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Research on the evaluation of academic journals based on structural equation modeling

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ABSTRACT

This paper classifies common journal evaluation indicators into three categories, namely three first-level indicators. They are respectively the indicators on journal impact, on timeliness, and on journal characteristics. The data used here is drawn from the medical journals in CSTPCD, a citation database built by the Institute of Scientific and Technical Information of China. The three categories of indicators are correlated with one another, so a structural equation may be established. Then we calculate the value of three first-level indicators and give subjective weights to the indicators. The comprehensive evaluation upon the medical journals yields satisfactory results. By simulating the complex relationship among journal indicators, the structural equation can be used for the estimation of some implicit indicators and the screening of indicators. This approach provides a new perspective for scientific and technological evaluation in general sense. It should be noted that the availability of basic data and the rationality of modeling bear much upon the evaluation results.

1. Introduction

Academic journals are an important window displaying the national scientific and technological development level, and also a wide channel for bridging the supply of scientific and technological achievements with the demand of industry. The evaluation of academic journals is a significant component of the bibliometric study. It involves the quantitative analysis upon the development regularity and growth trend of academic journals, reveals the distributional law about publications in journals, and offers an important reference point for optimizing the utilization of academic journals. At the same time, it helps to increase the intrinsic quality of academic journals and to promote their healthy growth and development.

Dr. E. Garfield, famous American information scientist, conducted a large-scale statistical analysis of the journal literature citations in the 1960s, which is regarded as the origin of the journal evaluation theory. Increasingly, evaluation studies of research performance conducted during the past decade focus on the identification of research with the “highest quality”, “top research” or “scientific excellence”. This shift in focus has lead to the development of new bibliometric methodologies and indicators (Thed et al., 2003). Evaluation of academic journals includes two categories of approaches, namely single-indicator evaluation and multiple attribute evaluation (MAE). Typical single indicators used in evaluations include Relative Citation Rate (Schubert et al., 1983), Relative Subfield Citedness (Vinkler, 1986), Normalized Mean Citation Rate (Braun & Glanzel, 1990), Field Citation Score (Moed, De Bruin, & Van Leeuwen, 1995), Hirsch index (Hirsch, 2005), and so on.

MAE is a mathematical aggregation of a set of individual indicators that measure multi-dimensional concepts but usually have no common units of measurement (Nardo et al., 2005). Despite the ceaseless debate on its use, MAE has been increasingly

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used for performance monitoring, benchmarking, policy analysis and public communication in wide ranging fields including economy, environment and society by many national and international organizations. Well-known examples of MAEs include the UN's Human Development Index (Sagar & Najam, 1998), and the Environmental Performance Index produced by a joint effort among Yale University, Columbia University, World Economic Forum and the Joint Research Center of European Commission (Esty et al., 2006). MAE is essentially concerned with the problem of how to evaluate and rank a finite set of alternatives in terms of a number of decision criteria. Most popular MAE approaches currently used are: Weighted Sum Model (WSM), Weighted Product Model (WPM), Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS), Data Envelopment Analysis (DEA), and Elimination Et Choice Translating Reality (ELECTRE).

Overall, there is not much research on the evaluation of journals with MAE. The main problem of MAE is that different evaluation approaches lead to inconsistent results when the same indicators and data for the same evaluation object are applied. Since such evaluation results can hardly be accepted, a new perspective must be explored for the evaluation of academic journals.

Structural equation modeling is an approach for simulation of the complex relationship in socio-economic systems. Vaughan and Tague-Sutcliffe (1997) conducted several studies on the use of SEM to assess the contribution of information to business success. Yue and Wilson (2004) develop and test an integrated conceptual model of journal evaluation from varying perspective of citation analysis based on the structural equation modeling. Using structural equation modeling, Yang and Ou (2008) analyze relationships among key causes of delay in construction. Murawski, Payakachat, & Koh-Knox (2008) study factors affecting job and career satisfaction among community pharmacists based on SEM. SEM has been used widely in fields such as sociology and psychology, but its use in the library and information science field is rare. Usually the evaluation system of academic journals is a complex system, and any journal involves such evaluation elements as impactability, journal characteristics, and timeliness. Complex interdependence relationships exist among them. Structural equations can simulate the complex relationships among the indicators and elements of academic journals, measure these elements, and screen out appropriate indicators, so as to lay a solid foundation for further evaluation. This paper adopts structural equation modeling for indicator screening and evaluation of the medical journals in CSTPCD, a citation database built by the Institute of Scientific and Technical Information of China (ISTIC).

2. Research methodologies

2.1. Structural equation modeling (SEM)

Structural equation modeling (SEM) is also known as the causality model, covariance structural model, or LISREL model. It is a multivariate statistical analysis technique for establishing, estimating and testing the causality model. It includes a series of multivariate statistical analysis approaches, such as multiple regression, factor analysis, path analysis and multivariate analysis of variance. It is a very generic, linear statistical modeling technique which tests hypotheses in accordance with theories. This model, which was put forward by Jöreskog (1970) and his colleagues in the 1970s and gradually improved and perfected from then on, has been widely used since the early 1990s. With the continuous development and improvement of SEM theory and analysis software, structural equation modeling becomes not only a good tool for data analysis and theory test in market research, but also in wider academic fields, such as psychology, sociology, econometrics, management science, behavioral science and communication studies.

Essentially, structural equation modeling is to solve the simultaneous equations. It is hoped that the fitted regeneration data approach the original data as close as possible. If so, the assumed causality structure and the interrelation pattern among variables are fitting or consistent. The equations in structural equation modeling are divided into the structural model (internal model) and the measurement model (external model). The structural model mainly measures causality between the latent variables. Its form is

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

where ξ is the model's exogenous latent variable, η is the model's endogenous latent variable, while $\mathbf{\Gamma}$ and $\mathbf{B}$ are the structural coefficient matrixes. $\mathbf{\Gamma}$ and $\mathbf{B}$ denote respectively ξ's impact on the endogenous latent variable η, and the mutual impact among η in the model. ζ is the model's residuals. The measurement model is

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

The measurement model mainly measures the corresponding relationship between the latent variables and significant variables. The two equations in (2) denote the relationships between the endogenous and exogenous latent variables and their corresponding significant variables respectively. π_η and π_ξ are their respective measurement coefficient matrixes. ε and δ are their respective residuals matrixes.

A path diagram is usually adopted to denote structural equation model, which is the simplest and most intuitive way to describe the model. Researchers can make use of path diagram to show the relationship among variables directly and clearly. Popularly applied AMOS7.0 software can directly convert a path diagram into the modeling equation and mark the analysis results on the map directly.

Structural equation modeling assumes that the causality exists in a group of latent variables, and these latent variables can be denoted by a set of observable variables. The assumed model usually includes a basic linear regression model and

Table 1
Indicators and classification.

First-level indicator	Second-level indicator	Variable name	First-level indicator	Second-level indicator	Variable name
Impactability X	Total cites	X1	Journal characteristics Z	Average number of authors	Z1
	Diffusion factor	X2		Numbers of provinces	Z2
	Disciplinary impact	X3		Share of overseas contributions in total papers	Z3
	Disciplinary Diffusion factor	X4		Share of grant-supported papers in total papers	Z4
	Impact factor	X5		Average references per article	Z5
Timeliness Y	Cited half-life	Y1			
	Immediacy Index	Y2			
	Citing half-life	Y3			

a lot of observation variables, and this basic linear regression model should be the structural relation model for a group of latent variables. The group of latent variables is a linear combination of some observation variables. Technically, through the verification of the covariance between observation variables, the coefficient values of the basic linear regression model may be estimated, and the assumed model's appropriateness for the studied process may be statistically tested, which is also the fitness test for the observation variables' covariance matrix and the extended covariance matrix after model fitting. If the assumed model is confirmed as appropriate, we can come to the conclusion that the assumed relationships among the latent variables are reasonable. In a sense, structural equation modeling is a confirmatory technique, rather than an exploratory technique.

2.2. Evaluation path diagram of academic journals

This paper evaluates the medical academic journals in CSTPCD. The originally selected 13 indicators are: Total Cites, Impact Factor (standard two-year synchronous impact factor), Immediacy Index, Ratio of Other Citations, Diffusion Factor (number of cited periodicals divided by number of citations per 100 times), Disciplinary Impact Indicator (ratio of number of within-discipline journals citing the evaluated journal over the total number of journals within the same discipline as the evaluated journal belongs), Disciplinary Diffusion Factor (ratio of number of all journals citing the evaluated journal to total number of journals within the same discipline as the evaluated journal belongs), Citing Half-life, Cited Half-life, Ratio of Funded Papers(ratio of papers sponsored by funds to total papers), Average Number of Authors per Paper, Average Citations per Article, Share of Overseas Contributions in Total Papers. These 13 are all of the indicators released by ISTIC. They cover the various aspects of the journal characteristics generally. So they are all selected as the analysis basis of this paper. According to these indicators' connotation, they could be classified into three categories, as shown in Table 1.

Journal impactability is the indicator about journal citation, including five second-level indicators, namely, total cites, diffusion factor, disciplinary impact, disciplinary diffusion factor, and impact factor. Timeliness reflects the vitality and activity of a journal, which is the journal's time-related indicators, including three second-level indicators, namely, cited half-life, immediacy index, and citing half-life. It is used to reflect the timeliness extent of journals. The shorter are a journal's cited half-life and citing half-life, the better is its timeliness. If a journal is cited many times in the year the same as the year when the papers get published, its timeliness is good. Journal characteristics refer to the journal's own parameters, which has nothing to do with the citation and time factors, including five second-level indicators, namely, share of grant-supported papers in total papers, average references per article, average number of authors, number of provinces. . ., and share of overseas contributions in total papers. These indicators reflect the journal's characteristics from different aspects.

The three variables, impactability, timeliness, and journal characteristics, are latent variables, which cannot be directly measured. For a certain discipline, the three variables are correlated with one another. There is a mutual causality between impactability and timeliness. The influential journals generally care about their timeliness very much. The journals with good timeliness are generally welcomed by readers. They possess great impactability, and get easily cited. There is also a mutual causality between impactability and journal characteristics. An influential journal often has a large circulation, and involves more provinces. Therefore, the influential journals usually involve more unique authors than less influential journals. The first class research cannot be carried on without grant support, and the high-quality papers often pay more attention to literature citation, so the influential journals attract more contributions with grant support and more references. Similarly, the impactability of journals with higher values of characteristics indicator is generally greater. Mutual causality also exists between timeliness and journal characteristics. The journals with high timeliness are easier to attract authors' contributions from many areas, and also easier to attract grant-supported contributions and contributions with more references. Generally, both the quality and the timeliness of journals with high characteristics indicator are better.

In addition, there is a correlation between the total cites and the impact factor. A correlation also exists between the disciplinary impact indicator and the disciplinary diffusion factor. Based on the above analysis, the path diagram for the relationship among significant and latent variables of evaluated journals can be shown in Fig. 1.

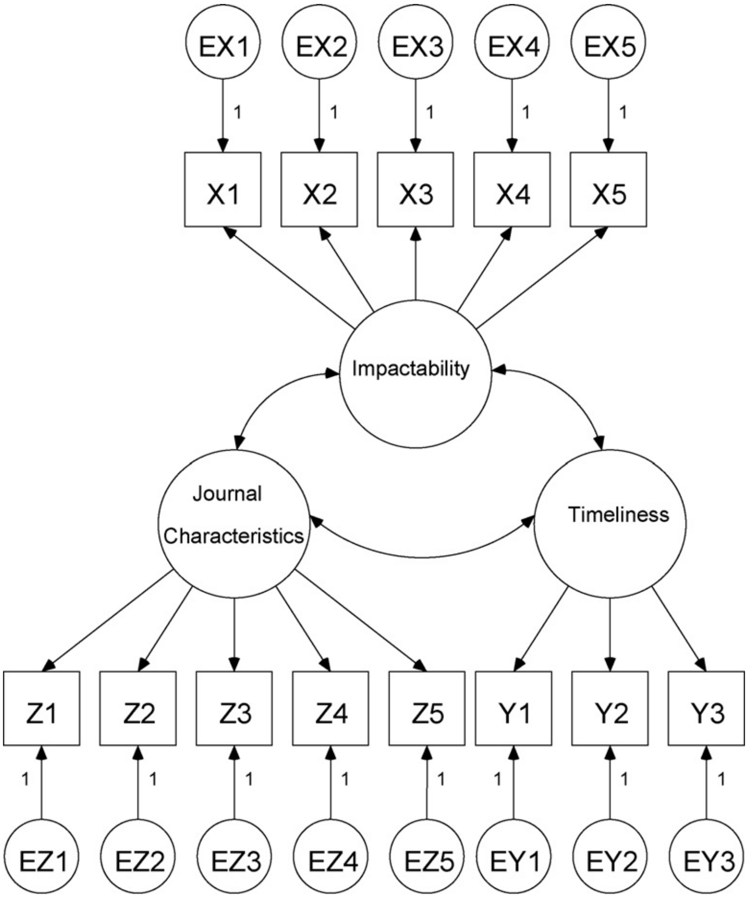

Fig. 1. Evaluation path diagram of academic journals.

3. Variables and data

The data for analysis in this paper is drawn from the medical journals in CSTPCD of the Institute of Scientific and Technical Information of China. The Institute of Scientific and Technical Information of China has collected data on domestic and international publications and citations of Chinese scientists since 1987. The statistical data collected is utilized to establish the Chinese Science and Technology Papers and Citation Database, and publish the annual "China Academic Journal Citation Report". The data used in this paper is about the medical academic journals in CSTPCD 2006, and the total medical journals recorded in the database is 518. All data is standard data (Table 2).

Table 2
The descriptive statistics value of variables.

Variable symbol	Name	Mean	Maximum	Minimum	Standard deviation
X1	Total cites	794.02	5805.00	17.00	811.65
X2	Diffusion factor	31.95	78.43	3.67	15.74
X3	Disciplinary impact	0.54	1.00	0.02	0.26
X4	Disciplinary diffusion factor	5.14	31.20	0.17	3.81
X5	Impact factor	0.44	1.86	0.06	0.28
Y1	Cited half-life	4.27	10.00	1.75	1.13
Y2	Immediacy index	0.05	0.33	0.00	0.04
Y3	Citing half-life	5.63	8.52	2.78	0.86
Z1	Average number of authors	4.04	8.16	2.04	0.87
Z2	Numbers of provinces	22.61	31.00	2.00	5.81
Z3	Share of overseas contributions in total papers	0.02	0.78	0.00	0.05
Z4	Share of grant-supported papers in total papers	0.26	0.97	0.01	0.19
Z5	Average references per article	9.25	34.72	3.12	3.88
n	Number of journals			518	

Data source: CSTPC database of the Institute of Scientific and Technical Information of China (2006).

Before starting the evaluation of journals, the normalization of data is necessary. The maximum value for each indicator was set to be 100, and then the other values would be adjusted in proportion. In addition, cited half-life and citing half-life are two negative direction indicators, which should be handled properly. Our algorithm for negative indicators is to minus the normalization result from 100, and then it would become a positive direction indicator.

4. Structural equation modeling evaluation

4.1. Structural equation estimates

In the model, each latent variable has a number of corresponding measurement indicators. Let one of the indicator coefficients to be 1, which is equivalent to stipulating the measurement units of the latent variables to be the same as the corresponding measurement indicators respectively. There were unavoidable measurement errors in each observation variable (EX1-EX5, EY1-EY3, EZ1-EZ5). Adopting the maximum likelihood estimation, we estimated the structural equation with AMOS7.0 software, and found that the coefficients of the diffusion factor X2 and citing half-life Y3 were negative, but the statistical test was significant. Such results do not make sense, so we decided to delete these two indicators, and went on with a re-simulation. This time we found that the coefficient of the number of provinces (Z2) was negative, and it did not pass the statistical test, so it was also deleted. The new model has 10 endogenous variables and 13 exogenous variables. The model is overspecifying and all the variables after solving pass the statistical test. The result is shown in Fig. 2 and Table 3.

The chi-square test value of structural equation is 420.06. GFI = 0.868. IFI = 0.801. CFI = 0.800. RMSEA = 0.159. The chi-square test value is big enough for us to accept the equation. The more closely the GFI, IFI and CFI values approach 1, the better

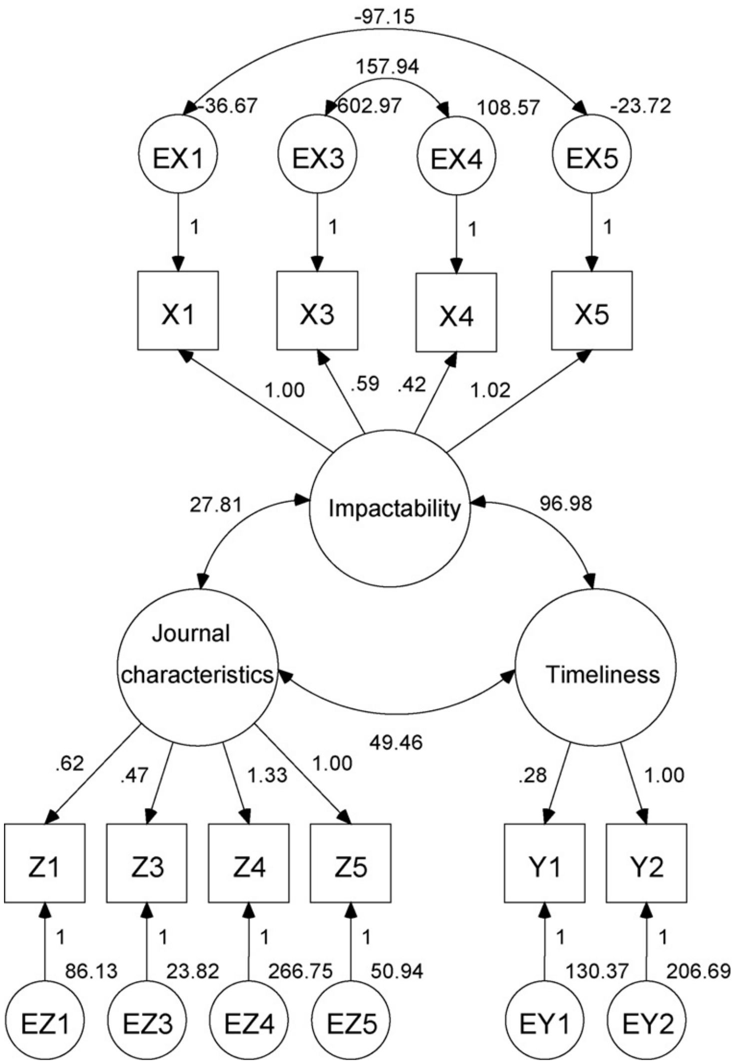

Fig. 2. Simulation results of structural equation.

Table 3
Solutions of structural equation.

Variable	Estimated value	Standard deviation	Critical ratio	Probability
X1 ← Impactability	1			
X3 ← Impactability	0.588	0.093	6.32	***
X4 ← Impactability	0.415	0.057	7.346	***
X5 ← Impactability	1.023	0.052	19.635	***
Z1 ← Journal characteristics	0.62	0.066	9.381	***
Z3 ← Journal characteristics	0.466	0.041	11.279	***
Z4 ← Journal characteristics	1.326	0.126	10.511	***
Z5 ← Journal characteristics	1			
Y1 ← Timeliness	0.281	0.064	4.39	***
Y2 ← Timeliness	1			

the fit degree of the model is. Hu and Bentler (1999) proposed that RMSEA should be lower than 0.06. As a whole, this model is acceptable. There are some reasons for failing to achieve the desired fitness level. The first reason is the bibliometric indicators' own shortcomings. For example, impact factor relies on the assumption that more citation mean higher impact, but sometimes too many self-citations are involved and some citations are criticisms rather than praises. The second reason is that some indicators are not fully subject to normal distribution although the sample size is adequate. In addition, there may be some other problems such as the statistical error and data missing.

Diffusion factor is the involved journal number when a journal of the statistical source is cited 100 times. The medical journals are highly specialized, so they are cited less by other disciplines. At the same time, the classification of medical journals is very fine, so diffusion factors of various sub-disciplines' journals are not high generally. Only some comprehensive medical journals achieve higher diffusion factors. Therefore, it is not appropriate to evaluate medical journal impactability with diffusion factor.

Citing half-life is used to reflect the novelty of literature used by the authors. The development rates of the academic levels for various sub-disciplines of medical science are not the same. The citing half-life of some journals whose corresponding sub-discipline is experiencing rapid development may be shorter, but the citing half-life of some other sub-disciplines (relatively mature discipline) may be relatively longer. Therefore, citing half-life cannot be used as a measure for timeliness.

Number of provinces refers to how many provinces are involved for all the papers published in a journal. The medical development level of Chinese regions is not balanced. Medicine in Beijing, Shanghai and the coastal developed areas are relatively advanced, and the number of publications from these areas is larger, while the medical levels of some underdeveloped areas are relatively low. The regional disparity of different medical sub-disciplines is even greater, so it is inappropriate to evaluate journals with number of provinces.

4.2. Evaluation of medical journals

Normalize the path coefficients in Table 3, and then the calculation formulas for the first-level indicators (impactability, timeliness, and journal characteristics) will be obtained:

Table 4
Evaluation results of the top 20 journals.

Journal name	Impactability	Timeliness	Journal characteristics	Total score	ranking order
Chinese Journal of Clinical Assemble	94.89	52.92	19.06	65.44	1
Chinese Journal of Pediatrics	73.44	52.30	30.92	57.53	2
World Journal of Gastroenterology	56.43	37.70	72.19	55.69	3
Chinese Journal of Endocrinology and Metabolism	45.26	78.91	41.67	52.78	4
Chinese Journal of Cardiology	61.07	49.81	37.43	52.34	5
Chinese Journal of Tuberculosis and Respiratory Diseases	62.84	50.65	31.75	52.02	6
National Medical Journal of China	65.45	35.20	39.03	51.28	7
Chinese Journal of Epidemiology	61.24	36.46	45.40	51.09	8
Chinese Journal of Integrated Traditional and Western Medicine	57.93	44.06	43.77	50.92	9
ACTA Pharmacologica Sinica	42.97	39.65	76.12	50.43	10
Chinese Journal of Hospital Administration	47.11	85.46	19.80	49.87	11
Chinese Journal of Orthopedics	59.19	49.94	30.02	49.58	12
Chinese journal of Clinical Rehabilitative Tissue Engineering Research	68.49	20.70	34.11	47.95	13
Acta Pharmaceutica Sinica	51.05	42.04	46.27	47.60	14
Chinese Journal of Oncology	64.31	24.70	36.86	47.54	15
Chinese Journal of Surgery	60.98	37.84	29.77	47.39	16
Chinese Critical Care Medicine	46.96	46.51	46.98	46.85	17
Chinese Journal of Internal Medicine	59.89	37.48	29.92	46.80	18
Chinese Journal of Radiology	64.47	29.93	28.22	46.77	19
Chinese Journal of Cancer	52.04	38.39	43.80	46.57	20

(impactability) = 0.33 × (total cites) + 0.19 × (disciplinary impact) + 0.14 × (disciplinary diffusion factor) + 0.34 × (impact factor)
timeliness = 0.22 × (cited half-life) + 0.78 × (immediacy index)
(journal characteristics index) = 0.18 × (average number of authors) + 0.14 × (share of overseas contributions in total papers) + 0.39 × (share of grant-supported papers in total papers) + 0.29 × (average references per article)

The weights of the three first-level indicators cannot be calculated according to the structural equation. Rather, they are determined by experts' judgment. Through the expert panels, we set the impactability's weight to be 0.5, and the weights of both timeliness and journal characteristics to be 0.25 respectively. We executed the calculation for all the medical journals, and the evaluation results of the top 20 medical journals is shown in Table 4.

5. Conclusion and discussion

5.1. Structural equation modeling can be used to assist evaluation

Compared with other evaluation approaches, structural equation modeling is a revolutionary approach. This evaluation method is on the basis of the simulation of the complex relationship among the evaluated object's own internal elements, and it can calculate and simulate some unobservable elements, many of which are often first-level indicators. Then we may directly compare the objects according to these indicators, or we may give weights to each indicator and carry out a weighted comprehensive evaluation. This paper takes both the inner relationship among relevant factors and the expert subjective weight into consideration in the evaluation of academic journals. It is a useful attempt to combine structural equation modeling with MAE.

5.2. Structural equation modeling can be used for indicator screening

The establishment and adjustment of structural equation is a dynamic process. Once we find problems in this process, it is necessary to make an adjustment. Indicator screening is an important component of the adjustment process. If there are too many indicators in a scientific and technological evaluation, data availability will be relatively difficult, and the evaluation cost will increase. If indicators are too few, they cannot provide all the necessary information. In some scientific and technological evaluation, there are often dozens of candidate indicators, and it is difficult to select indicators with an objective approach. Structural equation modeling provides a reasonable indicator screening approach. It should be noted that when applying structural equation modeling for indicator screening, the indicators with wrong symbol but having passed the statistical test should be removed. These indicators should be analyzed thoroughly. On the other hand, some indicators possess correct symbol but do not pass the statistical test. We recommend to make decision on keeping or deleting them according to specific circumstances involved.

5.3. The availability of the basic data is of great impact for the evaluation results

Evaluation cannot be separated from indicator screening. If the data is inaccurate or wrong, no satisfactory results will be got, which is the so-called "garbage in and garbage out". In scientific and technological evaluation, some data is very difficult to be obtained sometimes. People may only find data for a limited number of indicators, which cannot reflect the whole picture of certain element. In such circumstances, none of the evaluation approaches will get satisfactory evaluation result. The evaluation using structural equation modeling is no exception. In this case, the combination of peer review may improve the effectiveness and accuracy of evaluation.

5.4. Bias in model establishment will affect result

Structural equation is essentially a method combining the objective and subjective evaluation approaches. The relationship among variables is defined subjectively, No matter it is for the second-level indicator screening under journal impactability, timeliness, and journal characteristics, or for the relationships among those indicators impact people's subjective will are always involved. Any improperly set relationship among the elements of the structural equation, which is due to human incomplete understanding or misunderstanding of the inherent relationship among elements, is possible to lead to the calculation error and the evaluation results will be biased. To solve this problem, it is better to absorb the views of different experts when adopting structural equation modeling.

5.5. Evaluation results must meet the objective reality

To date, there have been dozens of multiple attribute evaluation approaches. In the selection of evaluation approach, in addition to the consideration of evaluation purpose, evaluation approach principle, distinction degree, sensitivity and other factors, a very important thing is that the selection must meet the objective reality. For example, a journal is acknowledged to be the best by all experts, but it is not ranked as the first place when using some kind of evaluation approaches. At this time some questions should be asked. Is the indicator screening appropriate? Is data processing correct? Are there any problems in evaluation approach selection? The adjustment may be carried out on this basis.

In short, as a new attempt, structural equation modeling provides a fresh perspective for the evaluation of academic journals. To optimize the structural equation modeling and improve the credibility of evaluation results, one can try to further increase the number of indicators and the number of journals.

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