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Mechanisms and Pathways for Enhancing Internal Audit Effectiveness in Universities through Artificial Intelligence

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Abstract: As artificial intelligence (AI) becomes increasingly embedded in university governance and auditing, a central concern in the intelligent transformation of internal auditing is how to leverage its technological advantages to improve audit effectiveness. This study examines the process through which AI enables internal auditing in universities, analyzes the mechanism by which audit effectiveness is generated, and develops an evaluation system comprising five dimensions and 17 indicators. The analytic hierarchy process (AHP) and fuzzy comprehensive evaluation are then applied to assess a case university. The results indicate that the university achieves an overall rating of good in AI-enabled internal audit effectiveness. Although it has established a certain level of digital infrastructure and capability for converting technological inputs into audit outcomes, further improvement is required in technological innovation, the in-depth application of intelligent tools, and data governance. Based on the weaknesses identified by the evaluation, this study proposes targeted improvement pathways. The findings provide a reference for universities seeking to advance intelligent internal auditing and enhance the effectiveness of AI applications.

Keywords: Artificial Intelligence; University Internal Auditing; Audit Effectiveness
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1. Introduction

Internal auditing currently faces increasingly complex business scenarios and risk profiles. Traditional audit approaches that rely on manual data extraction, sampling, and experience-based judgment have gradually revealed limitations, including restricted coverage, delayed risk identification, and inadequate follow-up of corrective actions. Technologies such as big data analytics, machine learning, and natural language processing provide new means of improving audit data processing, risk identification, and continuous monitoring, thereby enabling university internal auditing to shift from sample-based inspection to full-population analysis and from ex post supervision to process-oriented oversight. However, the adoption of AI does not automatically translate into greater audit effectiveness; its actual impact is also shaped by the data foundation, technological capabilities, staff competencies, and organizational mechanisms. Existing studies have largely focused on the digital transformation of internal auditing, the application of intelligent tools, or audit performance evaluation. Systematic analysis remains limited regarding how AI is converted into internal audit effectiveness in universities and how weaknesses in its application can be identified. Accordingly, this study analyzes the mechanism through which AI enhances university internal audit effectiveness, establishes a corresponding evaluation system, and proposes targeted improvement pathways based on the evaluation results.

2. Literature Review

Research in China on AI and internal auditing has gradually shifted from information-technology-assisted auditing toward digitalization and intelligent auditing. Zhang et al. argue that internal auditing should be data-driven and that digital technologies should be embedded in audit organization, processes, and methods [1]. Xing et al. further contend that intelligent tools can achieve their full potential only when integrated with audit process reengineering [2]. In the context of university internal auditing, Hu emphasizes coordination between business processes and technological support and discusses data security, algorithmic explainability, and human-AI collaboration [3]. Xu et al. analyze the conditions required to realize the value of big data auditing from the perspectives of data, technology, and institutions [4]. Yue finds that digital capabilities improve audit performance and that data quality plays an important role in this relationship [5]. Liu et al. demonstrate the applicability of AHP and fuzzy comprehensive evaluation to university audit assessment [6]. These studies provide a theoretical and methodological foundation for examining the enabling mechanism and evaluation of AI in university internal auditing.

International research has primarily examined the effects of AI on audit processes, the division of labor, and audit effectiveness. Alles and Gray argue that big data can expand audit coverage and strengthen risk identification, although its use is constrained by data reliability, technological costs, and staff skills [7]. Issa et al. note that AI is particularly suitable for structured and repetitive tasks, whereas complex audit judgments continue to require auditor involvement [8]. Kokina and Davenport emphasize the role of cognitive technologies in text analysis and decision support while also addressing algorithmic bias and the allocation of responsibility [9]. Moffitt et al. contend that robotic process automation can not only improve efficiency but also facilitate audit process redesign [10]. Barr-Pulliam et al. further show that individual capabilities, task characteristics, and the organizational environment jointly shape technological innovation in auditing [11]. Fedyk et al. find an association between investment in AI and improvements in audit quality and efficiency [12]. Nevertheless, most international studies focus on accounting firms and financial statement audits, with comparatively limited attention to internal auditing in universities.

Overall, prior research provides theoretical and methodological support for this study in the areas of digital capability, intelligent tools, data quality, human-AI collaboration, and audit performance. However, three limitations remain. First, the mechanism through which AI operates is insufficiently connected to the evaluation of audit effectiveness. Second, existing university audit evaluation frameworks rarely capture the distinctive characteristics of AI applications. Third, some studies emphasize technological tools themselves while paying inadequate attention to the relationships among the data foundation, organizational capabilities, and performance outcomes. This study therefore integrates the AI enabling mechanism with comprehensive evaluation and proposes corresponding improvement pathways after identifying weaknesses in university internal auditing.

3. Theoretical Mechanism through Which AI Enhances University Internal Audit Effectiveness

3.1 Theoretical Foundations

The resource-based view holds that sustained organizational performance derives from the acquisition, allocation, and organized deployment of valuable, rare, and difficult-to-imitate resources. In university internal auditing, business data, audit data platforms, system interfaces, computing environments, institutional knowledge bases, and interdisciplinary professionals do not automatically generate audit value. Audit effectiveness can emerge only when these resources are integrated into stable capabilities for data acquisition and analysis. Digital infrastructure and high-quality data therefore constitute the resource foundation for AI-enabled auditing.

Dynamic capabilities theory emphasizes an organization's ability to sense opportunities and risks, integrate resources, and reconfigure processes in response to environmental change. Audit departments must convert audit experience into rules and models and continuously adjust technological applications through sample validation, human review, performance assessment, and version iteration, thereby developing digital technology innovation capabilities.

Information management theory focuses on the quality and value of data throughout the processes of collection, processing, storage, transmission, and use [5]. AI models depend heavily on input data; missing data, inconsistent definitions, delayed updates, or untraceable sources can amplify the risk of erroneous model judgments.

3.2 Theoretical Transmission Process

AI-enabled university internal auditing does not involve a simple, direct conversion from tool adoption to improved effectiveness. Rather, under the combined influence of full audit coverage requirements, increasingly complex university governance, and the evolution of AI technologies, it develops through a transmission chain characterized by clear logical levels, complete conversion stages, binding governance constraints, and a closed-loop feedback mechanism. Digital infrastructure and data quality serve as prerequisites. The chain then proceeds through four core stages: technology integration, capability internalization, process reengineering, and value realization. Audit results subsequently feed back into model optimization, data improvement, and institutional upgrading. Governance constraints operate throughout the entire process to ensure the long-term and standardized application of AI in auditing. The transmission logic and implementation pathway comprise the following six components.

First, multiple external conditions constitute the core drivers of transformation. Full audit coverage requirements expand the boundaries of oversight, while the growing complexity of research funding, procurement, capital construction, asset management, and contract administration in universities requires risk identification to move upstream. Big data and AI technologies provide efficient means of processing massive and heterogeneous business information, thereby making intelligent transformation technically feasible.

Second, digital infrastructure and data quality provide dual prerequisite support for transformation. A unified audit data platform, cross-system interfaces, computing and storage resources, and access-control and security systems enable data aggregation. Only complete, accurate, standardized, timely, and traceable data can support the verification of intelligent analytical results and their incorporation into a legally valid audit evidence chain [4].

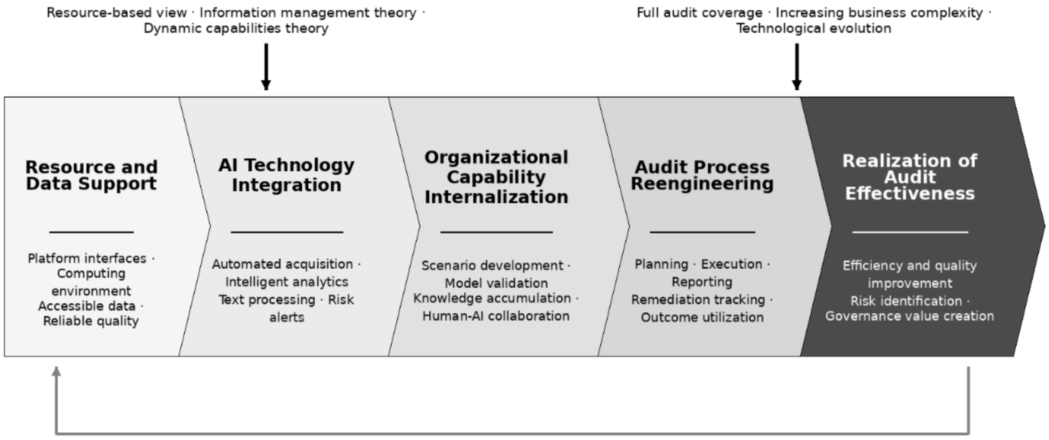
Third, the comprehensive deployment of intelligent tools achieves the initial integration of technology. Intelligent tools can realize their full potential only when combined with audit process reengineering [2]. In practice, automated acquisition reduces data preprocessing costs; machine learning and big data analytics expand the scope of anomaly and risk identification; and natural language processing (NLP) and generative AI support policy retrieval, contract compliance analysis, document synthesis, and working-paper preparation. Risk alerts and continuous auditing further shift oversight from ex post error detection toward dynamic risk control across the entire business process [9].

Fourth, scenario-specific adaptation internalizes digital audit capabilities. General-purpose intelligent tools must be tailored to university operations through business-specific configuration, model validation, and continuous iteration before they can become institution-specific audit capabilities. Audit, information technology, and operational departments should jointly decompose risk logic, standardize data fields, validate alert results, and calibrate model parameters. In this way, fragmented tool applications can be consolidated into reusable and iterative routine audit capabilities, providing the capability foundation for process reengineering [3].

Fifth, end-to-end process reengineering converts digital capabilities into actual audit effectiveness. AI can be embedded throughout risk scanning in audit planning, data-based evidence collection and verification, issue determination and reporting, and remediation follow-up, thereby transforming traditional segmented project audits into integrated and collaborative auditing [3].

Sixth, value outputs establish a closed-loop mechanism for continuous iteration. Audit findings and remediation conclusions can be used to update risk rules, recalibrate algorithmic models, and improve source-system data. Binding requirements relating to data security, algorithmic explainability, human review, and end-to-end accountability records should operate throughout the chain to prevent algorithmic outputs from being adopted as final audit conclusions without human verification [8].

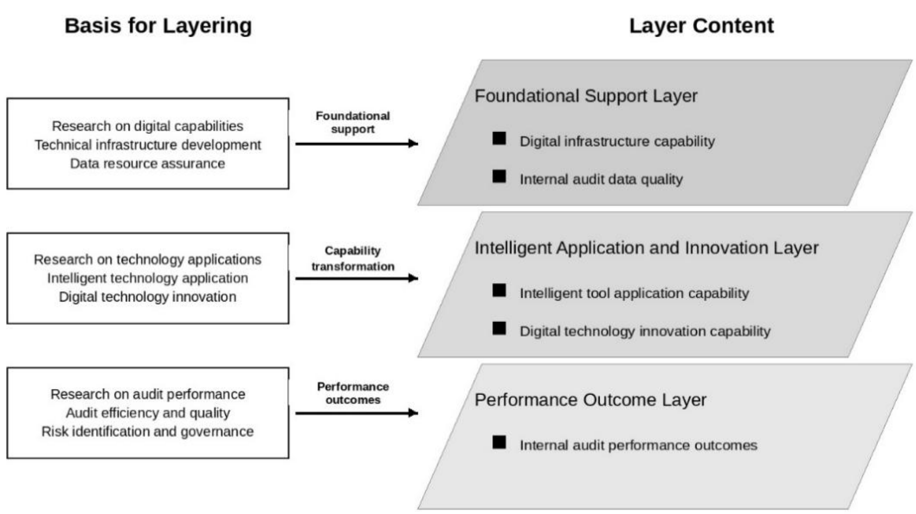
Figure 1. Theoretical mechanism through which AI enhances university internal audit effectiveness



3.3 Derivation of the Evaluation Dimensions

To further assess the development level and effectiveness of AI-enabled university internal auditing, this study translates the theoretical pathways described above into observable and assessable dimensions. Drawing on research concerning digital capabilities, technology application, and audit performance [5], and considering the practical characteristics of university internal auditing in terms of technological foundations, data support, intelligent applications, innovation development, and effectiveness improvement, five evaluation dimensions are derived: digital infrastructure capability, intelligent tool application capability, digital technology innovation capability, internal audit data quality, and internal audit performance outcomes, as shown in Figure 2.

Figure 2. Derivation of the evaluation dimensions



4. Construction of an AHP-Based Evaluation System for AI-Enabled University Internal Audit Effectiveness

4.1 Suitability of the AHP Method

AHP is suitable for complex evaluation problems involving multiple levels and factors. Its basic approach is to decompose an overall evaluation objective into a hierarchy, compare the relative importance of factors at the same level through judgment matrices, and calculate corresponding weights. This process transforms a complex evaluation object into a clearly structured hierarchical system with explicit relationships. AI-enabled university internal audit effectiveness involves several dimensions, including digital infrastructure, intelligent tool applications, digital technology innovation, audit data quality, and audit performance outcomes. These dimensions are interrelated but perform distinct evaluative functions, giving the system a clear hierarchical and systemic structure. AHP therefore aligns well with the structural characteristics of this evaluation system and provides a relatively standardized method for determining indicator weights at each level [6].

AI-enabled university internal auditing is also highly comprehensive. Its evaluation concerns not only the conditions and capabilities required for applying AI technologies, but also data support, business integration, and the resulting audit effectiveness. Through expert judgments and pairwise comparisons, AHP converts professional experience into relative weights. It can therefore incorporate perspectives from internal auditing, information technology, and university administration, improve the fit between the weighting scheme and actual audit settings, and reduce bias arising from the cognitive limitations of a single evaluator.

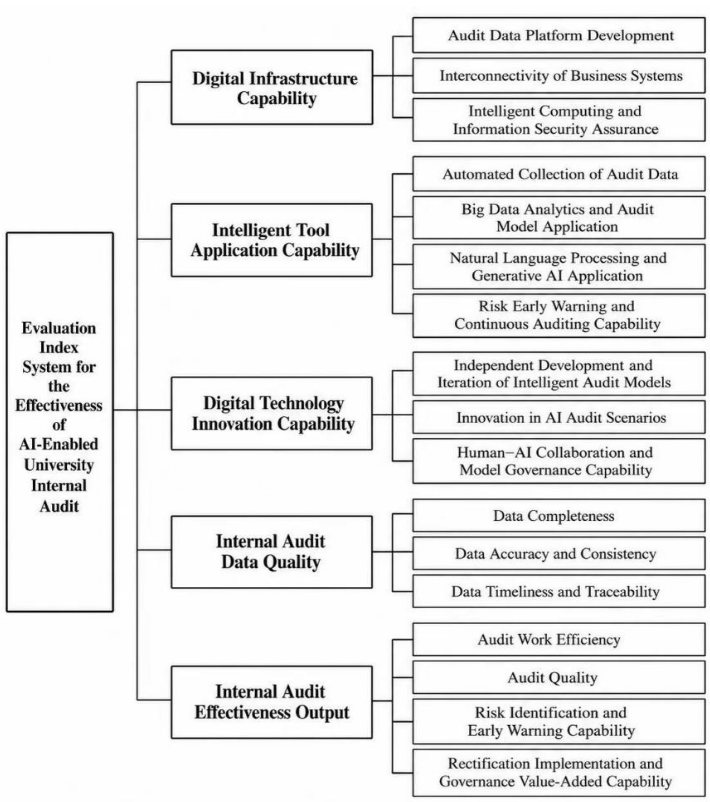
From an implementation perspective, AHP captures the multidimensional nature of AI-enabled university internal auditing while highlighting the relative importance of different indicators in the overall evaluation. While maintaining the completeness of the indicator system, it differentiates among the digital foundation, technology application, innovation capability, data quality, and performance outcomes, making the evaluation results more consistent with the operational characteristics of AI-enabled university internal auditing.

4.2 Construction of the Evaluation System for AI-Enabled University Internal Audit Effectiveness

4.2.1 Indicator System for AI-Enabled University Internal Audit Effectiveness

The evaluation content for AI-enabled university internal audit effectiveness is determined primarily by the requirements of digital transformation in university internal auditing, the application characteristics of AI technologies, and the functional positioning of internal audit. It includes: (1) the information systems, data platforms, computing resources, and security safeguards required for intelligent internal auditing; (2) the actual application of AI and related digital technologies in audit data acquisition, analytical processing, anomaly detection, and dynamic monitoring; (3) the development of intelligent models, technological optimization, and expansion of application scenarios by university internal audit departments in response to audit needs; (4) the completeness, accuracy, timeliness, and traceability of audit data during aggregation, processing, and use; and (5) the actual effects of AI applications on audit efficiency, audit quality, risk identification, remediation implementation, and governance value creation. Based on the preceding theoretical analysis and the derived evaluation dimensions, and in conjunction with relevant research and the operational characteristics of university internal auditing, these evaluation components are consolidated and refined into five first-level indicators and 17 second-level indicators, as shown in Figure 3.

Figure 3. Hierarchical structure of the evaluation system for AI-enabled university internal audit effectiveness



First, digital infrastructure capability. Digital infrastructure is an essential prerequisite for embedding AI technologies in university internal auditing. This dimension assesses whether a university has the data environment, system environment, and technical safeguards required to support intelligent auditing and whether the foundation for the sustained integration of AI into internal audit activities is sufficiently developed. Its second-level indicators are the development level of the audit data platform, the degree of interoperability among business systems, and intelligent computing and information security safeguards.

Second, intelligent tool application capability. The application of intelligent tools is the most direct manifestation of AI in university internal audit activities. The central issue is whether digital technologies are genuinely integrated into audit processes and contribute to analysis, identification, and decision support. This dimension assesses the extent to which AI technologies are applied in specific audit activities and the degree to which they improve traditional audit methods. Its second-level indicators are automated audit data acquisition capability, big data analytics and audit model application, NLP and generative AI application, and risk alert and continuous auditing capability.

Third, digital technology innovation capability. AI-enabled university internal auditing requires more than the introduction of existing technological tools; application approaches must be continuously optimized in accordance with university-specific operations and audit needs [11]. This dimension assesses whether an internal audit department can continually improve intelligent technologies, expand application scenarios, and standardize technology use in response to changes in business activities. Its second-level indicators are the independent development and iteration of intelligent audit models, innovation in AI-enabled audit scenarios, and human-AI collaboration and model governance capability.

Fourth, internal audit data quality. Data provide the foundation for AI-based audit identification, analysis, and judgment, and their quality directly affects the accuracy and reliability of intelligent audit results. This dimension assesses whether audit data completely reflect relevant economic activities and management processes, whether data from different sources remain accurate and consistent, and whether data generation and changes are recorded and traced in a timely and effective manner. It thereby determines whether the data can meet the requirements of intelligent audit analysis and risk identification. Its second-level indicators are data completeness, data accuracy and consistency, and data timeliness and traceability.

Fifth, internal audit performance outcomes. The ultimate purpose of enabling university internal auditing with AI is to improve audit performance and strengthen the role of internal auditing in risk prevention and university governance [12]. This dimension assesses the actual effects of AI applications on audit execution, issue detection, risk control, and the conversion of audit results into governance improvements. Its second-level indicators are audit efficiency, audit quality, risk identification and alert capability, and remediation implementation and governance value creation capability.

4.2.2 Determining Indicator Weights Using AHP

(1) Establishing the hierarchical structure model

In the hierarchical structure model, the target level is the evaluation system for AI-enabled university internal audit effectiveness (U). The criterion level comprises digital infrastructure capability (U_1), intelligent tool application capability (U_2), digital technology innovation capability (U_3), internal audit data quality (U_4), and internal audit performance outcomes (U_5). The indicator level comprises U_{11}, U_{12}, U_{13}, U_{21}, ..., and U_{54}.

(2) Constructing judgment matrices and assigning scale values

For the indicator system, pairwise-comparison judgment matrices are constructed according to AHP principles. The relative importance of factors at the same level is evaluated using the 1-9 scale shown in Table 1. Taking the target-level judgment of one valid expert as an example, the target U contains five factors: U_1, U_2, U_3, U_4, and U_5. Each pair of factors is compared in terms of its importance to U and assigned a value on the 1-9 scale, producing the judgment matrix shown in Table 2.

Table 1. The 1-9 scale and its interpretation

Scale	Definition	Interpretation
1	Equal importance	The two factors are equally important
3	Moderate importance	The former factor is moderately more important than the latter

Scale	Definition	Interpretation
5	Strong importance	The former factor is strongly more important than the latter
7	Very strong importance	The former factor is very strongly more important than the latter
9	Extreme importance	The former factor is extremely more important than the latter
2, 4, 6, 8	Intermediate values	Intermediate judgments between two adjacent scale values

Table 2. Example judgment matrix at the criterion level

U	U_1	U_2	U_3	U_4	U_5	W_i	CR
U_1	1	1/2	2	1/2	1/3	0.1208	
U_2	2	1	3	1	1/2	0.2154	
U_3	1/2	1/3	1	1/3	1/4	0.0735	CR=0.0074 <0.1
U_4	2	1	3	1	1/2	0.2154	
U_5	3	2	4	2	1	0.3750	

(3) Weight calculation and consistency testing

After the judgment matrix has been quantified, its consistency should be tested. Using the target-level judgment matrix U in Table 2 as an example, the root method is first applied to obtain the eigenvector P and the maximum eigenvalue λmax. The consistency test is then performed using the following formula:

$$CR = \frac{CI}{RI}$$

where CI denotes the consistency index,

$$CI = \frac{\lambda max - n}{n - 1}$$

where n is the order of the judgment matrix and RI is the average random consistency index, which can be obtained from a reference table. A matrix passes the consistency test when $CR < 0.1$, and its normalized eigenvector can then be used as the weight vector. When $CR \geq 0.1$, the judgment matrix should be revised. For the matrix shown in Table 2, $\lambda max = 5.0331$, $CI = 0.0083$, $RI = 1.12$, and $CR = 0.0074 < 0.1$; therefore, the matrix passes the consistency test. The matrices provided by the remaining experts and the indicator-level matrices under U_1-U_5 were tested using the same procedure, and all satisfied $CR < 0.1$.

(4) Aggregating and determining indicator weights

Twelve experts conducted pairwise comparisons of the indicators at each level of the evaluation system. After each expert's judgment matrices passed the consistency test, the geometric mean was used to aggregate each comparison item. This produced six composite judgment matrices for the target level and U_1-U_5, which were then subjected to a second consistency test. All composite matrices satisfied $CR < 0.1$, and the composite criterion-level matrix yielded $CR = 0.0012$. Indicator weights at each level were subsequently determined in accordance with the procedure described above. The composite weight vector at the criterion level was W = (0.0990, 0.1739, 0.0596, 0.2599, 0.4076). The local weights of the indicators under U_1-U_5 are reported in Table 3.

Table 3. Evaluation indicators and weights for AI-enabled university internal audit effectiveness

Target Level	Criterion Level	Indicator Level	Weight
AI-enabled university internal audit effectiveness	Digital infrastructure capability (U_1)	U_{11} Development level of the audit data platform	23.94%
		U_{12} Degree of interoperability among business systems	51.39%
		U_{13} Intelligent computing and information security safeguards	24.68%
	Intelligent tool application capability (U_2)	U_{21} Automated audit data acquisition capability	19.20%
		U_{22} Big data analytics and audit model application	33.99%
		U_{23} NLP and generative AI application	9.96%
		U_{24} Risk alert and continuous auditing capability	36.85%
	Digital technology innovation capability (U_3)	U_{31} Independent development and iteration of intelligent audit models	38.97%
		U_{32} Innovation in AI-enabled audit scenarios	18.59%
		U_{33} Human-AI collaboration and model governance capability	42.43%
	Internal audit data quality (U_4)	U_{41} Data completeness	22.96%
		U_{42} Data accuracy and consistency	23.79%
		U_{43} Data timeliness and traceability	53.25%
	Internal audit performance outcomes (U_5)	U_{51} Audit efficiency	11.78%
		U_{52} Audit quality	21.80%
		U_{53} Risk identification and alert capability	24.18%
		U_{54} Remediation implementation and governance value creation capability	42.24%

5. Evaluation of AI-Enabled University Internal Audit Effectiveness

5.1 Evaluation Criteria

Because the evaluation of AI-enabled university internal audit effectiveness includes both quantitative and qualitative indicators, the evaluation criteria should be determined according to the nature of each indicator. The assessment is based primarily on four types of criteria: (1) national laws and regulations, requirements issued by education authorities, and relevant university rules and regulations; (2) staged objectives and the completion of planned tasks for the digital and intelligent development of university internal auditing; (3) the development level of internal auditing at comparable universities, generally accepted industry practices, and statistics released by relevant functional departments; and (4) objective evidence, including audit data platform logs, audit project files, model operation records, remediation registers, and materials documenting the use of audit results.

5.2 Evaluation Using the Fuzzy Comprehensive Evaluation Method

5.2.1 Establishing the Evaluation Factor Sets

The establishment of evaluation factor sets is a prerequisite for constructing the fuzzy comprehensive evaluation model for AI-enabled university internal audit effectiveness [6]. Let the target-level evaluation factor set be U: $U = \{U_1, U_2, U_3, U_4, U_5\}$. Here, U_1, U_2, U_3, U_4, and U_5 denote digital infrastructure capability, intelligent tool application capability, digital technology innovation capability, internal audit data quality, and internal audit performance outcomes, respectively.

The corresponding indicator factor sets for each criterion are then established as follows:

$$U_1 = \{U_{11}, U_{12}, U_{13}\}$$

$$U_2 = \{U_{21}, U_{22}, U_{23}, U_{24}\}$$

$$U_3 = \{U_{31}, U_{32}, U_{33}\}$$

$$U_4 = \{U_{41}, U_{42}, U_{43}\}$$

$$U_5 = \{U_{51}, U_{52}, U_{53}, U_{54}\}$$

5.2.2 Determining the Weights of the Evaluation Indicators

Based on the AHP results, the criterion-level weight vector for evaluating AI-enabled university internal audit effectiveness is:

$$W = (0.0990, 0.1739, 0.0596, 0.2599, 0.4076)$$

The corresponding indicator-level weight vectors are:

$W_1 = (0.2394, 0.5139, 0.2468)$

$W_2 = (0.1920, 0.3399, 0.0996, 0.3685)$

$W_3 = (0.3897, 0.1859, 0.4243)$

$W_4 = (0.2296, 0.2379, 0.5325)$

$W_5 = (0.1178, 0.2180, 0.2418, 0.4224)$

5.2.3 Establishing the Evaluation Set

For the fuzzy comprehensive evaluation, the results for AI-enabled university internal audit effectiveness are classified into five levels:

$$V = \{V_1, V_2, V_3, V_4, V_5\} = \{\text{Excellent, Good, Moderate, Poor, Very Poor}\}$$

For quantification, scores of 95, 85, 75, 65, and 55 are assigned to the five evaluation levels, respectively. The corresponding score vector is:

$$C = (95, 85, 75, 65, 55)^T$$

The intervals for the comprehensive score H are defined as follows: $90 \leq H \leq 100$ indicates Excellent; $80 \leq H < 90$, Good; $70 \leq H < 80$, Moderate; $60 \leq H < 70$, Poor; and $H < 60$, Very Poor.

5.2.4 Evaluation Procedure

During the evaluation, the same 12 experts with expertise in university internal auditing, financial management, audit digitalization, and data governance assessed the 17 indicators. Using a consistent evaluation object, reference date, and set of criteria, each expert independently selected one of five levels: Excellent, Good, Moderate, Poor, or Very Poor. The number of expert ratings assigned to each level for each indicator was aggregated, and the proportion of experts selecting each level was used as the corresponding membership degree. Single-factor fuzzy relation matrices were then established for each criterion.

Five single-factor fuzzy relation matrices were constructed: R_1 for digital infrastructure capability, R_2 for intelligent tool application capability, R_3 for digital technology innovation capability, R_4 for internal audit data quality, and R_5 for internal audit performance outcomes.

5.2.5 Fuzzy Transformation and Evaluation Results

The product-sum method was used to calculate the fuzzy evaluation result for each criterion. The criterion-level evaluation vectors are:

$$U_1 = W_1 \times R_1$$

$$U_2 = W_2 \times R_2$$

$$U_3 = W_3 \times R_3$$

$$U_4 = W_4 \times R_4$$

$$U_5 = W_5 \times R_5$$

The vectors U_1-U_5 are arranged sequentially to form the target-level fuzzy relation matrix R. The comprehensive evaluation result for AI-enabled university internal audit effectiveness is:

$$U = W \times R$$

To eliminate minor errors caused by decimal rounding during calculation, the comprehensive evaluation vector is normalized:

$$U' = \text{Normalize}(U)$$

The final comprehensive evaluation score is:

$$H = U' \times C$$

5.3 Case Study

5.3.1 Expert Assessment

University A was selected as the evaluation object. Based on materials concerning its digital and intelligent internal audit development, the aforementioned 12 experts evaluated the 17 indicators of AI-enabled internal audit effectiveness. Each expert independently assessed the same object at the same reference date using the same criteria. The aggregated frequencies of the ratings are reported in Table 4.

Table 4. Expert ratings of AI-enabled internal audit effectiveness at University A

Second-Level Indicator	Number of Expert Ratings				
	Excellent	Good	Moderate	Poor	Very Poor
U_{11} Development level of the audit data platform	1	8	3	0	0
U_{12} Degree of interoperability among business systems	0	7	5	0	0
U_{13} Intelligent computing and information security safeguards	0	7	5	0	0
U_{21} Automated audit data acquisition capability	0	6	5	1	0
U_{22} Big data analytics and audit model application	0	7	5	0	0
U_{23} NLP and generative AI application	0	2	5	4	1
U_{24} Risk alert and continuous auditing capability	0	7	5	0	0
U_{31} Independent development and iteration of intelligent audit models	0	3	5	4	0
U_{32} Innovation in AI-enabled audit scenarios	0	6	6	0	0
U_{33} Human-AI collaboration and model governance capability	0	3	5	4	0
U_{41} Data completeness	0	7	5	0	0
U_{42} Data accuracy and consistency	0	6	6	0	0
U_{43} Data timeliness and traceability	0	5	6	1	0
U_{51} Audit efficiency	1	8	3	0	0
U_{52} Audit quality	1	8	3	0	0
U_{53} Risk identification and alert capability	1	8	3	0	0
U_{54} Remediation implementation and governance value creation capability	2	8	2	0	0

5.3.2 Fuzzy Transformation

Based on the expert ratings in Table 4, the number of ratings assigned to each of the five levels for each indicator was divided by the total number of experts (12) to obtain the corresponding membership degrees and construct R_1-R_5. The fuzzy transformations were then performed using the indicator-level weights determined in Section 4, as shown below.

All fuzzy transformations were calculated using unrounded original weights and membership degrees. The weights, membership degrees, and evaluation vectors presented in the text are rounded to the specified number of decimal places. Consequently, summing the displayed component values or recalculating directly from those values may produce negligible rounding differences; these do not affect the comprehensive score or evaluation level.

(1) Evaluation of digital infrastructure capability

$$W_1=(0.2394,\ 0.5139,\ 0.2468)$$

$$R_1=\begin{bmatrix} 0.0833, & 0.6667, & 0.2500, & 0.0000, & 0.0000 \\ 0.0000, & 0.5833, & 0.4167, & 0.0000, & 0.0000 \\ 0.0000, & 0.5833, & 0.4167, & 0.0000, & 0.0000 \end{bmatrix}$$

$$U_1 = W_1 \times R_1 = (0.0199,\ 0.6033,\ 0.3768,\ 0.0000,\ 0.0000)$$

(2) Evaluation of intelligent tool application capability

$$W_2 = (0.1920, 0.3399, 0.0996, 0.3685)$$

$$R2=\begin{bmatrix} 0.0000, & 0.5000, & 0.4167, & 0.0833, & 0.0000 \\ 0.0000, & 0.5833, & 0.4167, & 0.0000, & 0.0000 \\ 0.0000, & 0.1667, & 0.4167, & 0.3333, & 0.0833 \\ 0.0000, & 0.5833, & 0.4167, & 0.0000, & 0.0000 \end{bmatrix}$$

$$U_2 = W_2 \times R_2 = (0.0000, 0.5258, 0.4167, 0.0492, 0.0083)$$

(3) Evaluation of digital technology innovation capability

$$W_3 = (0.3897, 0.1859, 0.4243)$$

$$R3=\begin{bmatrix} 0.0000, & 0.2500, & 0.4167, & 0.3333, & 0.0000 \\ 0.0000, & 0.5000, & 0.5000, & 0.0000, & 0.0000 \\ 0.0000, & 0.2500, & 0.4167, & 0.3333, & 0.0000 \end{bmatrix}$$

$$U_3=W_3\times R_3=(0.0000, 0.2965, 0.4322, 0.2714, 0.0000)$$

(4) Evaluation of internal audit data quality

$$W_4 = (0.2296, 0.2379, 0.5325)$$

$$R4=\begin{bmatrix} 0.0000, & 0.5833, & 0.4167, & 0.0000, & 0.0000 \\ 0.0000, & 0.5000, & 0.5000, & 0.0000, & 0.0000 \\ 0.0000, & 0.4167, & 0.5000, & 0.0833, & 0.0000 \end{bmatrix}$$

$$U_4=W_4\times R_4=(0.0000, 0.4748, 0.4809, 0.0444, 0.0000)$$

(5) Evaluation of internal audit performance outcomes

$$W_5 = (0.1178, 0.2180, 0.2418, 0.4224)$$

$$R5=\begin{bmatrix} 0.0833, & 0.6667, & 0.2500, & 0.0000, & 0.0000 \\ 0.0833, & 0.6667, & 0.2500, & 0.0000, & 0.0000 \\ 0.0833, & 0.6667, & 0.2500, & 0.0000, & 0.0000 \\ 0.1667, & 0.6667, & 0.1667, & 0.0000, & 0.0000 \end{bmatrix}$$

$$U_5=W_5\times R_5=(0.1185, 0.6667, 0.2148, 0.0000, 0.0000)$$

The five criterion-level evaluation vectors are arranged sequentially to form the target-level relation matrix R. The comprehensive evaluation vector for AI-enabled internal audit effectiveness at University A is:

$$W = (0.0990, 0.1739, 0.0596, 0.2599, 0.4076)$$

$$U = W \times R = (0.050292, 0.563964, 0.348041, 0.036260, 0.001444)$$

5.3.3 Normalization

Because retaining a limited number of decimal places for weights and membership degrees may introduce minor rounding errors, the comprehensive evaluation vector U is normalized. After normalization, the membership degrees sum to 1, yielding:

$$U' = (0.050292, 0.563963, 0.348041, 0.036260, 0.001444)$$

5.3.4 Calculation of the Fuzzy Evaluation Result

Using the score vector $C = (95, 85, 75, 65, 55)^T$, the comprehensive score for AI-enabled internal audit effectiveness at University A is calculated as follows:

$$H = U' \times C = 81.25$$

The comprehensive score is 81.25, which falls within the interval of 80-90 and corresponds to the Good level.

5.3.5 Analysis of the Evaluation Results

University A obtained a comprehensive score of 81.25 for AI-enabled internal audit effectiveness, corresponding to an overall rating of Good. This indicates that the university has established a foundation in digital infrastructure, intelligent audit applications, and the conversion of technological capabilities into audit outcomes. However, substantial differences remain among the five dimensions, as discussed below.

Digital infrastructure capability scored 81.43, corresponding to the Good level. The results indicate that University A has a relatively stable audit data platform and basic computing safeguards that provide an operational environment for intelligent auditing. Nevertheless, interoperability among business systems can be further improved, particularly with respect to the stability of cross-system data interfaces and the efficiency of data sharing.

Intelligent tool application capability scored 79.60, corresponding to the Moderate level. NLP and generative AI application received a score of 71.67, making it a prominent weakness within this dimension. Although intelligent tools have been introduced into some audit activities, their application remains insufficiently developed in contract text analysis, policy retrieval, document synthesis, and working-paper support. Continuous auditing and risk alert capabilities also require further expansion.

Digital technology innovation capability scored 75.25, the lowest among the five criteria, and corresponded to the Moderate level. Both the independent development and iteration of intelligent audit models and human-AI collaboration and model governance scored 74.17. These results indicate that universities need to strengthen independent model development, version validation, performance feedback, and accountability mechanisms for human review. The continuous adaptation of technological tools to university-specific operations is critical to converting isolated AI applications into stable audit capabilities.

Internal audit data quality scored 79.30, corresponding to the Moderate level. Data completeness and accuracy generally meet current audit requirements; however, data timeliness and traceability scored 78.33 and remain important constraints on the reliability of intelligent analytical results. Delayed data updates and inadequate records of data processing can impede the review of model outputs and the construction of a defensible audit evidence chain.

Internal audit performance outcomes scored 84.04, corresponding to the Good level and representing the best-performing dimension. Audit efficiency, audit quality, and risk identification capability all received relatively high ratings, while remediation implementation and governance value creation scored 85.00. These results suggest that AI applications have already improved work efficiency, supported risk detection, and facilitated remediation and governance. Sustained improvement in performance outcomes, however, continues to depend on the coordinated development of data foundations, intelligent tools, and technological innovation capabilities.

6. Strategies for Enhancing AI-Enabled University Internal Audit Effectiveness

6.1 Strengthen Digital Technology Innovation and Improve Model Development and Governance

Digital technology innovation capability is the most prominent weakness identified by the evaluation. Universities should gradually establish mechanisms for developing intelligent audit models through the joint participation of auditors, information technology specialists, and relevant operational departments. Risk rules, anomaly characteristics, and business knowledge accumulated during audit projects should be converted into reusable models. Models characterized by persistently high false-positive rates, changes in the data environment, or insufficient explainability should be promptly adjusted, suspended, or retired to improve the stability and sustainable applicability of intelligent audit models.

6.2 Deepen the Application of Intelligent Tools and Expand AI-Enabled Audit Scenarios

The evaluation results show considerable room for improvement in intelligent tool application capability, particularly in the use of NLP and generative AI. University internal audit departments should adopt a scenario-oriented approach and prioritize areas with sound data foundations, relatively clear business rules, and frequent risk events. For example, anomaly detection and risk alert models can be developed for research funding, procurement and tendering, capital construction, asset management, and contract performance. Generative AI can initially be deployed in relatively controllable scenarios, including policy retrieval, comparison of contract clauses, synthesis of audit materials, evidence indexing, and working-paper assistance. For high-impact matters such as issue determination, responsibility attribution, and final audit conclusions, human review and evidence verification must remain mandatory, and model outputs should not be treated directly as audit conclusions.

6.3 Strengthen Audit Data Governance and Improve Data Timeliness and Traceability

The quality of internal audit data directly affects the reliability of AI-based analytical results. To address weaknesses in data timeliness and traceability, universities should establish an end-to-end data quality management mechanism covering completeness, accuracy, consistency, timeliness, and traceability. Data entering audit platforms and intelligent models should be subject to field-completeness checks, cross-system reconciliation, outlier detection, and update-timing checks. For data used in significant audit judgments, the source system, extraction time, processing procedures, and version information should be fully recorded to ensure that analytical results can be traced and reviewed. Data omissions, definitional inconsistencies, and delayed updates identified during audits should be promptly communicated to data-producing departments, shifting data quality governance from the audit-use stage to the source business processes.

6.4 Improve Digital Infrastructure and Strengthen System Interoperability

Digital infrastructure is a prerequisite for the continuous operation of AI-enabled auditing. Universities should further develop unified audit data platforms and gradually incorporate key systems for finance, research, procurement, assets, construction, human resources, and contracts into a common data acquisition and management framework. Standardized data interfaces, field definitions, and update mechanisms should be established. Where cross-system interfaces remain unstable and some data still require manual maintenance, frequently used audit data should transition from ad hoc extraction to automated acquisition and scheduled updating. Computing capacity, storage, access control, logging, and data security mechanisms should also be improved to provide a reliable technical environment for the stable operation of intelligent models.

6.5 Improve the Closed Loop for Risk Detection and Remediation to Sustain Audit Governance Value

Internal audit performance outcomes constitute the strongest dimension in the current evaluation. While preserving existing advantages in efficiency and quality, universities should further strengthen the conversion of audit findings into governance improvements. Recurrent issues across projects and departments should be analyzed jointly to identify institutional deficiencies and systemic risks, and remediation results should feed back into updates of risk rules and model parameters. Greater coordination among internal auditing, finance, internal control, disciplinary inspection, and supervisory mechanisms can promote the transformation of audit results from the detection of isolated issues into institutional improvement, risk prevention, and management decision support.

7. Conclusion

The enhancement of university internal audit effectiveness through AI is systemic and incremental. Its effects do not arise merely from the introduction of technological tools; rather, they depend on the coordinated development of digital infrastructure, internal audit data quality, intelligent tool applications, and technological innovation capabilities, and are ultimately reflected in improved audit efficiency, audit quality, risk identification, and governance value creation [12]. The study further finds that the intelligent development of university internal auditing continues to be constrained by insufficient depth of technology application, weak model development and governance capabilities, and inadequate data timeliness and traceability. University internal audit transformation should therefore place greater emphasis on the connections among foundational support, capability conversion, and performance realization. By improving data governance, deepening the application of intelligent audit scenarios, strengthening technological innovation, and establishing a closed loop for remediation and governance, universities can gradually transform AI from an auxiliary tool into an important capability for improving internal audit quality and university governance.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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