ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 3 - 2026

# Theoretical basis and empirical analysis of the construction of intelligent audit system for digital economy enterprises driven by artificial intelligence

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**SUMMARY:** *This article aims to use the improved entropy weight TOPSIS evaluation model to conduct decision analysis on the content of the intelligent audit system for digital economy enterprises driven by artificial intelligence in China, in order to solve the current dilemma of internal audit in China and explore new ideas for the development of internal audit. By using literature analysis and expert survey methods, a performance evaluation system for internal audit of enterprises was constructed, including four primary indicators and 19 secondary indicators. The qualitative indicators were quantified using the semantic difference membership degree assignment method, and the quantitative indicators were normalized using the hierarchical processing method. Using entropy method (EWM) to determine objective weights, combined with Lagrange multiplier method to calculate combined weights, and then using improved TOPSIS evaluation method for decision analysis. Taking the audit evaluation of the quality of scientific and technological development in Shandong Province from 2014 to 2024 as an example, the empirical results show that the improved TOPSIS evaluation method can effectively overcome the influence of subjective factors in the decision-making process, reflect the importance of various factors in the evaluation, and the operation is feasible and effective. Compared with the factor analysis method and the comprehensive scientific and technological progress rate of Shandong Province announced by the Shandong Provincial Department of Science and Technology, the ranking order of the comprehensive scores obtained by the improved TOPSIS evaluation method is consistent, which verifies the scientific and applicability of this method. Improving the TOPSIS evaluation method can achieve a transition from qualitative to quantitative, from local to comprehensive, and enhance the systematic and scientific nature of decision-making, providing assistance for content decision-making in intelligent audit systems for digital economy enterprises driven by artificial intelligence. However, the decision-making process is still inevitably influenced by subjective factors, and attention should be paid to the design of given strategies and plans to avoid limitations.*

***KEYWORDS:*** *Artificial intelligence; Digital economy; Audit system; Entropy weight; TOPSIS evaluation; Lagrange Multiplier*

## 1 Introduction

With the acceleration of global economic integration, rapid development of information technology, rapid changes in the economic environment, and increasingly fierce market competition, it is no longer possible for enterprises to become leaders in every business. Even if they do take the lead step by step, the cost will be very huge. Therefore, enterprises can

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https://doi.org/10.65102/is20261185
Published: 10 June, 2026

completely execute those businesses that they are not good at or in nonprofessional fields through AI driven systems. Therefore, AI driven digital economy enterprise intelligent audit systems have emerged [1]. The AI driven digital economy enterprise intelligent audit system, also known as internal audit informatization, refers to the process in which the management of an enterprise entrusts some or all of its internal audit functions to system development agencies or other professional organizations through contracts [2].

According to traditional concepts, internal audit work should naturally be carried out by internal audit institutions [3]. However, since the 1990s, some enterprises in developed countries have gradually completed some non-core businesses through the development of information systems, with the aim of restructuring enterprise processes and optimizing organizational structure [4]. The survey data conducted by the American Institute of Internal Auditors on the situation of AI driven digital economy enterprise intelligent audit systems in companies in countries such as the United States and Canada shows that the proportion of AI driven digital economy enterprise intelligent audit systems in companies in the United States and Canada has reached 38% and 34.8% respectively, and these companies are spread across various industries; Even enterprises that have not yet implemented AI driven digital economy enterprise intelligent audit systems have a great willingness to do so in the future, with a proportion of approximately 30% to 40%. The US SEC and Congress enacted the Sarbanes Oxley Act, and subsequently scholars conducted a survey of 1000 large and medium-sized enterprises in the United States, many of which were on the Fortune 500 list, in order to examine whether the implementation of the Act has had an impact on the intelligent audit system of AI driven digital economy enterprises, and to what extent. The survey results show that among all enterprises in the United States, the proportion of AI driven digital economy enterprise intelligent audit systems has reached as high as 63%, a significant increase from 38% in 2000, indicating that AI driven digital economy enterprise intelligent audit systems are already very common in the United States [5].

The scope of the AI driven digital economy enterprise intelligent audit system in Western countries is gradually expanding. Initially, the AI driven digital economy enterprise intelligent audit system only included reviewing IT systems, auditing existing electronic data processing (EDP) systems, fraud investigations, cost research, evaluating internal control systems, etc. Later, it gradually developed into the "full information system processing protocol", which means processing all business information systems as a whole [6]. In 2001, the US SEC explicitly stipulated that business audits can be processed by information systems, but if the client company's asset size is over $200 million, the portion provided by the system development agency in internal audit services related to internal accounting controls, financial systems, and financial statements shall not exceed 40%. So overall, both internal financial auditing and management auditing can be processed by information systems [7]. The above is the current situation of intelligent audit systems for digital economy enterprises driven by artificial intelligence abroad. As for which internal audit business content should Chinese enterprises choose information systems to handle in order to better serve their business development? This is the problem that this article attempts to solve, which is how to make decisions on the content of the intelligent audit system for digital economy enterprises driven by artificial intelligence.

The content decision-making of the intelligent audit system for digital economy enterprises driven by artificial intelligence is to choose from numerous internal audit business contents and make decisions on which information systems to process and which not to process. The intelligent audit system for digital economy enterprises driven by artificial intelligence can save costs, improve audit independence, ensure audit quality, and make enterprises pay more attention to core business to a certain extent. This approach has become a beneficial global trend and has attracted widespread attention from the domestic academic community. The research on content decision-making of intelligent audit systems for digital economy enterprises driven by artificial intelligence is conducive to solving the current difficulties in internal auditing in China, exploring new ideas for the development of internal auditing, and promoting the application of AI driven intelligent audit systems for digital economy enterprises in China. Therefore, this article aims to use the improved entropy weight TOPSIS evaluation model to conduct decision analysis on the content of China's AI driven digital economy enterprise intelligent audit system. In the TOPSIS analysis model, the advantages of the AI driven digital economy enterprise intelligent audit system are taken as intermediate influencing factors, and the different business contents of internal audit are taken as each scheme layer. By using the TOPSIS analysis method, the total weight of each scheme layer to the target decision-making layer is obtained, and then the content processed by the information system is selected based on the model results.

# 2 Related works

The content or scope of the intelligent audit system for digital economy enterprises driven by artificial intelligence essentially involves analyzing which parts of the internal audit business are suitable for information system processing and which are not. Since the end of the 20th century, the topic of intelligent audit systems for digital economy enterprises driven by artificial intelligence has been a subject of constant controversy. The Western academic and professional circles have paid great attention to it, and the content of intelligent audit systems for digital economy enterprises driven by artificial intelligence is also one of the focuses of many debates. Around this issue, scholars at home and abroad have conducted a lot of research on intelligent audit systems for digital economy enterprises driven by artificial intelligence [8, 9].

Regarding the content or scope of the intelligent audit system for digital economy enterprises driven by artificial intelligence, in the late 1990s, some foreign researchers believed that information system processing decisions should be made by dividing core and non-core businesses. Non-core areas of the enterprise can be freely processed by the information system, as this can protect the core functions of the enterprise. Matusik and Hill established a two-dimensional model to study the processing scope of information systems based on previous theoretical research, and strongly opposed the above viewpoint. They believe that information system processing is a rather complex decision-making process, influenced by various organizational factors [10]. Whether a certain function of an enterprise should be processed by information systems cannot be simply judged by dividing these functions into core and non-core functions. Decision makers should analyze from the perspective of enterprises that require internal audit information system processing services which internal audit functions can be processed by information systems and which should not.

Research on the decision-making aspect of intelligent audit systems for digital economy enterprises driven by artificial intelligence in foreign countries mainly focuses on the analysis of factors affecting decision-making, and empirical analysis methods are often used in the analysis. Due to the different samples selected, the research results also show diversity, but these studies have all demonstrated the correlation between reducing internal audit fees and improving audit quality and whether a company processes information system. Peter, Nava, and Karin mentioned in their article "Internal Audit Outsourcing in Australia" [11] that the factors that affect the AI driven digital economy enterprise intelligent audit system include enterprise size, transaction costs, technological factors, and company strategy. After selecting samples for regression analysis, they believe that transaction costs and technological factors are related to whether a company has an AI driven digital economy enterprise intelligent audit system, while there is no significant correlation between company size and strategy and whether a company has an AI driven digital economy enterprise intelligent audit system.

Adams uses agency theory to explain what types of companies voluntarily handle internal audit function information systems [12]. He believes that the agency theory assumes that the problem of information asymmetry within the enterprise hinders the principal from effectively supervising the agent. For industries that require specific knowledge, such as the insurance industry, hiring internal auditors may be a more cost-effective contractual mechanism. Through this mechanism, the principal can control the agent's lazy behavior, and the agent can send signals to the principal about their performance of duties. Adams predicts that in complex business environments, organizations are more likely to establish internal audit departments within the enterprise rather than processing internal audit functional information systems. Monoli believes that with the innovation and development of science and technology, limited enterprise resources will no longer be able to meet the needs of core enterprise functions. Therefore, information system processing should be expanded to: if an external organization performs a task more efficiently and at a lower cost than the organization itself, the external organization should be commissioned to perform the task; Otherwise, it will be executed by the organization itself.

Maltin and Lavine elaborated on four forms of information system processing for internal audit based on previous research: supplementation, audit management consulting, full information system processing, and substitution [13]. Aldritzer believes that internal audit information system processing became popular in the 1990s due to its expected win-win economic benefits for both enterprises and accounting firms. Companies implementing internal audit information system processing can reduce their internal audit costs and access the professional knowledge and skills of information system processing companies. If these professional knowledge and skills are supplied and maintained by a dedicated internal audit department, the corresponding costs will exceed the budget of the enterprise. James found that hiring full-time external auditors to perform internal audit tasks can significantly improve the technical level of internal audit within the professional scope, but there is no clear evidence to suggest that it will increase the confidence of company investors, because compared to internal auditors, external auditors lack in-depth understanding of the company.

For the content of intelligent audit systems for digital economy enterprises driven by artificial intelligence, the domestic academic community has not specifically defined which ones should be processed by information systems and how they should be processed by information systems. Regarding the form and content of intelligent audit systems for digital economy enterprises driven by artificial intelligence, some scholars first analyze the influencing factors of information system processing, and then select the optimal form and content of information system processing. Starting from the analysis of the functions and core values of modern internal auditing, Jiang Xinxin believes that in order for enterprises to reasonably choose the content of AI driven digital economy enterprise intelligent auditing systems, they should first understand the importance and role of various business contents of internal auditing, and make judgments based on this [14]. Dong Ai analyzed the content and procedures of internal audit from two aspects, and believed that companies can consider processing internal audit areas that are not closely related to core strategies, as well as specific audit procedures such as research background information, on-site audit tasks, tracking and follow-up audits, through information systems. This not only fully utilizes the professional knowledge and rich audit experience of external auditors to improve audit efficiency and quality, but also enhances the rationality and feasibility of audit conclusions and recommendations through internal and external cooperation. Guo Menglan believes that companies have different requirements for internal audit at different stages of development, and internal audit should make changes according to the situation. Therefore, it is better to choose the form and content of information system processing according to the growth cycle. If the AI driven digital economy enterprise intelligent audit system is divided into two forms: partial information system processing and full information system processing, Dai Jiemin and Fang Hongxing are more in favor of the former. They also believe that there are actually many contents of internal audit, and we can selectively process these contents for information system processing. As for which ones are suitable for information system processing and which ones are not, they can be divided according to their importance in the enterprise. In the key areas of internal audit, such as economic benefit audit, economic responsibility audit, human resources audit, customer satisfaction audit, price audit, etc., these audit projects generally involve the enterprise's trade secrets, core strategic planning, and key pricing strategies, so they are not suitable for outsourcing to external agencies. Non critical audit projects such as compliance audits, infrastructure project audits, compliance testing, program audits, and some environmental audit procedures can be processed through information systems.

In short, the forms and contents of intelligent audit systems for digital economy enterprises driven by artificial intelligence are diverse. Enterprises should fully consider various factors such as legal environment, enterprise size, the position of internal audit in the enterprise, integration ability, knowledge management, external resources, etc., and choose the most effective resource allocation method to greatly improve the effectiveness of internal audit.

# 3 Construction of Performance Evaluation System for Internal Audit of Enterprises

## 3.1 Principles of Network Audit

The intelligent audit system for digital economy enterprises driven by networked artificial intelligence, which is currently being researched and implemented in China, is a way of continuous auditing [15]. It can be seen as a data oriented networked audit, and its basic principle is shown in Figure 1. Its characteristics are as follows:

1) Implementing timely auditing: Auditors access the financial information database of the audited entity through the internet, reducing the interval and inspection time between each inspection activity. For specific financial revenue and expenditure matters, audits can be conducted either after the completion of the matter or during the process, thus achieving a combination of post audit and in-process audit, as well as a combination of static audit and dynamic audit.

2) Implementing remote auditing: In online auditing, auditing agencies can remotely access the financial management system and its database or database backup of the audited entity through the network. With the gradual improvement of the informatization level of the audited units, the degree of remote access to complete audits will also be enhanced, and the timeliness characteristics will become more apparent as a result.

3) Realize more efficient data collection and analysis: In traditional on-site audits, auditors use computer-aided implementation to collect and analyze audit data, which is limited in data volume by the equipment they carry and the scope of the audit, and affected in time by on-site networking and audit progress. In online auditing, the network connection is completed in one go, and the quantity of data collection and analysis is basically not limited by the equipment. The audit scope is determined in advance as the maximum possible range, and the time is not affected by the on-site networking time and audit period. Therefore, online auditing has higher efficiency in collecting and analyzing audit data.

4) Information systems have become a new audit content: in online auditing, information

systems composed of people, computer hardware, software, and data sources are responsible for collecting, processing, storing, transmitting, and providing decision-making information, becoming a new content of internal control, involving various elements of internal control.

The selection of evaluation indicators is crucial for evaluating the performance of intelligent auditing in digital economy enterprises driven by artificial intelligence on the Internet. This article is based on the implementation principle of online auditing in China, using expert survey and literature analysis methods to analyze the factors that affect the performance of online auditing. The main content includes [16]: 1) analyzing the main factors that affect the performance of online auditing from a cost-benefit perspective; 2) Analyze the main factors affecting the performance of online auditing from the perspective of risk control in the entire online auditing system; 3) Other factors, such as the quality of the design and development of the online audit system. On this basis, considering the one-time cost, recurring cost, tangible benefits, intangible benefits, and risk control status of the online audit system, performance evaluation indicators are designed.

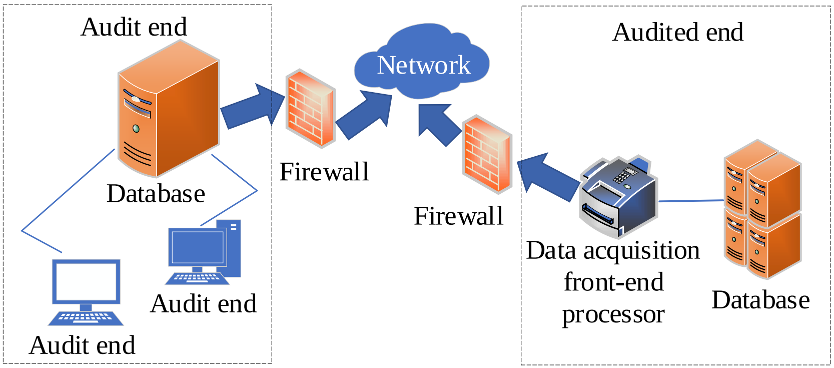


*Figure 1: Basic principle of intelligent audit system for digital economy enterprises driven by networked artificial intelligence*

## 3.2 Evaluation Indicator System

Selecting effective evaluation indicators and constructing a relatively reasonable indicator system is the cornerstone of performance evaluation for AI driven digital economy enterprise intelligent audit systems. The internal audit performance evaluation system should consist of a series of indicators designed to objectively reflect the audit performance level of the internal audit department, and is proposed for how to achieve overall quality and final work performance. Therefore, the indicator design for internal audit performance evaluation should consider various factors that affect the internal management audit performance of the enterprise [17]. Only by evaluating from multiple perspectives can objective conclusions be drawn. Although it is impossible to achieve 100% comprehensiveness in the selection of evaluation indicators, it is still possible to highlight key points while adhering to certain principles. This article believes that the selection principles for performance evaluation indicators of intelligent audit systems for digital economy enterprises driven by artificial intelligence are as follows:

(1) The principle of comprehensiveness. The content of internal audit work in enterprises is complex and trivial. Therefore, in order to correctly evaluate the performance of internal audit, a comprehensive examination must be conducted, which requires comprehensive indicators.

(2) Principle of representativeness. Although we hope to provide a perfect evaluation of internal audit performance, considering cost-effectiveness issues, auditors cannot achieve comprehensive coverage. Therefore, when selecting indicators, we should try to combine them with the actual situation of the enterprise and select representative indicators as much as

possible.

(3) Principle of practicality. The indicator system of the intelligent audit system for digital economy enterprises driven by artificial intelligence should have good hierarchy. The upper level indicators can cover the lower level indicators well, and the combination of lower level indicators can more accurately reflect the internal content of the upper level indicators. It should be practical and logically reasonable.

(4) The principle of independence. Because there are numerous indicators in the evaluation system, and if not selected properly, the indicators may have a high degree of mutual substitutability, and the reliability of the evaluation results is questionable. Therefore, it is required that each indicator has independence.

This article follows the above indicator design principles and designs the following indicators based on the objectives of internal audit, including four primary indicators and 19 secondary indicators (see Table 1).

*Table 1: Performance Evaluation Index System for Internal Audit of Enterprises*

| Evaluation objectives | First level indicator | Secondary indicators |
|---|---|---|
| Enterprise Internal Audit Performance A | Internal Audit Business Process Level B1 | The effectiveness of audit focus C1<br>Proportion of completed audit plan C2<br>Audit cost-benefit ratio C3<br>The value of audit recommendations C4<br>Actual audit coverage rate C5<br>Timeliness of Audit Report C6 |
| | Customer Satisfaction B2 | Satisfaction level of senior management C7<br>Satisfaction of the Board of Directors/Audit Committee C8<br>Satisfaction of Audit Object C9 |
| | Auditor Level B3 | Employee knowledge level C10<br>Employee Competency C11<br>Employee suggestion ability C12<br>Communication skills of internal auditors C13 |
| | | Employee training expenses C14<br>Number of staff training sessions C15 |
| | | Compliance with professional ethics C16<br>Professionalism C17 |
| | Audit department positioning B4 | Participate in risk management function positioning C18<br>Risk Management Culture C19 |

## 3.3 Performance evaluation indicator processing

In this study, the performance evaluation indicators of the AI driven digital economy enterprise intelligent audit system established include both subjective qualitative indicators and objective quantitative indicators, each with different dimensions [18]. The measurement results of internal audit performance evaluation are presented as a specific numerical value, and different indicators cannot be directly integrated to obtain an overall evaluation result. Qualitative indicators must be quantified and normalized.

To reduce errors caused by subjective judgments and increase the accuracy of qualitative indicators, the semantic difference membership degree assignment method can be used. The semantic difference membership degree assignment divides factor indicators into five levels: very good, good, average, poor, and very poor, and puts forward clear and specific requirements for the trend degree of the indicators reflected in each level. According to the assignment principle, the scoring personnel (usually experts) score the corresponding indicators based on the trend degree of the indicator content in each level [19]. The scoring adopts a 5-level scale method, which means that the indicators correspond to good, good, average, poor, and very poor levels, with values of 9, 7, 5, 3, and 1 respectively. The middle part is adjusted based on the degree of conformity. For qualitative indicators evaluated by non-experts, the processing method is to design corresponding market research tables based on the above assignment principles, and to statistically analyze the corresponding values through research on typical samples.

After quantifying the attribute values of the indicators, all indicators present the same directional data values. However, due to the different units and dimensions of each indicator, it is difficult to aggregate the comprehensive evaluation results. Therefore, the indicators should be normalized again. The methods for normalizing indicators include hierarchical processing, mean processing, centralization processing, maximization processing, and minimization processing. This article adopts the widely used hierarchical processing method, and the specific processing formula is shown in equation (1). In the formula, M and m represent the maximum and minimum observed values of various indicators in the industry, respectively (provided by industry analysis experts).

$$g(x_i) = \frac{x_i - m}{M - m} \tag{1}$$

# 4 Improve TOPSIS audit performance evaluation

The TOPSIS method ranks a limited number of evaluation objects based on their proximity to the idealized target, and evaluates their relative strengths and weaknesses among existing objects. The basic principle is to sort by detecting the distance between the evaluation object and the optimal and worst solutions. If the evaluation object is closest to the optimal solution but also farthest from the worst solution, it is the best; Otherwise, it is not optimal. Among them, the values of each indicator of the optimal solution have reached the optimal values of each evaluation indicator, and the values of each indicator of the worst solution have reached the worst values of each evaluation indicator. The TOPSIS method has been widely applied in multiple fields, such as evaluating health quality, planning immunization work quality, real estate investment site selection, enterprise economic benefits, macroeconomic benefits between cities, regional technological competitiveness, and rural well-off society in various regions. In addition, it is also used in supply chain management, defense industry, energy field, performance evaluation, environment field, Internet field, medical and health field, construction field, manufacturing industry and business field.

## 4.1 Traditional TOPSIS algorithm

TOPSIS is based on weighted decision matrices [20, 21], defining the positive and negative ideal solutions for the decision-making problem of the intelligent audit system for digital economy enterprises driven by multi index artificial intelligence. The distances between each evaluation scheme and the positive and negative ideal solutions are calculated separately, and then their comprehensive evaluation values are calculated. Based on the comprehensive evaluation values, each scheme is ranked. If the comprehensive indicator is closer to the positive ideal solution and farther away from the negative ideal solution, the evaluation result is better and the solution is better. The specific steps are as follows:

Step 1: Determine the positive ideal solution $\boldsymbol{V}^{+}$ and the negative ideal solution $\boldsymbol{V}^{-}$. After standardizing and objectively weighting the raw data, a weighted decision matrix is obtained, and the positive ideal solution is:

$$\boldsymbol{V}^{+}=\left[\boldsymbol{v}_1^{+} \quad \boldsymbol{v}_2^{+} \quad \cdots \quad \boldsymbol{v}_i^{+} \quad \cdots \quad \boldsymbol{v}_n^{+}\right] \tag{2}$$

where, $\boldsymbol{v}_i^{+}$ is the ***i***-th array of the positive ideal solution matrix.

The negative ideal solution is:

$$\boldsymbol{V}^{-}=\left[\boldsymbol{v}_1^{-} \quad \boldsymbol{v}_2^{-} \quad \cdots \quad \boldsymbol{v}_j^{-} \quad \cdots \quad \boldsymbol{v}_n^{-}\right] \tag{3}$$

where, $\boldsymbol{v}_j^{-}$ is the jth array of the negative ideal solution matrix.

Step 2: Calculate the distance $\boldsymbol{D}_p^{+}$ from scheme *p* to the positive ideal solution and the distance $\boldsymbol{D}_p^{-}$ to the negative ideal solution:

$$\boldsymbol{D}_p^{+}=\sqrt{\sum_{i=1}^{n}\left(\boldsymbol{v}_{ij,p}-\boldsymbol{v}_i^{+}\right)^2} \tag{4}$$

$$\boldsymbol{D}_p^{-}=\sqrt{\sum_{j=1}^{n}\left(\boldsymbol{v}_{ij,p}-\boldsymbol{v}_j^{-}\right)^2} \tag{5}$$

where, $\boldsymbol{v}_{ij,p}$ is the weighted normalization matrix of scheme *p*.

Step 3: Calculate the relative closeness $\boldsymbol{C}_p$ of scheme *p*:

$$\boldsymbol{C}_p=\frac{\boldsymbol{D}_p^{-}}{\boldsymbol{D}_p^{+}+\boldsymbol{D}_p^{-}} \tag{6}$$

Step 4: Sort the proposals based on their relative closeness. Normally, $\boldsymbol{C}_p \in (0,1)$, and the larger the $\boldsymbol{C}_p$ value, the better the solution.

## 4.2 Objective Weight Determination of Entropy Method (EWM)

In information theory, entropy is a measure of uncertainty. The greater the amount of information, the smaller the uncertainty and entropy; The smaller the amount of information, the greater the uncertainty and entropy [22, 23]. According to the characteristics of entropy, the randomness and disorder of an event can be determined by calculating the entropy value, and the degree of dispersion of a certain indicator can also be determined by using the entropy value. The greater the degree of dispersion of the indicator, the greater the impact (weight) of the indicator on the comprehensive evaluation, and the smaller its entropy value. Therefore, entropy values [22, 23] can be used to evaluate the degree of dispersion of performance indicators for an AI driven digital economy enterprise's intelligent audit system. The calculation steps for determining subjective weights using the entropy method (EWM) are as follows.

Step 1: Construct an evaluation matrix. Establish an evaluation matrix $\boldsymbol{B}$ with scores ranging from 0 to 100 based on *m* evaluation samples and *n* evaluation indicators for evaluating the performance of intelligent audit systems for digital economy enterprises driven by artificial intelligence, denoted as $\boldsymbol{B}=\left(b_{ij}\right)_{m\times n}$.

$$\boldsymbol{B}=\begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mn} \end{bmatrix} \tag{7}$$

Step 2: Standardized processing of sample data. To maintain the effectiveness of the evaluation matrix, the positive and negative indicators are dimensionless.

$$b_{ij}^{+}=\frac{b_{ij}-\min b_{ij}}{\max b_{ij}-\min b_{ij}} \tag{8}$$

$$b_{ij}^{-}=\frac{\max b_{ij}-b_{ij}}{\max b_{ij}-\min b_{ij}} \tag{9}$$

where, $b_{ij}^{+}$ is the positive indicator of matrix $\boldsymbol{B}$; $b_{ij}^{-}$ is the negative indicator of matrix $\boldsymbol{B}$.

Step 3: Calculate the entropy value and entropy weight of the evaluation indicators. After assigning weights to the performance evaluation indicators of the intelligent audit system for digital economy enterprises driven by artificial intelligence, the entropy value $\varphi_j$ and entropy weight $\omega_B$ are obtained.

$$\rho_{ij}=\frac{b_{ij}}{\sum_{i=1}^{m} b_{ij}} \tag{10}$$

$$\varphi_j=-\frac{1}{\ln m}\sum_{i=1}^{m}\rho_{ij}\ln \rho_{ij} \tag{11}$$

$$\omega_B=\frac{1-\varphi_j}{\sum_{j=1}^{n}\left(1-\varphi_j\right)} \tag{12}$$

where, $\rho_{ij}$ is the weight of the *i*-th evaluation sample and *j*-th evaluation indicator in the evaluation matrix.

The improvement of TOPSIS evaluation method relies on experts' own engineering experience to determine the weight of each evaluation index, which has strong subjective arbitrariness; The entropy method (EWM) determines weights based on the relationships between raw data, which has strong theoretical basis and a high degree of dependence on sample data. In order to balance the advantages and disadvantages of the two weighting methods and make the indicator weights more scientific and reasonable, the Lagrange multiplier method is used to calculate the combined weight $\omega$:

$$\omega=\frac{\sqrt{\omega_A\omega_B}}{\sum_{i=1}^{n}\sqrt{\omega_A\omega_B}} \tag{13}$$

### 4.3 Improving TOPSIS Algorithm

Due to TOPSIS's inability to weight the performance indicators of AI driven digital economy enterprise intelligent audit systems, entropy weighting method is used to objectively weight the indicators and obtain a weighted decision matrix. First, take the known measured values of the inverse analysis as the positive ideal solution, and then take the indicator farthest from the positive ideal solution as the negative ideal solution [24, 25]. Let the measured value of back analysis be $\boldsymbol{V}^{+}=\left[\boldsymbol{v}_1^{+} \quad \boldsymbol{v}_2^{+} \quad \cdots \quad \boldsymbol{v}_i^{+} \quad \cdots \quad \boldsymbol{v}_n^{+}\right]$, where, $\boldsymbol{v}_i^{+}=\left[v_1^{+} v_2^{+} \cdots v_i^{+} \cdots v_n^{+}\right]$. Since the positive ideal solution is not an extremum, two negative ideal solutions are set. If the weighted normalization matrix of the scheme is $\boldsymbol{v}_{ij}$, then the negative ideal solution 1 is $\boldsymbol{V}_1^{-}=\left[\boldsymbol{v}_{1,1}^{-}, \boldsymbol{v}_{1,2}^{-}, \cdots, \boldsymbol{v}_{1,j}^{-}, \cdots, \boldsymbol{v}_{1,n}^{-}\right]$, where when $\max_{1 \leqslant j \leqslant n}\left(\boldsymbol{v}_{ij}-\boldsymbol{v}_{1,j}^{-}\right)$, $\boldsymbol{v}_j^{-}=\boldsymbol{v}_{ij}$ is taken; Negative ideal solution 2 is $\boldsymbol{V}_2^{-}=\left[\boldsymbol{v}_{2,1}^{-}, \boldsymbol{v}_{2,2}^{-}, \cdots, \boldsymbol{v}_{2,j}^{-}, \cdots, \boldsymbol{v}_{2,n}^{-}\right]$, where when $\min_{1 \leqslant j \leqslant n}\left(\boldsymbol{v}_{ij}-\boldsymbol{v}_{2,j}^{-}\right)$, take $\boldsymbol{v}_{2,j}^{-}=\boldsymbol{v}_{ij}$.

By using two negative ideal solutions, two negative distances can be calculated, and the average negative distance is the desired negative distance solution. By calculating the relative closeness of each plan and ranking the performance indicators of the AI driven digital economy enterprise intelligent audit system based on the relative closeness, the optimal plan can be obtained.

# 5 Empirical analysis

Selecting the quality of technological development in Shandong Province from 2014 to 2024 for audit evaluation, based on the performance method of intelligent audit system for digital economy enterprises driven by artificial intelligence, the entropy weight combination assignment TOPSIS method is used to test the scientificity and applicability of the audit evaluation system. The data are sourced from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, Shandong Statistical Yearbook, as well as the websites of the Shandong Science and Technology Department and the National Bureau of Statistics [26]. The specific steps include: constructing a standardized matrix of performance indicators for an AI driven digital economy enterprise intelligent audit system - determining indicator weights using entropy weight method - constructing an evaluation matrix based on weight extraction - determining the distance between indicators and positive and negative ideal values - calculating the comprehensive evaluation index. Specifically, it can be divided into two major steps: calculating the weight of performance indicators for an AI driven digital economy enterprise intelligent audit system and evaluating them using TOPSIS method.

To ensure the rationality of evaluation indicators and the accuracy of comprehensive evaluation results, factor analysis is further used to determine indicator weights for analyzing the performance data of the original Shandong Province AI driven digital economy enterprise intelligent audit system. On the one hand, compared with the comprehensive evaluation results of factor analysis, by using SPSS20.0 to perform factor analysis on the standardized indicator data, five common factors were extracted according to the rule of eigenvalues greater than 1. The variance contribution rates of the five common factors were 48.349%, 22.876%, 11.6%, 7.127%, and 4.515%, respectively. The cumulative variance contribution rate was 94.467%, and the loss variance contribution rate was 5.533%. The loss information was relatively small. According to the contribution rate of each indicator in the rotation load matrix, the weight and comprehensive evaluation score of each indicator are calculated (see Table 2). It is evident that the development of science and technology has continued to rise since 2018, especially in 2021. Comparing the calculation results of two comprehensive evaluation methods, the ranking order of comprehensive scores for each year is completely consistent, with only differences in comprehensive scores. This is mainly due to the entropy method using the range method for normalization, and factor analysis using Z-SCORE to standardize the original data and directly participate in the calculation of comprehensive scores without normalization, as shown in Table 3.

*Table 2: Comprehensive evaluation score based on factor analysis to determine indicator weights*

| Year | 2024 | 2023 | 2022 | 2021 | 2020 | 2019 | 2018 | 2017 | 2016 | 2015 | 2014 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Comprehensive score | -0.625 | 1.295 | 0.227 | 0.156 | 0.137 | -0.284 | -0.375 | -0.238 | 0.059 | -0.413 | -0.585 |
| Ranking | 1 | 2 | 3 | 4 | 7 | 8 | 6 | 5 | 9 | 10 | 11 |

*Table 3: Comparison of Comprehensive Scores for Two Different Weight Determination Methods*

| Year | Factor analysis | | Entropy TOPSIS method | |
|---|---|---|---|---|
| | F (comprehensive score) | Ranking | F (comprehensive score) | Ranking |
| 2024 | 1.30 | 1 | 0.715 | 1 |
| 2023 | 0.23 | 2 | 0.551 | 2 |
| 2022 | 0.16 | 3 | 0.501 | 3 |
| 2021 | 0.14 | 4 | 0.420 | 4 |
| 2020 | -0.29 | 7 | 0.328 | 7 |
| 2019 | -0.38 | 8 | 0.317 | 8 |
| 2018 | -0.24 | 6 | 0.350 | 6 |
| 2017 | 0.06 | 5 | 0.376 | 5 |
| 2016 | -0.39 | 9 | 0.289 | 9 |
| 2015 | -0.61 | 10 | 0.282 | 10 |
| 2014 | -0.86 | 11 | 0.245 | 11 |

On the other hand, compared with the comprehensive scientific and technological progress rate of Shandong Province announced by the Science and Technology Department of Shandong Province. The contribution rate of technological progress (comprehensive index of technological progress level) is a composite indicator that objectively reflects the level of technological progress and the contribution share of technology to economic and social development. The calculation formula is: contribution rate of scientific and technological progress (comprehensive index of scientific and technological progress level)=index of scientific and technological progress environment and foundation x 30%+index of scientific and technological investment x 35%+index of scientific and technological progress x 35%. As shown in Figure 2, it can be seen that from 2014 to 2024, the trend of comprehensive scientific and technological progress rate has been on the rise, while the trend of TOPSIS method evaluation is steeper, mainly because the comprehensive scientific and technological progress rate covers three indicators of scientific and technological progress environment and foundation, scientific and technological investment, and scientific and technological progress. The evaluation index system constructed specifically quantifies the evaluation from five development task levels: "enhancing scientific and technological innovation creativity, supporting the development ability of key industries in science and technology, innovation ability of scientific and technological talents, transfer and transformation effectiveness of scientific and technological achievements, and stimulating scientific and technological innovation vitality". According to the TOPSIS comprehensive ranking, the scientific and technological effects in Shandong Province have been significant since 2016, mainly due to the introduction of a series of relevant laws and regulations to support the development of scientific and technological innovation, including "Several Measures to Support Scientific and Technological Innovation in Shandong Province (2016)", "Measures for the Construction and Operation Management of Scientific and Technological Innovation Platforms in Shandong Province (2017)", "Implementation Plan for Optimization and Integration of Scientific and Technological Innovation Bases in Shandong Province (2018)", "Several Measures to Deepen the Reform and Innovation of Scientific and Technological System Mechanisms and Promote High quality Development (2024)", etc. Since 2019, the effects have become more apparent.

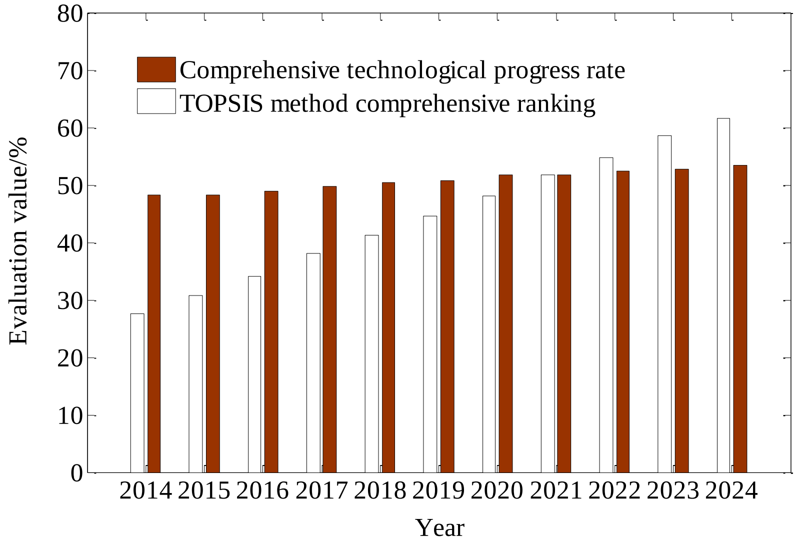


*Figure 2: Comparison between Ranking Analysis of Comprehensive Science and Technology Progress Rate in Shandong Province and Evaluation by Weighted TOPSIS Method*

# 6 Conclusion

After the previous analysis, we can draw the following conclusions and provide relevant suggestions.

(1) Adopting the improved TOPSIS evaluation method for decision analysis of the content of the intelligent audit system for digital economy enterprises driven by artificial intelligence, the logic is rigorous and can effectively overcome the influence of subjective factors in the decision-making process. The application of improved TOPSIS evaluation method to calculate weights reflects the importance of each factor in the evaluation, and is feasible and effective in practical operation. Therefore, in the context of the lack of effective quantitative and comprehensive research on content decision-making in the digital economy enterprise intelligent audit system driven by artificial intelligence, the introduction of improved TOPSIS evaluation method can achieve a transformation from qualitative to quantitative, from local to comprehensive, and improve the systematicity and scientificity of decision-making, which is also very easy to understand. The improved TOPSIS evaluation method solves the problem of systematic and subjective judgments in internal audit content decision-making, and is a highly accurate judgment method. Due to the clear and concise operation of Yaanalytic software, it eliminates a series of complex calculation processes and is easier to provide assistance for the operation and development of enterprise information system processing modes. We should further promote the application of this method in the content decision-making of intelligent audit systems for digital economy enterprises driven by artificial intelligence.

(2) The scientific nature of the model is relative. We see that subjective factors are inevitably influenced in the decision-making process, such as the determination of the importance of two factors in the same level relative to a certain factor in the upper level when constructing a judgment matrix, which poses a problem of personal subjective judgment. Given this situation, it is best for decision team members to jointly complete or hire internal audit experts to evaluate the weights of factors, such as using brainstorming, Delphi method, etc. It should be emphasized that whether using expert evaluation methods or conducting relative importance evaluations by enterprise decision-makers themselves, decision-makers should have a comprehensive understanding of the decision-making process and principles of the AI driven digital economy enterprise intelligent audit system, fully grasp relevant information, and maintain fairness, objectivity, rationality, and effectiveness throughout the entire decision-making process.

(3) The improved TOPSIS evaluation method can only select the optimal strategy from given strategies and schemes, and cannot provide new strategies. This is a limitation of this method, so we should pay attention to the design of given strategies and schemes to minimize this limitation.

In summary, although there are significant differences in the individual status quo of internal audits among different enterprises, the improved TOPSIS evaluation method can still be universally applicable. With the changes in the socio-economic environment and the development of internal audit theory, the general decision-making process mentioned above can be adjusted according to the specific situation and decision-making content of the enterprise. Due to the limitations of pairwise comparisons when constructing judgment matrices, it is recommended to minimize the number of factors while meeting the decision-making objectives.

# Funding

This work was supported by Research Project of Philosophy and Social Sciences in Jiangsu Province's Higher Education Institutions: Research on the Empowerment of Digital Economy to the Transformation and Upgrading of Jiangsu's Manufacturing (2023SJYB1725).

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