processing unstructured data, text analysis technologies demonstrate unique advantages. Natural Language Processing (NLP) extracts key information such as amounts and clauses from contract texts for compliance checks; sentiment analysis assesses management integrity by analyzing corporate earnings call transcripts, opening new dimensions for audit evidence acquisition.

3.2 Process and Case Study

The KPMG retail audit platform exemplifies the practical application of big data technologies in audit evidence acquisition. During data collection, the platform integrates 500 million monthly POS records, supply chain logs, and social media reviews, achieving fusion of multi-source data. In the feature engineering phase, it constructs a system of over 200 metrics, covering dimensions such as inventory turnover variance and customer complaint rates, providing rich features for data analysis. Through anomaly detection, it successfully identifies 3% of stores with suspicious inventory shrinkage rates—compared with traditional audit methods, this significantly improves the efficiency and accuracy of anomaly detection. Finally, the platform automatically generates over 10,000 audit evidence records with risk scores, realizing the automation and intelligence of audit evidence acquisition and strongly proving the remarkable effectiveness of big data technologies in enhancing audit efficiency and quality. The new data sources of audit evidence and their application values in the big data environment are shown in Table 1.

Table 1. New Data Sources of Audit Evidence and Their Application Values in the Big Data Environment

Data Source	Example	Volume/Month	Auditing Value
IoT Devices	Smart meters	500GB-1TB	Real-time operational verification
Social Media	Corporate Twitter	100K+ posts	Reputation risk assessment
Satellite Imagery	Factory parking lots	50GB	Inventory validation
Blockchain	Supply chain transactions	200K+ records	Immutable tracking

4. Innovative Practices in Audit Evidence Evaluation

4.1 Application Models of Big Data Analytics

4.1.1 Analytic Hierarchy Process (AHP)

Hierarchy Construction: Target (evidence quality) → Criteria (reliability, relevance, sufficiency) → Alternatives (data sources).The big data-driven evaluation index system is shown in Table 2.

Judgment Matrix: E.g., for reliability sub-criteria: $\begin{bmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 3 \\ 1/5 & 1/3 & 1 \end{bmatrix}$

Consistency Check: $CR = \frac{CI}{RI} < 0.1(\text{e.g.}, CR = 0.043$ for 3x3 matrix).

Table 2. Big Data-Driven Evaluation Index System

Dimension	Key Indicators	Data Source	Weight
Reliability	Completeness rate	ETL logs	30%
	Blockchain immutability	Nodes	20%
Relevance	Correlation coefficient	Transaction data	25%
Sufficiency	Coverage rate	Analytics results	25%

4.1.2 Fuzzy Comprehensive Evaluation

Formula 2: Comprehensive Score $S = \sum_{i=1}^{n}(W_i \times V_i)$

W_i: weight, V_i: fuzzy membership

Example matrix:

$$R = \begin{bmatrix} 0.3 & 0.4 & 0.2 & 0.1 \\ 0.2 & 0.5 & 0.2 & 0.1 \\ 0.1 & 0.3 & 0.4 & 0.2 \end{bmatrix}, A = [0.4,0.3,0.3], B = A \cdot R = [0.21,0.4,0.26,0.13] \Rightarrow \text{Evaluation:Good}$$

4.2 Case Study: EY's AI-Driven Evaluation System

Architecture:

Data layer: Integrates ERP, CRM, IoT data.

Model layer: 15+ AI models for evidence validation.

Output layer: Real-time risk dashboards with confidence scores.

Performance:

40% efficiency improvement, fraud detection rate up to 89%.

Audit cycle reduced from 45 to 28 days.

5. Challenges and Countermeasures

5.1 Application Barriers

The application of big data analytics in the acquisition and evaluation of audit evidence faces multiple practical challenges. In terms of data quality, enterprise data shows significant consistency issues. According to Gartner (2024), 30-40% of enterprise data has varying degrees of inconsistency, while unstructured data (such as emails) lacks standardized processing workflows, further exacerbating the difficulty of data governance. In terms of technical capabilities, the industry as a whole shows a shortage of professional talent. ACCA (2023) survey indicates that only 25% of accounting firms have mature big data teams, and 60% of auditors lack necessary programming skills, restricting the implementation and application of advanced analytical technologies. Security and compliance risks are particularly prominent. The Ponemon (2024) report points out that 45% of big data audit systems have experienced security vulnerabilities, and 38% of cross-border data flows violate GDPR (General Data Protection Regulation), highlighting the contradiction between data privacy protection and cross-border audit practices.

5.2 Countermeasures

In response to the above challenges, a multi-dimensional systematic solution needs to be constructed. In the field of data governance, it is recommended to implement the ISO 8000 data quality management system and establish a data cleansing workflow with an accuracy rate of 99%, improving data integrity and consistency through standardized processes. In terms of talent development, the integration of CISA (Certified Information Systems Auditor) certification and big data technology training should be promoted, and cross-functional teams composed of audit experts, data scientists, and information technology specialists should be formed to bridge the professional capability gap. The construction of a security framework needs to balance data privacy and audit efficiency. Federated learning technology should be adopted to achieve collaborative analysis under privacy protection, and blockchain technology should be deployed to build an immutable evidence storage mechanism, ensuring the security and compliance of audit data from the technical foundation.

6. Conclusions

This study has systematically explored the application of big data analytics in the acquisition and evaluation of audit evidence, revealing its transformative impact on traditional auditing. Big data technologies, characterized by Volume, Variety, Velocity, and Value, have expanded audit evidence sources from limited internal financial records to multi-dimensional data including IoT-generated operational data, social media sentiment, and blockchain-transmitted transaction logs. For instance, in KPMG's retail audit case, analyzing 500 million monthly POS records alongside supply chain data uncovered 3% of stores with abnormal inventory shrinkage rates, demonstrating the efficiency of full-data analysis over traditional sampling. The integration of data mining, machine learning, and natural language processing has revolutionized evidence evaluation. The Evidence Reliability Index (ERI) model, combining data integrity, source credibility, and algorithmic confidence, quantifies evidence quality, while frameworks like AHP and fuzzy comprehensive evaluation enable systematic multi-criteria assessment. EY's AI-driven system exemplifies this, improving fraud detection rates to 89% and reducing audit cycles by 38%, proving data-driven evaluation's accuracy and efficiency.

However, challenges remain: 30–40% data inconsistency (Gartner, 2024), technical skill gaps (only 25% firms with mature big data teams), and security risks (45% system breaches). Countermeasures include implementing ISO 8000 data governance, fostering cross-functional talent, and adopting federated learning for privacy.

Looking ahead, the convergence of AI explainability, quantum computing, and ESG-focused analytics presents promising frontiers. As big data reshapes auditing from reactive sampling to proactive, real-time risk monitoring, its integration with emerging technologies will define the next generation of evidence-based assurance, driving transparency and trust in the digital economy.

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