

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Wu, Gongxing; Addai, Bismark; Yu, Liping; Ran, Jiarui

Article

Evaluation of economics journals based on structural equation dimension reduction method

Journal of Applied Economics

Provided in Cooperation with: University of CEMA, Buenos Aires

Suggested Citation: Wu, Gongxing; Addai, Bismark; Yu, Liping; Ran, Jiarui (2021) : Evaluation of economics journals based on structural equation dimension reduction method, Journal of Applied Economics, ISSN 1667-6726, Taylor & Francis, Abingdon, Vol. 24, Iss. 1, pp. 592-608, https://doi.org/10.1080/15140326.2021.1984163

This Version is available at: https://hdl.handle.net/10419/314147

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.



https://creativecommons.org/licenses/by/4.0/

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



WWW.ECONSTOR.EU





Journal of Applied Economics

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/recs20

Evaluation of economics journals based on structural equation dimension reduction method

Gongxing Wu, Bismark Addai, Liping Yu & Jiarui Ran

To cite this article: Gongxing Wu, Bismark Addai, Liping Yu & Jiarui Ran (2021) Evaluation of economics journals based on structural equation dimension reduction method, Journal of Applied Economics, 24:1, 592-608, DOI: 10.1080/15140326.2021.1984163

To link to this article: https://doi.org/10.1080/15140326.2021.1984163

© 2021 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



6

Published online: 22 Oct 2021.

| | • |
|---|---|
| ம | |

Submit your article to this journal 🖸

Article views: 1271



View related articles 🗹

View Crossmark data 🗹

RESEARCH ARTICLE

OPEN ACCESS Check for updates

Routledge

Taylor & Francis Group

Evaluation of economics journals based on structural equation dimension reduction method

Gongxing Wu^a, Bismark Addai^b, Liping Yu^a and Jiarui Ran^a

^aSchool of Statistics and Mathematics, Zhejiang Gongshang University, Hangzhou, China; ^bSchool of Economics and Management, Changsha University of Science and Technology, Changsha, China

ABSTRACT

Evaluation of economic journals is helpful to improve the quality of these journals. In this study, we adopt a new structural equation dimension reduction method to evaluate economics journals. We classify evaluation indexes based on cluster analysis and factor analysis to establish a structural equation model, normalize the regression coefficients to obtain the weight, and then weigh and summarize the first-level evaluation indexes for the ultimate dimension reduction and evaluation. The evaluation based on JCR 2019 Economics journals shows that the structural equation dimension reduction method overcomes the randomness of manual classification of evaluation indicators. The linear dimension reduction method is conducive to preserving a large amount of information of the original indicators; evaluating the first-level indicators facilitates the comprehensive evaluation of journals; the first-level indicators evaluation approach is more objective and reflects systematic academic evaluation. It should be noted that the stability of the structural equation has a significant impact on evaluation, which is generally suitable for a relatively mature academic evaluation.

ARTICLE HISTORY

Received 3 June 2021 Accepted 20 September 2021

KEYWORDS

Economics; evaluation index; structural equation reduction method; cluster analysis; factor analysis

1. Introduction

Academic journals demonstrate scientific research achievements and play an essential role in academia and other spheres of life. As the media of scholarly communication, academic journals have the critical mission of knowledge innovation and value creation. Selecting a number of indicators from a bibliometric perspective, classifying them, and evaluating journals on this basis can help to grasp the influence and timeliness of journals, as well as the overall score and ranking of journals, which is conducive to the competition among journals, improving the quality of academic journals, and author's contribution. The selection and evaluation of journals also have a specific potential significance for the development of the related disciplines.

As a discipline to study human social behavior, economics plays a vital role in the development of human society and economy. Domestic and foreign economists have done extensive and in-depth research on journal evaluation. Foreign scholars mainly study the quality and influence of journals from the perspective of statistical data analysis and

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/ licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited

CONTACT Liping Yu 🖾 yvliping@zjgsu.edu.cn 🖃 School of Statistics and Mathematics, Zhejiang Gongshang University, Hangzhou 310018, China

^{© 2021} The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

innovation in journal evaluation method (Quandt, 1976; Stigler & Friedland, 1975). Hawkins, Ritrer, and Walter (1973) ranked economic journals through questionnaires to economists. Liebowitz and Palmer (1984) controlled the size and age of journals from the perspective of journal professionals, and constructed a measure of journal impact. Laband and Piette (1994) further analyzed the mutual effect of economic journals based on review of previous studies. Kim, Morse, and Zingales (2006) summarized modern economics research characteristics and speculated the future research trend and development through excellent papers based on cited frequency. Axarloglou and Theoharakis (2004) collected 2103 American Economic Association members' perceptions of journal quality and analyzed the reasons for the differences. Hirsch (2005) proposed h-index to evaluate the quality of scientific research. Palacios - Huerta and Volij (2004) studied academic influence through internet search engine ranking. Domestic scholars are mainly engaged in the innovation of journal evaluation system and research methods. Wang and Chu (2005) established a set of evaluation indexes suitable for Chinese economic journals. Tang, Wu, and Wang (2014) studied the relationship between zero citation rate and journal influence. Yu and Zhang (2020) established an evaluation method to evaluate journals and proposed an index that reflects academic journals' research hotspots. Research on the evaluation of economic journals is not only conducive to the development of economic journals but also academic communication. For the development of journals, journal evaluation can improve the quality of journals, expand academic influence, and enhance value creation for academic research. For readers, journals can provide them with representative, innovative and applicable high-quality journals, a timely understanding of the academic frontier trends, provide the theoretical basis for academic research, and promote the application of economics.

The multi-attribute evaluation of academic journals has gone through a long process of development. Since Garfield (1963) pioneered bibliometric research, academic evaluation was carried out using a single bibliometric indicator such as Total Cites, Journal Impact Factor, Citing Half-life, and Immediacy Index. Later, the use of the single indicator evaluation developed to include multimeric indexes that contain a large amount of information, such as the h index (Hirsch, 2005), mean cited times of academic articles FCSm (Moed, De Bruin, & Van Leeuwen, 1995), article count impact factor ACIF (Markpin et al., 2008), and the normalized mean citation rate NMCR (Braun & Glanzel, 1990). The use of the multi-attribute evaluation method to evaluate academic journals has a broader perspective than a single indicator, and the former is more comprehensive than the latter.

Multi-attribute evaluation is widely used in the evaluation of academic journals. Shotton (2012) proposed five journal evaluation indicators, including journal content richness, peer review, open access, data, and computer-readable metadata. Sombatsompop, Kositchaiyong, Markpin, and Inrit (2013) evaluated academic journals from three perspectives: Journal Impact Factor (JIF), Article Impact Factor (AIF), and Position Impact Factors (PIF). Mayr (2006) constructed open access journal evaluation indicators from three angles: search engine, direct path, and back path. The study established that network usage indicator is an essential measure to promote the acceptance and use of open access research.

The evaluation of academic journals by multi-attribute evaluation method has its advantages, such as its comprehensive evaluation due to the use of multiple evaluation indicators, but there are also some problems associated with the method. First, it is difficult to classify some evaluation indicators. In the evaluation of academic journals, for various reasons, the classification of some indicators is unclear. They can be classified into type A and type B, but different classifications will undoubtedly affect the evaluation results. For example, the Immediacy Index is the mean cited times of the published article in that year. It has the characteristics of the academic journal's impact indicators and the characteristics of the academic journal's timeliness index. The existing research tends to classify them subjectively and rarely uses objective classification or the combination of subjective and objective classification. Second, the evaluation of the first-level indicators is not given much attention. In the evaluation of academic journals, many evaluation methods can only produce the comprehensive evaluation scores of journals, but not the scores of first-level indicators. For example, evaluation methods such as the gray correlation, VIKOR, and entropy weight evaluation methods often only obtain comprehensive evaluation results.

Third, the evaluation of the first-level indicators lacks objectivity. For the evaluation of existing academic journals, most of the underlying indicators are summarized by linear weighted aggregate method. For example, the summarized weights of the underlying indicators is used to obtain the first-level indicators such as the influence value and timeliness value of academic journals. The weight of the underlying indicators is determined by subjective or objective methods. The problem is that there are dozens of methods at present to obtain the weights, so how do we choose the appropriate method? For example, if only Journal Impact Factor and Total Cites are used to evaluate the influence of the journal, the manual weight impact factor is 0.8, and Total Cites 0.2. If the entropy weight method is used to determine the weight, Journal Impact Factor is 0.427 if the discrete coefficient method is used o obtain the weight. There may be more methods to obtain the weights, so how do we choose the right method to get the weights to ultimately ascertain the influence value of academic journals?

In order to solve the above problems, we must first solve the problem relating to the classification of evaluation indicators, and then solve the problem associated with first-level indicators evaluation. Since the first-level indicator is the overall classification of academic journal evaluation indicators, the number is often small. The solution to this problem is beneficial in the evaluation of journals from the perspective of first-level indicators, enhances the objectivity of the evaluation of first-level indicators, greatly reduces the difficulties involved in comprehensive evaluation of academic journals.

The primary contribution of this study is the application of a new structural equation dimension reduction method to evaluate economics journals. The new evaluation method overcomes the randomness of manual classification of indicators, retains a lot of information about the original indicators and reduces the correlation between indicators. The new method also guarantees the objectivity and rationality of the evaluation results and embodies a systematic evaluation of academic journals. In this study, we first classify the evaluation indicators of academic journals based on factor analysis and cluster analysis, and then we use the structural equation dimension reduction method to evaluate first-level indicators. Finally, we do a comprehensive evaluation of economic journals using the TOPSIS evaluation method proposed by Hwang and Yoon (1981).

2. Materials and method

This section contains the classification of journal evaluation indicators, the structural equation method, the structural equation dimension reduction method, the evaluation steps, the TOPSIS method, and the research data.

2.1. Subjective and objective classification of academic journal evaluation indicators

The subjective classification of evaluation indicators is the qualitative classification of journals based on the perception and judgment of experts or active researchers in a certain field (Walters, 2017). The advantage of this method is the use of peer opinions to evaluate academic journals, and it reflects the accumulated opinions of representative experts in a certain field. During the survey, experts are usually given the weight of each index (Yu, Pan, & Wu, 2010). The evaluation forms are mainly divided into off-line and online questionnaires, which are generally scored using a Likert scale (Kohl & Davis, 1985; Manzari, 2013).

The objective classification of evaluation indicators is essentially a machine-assisted classification. Luhn (1957) pioneered research on automatic classification and proposed the idea of applying word frequency statistics to automatic classification. Maron and Kuhns (1960) studied the automatic classification of the keywords of articles, which marked the birth of the automatic classification discipline. Cluster analysis and factor analysis are two typical objective classification methods. In the case of multi-attribute evaluation, the objective classification is not devoid of issues, but the nature of the problem depends on how the manual classification is done. A combination of subjective and objective classification methods is better than just singling out any of these classification methods.

Cluster analysis is a common classification method. System clustering includes Q-type clustering and R-type clustering. Q-type clustering is the clustering of samples. R-type clustering is the clustering of variables and indicators and this is usually used to classify evaluation indicators.

Factor analysis is essentially a data mining method that can be used for both data analysis and evaluation. In addition, factor analysis can also classify the evaluation indicators; that is, for the common factors whose feature root is greater than 1.0, the analysis of the evaluation indicators and their relationship can assist in the classification.

The classification results of cluster analysis and factor analysis are not necessarily the same. According to the two classification results, supplemented by manual analysis, the evaluation indicators of academic journals can be better classified. Compared with the existing manual classification of indicators in academic journal evaluation, classification based on the combination of cluster analysis, factor analysis, and manual analysis is more reasonable.

2.2. Structural equation model

The Structural Equation Model (SEM) is an analytical technique for establishing, estimating, and testing causality models. It includes multiple regression analysis, factor analysis, path analysis, and multiple variance analysis techniques, and it has been used widely in economics (Hellier, Geursen, Carr, & Rickard, 2003), management (Liu, Yi, & Wang, 2020), sociology (Ijaiya, Dayang, & Ramli, 2016), psychology (Gerino, Rollè, & Sechi, 2017), behavioral science (Hussey & Eagan, 2007), academic evaluation (Servet & Çelik, 2021), and other fields (Hermida, 2015). 596 👄 G. WU ET AL.

The structural equation model includes two major elements: structural model and measurement model. The structural model can be specified as:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{1}$$

The structural model mainly measures the causal relationship between the latent variables, where ξ is the exogenous latent variable in the model, η is the endogenous latent variable in the model, and Γ and B are structural coefficient vectors, respectively representing the relation between the exogenous latent variable ξ and the endogenous latent variable η , while ζ is the residual. For the purpose of this study, the structural model is adopted to measure the relationship between the timeliness indicators and the impact indicators of academic journals.

The measurement model is expressed as:

$$X_{\eta} = \pi_{\eta} \eta + \varepsilon \tag{2}$$

$$X_{\xi} = \pi_{\xi}\xi + \delta \tag{3}$$

The measurement model mainly measures the relationship between the latent variable and the explicit variable. Equation (2) represents the relationship between the endogenous latent variable and the corresponding explicit variable, π_{η} is the measured coefficient vector while ε is the residual vector. Equation (3) represents the relationship between the exogenous latent variable and the corresponding explicit variable, π_{ξ} is the measured coefficient vector while δ is the residual vector.

The structural equation model estimates the coefficient value of the linear regression model by verifying the covariance between the observed variables and tests whether the hypothesized model is suitable for the research process, that is, tests the fitting degree between covariance vector of the observed variables and the extended covariance vector after fitting the model. From this perspective, the structural equation model is a confirmatory technique, not an exploratory technique, and it is more suitable for studying the complex relationship between the latent variables in a given theoretical framework. The structural equation model adopted in this study is asymptotically distribution-free. This method was proposed by Browne (1984), and compared with the least-square estimation method used in traditional multiple regression; it has lower requirements on data distribution and greater advantages when dealing with data that involve fewer observations, more variables, and complex relationships.

Some of the concerns that arise from the use of the SEM are sensitivity of the method to data and distribution of the data. The periodical index deviates from normal distribution, resulting in large error between the individual index and the structural factor. Under normal circumstances, the data processed by SEM are large samples. As a rule of thumb, if the sample size is less than 200, the conclusion could be unstable, and the data size above 200 can be considered as a medium-sized sample. Of course, as the number of subjects and indicators vary, the requirements for sample size will also change, which can be analyzed on a case-by-case basis. The asymptotically distribution free SEM (with lower requirement on data distribution) and the sample used in this study help to overcome these limitations usually associated with the method.

2.3. Structural equation dimension reduction method

In structural equations, latent variables are estimated by explicit variables, and the regression coefficients of explicit variables can be observed. In essence, this is the weight. In other words, if the structural equation model has passed the main statistical test, then the latent variable is objective to some extent, and the regression coefficient of the evaluation index, which is the explicit variable related to the latent variable, is known, then the latent variable can be accurately calculated. The latent variable is the first-level indicator. By using the structural equation model and adopting the objective method, the classification and the weight problems associated with journal indicators evaluation are skillfully solved, and the effect of dimension reduction is achieved. At the same time, the relationship between different types of journal indicators is considered systematically. In this paper, the structural equation method used is called the structural equation dimension reduction method.

2.4. Evaluation steps

The evaluation steps are shown in Figure 1. First, determine the purpose and the object of evaluation. The evaluation object of this study is economics journals, which is mainly evaluated by means of the literature measurement indicators that can be obtained from the JCR database.

Second, the screening of evaluation indicators. From the perspective of evaluation, the more the indicators, the better, but some indicators have high acquisition costs, and that should be properly taken into account. There are some subjective indicators, and the researcher must pay attention to them to ensure the data quality. In addition, the researcher must pay attention to indicator data types. Generally, the selection of non-parametric indicators needs to be done cautiously. For example, some indicators are sorting serial numbers, which are generally not suitable.

Third, comprehensive classification of evaluation indicators. Cluster analysis and factor analysis are used to classify the indicators, then compare the results of the two and combine manual judgment, and carefully determine the indicator classification, which is essential to determine the first-level indicators.

Fourth, structural equation modeling. Based on the classification results, the relationship among the first-level indicators is carefully analyzed to model the structural equation. Import the data and perform a preliminary estimate, and at the same time test the important statistics, if necessary, further adjust the model and get the final estimate.

Fifth, calculate the first-level indicator. Normalize the regression coefficients of the explicit variable (first-level indicator) and the latent variable (evaluation indicator) in the structural equation estimation results to obtain the weights, and standardize the evaluation indicators, then summarize the weights to obtain the values of first-level indicators.

Sixth, conduct a comprehensive evaluation. Based on the existing first-level indicators, the comprehensive evaluation of the journal can be conducted to obtain the total score and ranking.

598 👄 G. WU ET AL.



Figure 1. Dimension reduction evaluation process.

2.5. The TOPSIS method

TOPSIS is a sort method of approaching an ideal solution, which is mainly used for multi-objective decision-making of finite schemes (see Hwang & Yoon, 1981). The method is employed to find out the ideal positive solution and the ideal negative solution based on the normalized original data matrix (Chen, Lin, & Huang, 2006). The TOPSIS approach estimates the ideal alternative that has the furthest distance from the ideal negative solution and the closest from the ideal positive solution. By calculating the distance between the evaluation object and the best scheme and the worst scheme, the proximity between the evaluation object and the best scheme can be obtained. The method is advantageous because it has no strict requirements on the distribution and

JOURNAL OF APPLIED ECONOMICS 😔 599

size of samples, it can make full use of information in the original data information, and it can also rank the advantages and disadvantages of each evaluation object, making the outcome more consistent with reality. In line with studies that have applied the method in selection and evaluation criteria (see e.g., Chen et al., 2006; Hwang & Yoon, 1981; Wang & Elhag, 2006), the TOPSIS is calculated as follows:

$$C_{i} = \frac{\sqrt{\sum_{j=1}^{n} w_{i}(x_{ij} - \overline{x_{j}})^{2}}}{\sqrt{\sum_{j=1}^{n} w_{j}(x_{ij} - x_{j}^{+})^{2}} + \sqrt{\sum_{j=1}^{n} w_{j}(x_{ij} - x_{j}^{-})^{2}}}$$
(4)

Where C_i represents the evaluation result of TOPSIS; n is the number of evaluation indexes, i is the serial number of the evaluation target, j is the serial number of the evaluation index; x_{ij} is the standardized evaluation index, x_j^+ is the maximum value after the standardization, which is the positive ideal solution; x_j^- is the negative ideal solution, that is the minimum value after the standardization; w_j is the weight. The numerator represents the distance from the evaluation object to the negative ideal solution, and the denominator is the sum of the distance from the evaluation object to the positive and negative ideal solutions.

2.6. Research data

Based on JCR 2019 database, this paper evaluates economic journals. There are 373 economic journals in the database; however, due to the non-availability of data on some journals, 36 journals were excluded from our study. Thus, this study employs a sample of 337 economics journals. There are 12 indicators in the JCR 2019 report: Total Cites (TC), Journal Impact Factor (JIF), Impact Factor without Journal Self Cites (IFW), 5-Year Impact Factor (IF5), Immediacy Index (II), Eigenfactor Score (ES), Article Influence Score (AIS), Normalized Eigenfactor (NES), Cited Half-Life (CHL1), Citing Half-life (CHL2), Average Journal Impact Factor Percentile (AJIFP), and Citable Items (CI).

It should be noted that the Cited Half-Life rate period and the Citing Half-Life rate period are reverse indicators. The larger the value, the worse the timeliness of academic journals. Therefore, the values must be reversed through standardization. We adopt the reverse index standardization method proposed by Yu et al. (2010). The standardization method is specified as follows:

$$y_k = 1 - \frac{x_k}{\max(x_k)} + \left\{ 1 - \max\left[1 - \frac{x_k}{\max(x_k)}\right] \right\}$$
(5)

Where x_k is the original index, y_k is the standardized index, K is the index serial number.

Table 1 provides the descriptive statistics of the indicators used in this study.

| Evaluation indicators | Variable | Mean | Min | Max | Std. Dev. |
|--|----------|----------|-------|--------|-----------|
| Total Cites | TC | 3269.210 | 111 | 56,685 | 6523.601 |
| Journal Impact Factor | JIF | 1.843 | .184 | 11.375 | 1.523 |
| Impact Factor without Journal Self Cites | IFW | 1.688 | .124 | 11.125 | 1.465 |
| 5-Year Impact Factor | IF5 | 2.252 | .262 | 16.095 | 1.958 |
| Immediacy Index | 11 | .538 | .000 | 6.000 | .584 |
| Cited Half-Life | CHL1 | 10.083 | 2.200 | 31.500 | 4.332 |
| Citing Half-life | CHL2 | 10.849 | 4.900 | 36.600 | 3.070 |
| Eigenfactor Score | ES | .005 | .000 | .121 | .010 |
| Article Influence Score | AIS | 1.287 | .019 | 22.016 | 2.110 |
| Normalized Eigenfactor | NES | .596 | .006 | 14.760 | 1.237 |
| Average Journal Impact Factor Percentile | AJIFP | 48.930 | 1.023 | 99.866 | 28.330 |
| Citable Items | CI | 61.05 | 4 | 746 | 70.005 |

 Table 1. Descriptive statistics of the indicators.

3. Empirical results

3.1. Indicator selection

First, the primary selection of indicators should be done. Among the 12 indicators, Citable Items is the only indicator that is not suitable to be selected because that indicator simply reflects the scale of academic journals, and it has nothing to do with academic quality. When evaluating academic journals, Citable Items is generally not used as an evaluation indicator (see Kiesslich, Weineck, & Koelblinger, 2016). The results of this analysis point out the potentially delusive effect of IF increases gained through effective shrinkage of publication output. The difference between the total number of articles and "citable" articles when calculating the impact factor is significant. For example, 22 percent of entries in the Science Citation Index fall into the "unquotable" category. In the Social Sciences Citation Index, these non-quotable items make up 46% of the total entries, and in the Humanities and Arts Citation Index (which has no JCR counterpart), the percentage is even higher (70.5%) (Jacsó, 2001).

To some extent, the larger the Citable Items, the lower the impact of academic journals.

Second, the Average Journal Impact Factor Percentile is calculated. This indicator is further calculated based on the order of the size of the Journal Impact Factor. The calculation formula of Clarivate Analytics is as follows:

$$AJIFP = \frac{(N - R + 0.5)}{N} \times 100\%$$
 (6)

Where AJIFP is the Average Journal Impact Factor Percentile, N is the number of subject journals, and *R* is the order of Journal Impact Factor in descending order. The Average Journal Impact Factor Percentile belongs to the ranking indicator and has non-parametric properties, so it should not be evaluated together with the indicators of other parameter properties.

3.2. Indicator classification

Cluster analysis is carried out to classify the indicators, and the system clustering approach is used. The cluster method uses inter-group connection, and the distance function uses the Pearson correlation coefficient. The results are shown in Figure 2.



Dendrogram using Average Linkage (Between Groups)

Figure 2. Cluster analysis result.

The results of cluster analysis can be roughly divided into five categories: the first category is Eigenfactor Score, Normalized Eigenfactor and Total Cites; the second category is Journal Impact Factor, Impact Factor without Journal Self Cites, 5-Year Impact Factor, Article Influence Score; the third is Immediacy Index; the fourth is the Cited Half-Life; the fifth is the Citing Half-Life. The results of the cluster analysis signify that the first, second, and third categories are essentially the influential indicators of academic journals, which can be combined into one category to reflect the influence of journals; while the fourth and fifth categories, which reflect the timeliness of journals, can be collectively referred to as the timeliness index of journals, and the two indicators, Cited Half-Life and Citing Half-Life are combined. From the cluster analysis, we can see that a completely objective evaluation method does not exist and as such manual intervention is also needed.

The KMO test and Bartlett test are needed for factor analysis. The results show that the KMO test value is 0.821, the Bartlett test value is 9677.087, and the associated probability is 0.000, which meets the preconditions of factor analysis. There are two factors with an eigenvalue greater than 1.0 in factor analysis. The variance contribution rate of the first factor is 59.80%, and that of the second factor is 15.831%. The total contribution rate of the two factors is 75.63%. The factor rotation matrix is shown in Table 2.

It can be seen from the rotation matrix that the first factor includes: Total Cites, Eigenfactor Score, Normalized Eigenfactor, Journal Impact Factor, Impact Factor without Journal Self Cites, 5-Year Impact Factor, Immediacy Index, Article Influence Score; the second factor includes Cited Half-Life and Citing Half-Life. The results of the classification and cluster analysis are consistent. The two classification methods do not classify the immediacy index into the timeliness index; that is, they are classified as Cited Half-Life and the Citing Half-Life.

Based on the results of the cluster analysis and the factor analysis, the first, second, and third categories in the cluster analysis are the same as the first factor in factor analysis, which is essentially an academic journal's influential indicators. Therefore, they are combined into one category, which is collectively referred to as academic journal influence, and

602 😔 G. WU ET AL.

| Evaluation indicators | Abbreviation | Factor 1 | Factor2 |
|--|--------------|----------|---------|
| Total Cites | TC | 0.872 | 0.185 |
| Eigenfactor Score | ES | 0.907 | 0.172 |
| Normalized Eigenfactor | NES | 0.907 | 0.172 |
| Journal Impact Factor | JIF | 0.839 | -0.437 |
| Impact Factor without Journal Self Cites | IFW | 0.844 | -0.420 |
| 5-Year Impact Factor | IF5 | 0.892 | -0.332 |
| Immediacy Index | II | 0.655 | -0.384 |
| Article Influence Score | AIS | 0.879 | -0.013 |
| Cited Half-Life | CHL1 | 0.377 | 0.675 |
| Citing Half-Life | CHL2 | -0.177 | 0.711 |

Table 2. Factor rotation matrix.

they include Total Cites, Eigenfactor Score, Normalized Eigenfactor, Journal Impact Factor, Impact Factor without Journal Self Cites, 5-Year Impact Factor, Immediacy Index, and Article Influence Score. In other words, the first level index of economic journals is divided into two indicators: influence and timeliness.

3.3. Structural equation model estimation

The result of the structural equation model is illustrated in Figure 3. The AVE value of influence is 0.805, the combination reliability is 0.966, the AVE value of timeliness is 0.421, the combination reliability is 0.748, the model has high reliability. Except for Immediacy Index and Cited Half-Life, the regression coefficients of other indexes all passed the statistical test. Since this article is based on evaluation, the statistical test requirements for the model can be appropriately reduced (Yu, 2020; Yu, Chen, & Pan, 2009).



Figure 3. Structural equation model estimation result.

The timeliness indicator of journals is an important factor influencing the impact of journals. It is generally believed that the stronger the timeliness of an academic journal, the more attention given to such journals, which makes it easier to attract readers and enhance the journal's influence. The elasticity coefficient of timeliness to influence is 0.940, which means that for every 1% increase in journal timeliness, the influence increases by 0.940%. The timeliness of journals explains 36.2% of the influence, and the goodness of fit is 0.362.

3.4. Weight normalization

The weight normalization results of the academic journal influence index are shown in Table 3. The indexes with larger weight are Journal Impact Factor, Impact Factor without Journal Self Cites, and 5-Year Impact Factor and the weight of Article Influence Score is the smallest.

The weight normalization results of timeliness index of academic journals are shown in Table 4. The weight of Citing Half-Life is 0.508, and the weight of Cited Half-Life is 0.492.

3.5. Final evaluation result

All the evaluation indicators were standardized and then weighted and aggregated based on the weights to obtain journals' influence and timeliness. Then, by the TOPSIS approach, the influence and timeliness were evaluated to obtain the final evaluation results for the top 30 economic journals, as shown in Table 5.

It can be seen from Table 5 that the top five journals in total (TOPSIS) ranking are Q J ECON, J ECON PERSPECT, ECON GEOGR, BROOKINGS PAP ECO AC, and J FINANC; the top five journals based on their influence are J FINANC, Q J ECON, J FINANC ECON, AM ECON J-APPL ECON, J ECON PERSPECT; the top five journals in terms of timeliness are SOCIO-ECON PLAN SCI, REV ECON STAT, ECOL ECON, ECON POLICY, J ECON LIT.

The ranking of influence, timeliness ranking, and the overall ranking of economic journals are segregated so that we can analyze the influence, timeliness, and the overall ranking of each journal more clearly, and provide more comprehensive information. If we only focus on the overall comprehensive evaluation, the influence, timeliness and other further details will be ignored.

| Influence indicator | Notation | Regression coefficient | Normalized weight | Weights ranking |
|--|----------|------------------------|-------------------|-----------------|
| Total Cites | TC | 0.508 | 0.074 | 5 |
| Eigenfactor Score | ES | 0.443 | 0.064 | 6 |
| Normalized Eigenfactor | NES | 0.443 | 0.064 | 6 |
| Journal Impact Factor | JIF | 1.496 | 0.217 | 1 |
| Impact Factor without Journal Self Cites | IFW | 1.402 | 0.203 | 2 |
| 5-Year Impact Factor | IF5 | 1.355 | 0.197 | 3 |
| Immediacy Index | II | 1.000 | 0.145 | 4 |
| Article Influence Score | AIS | 0.248 | 0.036 | 8 |

Table 3. The weight of journal influence indicators.

| | T | al | bl | e · | 4. | The | weigh | nt of | journal | time | liness | ind | icato | ors. |
|--|---|----|----|-----|----|-----|-------|-------|---------|------|--------|-----|-------|------|
|--|---|----|----|-----|----|-----|-------|-------|---------|------|--------|-----|-------|------|

| Timeliness indicator | Regression coefficient | Normalized weight | Weights ranking |
|----------------------|------------------------|-------------------|-----------------|
| Cited Half-Life | 1.000 | 0.492 | 2 |
| Citing Half-Life | 1.031 | 0.508 | 1 |

604 🕒 G. WU ET AL.

| JCR Abbreviated Title | Influence | Rank | Timeliness | Rank | TOPSIS | Rank |
|-----------------------|-----------|------|------------|------|--------|------|
| Q J ECON | 94.38 | 2 | 71.73 | 24 | 0.84 | 1 |
| J ECON PERSPECT | 91.90 | 5 | 73.87 | 21 | 0.84 | 2 |
| ECON GEOGR | 89.17 | 7 | 77.41 | 19 | 0.83 | 3 |
| BROOKINGS PAP ECO AC | 88.32 | 9 | 79.97 | 18 | 0.83 | 4 |
| J FINANC | 99.30 | 1 | 69.09 | 26 | 0.82 | 5 |
| J ECON LIT | 86.14 | 12 | 90.20 | 5 | 0.82 | 6 |
| REV ENV ECON POLICY | 86.41 | 11 | 87.56 | 12 | 0.82 | 7 |
| J FINANC ECON | 94.31 | 3 | 65.09 | 27 | 0.81 | 8 |
| AM ECON REV | 84.40 | 14 | 89.85 | 7 | 0.79 | 9 |
| J POLIT ECON | 88.50 | 8 | 70.93 | 25 | 0.79 | 10 |
| ENERG ECON | 85.34 | 13 | 80.58 | 17 | 0.78 | 11 |
| J ASSOC ENVIRON RESO | 89.92 | 6 | 63.35 | 28 | 0.77 | 12 |
| ENERG POLICY | 82.48 | 16 | 89.47 | 8 | 0.75 | 13 |
| AM ECON J-APPL ECON | 93.65 | 4 | 49.29 | 29 | 0.75 | 14 |
| J POLICY ANAL MANAG | 81.87 | 18 | 83.71 | 14 | 0.73 | 15 |
| REV ECON STUD | 82.74 | 15 | 73.59 | 22 | 0.71 | 16 |
| SMALL BUS ECON | 80.13 | 19 | 87.94 | 11 | 0.71 | 17 |
| TRANSPORT RES B-METH | 79.82 | 20 | 88.98 | 9 | 0.70 | 18 |
| VALUE HEALTH | 82.36 | 17 | 72.41 | 23 | 0.70 | 19 |
| TRANSPORT RES E-LOG | 78.99 | 23 | 90.06 | 6 | 0.69 | 20 |
| REV FINANC STUD | 87.21 | 10 | 45.35 | 30 | 0.69 | 21 |
| J ECON GROWTH | 79.75 | 21 | 81.88 | 16 | 0.69 | 22 |
| NBER MACROECON ANNU | 78.79 | 24 | 83.31 | 15 | 0.67 | 23 |
| ECON POLICY | 77.73 | 25 | 90.28 | 4 | 0.67 | 24 |
| CAMB J REG ECON SOC | 79.45 | 22 | 75.76 | 20 | 0.66 | 25 |
| ECOL ECON | 76.91 | 27 | 91.76 | 3 | 0.66 | 26 |
| REV ECON STAT | 76.56 | 28 | 93.49 | 2 | 0.66 | 27 |
| FOOD POLICY | 77.02 | 26 | 85.46 | 13 | 0.65 | 28 |
| SOCIO-ECON PLAN SCI | 75.97 | 29 | 93.61 | 1 | 0.65 | 29 |
| ECONOMETRICA | 74.93 | 30 | 88.63 | 10 | 0.62 | 30 |

The correlation coefficients for journal influence, timeliness, and total evaluation score are shown in Table 6. The correlation coefficient between influence and total evaluation is 0.688, and that of timeliness and total evaluation is 0.426. When journals with greater influence have more advantages in the overall evaluation. The correlation coefficient between influence and timeliness is 0.114, which is the lowest, and the reason may be that journals with good timeliness are generally relatively easy to obtain good influence, but journal influence essentially depends on the quality of papers, so it is normal that the correlation coefficient is the lowest.

4. Research conclusion

4.1. It is of great significance to use the indicator system to evaluate economics journals

The use of the indicator system to evaluate economic journals can be analyzed from many perspectives, avoiding the lack of information when the evaluation indicators such as Journal Impact Factor and h index are used for evaluation. The first-level indicator evaluation can provide some information to make the evaluation more comprehensive. The evaluation results are conducive to the analysis of the various economic journals, so as to further improve the quality of the journals, and also provide reference for scholars when they choose journals to submit their articles.

| | Total score | Influence | Timeliness |
|-------------|-------------|-----------|------------|
| Total score | 1.000 | | |
| | - | | |
| Influence | 0.688** | 1.000 | |
| | 0.000 | - | |
| Timeliness | 0. 426** | 0.114** | 1.000 |
| | 0.000 | 0.002 | - |

Table 6. Correlation coefficients between evaluation results and first-level indicators.

**Correlation is significant at the 0.01 level (2-tailed)

4.2. The structural equation dimension reduction is of great significance in academic evaluation

This article proposes the use of cluster analysis and factor analysis to assist the manual classification of evaluation indicators, and then use the structural equation model to summarize the weights of evaluation indicators, so as to obtain the first-level indicators for dimension reduction. The significance of this work is shown along the following six angles:

First, the classification methods overcome the randomness of manual classification of evaluation indicators. Due to the complexity of evaluation indicators, it is often difficult to appraise manual classification, and it may be misleading to rely on subjective classification. Combining cluster analysis and factor analysis for classification improves the scientific classification of evaluation indicators.

Second, in the case of numerous academic evaluation indicators and complex attributes, the linear dimension reduction approach greatly reduces the number of indicators through classification and aggregation, making the original hundreds of indicators become a few first-level indicators. Unlike factor analysis, principal component analysis and other dimension reduction techniques, structural equation dimension reduction is essentially a linear dimension reduction of the evaluation indicator, without sacrificing the large amount of information contained in the original indicator.

Third, the study approach facilitates comprehensive evaluation by making it easier to obtain the weights of indicators. In the past, all indicators were weighted and then evaluated. When the indicators were numerous, the work was very complicated and even surpassed human's resolution capability. The dimension reduction reduces the complexity of the evaluation system, making the comprehensive evaluation become an evaluation of a few first-level indicators so that only the first-level indicators should be weighted. Thus the evaluation efficiency is improved, the complexity of obtaining the weights is reduced, and possible errors are avoided.

Fourth, the correlation between first-level indicators is reduced. Unlike the factor analysis dimension reduction, a kind of non-linear dimension reduction that sacrifices a lot of information in the original indicators and eliminates correlation among factors, the indicators of structural equations dimension reduction are still related, but the correlation is greatly reduced. The structural equation dimension reduction is a linear dimension reduction. Therefore, the attributes of the first-level indicators are distinct, which is convenient for further evaluation and also facilitates the quantitative analysis that may be required, which can reduce the multi-collinearity.

Fifth, the evaluation of first-level indicators is unique and objective. In this article, based on the structural equation model, the first-level indicator is regarded as the latent variable, and the related evaluation indicators are regarded as the explicit variable. The regression coefficient estimated by the structural equation model is used as the "weight", and then the first-level indicator is calculated. This method is objective and unique and it avoids the influence of multi-attribute evaluation methods that result in many evaluation results.

Sixth, the approach reflects the systematic thinking of academic evaluation. In academic evaluation, different types of indicators are often interrelated, such as the timeliness of journals affecting the influence of journals, Journal Impact Factories related to 5-Year Impact Factor, and Eigenfactor Score is related to h-index, but all academic evaluation so far is based on indicators, they seldom consider the internal relationship between different types of indicators, lack of systematic thinking. Structural equation dimension reduction essentially reflects the systemic thinking of academic evaluation, which is a systematic evaluation.

4.3. The stability of the structural equation has a significant influence on evaluation

In a mature academic evaluation domain, the structural equation model is relatively stable, such as academic journal evaluation, university science and technology performance evaluation, and enterprise innovation evaluation, but the reality is not always the case. For some novel evaluation objects, if the evaluation mechanism is not stable, the relationship between different types of indicators is not clear enough, then it is not appropriate to use this method for evaluation.

It is important to emphasize that in academic evaluation, the structural equation model helps in the classification and aggregation of indicators which plays a dimension reduction role, and it does not simply focus on the relationship between different latent variables. Therefore, the requirements for too many statistical tests for the stability of the equation can conveniently be lowered.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This article is supported by Key projects of Natural Science Foundation of Zhejiang Province: Research on the transformation mechanism of manufacturing industry from quantitative innovation to quality-oriented innovation [Z21G030004]; Zhejiang first-class discipline project (statistics, management science and engineering of Zhejiang Gongshang University).

Notes on contributors

Gongxing Wu, associate professor, is now the director of Platform Center of Management Engineering and E-Commerce School, Zhejiang Gongshang University, and the deputy director of National E-Commerce Virtual Simulation Experimental Teaching Center in China. He has long been engaged in research on e-commerce platform and operation, business big data analysis, scientific and technological innovation, and national poverty alleviation big data.

Bismark Addai is a postdoctoral research associate at the School of Economics and Management, Changsha University of Science and Technology in China. His current research interests span across financial economics, environmental economics, agricultural economics, corporate finance, and corporate governance.

Liping Yu is working as a professor at the School of Statistics and Mathematics, Zhejiang Gongshang University in China. His area of interest includes technical economy, academic evaluation, and scientific & technological performance evaluation. He has published in leading mainstream journals in the area of management and information science. At present, the number of first author CSSCI papers has entered the top 15 national humanities and social sciences. In the past 10 years, his first author CSSCI papers have entered the top 5 in the country. In 2020, his papers were selected as the most influential list of philosophy and social sciences in the first-level discipline of management.

Jiarui Ran is a student pursuing a PhD degree at the School of Statistics and Mathematics, Zhejiang Gongshang University in China. Her current research interests include technical economy, academic evaluation, and scientific & technological performance evaluation.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

References

- Axarloglou, K., & Theoharakis, V. (2004). Diversity in economics: An analysis of journal quality perception. *Journal of the European Economic Association*, 1(6), 1402–1423.
- Braun, T., & Glanzel, W. (1990). World flash on basic research. A topographical approach toworld publication output and performance in science. *Scientometrics*, *19*(3–4), 159–165.
- Browne, M. W. (1984). Asymptotically distribution-free methods for the analysis of covariance structures. *British Journal of Mathematical and Statistical Psychology*, *37*(1), 62–83.
- Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. *International Journal of Production Economics*, *102*(2), 289–301.
- Garfield, E. (1963). Citation indexes in sociological and historical research. American Documentation, 14(14), 289–291.
- Gerino, E., Rollè, L., & Sechi, C. (2017). Loneliness, resilience, mental health, and quality of life in old age: A structural equation model. *Frontiers in Psychology*, *8*, 2003.
- Hawkins, R. G., Ritrer, L. S., & Walter, I. (1973). What economists think of their journals. *Journal of Political Economy*, 81(4), 1017–1032.
- Hellier, P. K., Geursen, G. M, Carr, R., & Rickard, J. A. (2003). A customer repurchase intention: A general structural equation model. *European Journal of Marketing*, Vol. 37 No. 11/12, pp. 1762-1800.
- Hermida, R. (2015). The problem of allowing correlated errors in structural equation modeling: Concerns and considerations. *Computational Methods in Social Sciences*, 3(1), 5–17.
- Hirsch, J. E. (2005). An index to quantify an individuals scientific research output. *Proceedings of the National Academy of Sciences*, *102*(46), 16569–16572.
- Hussey, D. M., & Eagan, P. D. (2007). Using structural equation modeling to test environmental performance in small and medium-sized manufacturers: Can SEM help SMEs? *Journal of Cleaner Production*, 15(4), 303-312.
- Hwang, C. L., & Yoon, K. P. (1981). *Multiple attribute decision making: Methods and applications*. Berlin: Springer – Verlag.
- Ijaiya, M. A., Dayang, A. A. M., & Ramli, N. R. (2016). Social capital and poverty reduction in Niger state, Nigeria: A structural equation modelling approach.
- Jacsó, P. (2001). A deficiency in the algorithm for calculating the impact factor of scholarly journals: The journal impact factor. *Cortex*, 37(4), 590–594.

- Kiesslich, T., Weineck, S. B., & Koelblinger, D. (2016). Reasons for journal impact factor changes: Influence of changing source items. *PloS One*, *11*(4), e0154199.
- Kim, E. H., Morse, A., & Zingales, L. (2006). What has mattered to economics since 1970. *Journal* of *Economic Perspectives*, 20(4), 189–202.
- Kohl, D. F., & Davis, C. H. (1985). Ratings of journals by ARL library directors and deans of library and information science schools. *College and Research Libraries*, 46(1), 40–47.
- Laband, D. N., & Piette, M. J. (1994). The relative impacts of economics journals: 1970–1990. *Journal of Economic Literature*, 32, 640–666.
- Liebowitz, S. J., & Palmer, J. P. (1984). Assessing the relative impacts of economics journals. *Journal of Economic Literature*, 22(1), 77–88.
- Liu, J., Yi, Y., & Wang, X. (2020). Exploring factors influencing construction waste reduction: A structural equation modeling approach. *Journal of Cleaner Production*, *276*, 123185.
- Luhn, H. P. (1957). A statistical approach to mechanized encoding and searching of literary information. *IBM Journal of Research and Development*, 1(4), 309–317.
- Manzari, L. (2013). Library and information science journal prestige as assessed by library and information science faculty. *The Library Quarterly: Information, Community, Policy, 83*(1), 42–60.
- Markpin, T., Boonradsamee, B., Ruksinsut, K., Yochai, W., Premkamolnetr, N., Ratchatahirun, P., & Sombatsompop, N. (2008). Article-count impact factor of materials science journals in SCI database. *Scientometrics*, 75(2), 251–261.
- Maron, M. E., & Kuhns, J. L. (1960). On relevance, probabilistic indexing and information retrieval. *Journal of the ACM*, 7(3), 216–244.
- Mayr, P. (2006). Constructing experimental indicators for open access documents. *Research Evaluation*, 15(2), 127-132.
- Moed, H. F., De Bruin, R. E., & Van Leeuwen, T. N. (1995). New bibliometric tools for the assessment of national research performance. *Scientometrics*, 33(3), 381–422.
- Palacios Huerta, I., & Volij, O. (2004). The measurement of intellectual influence. *Econometrica*, 72(3), 963–977.
- Quandt, R. E. (1976). Some quantitative aspects of the economics journal literature. *Journal of Political Economy*, 84(4, Part 1), 741–756.
- Servet, A., & Çelik, O. T. (2021). Analysis of the relationships between academic motivation, engagement, burnout and academic achievement with structural equation modelling. *International Journal of Contemporary Educational Research*, 8(2), 118–130.
- Shotton, D. (2012). The five stars of online journal articles A framework for article evaluation. *D-Lib Magazine*, 18(1/2).
- Sombatsompop, N., Kositchaiyong, A., Markpin, T., & Inrit, S. (2013). Evaluations of citation quality of international research articles in the SCI database: Thailand case study. *Scientomtrics*, 66(3), 521–535.
- Stigler, G. J., & Friedland, C. (1975). The citation practices of doctorates in economics. *Journal of Political Economy*, 83(3), 477–507.
- Tang, X., Wu, Q., & Wang, J. (2014). Relationship between non-cited rates and journal evaluation indicators: A case study in economics. *Library and Information Service*, 58(19), 100–104.
- Walters, W. H. (2017). Composite journal rankings in library and information science: A factor analytic approach. *Journal of Academic Librarianship*, 43(5), 434–442.
- Wang, X., & Chu, X. (2005). An evaluation system design of China economics journal. *Science Research Management*, (2), 147–151.
- Wang, Y. M., & Elhag, T. M. S. (2006). Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. *Expert Systems with Applications*, 31(2), 309–319.
- Yu, L. (2020). Structural equation dimensionality reduction: A new method of dimensionality reduction for academic evaluation indexes. *Journal of Information Resources Management*, 10(5), 76–84+65.
- Yu, L., Pan, Y., & Wu, Y. (2010). Comparative study on synthesis methods of utility function in scientific and technological evaluation. *Scientific & Technology Progress Policy*, 27(1), 106–110.
- Yu, L., & Zhang, Z. (2020). A new index reflecting the research hotspot of academic journal: Hot index. *Library Journal*, 39(6), 19–25.
- Yu, L. P., Chen, Y. Q., & Pan, Y. T. (2009). Research on the evaluation of academic journals based on structural equation modeling. *Journal of Informetrics*, *3*(4), 304–311.