Complementarity of Different Metrics in Academic Journal Evaluation (Postprint)

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Abstract

[Purpose/Significance] This paper addresses the implicit complementarity problem among indicators in science and technology evaluation, wherein a deficiency or minimal increase in one indicator is compensated by substantial increases in other indicators. Complementarity is classified into three categories: equal complementarity, excess complementarity, and deficit complementarity, and the impact of indicator complementarity on different evaluation methods is subsequently analyzed. [Method/Process] A testing and determination method is designed for a certain nonlinear evaluation method, wherein one indicator is held constant, the magnitude of change in evaluation values resulting from increasing the mean of other different-attribute indicators is calculated, and compared with the magnitude of change in evaluation values from the linear weighting method. [Results/Conclusion] The study reveals that complementarity among indicators in multi-attribute evaluation methods is a complex issue, influenced by various factors including the evaluation method, indicator data, weight settings, and compensation magnitude; ratio-based multi-attribute evaluation methods exhibit a higher propensity for deficit complementarity; due to correlations among similar evaluation indicators, discussions of inter-indicator complementarity should be conducted across different-attribute indicators; the indicator complementarity issue has profound implications for the selection of multi-attribute evaluation methods, essentially altering indicator weights in a disguised manner, and can serve as an approach for evaluation result verification and management control.

Full Text

Preamble

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A Study on Complementarity among Different Evaluation Indexes in Academic Journal Evaluation

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Abstract: [Purpose/Significance] This paper discusses the implicit complementarity problem among indexes in science and technology evaluation, where one index that does not increase or increases only slightly can be compensated by other indexes increasing more substantially. Complementarity is divided into three categories: equal complementation, excess complementation, and underbalance complementation, and the impact of index complementarity on different evaluation methods is analyzed. [Method/Process] A testing and judgment method is designed: for a certain nonlinear evaluation method, while maintaining one index constant, the change in evaluation value caused by increasing the means of other different attribute indexes is calculated and compared with the change in evaluation value of the linear weighted method. [Result/Conclusion] The study finds that complementarity among indexes in multi-attribute evaluation methods is a complex issue influenced by various factors such as the evaluation method, index data, weight setting, and compensation value magnitude. Ratio-based multi-attribute evaluation methods are more prone to underbalance complementation. Due to correlations among similar evaluation indexes, discussions of index complementarity should be conducted between indexes of different attributes. The index complementarity issue has profound implications for the selection of multi-attribute evaluation methods, essentially altering index weights in a disguised manner, and can serve as a method for evaluating result verification and management control.

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Introduction

Against the backdrop of building an innovative country, the status and role of science and technology evaluation are increasingly important, and evaluation methods are becoming increasingly diverse. Currently, there are three main categories of evaluation methods in science and technology evaluation: (1) peer review, which is primarily a qualitative evaluation conducted by domain experts, such as fund review and professional title evaluation; (2) evaluation using a single index, such as using the number of authorized invention patents to evaluate innovation output or using the h-index to evaluate scholars' influence; and (3) evaluation using an index system, where several evaluation indexes are selected for a certain evaluation domain. Multi-attribute evaluation methods are numerous, such as linear weighting, analytic hierarchy process, entropy weighting, principal component analysis, rank-sum ratio, TOPSIS, VIKOR, etc., with hundreds of multi-attribute evaluation methods having been developed. Due to the large amount of information contained in multi-attribute evaluation methods, they have been widely applied.

The diversity of multi-attribute evaluation methods has led to the complexity of complementarity among evaluation indexes. Early science and technology evaluation often employed linear evaluation methods, but in the past decade or more, research using complex mathematical models for science and technology evaluation has increased, with different principles and 各自的优点和不足. However, because multi-attribute evaluation methods are generally broadly applicable, hundreds of evaluation methods have been applied in science and technology evaluation, with the vast majority being nonlinear methods. While these methods have enriched the theory and practice of science and technology evaluation, they have also introduced uncertainty regarding complementarity among evaluation indexes, which is a fundamental theoretical issue in science and technology evaluation and widely exists in economic, social, and other evaluations. Measuring and classifying the complementarity among evaluation indexes and analyzing their mechanism and impact on science and technology evaluation are of great significance for selecting multi-attribute evaluation methods and preventing manipulation of evaluation indexes.

Research on complementarity among indexes in multi-attribute evaluation is generally limited. Qiu Dong argued that the geometric mean synthesis method is a synthesis method that does not allow or rarely allows mutual "compensation" among individual variable values. Su Weihua studied compensation issues among indexes in geometric mean synthesis, harmonic mean synthesis, and quadratic mean synthesis methods, arguing that the magnitude of compensation depends on both the size of the variation and the degree of difference among evaluation indexes, and that one cannot absolutely assert which averaging method has smaller or larger compensation. Since early multi-attribute evaluation methods were limited in variety, and with the increasing diversity of such methods, research on compensation among evaluation indexes needs to be expanded in the following aspects: (1) fundamental theoretical issues of complementarity among indexes in multi-attribute evaluation methods, such as definitions, classification, measurement, and impact on evaluation; (2) measurement of complementarity among indexes in linear weighted evaluation methods; and (3) measurement of complementarity among indexes in nonlinear weighted evaluation methods.

Using JCR 2016 mathematics journals as an example, this paper establishes a theoretical analysis framework for complementarity among evaluation indexes in multi-attribute evaluation methods, designs research methods, extracts common factors through factor analysis, and then uses these uncorrelated common factors with different multi-attribute evaluation methods to analyze complementarity issues among public factors, drawing conclusions and discussions.

Research Methods

First, the complementarity problem among evaluation indexes is classified, and then an experimental method is proposed along with selection of the number of experimental indexes. Since increasing index values in the experiment will raise the maximum value of standardized indexes, the index standardization method must be redesigned. Finally, using five evaluation methods—linear weighted summation, harmonic mean, geometric mean, TOPSIS, and VIKOR—as examples, the impact of different evaluation methods on index complementarity is compared.

2.1 Classification of Complementarity among Indexes

In science and technology evaluation, complementarity among evaluation indexes can be divided into three types: equal complementation, excess complementation, and underbalance complementation.

Equal complementation means that a certain weighted reduction in the compensated index can be compensated by an equal weighted increase in the complementary indexes, thereby maintaining the total evaluation value unchanged. Assuming X_1 is the compensated index, X_2 and X_3 are complementary indexes, with weights ω_1, ω_2, and ω_3 respectively, X_1 decreases by Δ_1, X_2 increases by Δ_2, and X_3 increases by Δ_3. Equal complementation means that when Formula (1) holds, the evaluation value remains unchanged:

$$\omega_1\Delta_1 = \omega_2\Delta_2 + \omega_3\Delta_3 \quad \text{Formula (1)}$$

It can be proven that linear weighted evaluation methods are equal complementation, which is an important property and the basis for analyzing complementarity issues in other multi-attribute evaluation methods.

Excess complementation means that after compensating for a certain weighted reduction in the compensated index with an equal weighted increase in complementary indexes, the total evaluation value increases.

Underbalance complementation means that after compensating for a certain weighted reduction in the compensated index with an equal weighted increase in complementary indexes, the total evaluation value decreases.

2.2 Experimental Design

To compare complementarity among evaluation indexes in different multi-attribute evaluation methods, the linear weighted method with equal complementation characteristics can be used as a baseline. For simplicity, weights are temporarily ignored. Assuming X_1 is maintained constant, and X_2 and X_3 each increase by 10%, the evaluation value increases by $0.1(X_2 + X_3)$. For other multi-attribute evaluation methods, if the evaluation value increases by more than $0.1(X_2 + X_3)$ when X_2 and X_3 each increase by 10%, it is excess complementation; if the increase is less than $0.1(X_2 + X_3)$, it is underbalance complementation.

Based on the linear weighted method, this paper selects traditional nonlinear evaluation methods including geometric mean, harmonic mean, and recently widely applied TOPSIS and VIKOR to analyze the complementarity characteristics and types of different multi-attribute evaluation methods. The technical route is shown in Figure 1 [Figure 1: see original paper].

2.3 Selection of Base Evaluation Indexes

When studying complementarity among evaluation indexes in multi-attribute evaluation methods, selecting evaluation indexes is crucial. The main considerations are:

(1) **Number of evaluation indexes**: As a case study, the number should be sufficient to illustrate the complementarity issue but not excessive, following the principle of simplicity. Therefore, 3-4 indexes are appropriate. With two indexes, only one-to-one substitution exists, making the problem too simple and unrepresentative. With ten indexes, the problem becomes too complex as the substitution issue is diluted and insensitive to evaluation values. Thus, one substituted index and two substituting indexes are selected, totaling three indexes.

(2) **Compensation among different attributes**: This is an implicit issue concerning correlations among evaluation indexes. Generally, similar evaluation indexes have high correlations. For example, among academic journal impact indexes, total citations, h-index, and Eigenfactor often have high correlations. Theoretically, one could study the substitution of total citations by h-index and Eigenfactor, but in practice, this is almost impossible because journals with high h-index also have high total citations and Eigenfactor, making it rare for h-index and Eigenfactor to increase while total citations decrease or remain unchanged. When studying substitution relationships among evaluation indexes, it is best for them to be uncorrelated. There are two ways to achieve low correlation: selecting uncorrelated indexes or extracting common factors through factor analysis. This paper adopts the second method because it provides better index representation and higher independence.

2.4 Data Standardization after Index Increase

In the research design, it is desired that X_2 and X_3 each increase by 10%. However, simply multiplying these indexes by 1.1 for evaluation is incorrect because in multi-attribute evaluation, the maximum value after standardization must be 1. After increasing X_2 and X_3 by 10%, their maximum values become 1.1, requiring re-standardization. However, re-standardization cannot guarantee that X_2 and X_3 each increase by 10%. In this case, the dynamic maximum-mean approximation standardization method (Figure 2 [Figure 2: see original paper]) can increase the index mean by 10% while ensuring the maximum value remains 1.

Taking X_j as an example, the main steps are:

First, standardize all evaluation indexes by dividing positive indexes by the maximum value and multiplying by 100 (using a percentage scale), and converting negative indexes to positive indexes by subtracting from the maximum value before standardizing. Then calculate the mean of each standardized index.

Second, calculate the mean of X_j to obtain K. The standardization goal is to make the mean of X_j equal to $1.1K$ while keeping the maximum value at 1.

Third, add $0.1K$ to all X_i, making the maximum value of X_j become $1 + 0.1K$.

Fourth, perform a second standardization on X_i by dividing by $1 + 0.1K$, but this reduces the mean of X_j to less than $1.1K$. Therefore, continue adding the difference between K and the current mean to X_j, perform a third standardization, and repeat this cycle until the difference between the increased mean target $1.1K$ and X_j is within an allowable range, such as 1%, at which point standardization ends.

The proof that the mean increases with each cycle of the dynamic maximum-mean approximation standardization method is as follows. Before the second standardization, the mean is increased using:

$$X_j' = X_j + K - \bar{X}_j \quad \text{Formula (2)}$$

Then the second standardization is performed using:

$$X_j'' = \frac{X_j + K - \bar{X}_j}{\max(X_j + K - \bar{X}_j)} = \frac{X_j + K - \bar{X}_j}{100 + K - \bar{X}_j} \quad \text{Formula (3)}$$

To prove that the mean of X_j'' increases, we calculate:

$$X_j'' - X_j = \frac{X_j + K - \bar{X}_j}{1 + K - \bar{X}_j} - X_j = \frac{(K - \bar{X}_j)(1 - X_j)}{1 + K - \bar{X}_j} \quad \text{Formula (4)}$$

Since K is the target mean after standardization, $K - \bar{X}_j > 0$, and the mean of X_j is certainly less than the standardized maximum value of 1, so $1 - X_j > 0$. Therefore, Formula (4) is certainly greater than 0.

The dynamic maximum-mean approximation standardization method requires multiple iterations, which can be easily solved through programming. After standardization, the index mean can absolutely reach the set target, such as a 10% increase, and the maximum value will be slightly greater than 1, which can be controlled through a designed threshold, such as not exceeding 1%, thus having minimal impact on evaluation result ranking. Importantly, it is a linear standardization method that does not destroy the large amount of information hidden in the original indexes or change data distribution characteristics.

2.5 Several Multi-Attribute Evaluation Methods

(1) Weighted Linear Summation. The linear weighted method is the most traditional evaluation method, also known as additive synthesis. It standardizes raw indexes first, then assigns weights using subjective, objective, or combined methods, and finally performs weighted summation:

$$C_i = \sum_{j=1}^{n} \omega_j x_{ij} \quad \text{Formula (5)}$$

where C_i represents the evaluation result, ω_j represents the weight, x_{ij} represents the evaluation index, m is the number of evaluation objects, and n is the number of evaluation indexes.

(2) Harmonic Mean. The harmonic mean is also a traditional evaluation method, being the reciprocal of the sum of squared reciprocals of evaluation indexes. It is greatly influenced by extreme values, particularly by minimum values, and is suitable for evaluations requiring coordinated development among indexes:

$$C_i = \frac{1}{\sum_{j=1}^{n} \frac{\omega_j}{x_{ij}}} \quad \text{Formula (6)}$$

(3) Geometric Mean. The geometric mean is also a traditional synthesis method, being more influenced by extreme values than the harmonic mean:

$$C_i = \prod_{j=1}^{n} x_{ij}^{\omega_j} \quad \text{Formula (7)}$$

(4) TOPSIS Evaluation. TOPSIS is a multi-attribute decision-making method proposed by C.L. Huang that can also be used for evaluation. It scores by calculating the relative distance of evaluation objects to the ideal and negative-ideal solutions. The best evaluation value is called the ideal solution (1 if indexes are standardized to a maximum of 1), and the worst is called the negative-ideal solution:

$$C_i = \frac{\sqrt{\sum_{j=1}^{n} \omega_j (x_{ij} - x_j^-)^2}}{\sqrt{\sum_{j=1}^{n} \omega_j (x_{ij} - x_j^+)^2} + \sqrt{\sum_{j=1}^{n} \omega_j (x_{ij} - x_j^-)^2}} \quad \text{Formula (8)}$$

where x_j^+ is the ideal solution, x_j^- is the negative-ideal solution, and the evaluation value ranges between 0 and 1.

(5) VIKOR Evaluation. VIKOR is a method proposed by S. Opricovic that considers maximizing "group benefit" and minimizing "individual regret." The basic steps are:

Select and standardize evaluation indexes, determine the positive-ideal solution f_{ij}^+ and negative-ideal solution f_{ij}^-.

Calculate the group benefit S value and individual regret R value for evaluation objects:

$$S_i = \sum_{j=1}^{n} \frac{\omega_j (f_{ij}^+ - f_{ij})}{f_{ij}^+ - f_{ij}^-} \quad \text{Formula (9)}$$

$$R_i = \max_j \left[\frac{\omega_j (f_{ij}^+ - f_{ij})}{f_{ij}^+ - f_{ij}^-} \right]$$

Calculate the evaluation value Q:

$$Q_i = v \frac{S_i - S^-}{S^+ - S^-} + (1 - v) \frac{R_i - R^-}{R^+ - R^-} \quad \text{Formula (10)}$$

where $S^+ = \max S_i$, $S^- = \min S_i$, $R^+ = \max R_i$, $R^- = \min R_i$. v represents the adjustment coefficient between group utility R and individual regret S. When $v > 0.5$, it emphasizes group satisfaction evaluation; when $v < 0.5$, it emphasizes individual regret evaluation. Generally, $v = 0.5$.

Sort by S, R, and Q in ascending order, with those ranked higher being better.

Validate the compromise solution. Sort Q in ascending order, assuming A is the optimal solution and B is the second. Q must satisfy the following conditions (if any condition is not met, there exists a set of compromise solutions):

Condition 1: Assuming M is the number of schemes, $DQ = 1/(M - 1)$, then $Q(B) - Q(A) \geq DQ$.

Condition 2: According to S and R values, A is also the optimal solution.

Empirical Research Results

3.1 Research Data

Using JCR 2016 mathematics journals as an example, the published evaluation indexes mainly include 11 items: total citations, impact factor without self-citations, impact factor, impact factor percentile, 5-year impact factor, Eigenfactor score, normalized Eigenfactor, article influence score, immediacy index, cited half-life, and citing half-life. JCR 2016 mathematics journals include 310 journals, with a few having missing data. After cleaning, 294 journals remain.

3.2 Preparation of Evaluation Indexes

As analyzed previously, to study complementarity among evaluation indexes in different multi-attribute evaluation methods, 3-4 evaluation indexes need to be selected, preferably uncorrelated. Therefore, the first step of empirical research is to extract common factors through factor analysis, as the number of common factors is generally small and they are uncorrelated. Factor analysis of 294 journals in JCR 2016 yields a KMO value of 0.823 (>0.5) and a Bartlett's test value of 8100.961 (p=0.000), meeting the prerequisites for factor analysis. The common factor extraction is shown in Table 1 .

Three factors with eigenvalues greater than 1 have a cumulative variance contribution rate of 81.643%, providing good representativeness. The rotation matrix is shown in Table 2 . In the first factor, impact factor, impact factor without self-citations, 5-year impact factor, immediacy index, Eigenfactor, and article influence score have large coefficients, which can be called the journal impact factor. In the second factor, total citations, cited half-life, and citing half-life have large coefficients, related to journal history and timeliness, which can be called the journal timeliness factor. In the third factor, average impact factor percentile and normalized Eigenfactor have large coefficients, both being appropriately transformed versions of original impact indexes, which can be called the journal transformed impact factor.

3.3 Comparison of Original Index Evaluation Results

These three factors are selected as evaluation indexes to test complementarity among evaluation indexes in different multi-attribute evaluation methods. The impact factor X_1 serves as the compensated index, while the timeliness factor X_2 and transformed impact factor X_3 serve as complementary indexes. First, these three indexes are used for evaluation with five methods. For simplicity, weights are temporarily ignored and treated as equal weights. The evaluation results and rankings are shown in Table 3 . Due to space limitations, only the top 30 journals by linear weighted method are published. Different evaluation methods yield significantly different results and rankings.

3.4 Evaluation Results after Complementary Index Increase

After standardizing the original indexes, the means of impact factor X_1, timeliness factor X_2, and transformed impact factor X_3 are 17.815, 20.199, and 9.257, respectively. Now, keeping impact factor X_1 constant as the compensated index, the means of complementary indexes X_2 and X_3 are each increased by 10% to 22.219 and 10.183, respectively. Then the five evaluation methods are applied again. The top 30 journals by linear evaluation are shown in Table 4 . Note that even for the same evaluation method, the top 30 journals differ after complementarity, which is normal.

3.5 Comparison of Evaluation Means Before and After Complementarity

Comparing the means of evaluation results before and after complementarity yields the results shown in Table 5 . The linear weighted method is the baseline. After maintaining impact factor X_1 constant and increasing timeliness factor X_2 and transformed impact factor X_3 by 10% each for complementarity, the mean of evaluation results increases by 6.15%, which is equal complementation. The harmonic mean and geometric mean methods increase by 8.65% and 7.79%, respectively, both greater than the linear weighted method, indicating excess complementation. The VIKOR method increases by only 1.58%, which is underbalance complementation. The TOPSIS method is special, with the evaluation value decreasing by 5.59% after compensation, also belonging to underbalance complementation.

Su Weihua argued that regardless of the synthesis method, since it is a comprehensive index, mutual "compensation" is inevitable, with only degree differences. However, in reality, underbalance complementation may result in negative compensation values. Furthermore, according to this paper's definition, distinguishing equal, excess, and underbalance complementation can better analyze complementarity relationships among indexes. Qiu Dong believed that compensation among indexes is difficult in geometric mean methods, but this study finds that geometric mean methods have relatively large complementarity, belonging to excess complementation, exceeding linear weighted methods.

Conclusions and Discussion

4.1 Research Conclusions

(1) **Complementarity among indexes in multi-attribute evaluation methods is a complex issue.** Due to differences in evaluation principles, index data characteristics, weight settings, and compensation values among different multi-attribute evaluation methods, complementarity issues are complex. Linear weighted methods are equal complementation, where a weighted mean reduction in one index can be compensated by an equal weighted mean increase in other indexes. Other nonlinear

evaluation methods may exhibit excess or underbalance complementation. Excess complementation means the evaluation value increases after equal weighted mean compensation, while underbalance complementation means the evaluation value decreases. Empirical results show that harmonic mean and geometric mean methods exhibit excess complementation, while TOPSIS and VIKOR methods exhibit underbalance complementation. However, this is not a proof but a result under specific data and methods; changing complementary indexes may alter complementarity results.

(2) **Ratio-based multi-attribute evaluation methods are more prone to underbalance complementation.** Multi-attribute evaluation methods are complex and can be roughly divided into ratio-based methods, total-value-based methods, and other methods. Linear weighted, harmonic mean, and geometric mean methods generally belong to total-value-based methods, while TOPSIS, VIKOR, and data envelopment analysis belong to ratio-based methods. Principal component analysis and factor analysis belong to other methods. For ratio-based methods, since evaluation values are relative numbers, underbalance complementation is more likely to occur after index complementarity. Furthermore, methods with good monotonicity (where evaluation results increase when the mean of an evaluation index increases) may exhibit equal, excess, or underbalance complementation, while methods with poor monotonicity (where evaluation results decrease when the mean increases) are more prone to underbalance complementation.

4.2 Discussion

(1) **Discussions of index complementarity should be conducted among indexes of different attributes.** In science and technology evaluation, due to high correlations among indexes, when one index increases, another normally also increases. In rare cases where one index decreases while another increases, people might consider this index complementarity that maintains ranking, but this is a special case and pseudo-complementation. Therefore, discussions of complementarity should preferably be conducted among indexes of different attributes and types.

(2) **Index complementarity has profound implications for selecting multi-attribute evaluation methods.** Index complementarity significantly impacts method selection. Generally, equal complementation methods should be preferred. Excess complementation 变相 increases the weight of complementary indexes, while underbalance complementation 变相 increases the weight of compensated indexes. Selection should be based on evaluation purposes. Due to the complexity of index complementarity, even within the same method, different index pairs may exhibit different complementarity types. Therefore, index complementarity can serve

as a method for evaluation result verification and management control, clarifying pairwise complementarity relationships among different types of indexes to deepen understanding of different index weights.

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Author Contributions

Xu Xinhua: Conceptualization of index complementarity ideas.
Yu Liping: Overall conception and writing of the paper.
Wang Zuogong: Literature retrieval and data processing.

The Complementary Study among Different Evaluation Indexes in Academic Journal Evaluation

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Abstract: [Purpose/significance] This paper discusses the complementary problem among implicit indexes in science and technology evaluation, where an index that does not increase or increases rarely can be compensated by other indexes increasing more, dividing complementation into equal complementation, excess complementation, and underbalance complementation, and analyzing the impact of index complementation on different evaluation methods. [Method/process] It designed a testing and judgment method, aiming at a certain nonlinear evaluation method, maintaining an index constant, calculating the change of evaluation value caused by increasing other different attribute index averages, and comparing it with the change of linear weighted method evaluation value. [Result/conclusion] Research shows that complementation among indexes of multi-attribute evaluation methods is a complex problem, influenced by various factors such as evaluation method, index data, weight arrangement, and compensation value; the method of multi-attribute evaluation based on ratio is more likely to be underbalance complementation; due to correlation between similar evaluation indexes, complementary indexes should be carried out between different attribute indexes; the complementation problem of indexes has a profound influence on the selection of multi-attribute evaluation methods, and in essence the index weight is changed euphemistically, which can be used as a method of evaluation test and management control.

Keywords: science and technology evaluation; indexes of complementary; linear evaluation; nonlinear evaluation