Postprint: Comprehensive Evaluation of Academic Journals Using Entropy-Weighted TOPSIS and Factor Analysis

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Abstract

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Full Text

Preamble

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Research on Comprehensive Evaluation of Academic Journals Based on Entropy Weight TOPSIS and Factor Analysis

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Abstract

[**Purpose/Significance**] This study evaluates the comprehensive quality of library and information science journals, identifies quality changes among sample journals during the evaluation period, and provides new insights for journal evaluation research. [**Method/Process**] Using data from the 2011-2017 editions of the *Chinese S&T Journal Citation Reports*, we selected 34 library and information science journals as samples. After screening, seven indicators were retained. The entropy weight method combined with factor analysis was employed to calculate indicator weights, and the TOPSIS method was used to compute annual comprehensive scores and construct a comprehensive evaluation matrix. Finally, cluster analysis was applied to the evaluation matrix to categorize the journals into different tiers for 2010-2016. [**Result/Conclusion**] The findings indicate: (1) Evaluation indicators must be rigorously screened; (2) The common factors underlying the indicators remain stable; (3) Different weights should be assigned to indicators to reflect their significance; (4) Article quality outweighs quantity; (5) A "Matthew effect" exists in library and information science journals; and (6) These journals require further development.

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Keywords: journal evaluation, entropy weight method, TOPSIS method, panel data, factor analysis
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Introduction

Journal evaluation has long attracted widespread scholarly attention, with evaluation results guiding libraries and information institutions in journal procurement and authors in manuscript submission, while also significantly influencing journal development and academic progress. Scholars have actively researched and designed various evaluation systems and indicators, such as SCI (Science Citation Index), EI (Engineering Index), ISTP (Index to Scientific & Technical Proceedings), and JCR (Journal Citation Reports). In China, the first *Chinese Core Journals Overview* published by Peking University Library in 1992 marked the earliest domestic scientific journal evaluation system. Subsequently, Nanjing University, the Chinese Academy of Social Sciences, and Wuhan University established different evaluation frameworks. Currently, seven major domestic evaluation institutions operate systems including the Chinese Core Journals Overview, Chinese S&T Journal Citation Reports, Chinese Social Sciences Citation Index, Chinese Humanities and Social Sciences Core Journals Overview, Chinese Scientific Citation Database Source Journals, Chinese Academic Journal Comprehensive Citation Report, and Chinese Academic Journal Evaluation Report [1].

Since Garfield pioneered bibliometrics, numerous bibliometric indicators have been proposed, including impact factor, h-index, total citations, and immediacy index, all becoming important evaluation metrics. However, the complexity of journal evaluation means single indicators provide limited information, necessitating multi-attribute evaluation approaches. Key challenges in multi-attribute evaluation include indicator selection, weight design, and dynamic annual comparisons. This paper proposes using entropy-weighted TOPSIS to determine annual indicator weights, constructing a panel data matrix from annual journal scores, and applying panel data factor analysis to obtain comprehensive rankings across the study period.

Research Status

Multi-attribute journal evaluation methods have gained increasing attention. Critical issues include determining indicator weights, analyzing inter-indicator correlations, and dimensionality reduction. Various methods have been applied, including rank-sum ratio [2], grey relational analysis [3], neural networks [4], clustering [1], structural equation modeling [5-6], DEA models [7], and principal component or factor analysis [8-13]. Factor and principal component analyses reduce multiple indicators to a few comprehensive components that capture most information while ensuring orthogonality, thereby overcoming redundancy from high inter-indicator correlations. These methods have been widely adopted in journal evaluation.

In 2008, Zhang Hong et al. [8] used principal component analysis to partition evaluation indicators into independent components, using variance contribution rates as weights to calculate comprehensive scores. They concluded that this approach reduces dimensionality, simplifies indicator selection, yields more objective results, and mitigates excessive self-citation effects. Xin Duqiang et al. [9-10] applied principal component and factor analysis to evaluate mechanics and physics core journals in 2011 and 2014, similarly finding these methods objective and fair. However, most studies using these techniques rely on single-year data, preventing analysis of multi-year development trends. Liu Yan [11] proposed a panel data factor analysis approach for journal evaluation, using multi-year data to derive annual factor scores and then analyzing these scores to assess comprehensive development.

As these methods gained popularity, scholars identified limitations. Yu Liping [12] argued that principal component and factor analyses have two major flaws: using variance contribution rates as weights lacks theoretical justification, and their linear aggregation employs indirect rather than direct distance measures. They proposed a "factor ideal solution" method combining factor analysis with TOPSIS, yielding satisfactory results. Xiong Guojing et al. [13] similarly criticized variance contribution rates for lacking bibliometric meaning, instead using entropy weights to calculate difference coefficients and adjust variance contributions and factor score coefficients to determine final weights, then applying TOPSIS for comprehensive evaluation.

Building on these studies, we identify several gaps: (1) inconsistent indicator selection without clear justification; (2) failure to analyze the meaning of indicator weights despite using entropy-weighted TOPSIS; (3) focus on core journals only, overlooking high-performing non-core journals and problematic ones; and (4) limited analysis of annual development trends, with most studies reflecting only single-year performance. This paper addresses these gaps by: (1) synthesizing indicators from previous studies, conducting comprehensive analysis to exclude unsuitable ones and add valuable ones; (2) analyzing weight meanings to assess indicator applicability; (3) using both core and non-core library and information science journals to analyze quality changes and disciplinary characteristics; and (4) constructing annual comprehensive score matrices for cluster analysis.

Methods and Models

This study employs entropy-weighted TOPSIS combined with factor analysis. We first calculate annual indicator weights using entropy weights, obtain cross-sectional comprehensive score matrices, construct a panel data matrix from these matrices, apply factor analysis to derive statistical-period comprehensive rankings, and finally perform cluster analysis based on annual scores to categorize journals. The specific steps are as follows:

Step 1: Construct Multi-Indicator Panel Data Matrix

Let the journal dataset be X, including m journals, n indicators, and T time periods. The three-dimensional matrix representation of X is:

$$X = \begin{pmatrix} X_{111} & \cdots & X_{11j} & \cdots & X_{11n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{1m1} & \cdots & X_{1mj} & \cdots & X_{1mn} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{T11} & \cdots & X_{T1j} & \cdots & X_{T1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{Tm1} & \cdots & X_{Tmj} & \cdots & X_{Tmn} \end{pmatrix}$$

Unfolding X along the time dimension yields a two-dimensional matrix X_T of indicators and journals:

$$X_T = \begin{pmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{pmatrix}$$

After obtaining this matrix, we standardize the data to get standardized matrix $R = (r_{ij})_{m\times n}$ using linear scaling: $r_{ij} = X_{ij}/\max(X_{ij})$, where $1 \le i \le m$, $1 \le j \le n$.

Step 2: Determine Entropy Values and Difference Coefficients for Each Indicator

Using the annual standardized matrices, we calculate each indicator's entropy value and difference coefficient:

Entropy value: $e_j = -\sum_{i=1}^{m} b_{ij} \cdot \ln b_{ij}$, where $b_{ij} = r_{ij}/\sum_{i=1}^{m} r_{ij}$ represents the weight of the ith sample journal's indicator value in the jth indicator. We assume $b_{ij} \cdot \ln b_{ij} = 0$ when $b_{ij} = 0$ [14]. After obtaining e_j, we calculate the difference coefficient $g_j = 1 - e_j$.

Step 3: Factor Analysis and Weight Calculation

Perform factor analysis on each year's data to obtain variance contribution rates p_i and component score coefficients β_i. Assuming y common factors are extracted, each indicator's weight is:

$$w_j = \frac{\sum_{k=1}^{y} p_k \cdot \beta_j \cdot g_j}{\sum_{j=1}^{n} \sum_{k=1}^{y} p_k \cdot \beta_j \cdot g_j}, \quad 1 \le j \le n, \quad 1 \le k \le y$$

Step 4: Construct Weighted Indicator Matrix

From Step 3, we obtain weight matrix $[w_1 \cdots w_n]^T$. Combining this with standardized matrix $R = (r_{ij})_{m\times n}$ from Step 1 yields weighted matrix $Q = (q_{ij})_{m\times n}$, where $q_{ij} = r_{ij} \cdot w_j$.

Step 5: Calculate Comprehensive Scores for Sample Journals

From weighted matrix $Q = (q_{ij})_{m\times n}$, we calculate each indicator's ideal solution and negative-ideal solution. The ideal solution $a^* = \{\max q_{ij}\} = \{a_1^*, a_2^*, \dots, a_n^*\}$; the negative-ideal solution $a^0 = \{\min q_{ij}\} = \{a_1^0, a_2^0, \dots, a_n^0\}$.

After obtaining these solutions, we calculate each journal's distance to the ideal and negative-ideal solutions and relative closeness (comprehensive score):

Distance to ideal solution: $d_i^* = \sqrt{\sum_{j=1}^{n} (q_{ij} - a_j^*)^2}$
Distance to negative-ideal solution: $d_i^0 = \sqrt{\sum_{j=1}^{n} (q_{ij} - a_j^0)^2}$

Relative closeness (comprehensive score): $D_i = \frac{d_i^0}{d_i^* + d_i^0}$

We know $0 \le D \le 1$. When $D = 1$, a sample journal reaches the ideal solution; when $D = 0$, it reaches the negative-ideal solution. The closer D is to 1, the higher the score.

Step 6: Journal Classification

By calculating annual relative closeness values (comprehensive scores) for each journal, we construct matrix Y_T and perform cluster analysis to obtain different journal tiers.

Empirical Analysis

4.1 Data Sources and Indicator Selection

4.1.1 Data Sources

The *Chinese S&T Journal Citation Reports*, published annually by Wanfang Data, includes over 6,000 journals with nine source indicators and nine citation indicators. This study uses 2011-2017 editions, selecting library and information science journals as samples. After excluding journals with missing data, 34 journals remained.

4.1.2 Evaluation Indicators

Based on literature using *Chinese S&T Journal Citation Reports* for multi-attribute evaluation, 14 indicators were initially considered: total citations, impact factor, immediacy index, citation rate, subject impact indicator, subject diffusion indicator, H-index, cited half-life, source literature volume, citing journals, average authors, average references, funded paper ratio, and citation half-life. After further screening, the final indicator system was determined through:

1. **Excluding negatively correlated indicators**: Yu Liping [15] found indicators with negative evaluation results are unsuitable. Statistical analysis showed citation rate was negatively correlated, so it was excluded.

2. **Excluding non-cost/benefit indicators**: TOPSIS ranks alternatives based on distances to ideal and negative-ideal solutions, requiring "cost-type (smaller-is-better)" or "benefit-type (larger-is-better)" indicators. Source literature volume is neither, so it was excluded.

3. **Excluding low-discrimination indicators**: Some indicators show minimal variation and lack evaluative significance. Subject impact indicator, average authors, cited half-life, and citation half-life fell into this category. Because library and information science has relatively few journals with frequent mutual citations, subject impact indicators are uniformly high. Author count and half-life metrics also cannot judge journal quality, so these four indicators were excluded.

4. **Using Composite Index (CI) instead of total indicators**: Total indicators (e.g., total citations, citing journals) are easily influenced by publication volume and journal age. Long-established or high-volume journals accumulate more citations, skewing weights. Some low-quality non-core journals artificially inflate total citations through increased publication and mutual citation of low-quality articles, distorting evaluation models. However, total citations remain necessary for measuring impact volume. CNKI's *Chinese Academic Journal International Citation Annual Report*

[16] proposes the Composite Index (CI), widely adopted and calculated by projecting total citations and impact factor into a "journal influence ranking space" using vector equal-weighting. This metric considers both impact volume and quality while reducing distortion from long-established, low-quality journals. Therefore, we use CI instead of total citations. The CI formula is:

$$CI = \sqrt{2 - (1 - A)^2 + (1 - B)^2}$$

where $A = \frac{IF(\text{journal}) - IF(\text{group min})}{IF(\text{group max}) - IF(\text{group min})}$ and $B = \frac{TC(\text{journal}) - TC(\text{group min})}{TC(\text{group max}) - TC(\text{group min})}$.

To further eliminate total indicator effects, we propose using average citing journals and average subject diffusion indicators instead of total citing journals and total subject diffusion. Average citing journals = $\frac{\text{Number of journals citing the evaluated journal}}{\text{Annual publication volume of evaluated journal}}$, reflecting how many journals on average cite the journal's articles. Average subject diffusion indicator = $\frac{\text{Number of citing journals}}{\text{Total journals in discipline} \times \text{Annual publication volume}}$, reflecting cross-disciplinary citation per article.

5. **Excluding highly correlated, similar-meaning indicators**: After the above analysis, eight indicators remained: CI, impact factor, immediacy index, H-index, average references, funded paper ratio, average citing journals, and average subject diffusion indicator. Correlation analysis showed average subject diffusion indicator and average citing journals were nearly perfectly correlated. From their formulas, average subject diffusion equals average citing journals divided by total discipline journals (a constant), making them effectively one indicator. We retained average subject diffusion and excluded average citing journals.

6. **Indicator standardization**: The final indicator system includes CI, impact factor, immediacy index, H-index, average references, funded paper ratio, and average subject diffusion indicator. Both entropy calculation and factor analysis require standardization. For entropy calculation, standardization follows Step 1; factor analysis standardization is handled automatically by statistical software.

4.1.3 Reference Indicator Selection

We use the Composite Index (CI) as a reference to explore advantages of multi-indicator comprehensive evaluation over single or composite indicator evaluation. Comparing with CI reveals model characteristics.

4.2 Descriptive Statistics

Tables 1 and 2 present descriptive statistics. Due to space limitations, only six-year averages are shown, separated into evaluation and excluded indicators. Journals are listed under their most recent names. Table 1 shows *Chinese Journal of Library Science* had the highest average impact factor, followed by *Jour-*

nal of Academic Libraries. *Modern Library and Information Technology* was renamed *Data Analysis and Knowledge Discovery* in 2017, but we retain its original name as data cover 2010-2016.

4.3 Sample Adequacy Test

KMO and Bartlett's tests were conducted to assess factor analysis suitability. All years passed (KMO > 0.5, Bartlett's test $p < 0.05$), indicating appropriateness for factor analysis (Table 3).

4.4 Common Factor Analysis

Annual factor analysis of 2010-2016 data consistently yielded two common factors (Table 4). Impact factor, immediacy index, H-index, CI, and average subject diffusion indicator loaded on the first factor; funded paper ratio and average references loaded on the second. Average subject diffusion belonged to the second factor in 2010 and 2014. The first factor, named "Influence Factor," reflects journal impact; the second, "Author Characteristics Factor," reflects funding status and literature absorption. All indicators stably belonged to consistent factors across years, demonstrating data continuity.

4.5 Weight Calculation

Following the model, we calculated annual indicator weights. Due to space constraints, we detail only 2010 calculations.

4.5.1 2010 Entropy and Difference Coefficients

After constructing and standardizing the 2010 data matrix, we calculated entropy and difference coefficients. For impact factor:

Given max(impact factor) $= 3.451$, we compute $r_{1,1} = \frac{2.841}{3.451} = 0.823$, ..., $r_{34,1} = \frac{1.031}{3.451} = 0.299$.

Then $b_{1,1} = \frac{0.823}{0.823+\cdots+0.299} = 0.077$, ..., $b_{34,1} = 0.028$.

Entropy $e_1 = -\sum_{i=1}^{34} b_{i,1} \cdot \ln b_{i,1} = 0.9626$, and difference coefficient $g_1 = 1 - e_1 = 0.0373$.

Other indicators were calculated similarly (Table 6).

4.5.2 2010 Factor Analysis Results

SPSS factor analysis of 2010 data yielded two factors explaining 76.279% of variance after rotation (Table 7). Component score coefficients are shown in Table 8 .

4.5.3 2010 Weight Calculation

Using rotated variance contributions (p_k) and component score coefficients (β_j), we adjust difference coefficients to obtain weights $w_j = \frac{p_k \cdot \beta_j \cdot g_j}{\sum_{j=1}^{n} p_k \cdot \beta_j \cdot g_j}$.

For impact factor (first factor, $\beta_1 = 0.281$, $p_1 = 46.611$):
$c_1 = p_1 \cdot \beta_1 \cdot g_1 = 46.611 \times 0.281 \times 0.0373 = 0.4909$.

Similarly computing c_2 through c_7, we obtain $w_1 = \frac{0.4909}{0.4909+0.4893+\cdots+0.1010} = 0.155672$.

Other weights were calculated analogously (Table 9).

4.5.4 Comprehensive Weight Analysis
Applying the same process to 2011-2016 data yields seven years of varying weights (Table 10). CI consistently has the highest average weight, followed by immediacy index and impact factor, indicating rapid citation rates in library and information science research. Funded paper ratio ranks fourth, showing funding status significantly affects paper quality.

4.6 Annual Journal Scores

Comprehensive scores were calculated for all journals (Table 11). *Chinese Journal of Library Science* ranked first all seven years with rising scores, demonstrating its dominant position and quality improvement. Table 12 and Figure 1 [Figure 1: see original paper] summarize score distributions. Declining averages with increasing standard deviations, ranges, and maximum-minimum gaps indicate growing disparities—high-quality journals improve while average journals stagnate, a phenomenon known as the "Matthew effect."

4.7 Annual Rankings

We computed 2010-2016 rankings and compared them with CI rankings (Table 13). Based on standard deviation and correlation with year, journals were classified as: stable (low SD, correlation between -0.6 and 0.6), rising (SD in top 50%, correlation < -0.6), declining (SD in top 50%, correlation > 0.6), or fluctuating (remaining cases) (Table 14).

Stable journals include mostly non-core journals with consistently low rankings. Fluctuating journals like *Library Development* need quality stabilization. Rising journals include *Library and Information Service*. Declining journals like *Journal of Intelligence* (from 4th in 2010 to 20th in 2016) require editorial attention.

Comparing comprehensive rankings with CI rankings reveals journals ranking significantly higher or lower than CI (Table 15). Journals outperforming CI (*Library and Information Service Knowledge*, *Modern Library and Information Technology*, etc.) generally have lower total citations and publication volumes than those underperforming CI (*Library*, *Library Development*, etc.). This confirms that article quality outweighs quantity. Journals with excessive low-quality publications cannot improve quality simply by increasing volume. Our multi-indicator model with objective weighting reduces distortion from high publication volumes while considering impact magnitude.

4.8 Journal Classification

Cluster analysis of the comprehensive score matrix using K-Means (4 clusters) yielded four tiers (Table 16): (1) Top-tier journal—*Chinese Journal of Library Science* alone; (2) Developing journals—10 non-core journals with low rankings; (3) Potential journals—mid-ranked core and high-performing non-core journals; (4) Quality journals—high-ranked core journals. This pyramid structure shows only one top-tier journal, suggesting quality journals should strive for top-tier status.

Research Conclusions

5.1 Main Conclusions

Using 2011-2017 *Chinese S&T Journal Citation Reports* data, we evaluated 34 library and information science journals (2010-2016) using entropy-weighted TOPSIS and factor analysis, then performed cluster analysis. Key findings:

1. **Rigorous indicator screening is essential.** We systematically examined the indicator system, ultimately selecting seven most representative indicators. Comprehensive evaluation requires strict screening to exclude meaningless or distorting indicators.

2. **Common factors remain stable annually.** Factor analysis consistently extracted two factors across seven years: "Influence Factor" and "Author Characteristics Factor." Nearly all indicators stably belonged to the same factor, enabling cross-year dynamic evaluation.

3. **Different weights reflect indicator value.** Entropy weights adjust factor variance contributions and score coefficients, providing more objective weighting than assigning equal weights within factors. Weight variations reveal discipline characteristics—CI, immediacy index, and impact factor have highest weights, reflecting rapid citation patterns in this field.

4. **Article quality exceeds quantity.** Improving journal quality requires enhancing article quality, not quantity. Publishing many low-quality articles does not help; strict peer review and reducing low-level submissions are essential for progress.

5. **Strong scientific rigor.** Comparing our rankings with CI shows the proposed indicator system and model can reduce or eliminate distortion from excessive publication volumes inflating total citations. Using average indicators instead of totals is validated.

6. **Matthew effect exists.** High-quality journals' scores rise annually while average journals' scores decline, demonstrating a Matthew effect. Development should balance top-tier support with improving average journals for coordinated growth.

7. **Further development needed.** Ranking data classified journals as stable, fluctuating, rising, or declining. Few high-level journals are stable; most non-core journals show no improvement. Fluctuating journals need quality stabilization; declining journals require identifying and addressing causes. The four-tier classification (top, quality, potential, developing) forms a pyramid, but top-tier journals are scarce.

5.2 Reflections on Multi-Attribute Journal Evaluation

1. **Build more comprehensive indicator systems.** Current indicators extend beyond traditional ones (impact factor, immediacy index, h-index) to include G-index, E-index, P-index, and historical impact factor. Limited by data availability and accuracy, this study didn't incorporate these emerging indicators. Future research should include more meaningful indicators after scientific screening to establish comprehensive systems.

2. **Explore more scientific evaluation methods.** While entropy-weighted TOPSIS and factor analysis proved scientifically sound, many other multi-attribute decision methods exist. Different methods should be tested and compared to identify the most effective approaches.

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Author Contributions

Feng Guohe: Proposed research theme, revised content, finalized manuscript
Zhou Rongxin: Data screening and processing, conducted experiments, drafted initial manuscript
Wu Jiajia: Proofread manuscript

Research on the Comprehensive Evaluation of Academic Journals Based on Entropy Weight TOPSIS and Factor Analysis

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Abstract: [**Purpose/significance**] This paper evaluates the comprehensive quality of Library Science and Information Science journals to identify quality changes among sample journals during the evaluation period and provide new thoughts for journal evaluation research. [**Method/process**] Using data from the *Chinese S&T Journal Citation Reports* (2011-2017), we selected seven indicators after rigorous screening and used entropy weight method combined with factor analysis to calculate indicator weights. TOPSIS model evaluated comprehensive scores and ranks for 34 library and information science journals during

2010-2016, and built a comprehensive evaluation matrix. Finally, clustering method was used to set journal grades. [**Result/conclusion**] Results show: Attributes should be strictly filtered when evaluating academic journals; Common factors of each index tend to be stable; Different weights set for indicators show their significance; For published articles, quality is more important than quantity; "Matthew effect" exists in library and information science journal evaluation; Library and information science journals need further development.

Keywords: journal evaluation; entropy weight method; TOPSIS model; panel data; factor analysis

Note: Figure translations are in progress. See original paper for figures.