Journal influence evaluation model based on citation analysis and altmetrics

Zhidong Zang[a]*, Xiuxia Li[a], Jingqi Zhang[b]

a. Department of Media, Qufu Normal University, Rizhao, China

b. Library, Hangzhou Dianzi University, Hangzhou, China

ABSTRACT

To optimize the evaluation method of journals and establish the evaluation system of academic journals, this paper combines the citation indicators and Altmetrics indicators to build a journal impact evaluation model. Firstly, we collected 7 citation indicators and 17 Altmetrics indicators as the initial indicator of journal evaluation. Then we used correlation analysis, reliability and validity analysis, principal component analysis to determine the core evaluation indicators and used the weighted grey correlation method to calculate academic impact (F_1) and social impact (F_2). On this basis, build a journal evaluation model, the Traditional and Altmetrics model. Finally, we conducted an empirical study using 74 SSCI geography journals. The study results show that F_1 and F_2 have differences in the evaluation of journal influence. The TA model has good stability in journal evaluation, and the journal partition effect of the model is similar to JCR. The TA model integrates F_1 and F_2 dimensions to evaluate journal influence, which provides a new idea for evaluating academic journal influence.

1 Introduction

Academic journals are important knowledge dissemination and communication carriers and essential for scientific exchange (Wang, 2019). The development of academic journals is inseparable from journal evaluation, and the evaluation of journals has always been a hot topic of concern in academic circles. The growth of the Internet and the rise of social media have changed how academic journals communicate (Costas et al., 2015). The evaluation of journals has gradually shifted from qualitative evaluation (e.g., peer review) to quantitative e-valuation. Since the 1960s, the citation indicator-based academic journal evaluation system has been one of the most common evaluation methods in academic evaluation at home and abroad. Up to now, citation analysis indicators such as impact factor and h-index are still significant indicators for journal impact evaluation. However, citation indicators have shortcomings such as time lag, one-sidedness, and Matthew effect, which are not conducive to reflecting the impact of journals comprehensively and scientifically (Zhai et al., 2020). Other researchers believe that the citation indicator is only a reflection of the citation status of the

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published papers and lacks the evaluation of social impact. With the rise of the open access movement, digital publishing and social media networking have become essential components of the overall influence of journals. They are integrated into the structure of academic communication systems (Xu, 2019). American scientists have noticed the impact of academic publications in social media, such as Priem, who first proposed Altmetrics indicators on his Twitter in 2010 (Li et al., 2020). Liu (2012) introduced this metric to China in 2012.

Since the emergence of the Altmetrics indicators, many researchers have evaluated papers and journals by Altmetrics indicators and expect to make up for the problems and shortcomings of citation measurement methods by using innovative scientific evaluation methods. For example, Zhai (2017) proposed the Altmetrics journal evaluation system based on the principal component analysis method and found that using Altmetrics to evaluate the influence of academic journals has a unique perspective and research value through empirical research. Wang (2017) constructed a journal influence evaluation model by synthesizing Altmetrics data of domestic journals. In the same year, Hassan et al. (2017) proposed the Alt index based on Altmetrics data and found through analysis that Alt index and h index have high correlation at three levels: field, journal and author.

Other researchers have made comparative studies between citation indicators and Altmetrics indicators. For example, Costas et al. (2015) compared Altmetrics indicators and citation indicators, emphasizing the value of Altmetrics indicators as an auxiliary tool for citation analysis. Nabout et al. (2018) correlated Altmerics metrics with citation indicators and clarified the complementary role of Altmerics to citation indicators. In the same year, Markusova et al. (2018) found an inverse logarithmic dependence between citation half-life and Altmerics indicators. They argued that Altmetrics should not be opposed to classical bibliometrics but should be used as an additional indicator to assess the impact of articles. Wang and Zhao (2021) explored the relationship between academic journal discourse guidance indicators and citation frequency and further explained the connotation and essential features between the indicators.

Altmetrics indicator has become a vital complement indicator to citation indicator, and researchers have already combined citation indicator with Altmetrics indicator to conduct academic evaluation research (Ding et al., 2022). Li et al (2017). combined Altmetrics data from XiaoMuChong Forum and impact factor to build a multidimensional journal evaluation indicator. Zhao and Wang (2019). divided the journal influence into academic impact and social impact and constructed a journal influence evaluation system through correlation analysis, reliability analysis, and principal component analysis combined the "academic Impact" indicator, "social Impact" indicator. Zhou (2020) built a comprehensive model of journal influence by integrating "knowledge transformation", "Social Impact" and "Academic Impact" indicators.

In summary, the combination of citation and Altmetrics indicators can reflect the influence of journals comprehensively, but there are still shortcomings in the existing studies:

· The citation indicators used are not comprehensive because the impact factor alone is not enough to represent the role of citation indicators on journal evaluation.

· The number of citation indicators used is significant, but the problem of multicollinearity among citation indicators has been ignored.

· Most studies conducted interdisciplinary research through principal component analysis, but we found that the extracted principal components do not explain the realistic context

and meaning of indicators when using principal component analysis to evaluate single-disciplinary journals. This results in the extracted principal components will be empty of information without real meaning.

To sum up, this paper proposes to use credibility analysis, principal component analysis, and correlation analysis to screen indicators. It combines the combination of citation and Altmetrics indicators to construct a journal evaluation model: TA model (Traditional and Altmetrics Model). Finally, we take the international journal of geography included in SSCI as an example to conduct an empirical study to realize the comprehensive evaluation of journal impact in a single discipline field.

2 Process and method of constructing the journal influence evaluation model

2.1 The architecture of the journal impact evaluation model integrating citation analysis and Altmetrics

This paper uses citation and Altmetrics indicators to reflect journals' academic and social impact. The academic impact of journals generated by formal scientific communication processes (citation among academic papers). The social impact of journals generated by informal scientific communication processes (dissemination and use of social media and website platforms). The number of citation and Altmetrics indicators is large, so selecting the appropriate indicators for the evaluation is necessary. In order to ensure the scientificity of the model construction, this paper selects the evaluation tools with high recognition in the academic community and the most widely used to collect the initial indicators.

The Journal Citation Reports (JCR) and the Scopus database are the most widely used and influential tools for evaluating journals based on citation analysis internationally (Yang & Gao, 2017). However, Scopus database data are missing more when evaluating the influence of journals within subject areas. Therefore, to ensure the comparability and wholeness of the data, this paper uses the citation indicator in JCR to reflect the academic impact of journals. The citation indicators in JCR include Impact Factor, 5-year Impact Factor, Immediacy index, Self-citation Impact Factor, Eigenfactor score, Article influence score, and Normalized Eigenfactor score.

Altmetric.com is a tool developed by Digital Science that includes a variety of widely used and accepted Altmetrics indicators such as Twitter, Facebook, and Google+. It is used by Nature, PLoS, Science, Elsevier, and other publishers as a paper an early potential indicator of academic impact (i.e., social impact). Therefore, we chose the Altmetrics indicator in Altmetric.com to reflect the social impact of the journal. The indicators include Twitter, Facebook, Google+, Reddit posts, Weibo, Pinterest, and LinkedIn indicators. Patents and Patents indicator reflects the impact of policy and patent. The indicators include Twitter, Facebook, Google+, Reddit posts, Weibo, Pinterest, LinkedIn, Patents, Policy documents News, Blog, Peer review, F1000, Syllabi, Wikipedia, Q&A posts, and Video. After determining the initial evaluation indicators, this study constructed a journal impact evaluation model according to the logical structure of Figure 1.
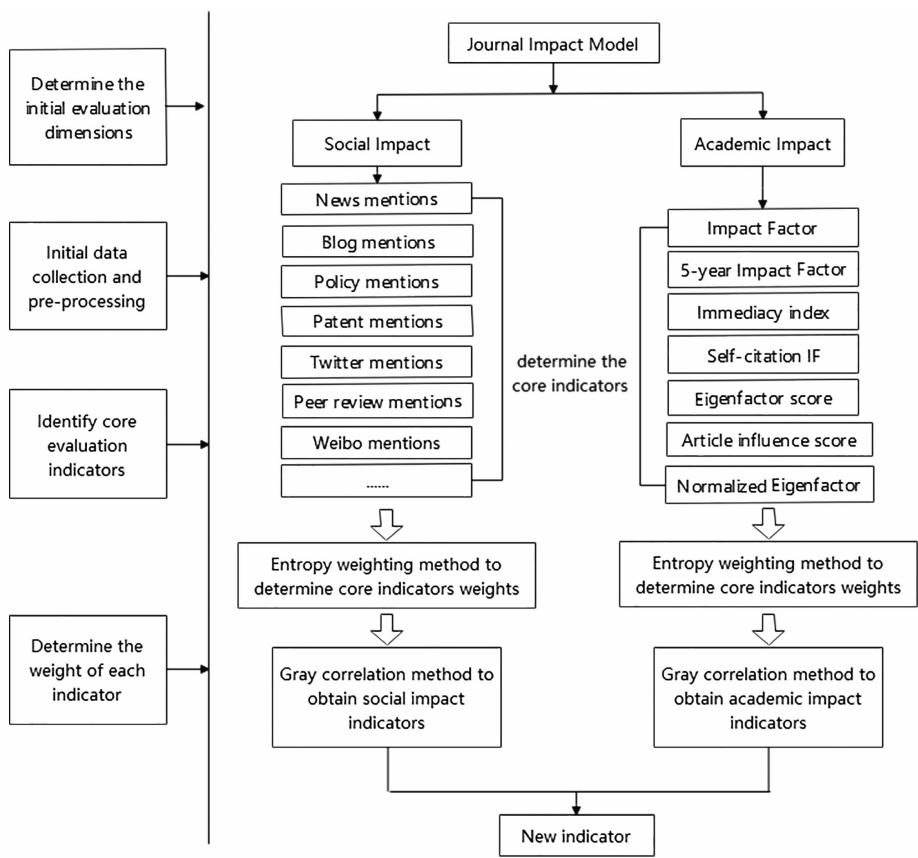
Figure 1 The logical structure of the journal impact evaluation model

2.2 Introduction to TA model construction methods

2.2.1 Entropy method

Entropy is a sign that reflects the degree of chaos in the movement of molecules during the thermal movement of matter. Later, researchers introduced its principal concept into information theory to reflect the amount of information based on its entropy value. This paper uses the entropy method to assign weights to journal indicators and determine the degree of dispersion of a given indicator.

With n journals and m evaluation indicators, the value of the j-th indicator of the i-th journal is denoted by x_{ij} Then, the formula of the entropy method is defined as follows:

(1) The data are normalized to form a new matrix. Then, the elements of the matrix x'$_{ij}$ is defined as:

$$x'_{ij} = \frac{x_{ij} - \min\{x_{1j}, x_{2j}, ..., x_{nj}\}}{\max\{x_{1j}, x_{2j}, ..., x_{nj}\} - \min\{x_{1j}, x_{2j}, ..., x_{nj}\}} \tag{1}$$

To avoid the case of ln0, we used linear interpolation by adding 0.0001 to the normalized value of each column at the same time (Huang et al., 2015).

(2) Calculating the entropy value of the j-th indicator.

$$y_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{2}$$

$$E_j = -\frac{1}{\ln n} \times \sum_{i=1}^{n} y_{ij} \ln y_{ij} \qquad (3)$$

(3) Calculating the entropy weight of the j-th indicator.

$$W_j = \frac{1 - E_j}{m - \sum_{j=1}^{m} E_j} \qquad (4)$$

2.2.2 Gray correlation analysis method

Gray correlation analysis is a standard multi-attribute evaluation method, which determines the degree of influence of system factors or the contribution of different factors to the system through gray correlation degree. The advantage of the gray correlation method is that it is not limited by the size and regularity of the sample, and it is easy to calculate. The specific steps are defined as follows:

(1) Determine the original matrix, i.e., the evaluation has n journals to be evaluated and m evaluation indicators, then its original matrix is defined as :

$$M_{nm} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & ... & x_{1m} \\ x_{21} & x_{22} & x_{23} & ... & x_{2m} \\ x_{31} & x_{32} & x_{33} & ... & x_{3m} \\ ... & ... & ... & ... & ... \\ x_{n1} & x_{n2} & x_{n3} & ... & x_{nm} \end{bmatrix} \qquad (5)$$

We used the optimal value of each column as the reference series.

(2) The raw indicators were normalized (by the same method as Formula (1)).

(3) Compare each column of indicators with the reference series and find its correlation coefficient $\xi_i(k)$:

$$\xi_i(k) = \frac{\min_i \min_k |y(k) - x_i(k)| + \rho \max_i \max_k |y(k) - x_i(k)|}{|y(k) - x_i(k)| + \rho \max_i \max_k |y(k) - x_i(k)|} \qquad (6)$$

where ρ is the resolution factor, which is generally taken as 0.5.

(4) We used the entropy weighting method to determine each indicator's weights, then derived the weighted gray correlation for each group of journals, and finally ranked the results from largest to smallest.

$$r_i = \frac{1}{m} \sum_{k=1}^{m} W_k \xi_i(k) \qquad (7)$$

2.2.3 TA Model for integrating academic impact and social impact journal impact

We use the entropy weighted gray correlation method to calculate the gray correlation value F1 for the citation indicator and F2 for the Altmetrics indicator of journals, which characterize journals' academic and social impact. Then, we use the average of F1 and F2 entropy weight coefficients as the weights of both, and combine them to obtain the TA model, representing the combined impact of journals. It is worth noting that the number of citation core indicators screened by the principal component analysis method is different from the Altmetrics, so the fusion needs to use the gray correlation value of the two divided by the number of respective core indicators (S_1, S_2) to ensure the consistency of the values.

$$TA = 0.478 * \frac{F_1}{S_1} + 0.522 * \frac{F_2}{S_2} \qquad (8)$$

3   Empirical study

3.1   Data acquisition

We used 84 journals in the field of geography indexed by SSCI in 2018 for our study. We obtained data corresponding to journal citation and Altmetrics indicators through the ISSN

number of each journal in JCR and Altmetric.com platforms, respectively. We selected citation indicator from 2018 and Altmetrics indicator from 2014 to 2018 to align the time windows across indicators. At the same time, we excluded journals with missing data in JCR or Altmetric.com to keep the data comparable and holistic. Finally, we kept 74 geography journals.

3.1.1 Citation indicator selection

We subjected the collected citation indicators to KMO and Bartlett's test. The test value was 0.844, indicating that the citation indicators of geography journals can be analyzed using principal components.

According to the loading matrix and gravel plot, the cumulative contribution of the citation indicators reached 72.431% when extracting one principal component, which contains the primary information of the indicators. Furthermore, we screened the citation core indicators based on the principal component load matrix value ≥ 0.66 (Zhang et al., 2021). The firstly selected citation core indicators were Impact Factor, 5-year Impact Factor, Self-citation Impact Factor, Article influence score, and Normalized Eigenfactor score.

Table 1 Citation indicator load matrix

	Principal Components Citation indicators 1
Impact Factor	0.974
5–year Impact Factor	0.981
Immediacy index	0.644
Self–citation Impact Factor	0.972
Eigenfactor score	0.449
Article influence score	0.95
Normalized Eigenfactor score	0.834
Eigenvalue	5.07
Contribution rate	72.431
Cumulative contribution rate	72.431

Table 2 Citation indicator spearman correlation

	Impact Factor	5–year Impact Factor	Self–citation Impact Factor	Article influence score	Normalized Eigenfactor
Impact Factor	1.000**	0.958**	0.989**	0.883**	0.823**
5–year Impact Factor		1.000**	0.948**	0.934**	0.867**
Self–citation Impact Factor			1.000**	0.886**	0.820**
Article influence score				1.000**	0.858**
Normalized Eigenfactor					1.000**

The results of Spearman correlation analysis for the citation indicators screened by principal component analysis are shown in Table 2. We compared the core indicators with a correlation ≥ 0.95 and only retained the indicators with the largest eigenvalues in the principal components. The finally selected core indicators for citation of geography journals were 5-year Impact Factor, Article influence score, and Normalized Eigenfactor score.

3.1.2 Altmetrics indicator selection

Since the LinkedIn, Pinterest, and Syllabi values of geography journals are 0, this paper removes these three indicators. In addition, F1000 is a systematic platform for discovering,

publishing and reviewing literature specifically for researchers in medicine and biology, so it does not apply to geography journal evaluations. After the initial screening, we conducted KMO and Bartlett tests on these remaining 13 Altmetrics indicators. The test value was 0.847, indicating that the core Altmetrics indicators can also be analyzed using principal components.

We use principal component analysis to analyze the 13 Altmetrics indicators of geography journals. The method extracted three principal components with a cumulative contribution of 73.497%, representing the primary information of the indicators. Same as citation indicators, we screened the Altmetrics core indicators based on the principal component load matrix value ≥ 0.66 (Zhang et al., 2021).

The indicators screened by principal component 1 are News, Blogs, Policies, Twitter, Facebook, Wikipedia, Google+, Reddit, Video. Moreover, the indicators screened by principal component 2 is Patent, while the indicator contribution of principal component 3 is low. According to the analysis results, the indicators screened in principal component 1 were all positively correlated and highly correlated. Altmetrics indicators such as News, Blogs and Twitter are also widely recognized by the academic community. The principal component 2 indicators are less correlated with other indicators, but patent mentions are also critical in the social impact of journals. We performed Spearman correlation analysis on the screened Altmetrics indicators and found that the correlation between Altmetrics indicators was low, so the results of the principal component analysis were used as the core Altmetrics indicators. In brief, the selected core indicators for Altmetrics of geography journals were News, Blogs, Policies, Twitter, Patents, Facebook, Wikipedia, Google+, Reddit, and Video.

3.2 Analysis of results

3.2.1 Results of journal evaluation based on TA model

After the core evaluation indicator was determined, we used the entropy-weighted gray correlation method [formulas (1) to (7)] to calculate the F_1 and F_2 values of geography journals, and the results are shown in Table 3. We numbered the journals using JCR rankings to facilitate statistical description and later comparison with JCR partition results.

Table 3　F_1 and F_2 scores of geography journals (part of the data)

	Number	Journal Name	ISSN	Score	Ranking
	3	GLOBAL ENVIRONMENTAL CHANGE	0959–3780	1.10752	1
	1	PROGRESS IN HUMAN GEOGRAPHY	0309–1325	0.56300	2
	4	LANDSCAPE AND URBAN PLANNING	0169–2046	0.54680	3
	2	ECONOMIC GEOGRAPHY	0013–0095	0.53615	4
Citation score (F_1)	17	GEOFORUM	0016–7185	0.49965	5
	8	J OF ECONOMIC GEOGRAPHY	1468–2702	0.48983	6
	12	APPLIED GEOGRAPHY	0143–6228	0.47035	7
	25	ENVIRONMENT AND PLANNING A	0308–518X	0.46684	8
	14	JOURNAL OF TRANSPORT GEOGRAPHY	0966–6923	0.46502	9
	23	I J OF URBAN AND REGIONAL RE	0309–1317	0.46488	10

	Number	Journal Name	ISSN	Score	Ranking
	3	GLOBAL ENVIRONMENTAL CHANGE	0959–3780	3.00543	1
	1	PROGRESS IN HUMAN GEOGRAPHY	0309–1325	1.82684	2
	25	ENVIRONMENT AND PLANNING A	0308–518X	1.82651	3
	37	GENDER PLACE AND CULTURE	0966–369X	1.68616	4
Alternative scores	13	ANTIPODE	0066–4812	1.66208	5
(F_2)	4	LANDSCAPE AND URBAN PLANNING	0169–2046	1.55990	6
	17	GEOFORUM	0016–7185	1.39547	7
	36	JOURNAL OF MAPS	1744–5647	1.33505	8
	7	POLITICAL GEOGRAPHY	0962–6298	1.32345	9
	35	PAPERS IN REGIONAL SCIENCE	1056–8190	1.31814	10

Based on formulas (8), we combine the F_1 and F_2 values given in Table 3 to calculate the TA values for each journal The results are shown in Table 4 (sorted by journal TA values from highest to lowest).

Table 4 TA ranking of geography journals (part of the data)

| 编号	ISSN 号	F_1	F_2	TA	排名
3	0959–3780	1.107517	3.005432	0.333348	1
1	0309–1325	0.562997	1.826835	0.185065	2
25	0308–518X	0.466844	1.826514	0.169728	3
4	0169–2046	0.546796	1.559902	0.168550	4
13	0066–4812	0.460448	1.662076	0.160125	5
17	0016–7185	0.499645	1.395465	0.152453	6
2	0013–0095	0.536148	1.262830	0.151346	7
37	0966–369X	0.397291	1.686163	0.151319	8
8	1468–2702	0.489827	1.244811	0.143025	9
12	0143–6228	0.470350	1.289043	0.142230	10

3.2.2 PLS model test

In order to explore the interrelationship between indicators and ensure the scientific accuracy and reliability of the TA model, this paper uses the partial least squares (PLS) model to perform systematic analysis and regression estimation of the TA model. The results are shown in Figure 2. We chose the PLS model for analysis reasons are as follows:

· The model integrates statistical methods such as multiple linear regression, principal component analysis, and correlation analysis to facilitate handling multiple covariance problems (Xiong et al., 2017).

· The model applies to sample size data more significant than 30 and less than 100.

As shown in Figure 2, the elasticity coefficients of the three core indicators in the citation indicator are high, indicating that all three contribute highly to the regression estimates of F_1. Among the Altmetrics indicators, Patents has the smallest elasticity coefficient of 0.209, indi-
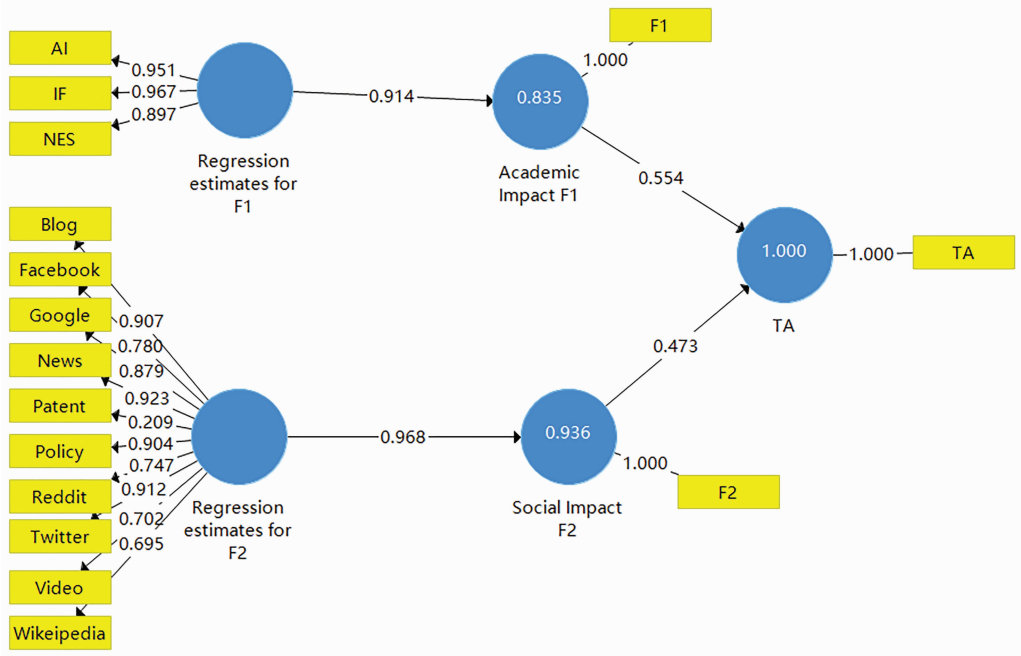
Figure 2 PLS model and results

cating its small contribution to the regression estimates of F_2. Nevertheless, Blog, News, Policy and Twitter all have elasticity coefficients greater than 0.9, indicating the high contribution of these four indicators to the regression estimates of F_2. The elasticity coefficients of Blog, News, Policy and Twitter are all greater than 0.9, indicating that these four indicators have a high contribution to the regression estimates of F_2. The elasticity coefficient of the regression estimate of F_1 to F_1 is 0.914, and the regression estimate of F_2 to F_2 is 0.968. It proves that the F_1 and F_2 values agree with the two PLS regression estimates.

From the PLS regression results, the fit of TA values with F_1 and F_2 are 0.835 and 0.936. It shows that both pass the statistical test and indicate that TA values are strongly associated with F_1 and F_2. The elasticity coefficients of F_1 and F_2 values to TA values are 0.554 and 0.473, proving that they can positively influence journal influence, i.e., the higher the citation and Altmetrics indicators, the higher the TA values and the higher the journal impact.

3.2.3 Analysis of journal F1, F2 rankings

Based on the values of F_1 and F_2 in Table 3, we analyzed the ranking results in two dimensions, respectively.

(1) Academic impact analysis

Among geography journals, the three citation core indicators of 0959-3780 journals are higher than other journals, ranking first in F_1. The reason for the high ranking of journals 0308-518X and 0309-1317 are as follows:

· The Normalized Eigenfactor has the most extraordinary academic impact indicator in the core indicator.

· The Normalized Eigenfactor of the two journals is much higher than those of other journals.

The top 4 journals in the F_1 ranking all have high citation indicators, and they are also in the top 4 of the JCR ranking. Similarly, four of the last 5 journals in the F_1 ranking belong to

the last 5 of the JCR partition ranking, which shows that the F_1 value is highly similar to the JCR ranking.

(2) Social impact ranking analysis

Journal 0959-3780 remains in first place in the ranking of Altmetrics indicator, and the journal has a high social impact score as 6 of the 10 core indicators screened by the principal components are at the top of the list. Maflahi and Thelwall (2018) found that the timeliness of journals based on the Altmetrics evaluation indicator is significantly better than the citation indicator. By checking the journal 0959-3780, the Impact Factor and other citation indicators have improved significantly after 2018.

Journal 0966-369X has a JCR ranking of 37 places, while its F_2 ranked 4 places. The reasons are as follows:

· Both Reddit and Video indicators are heavily weighted.

· Reddit and Video are highly weighted in the Altmetrics indicator.

· The journal's other Altmetrics indicator also performed well.

Journal 0016-7376 has a JCR ranking of 32 places, while its F_2 ranked 69 places. The reasons are as follows:

· The journal's Blog, Patent, Wikipedia, Google+, Reddit, Video indicators are 0.

· The journal's News, Policy, and Facebook indicators are less than 10.

In summary, the principal component analysis method can more reasonably screen the core evaluation indicators of journals. After the screening, the entropy method can scientifically assign weights according to the information dispersion of the data itself to achieve the effect of scientific evaluation of journal impact. The overall analysis of the F_1 and F_2 rankings shows that the F_1 ranking is more consistent with the JCR ranking and the F_2 ranking is less consistent with the JCR ranking.

3.2.4 Stability and variability analysis of journals F_1 and F_2

To facilitate comparative analysis of journals' F_1 and F_2 evaluation results, we plotted a line graph of geography journal rankings based on Table 3, as shown in Figure 3. In Figure 3, the horizontal coordinate is the journal number, and the vertical coordinate is the journal ranking.
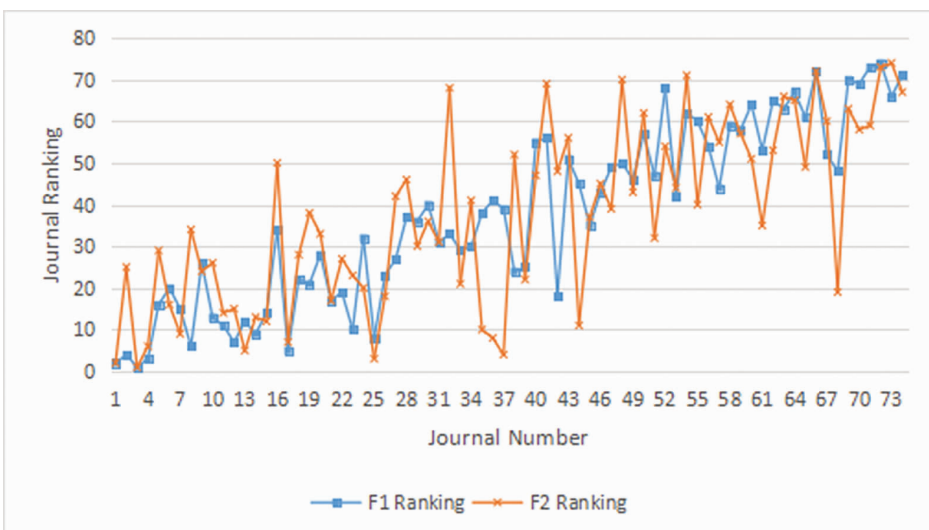
Figure 3   Line graph of F_1, F_2 ranking of geography journals

As shown from Figure 3, there are 43 journals with F_1 and F_2 ranking changes of less than 10, accounting for 58.1% of the total number of journals, i.e., nearly half of the journals have negligible differences in academic and social impact in 2018. The analysis results indicated that citation and Altmetrics indicators ' evaluation results are stable.

Analyzing the journals with significant differences in the citation indicator and Altmetrics indicator rankings of geography journals, we found three journals whose F_2 rankings increased by more than 30 compared to F_1. All three journals had higher Altmetrics indicator score rankings than the citation indicator. The reasons are as follows:

· The low F_1 ranking of these 3 journals is ranked 39th, 41st and 45th, respectively. F_1 values consist of 5-year Impact Factor, Article influence score and Normalized Eigenfactor score, while all three have low 5-year Impact Factor and Article influence score. The most considerable weight of the three core indicators calculated by the entropy weighting method is the Normalized Eigenfactor score. However, the Normalized Eigenfactor score of 0004-9182 journal is low, so the F_1 ranking is lower. In addition, these 3 journals have high values for News, Blog, and Policy indicators which have high weights for Altmetrics indicator, so these 3 journals move up significantly in the rankings.

· 2 journals dropped more than 30 places (1360-7456 and 0016-7363). These journals are ranked much higher than the Altmetrics score rankings for citation indicators. Its F_1 ranking is higher because both journals have higher citation indicators, especially the Normalized Eigenfactor score with high weight is much higher than most journals. Hence, the journal citation impact is high. In addition, these 2 journals have lower F_2 values among the 74 journals, but their ranking changes significantly because of their high citation impact ranking. The difference in the evaluation results of F_1 and F_2 show that the role of citation and Altmetrics indicator in evaluating journals are different, which justifies the combination of both in this paper to evaluate the journals.

3.2.5 Comparative analysis of journal partition results between TA model and JCR

In order to facilitate comparative analysis, we give the results (Q1, Q2, Q3, Q4) of the JCR partition of geography journals in 2018 using bar charts. The sample journals were repartitioned according to the journal rankings of the TA model, as shown in Figure 4.
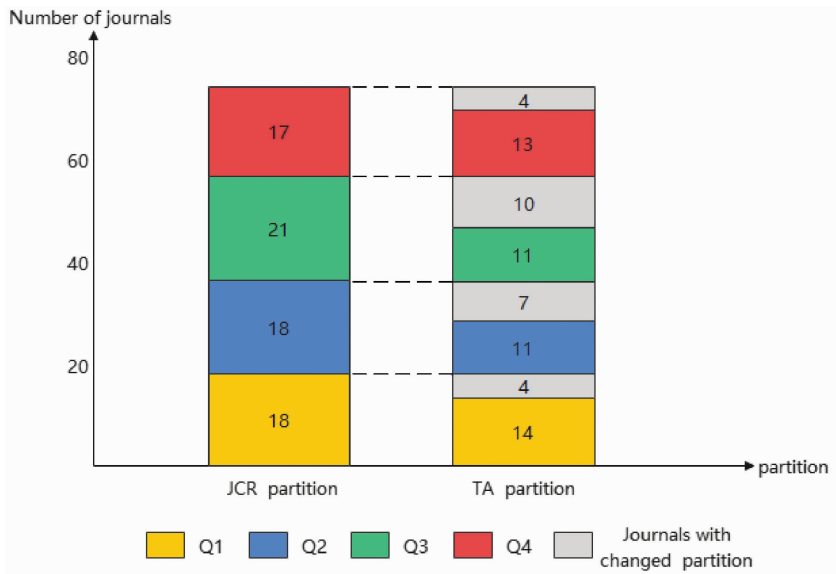
Figure 4 JCR and TA partition of geography journals

From Figure 4, 49 journals under the TA model partition have not changed their partition, accounting for 66.25% of the total number of journals, indicating that more than half of the journals have not changed their TA in terms of ranking partition JCR partitions. The percentage of journals that did not change in the Q1, Q2, Q3, and Q4 partition were 77.8%, 61.1%, 52.4%, and 76.5%, respectively. It can be seen that journals in Q1 and Q4 are more stable than Q2 and Q3, i.e., high-impact and low-impact journals have slight variation in the JCR and TA model partitions. We consider journals in Q1 and Q2 as high-impact partitions under JCR, Q3 and Q4 as the low-impact partition. Then most of the geography journals in Q1 and Q2 are stable in the high-impact partition, while Q3 and Q4 are similarly stable in the low-impact partition.

Eight of the journals ranked in the top 10 under the TA model partition ranking belong to the Q1 partition. 0959-3780 and 0309-1325 journals have very high scores for both citation and Altmetrics indicators, so these F_1 and F_2 values of these two journals rank in the top two. The TA value is calculated by combining the F_1 and F_2 dimensions, so these two journals have a high ranking. Journal 0308-518X is promoted to Q1 because it is ranked in the top 10 for F_1 and F_2. In the calculation principle of the TA model, the Altmetrics indicator is weighted higher than the citation indicator, so the journal enters the Q1 partition.

The partition results of the TA model and JCR have similarities and some differences. From the construction of indicators, we can know two things:

· The JCR statistics and calculations through citation and cited data between journals , and do not consider the journal's social impact.

· The TA model reasonably screens citation and Altmetrics indicators, taking into account the journal's academic and social impact.

In summary, the TA model considers more journal influence factors more comprehensively than the JCR. It also indicates that the TA model is more applicable to the comprehensive evaluation of journal impact within a discipline.

4   Conclusion and insights

4.1   Research conclusion

In recent years, scholars have argued that citation indicators have deficiencies and that evaluation indicators from the citation perspective alone cannot objectively evaluate things (Qiu et al., 2021). The open-access movement is prevalent in the new media environment, and online scholarly communication activities are becoming more frequent (Zhao & Wang, 2019). Papers published in academic journals are cited by other papers and shared, retweeted, and commented on social media. Generally speaking, the output of academic papers requires meticulous research and sufficient time for preparation. At the same time, the behaviors of sharing and forwarding can be carried out promptly according to readers' preferred interests, so Altmetrics indicators have higher timeliness than citation indicators. At the same time, academic papers will confuse general readers and professional readers of other disciplines because of their high academic nature.

Consequently, academic impact and social impact are essential components of journal impact, and Altmetrics indicators should be used together with citation indicators to evaluate journal impact. This paper conducted reliability and validity analysis, principal component analysis and correlation analysis on 7 citation indicators and 17 Altmetrics indicators from two perspectives of academic impact and social impact, and constructed a TA model for

comprehensive influence evaluation of journals through entropy weight method and gray correlation. Then, we tested the TA model's evaluation effectiveness using geography SSCI journals. The PLS analysis shows that constructing the TA model is scientific, and its evaluation is comprehensive and scientific. The empirical study found are as follows:

· The ranking results of F_1 have high consistency with JCR.

· The ranking results of F_2 have low consistency with JCR.

· The TA model's ranking and partition results are similar to JCR.

There are shortcomings in this study. For example, the model's differentiation is low because of the normalization of the data in this paper. In addition, this study only selects 24 indicators from the JCR and Altmetric.com platforms for the initial indicators. The model does not incorporate many official citations and Altmetrics indicators. In the subsequent study, we will use methods such as log-median standardization to improve the differentiation of indicators and integrate more evaluation indicators to expand the evaluation model to make the evaluation more scientific and reasonable.

4.2   Research Insights

In the new user-oriented media environment, the evaluation criteria of journal impact should rely on citation indicators and include Altmetrics indicators in the network (Zhao & Wang, 2019). Academic journal publishers should analyze the differences in their citation and Altmetrics indicators and develop their development plans. This paper gives methods and recommendations for improving the impact of academic journals based on the study's findings.

· Journals should broaden the way of publicity and apply new media thinking to journal development. Nowadays, social media has become one of the critical ways for journals to face society and go to the public. The development of journals should pay attention to their social impact and reasonably use websites, short video accounts, blogs, forums, and other shared information to enhance the scope and ways of influence.

· Journals take into account the social impact of the journal while improving the academic quality of papers and taking the path of high-quality development. Journals with high Altmetrics indicators should balance their articles' academic and public opinion hotspots. Meanwhile, it also maintains their social impact while enhancing their scholarship, focusing on hot topics and conferences in the field, and purposefully soliciting manuscripts for the appointment.

References

Costas, R., Zahedi, Z., & Wouters, P.   (2015). Do "altmetrics" correlate with citations? Extensive comparison of altmetric indicators with citations from a multidisciplinary perspective. *Journal of the Association for Information Science & Technology, 66* (10), 2003–2019. doi: 10.1002/asi.23309.

Ding, J. D., Cai W., Guo J., Liu, X. J., & Liu, C.   (2022). Citation versus altmetrics of papers published in Plos One: A comparative analysis of six countries. *Data Science and Informetrics, 2* (1), 68–80.

Huang, P., Guo, M., & Lan, S. R. (2015). Dynamic evaluation and comparison of the land eco–security of fujian province with the methods of AHP and entropy weight. *Journal of Shenyang Agricultural University (Social Sciences Edition), 17* (3), 337–341. doi: 10.3969/j.issn.1008–9713.2015.03.020.

Hassan, S. U., Iqbal, S., Aljohani, N. R., Alelyani, S., & Zuccala, A.   (2020). Introducing the ´alt–index´ for measuring the social visibility of scientific research. *Scientometrics, 123* (3), 1407–1419. doi: 10.1007/s11192–020–03447–z.

Liu, C. L. (2012). Scientometrics in the Web 2.0 environment: Altmetrics. *Library and Information Service, 56* (14), 52–56, 92.

Li, Y., Shao, Z. Y., & Zhao, X. (2017). The multidimensional altmetrics measures for academic journals. *Journal of the China Society for Scientific and Technical Information, 36* (2), 190–196. doi: 10.3772/j.issn.1000–0135.2017.02.009.

Li, J. B., Zhang, L., & Jiang, C. L. (2020). Research on influence evaluation of humanities and social sciences academic monographs from the perspective of altmetrics: Comparative analysis based on BkCI, Amazon and Goodreads. *Journal of the China Society for Scientific and Technical Information, 39* (9), 896–905. doi: 10.3772/j.issn.1000–0135.2020.09.002.

Markusova, V. A., Mindeli, L. E., Bogorov, V. G., & Libkind, A. N. (2018). An altmetric as an indicator of a publi–cation´s scientific impact. *Herald of the Russian Academy of Sciences, 88* (5), 394–400. doi: 10.1134/S1019331618040123.

Maflahi, N., & Thelwall, M. (2018). How quickly do publications get read? The evolution of mendeley reader counts for new articles. *Journal of the American Society for Information Science & Technology, 69* (1), 158–167. doi: 10.1002/asi.23909.

Nabout, J. C., Teresa, F. B., Machado, K. B., Do Prado, V. H. M., Bini, L. M., & Diniz–Filho, J. A. F. (2018). Do traditional scientometric indicators predict social media activity on scientific knowledge? an analysis of the e–cological literature. *Scientometrics, 115* (2), 1007–1015. doi: 10.1007/s11192–018–2678–x.

Qiu, J. P., Cui, T. T., & Chen, S. J. (2021). Analysis of document features of altmetric top list based on cluster–ing and association rules. *Journal of Modern Information, 41* (9), 12–21+63.

Wang, L. (2019). Evaluation of domestic academic journals Impact based on altmetrics. *Journal of Academic Li–braries, 37* (3), 74–83. doi:10.16603/j.issn1002–1027.2019.03.011.

Wang, Y. W. (2019). Research on evaluation index system of journal influence based on altmetrics [M.A. The–sis.]. Changchun: Northeast Normal University.

Wang, X., & Zhao, R.Y. (2021). Research on the relationship between discourse leading indicators and citation counts based on altmetrics: A case study of Chinese academic journals in English. *Information Studies: Theory & Application, 44* (7), 37–43+36. doi: 10.16353/j.cnki.1000–7490.2021.07.006.

Xiong, G. J., Xiong, L. L., & Chen, X. S. (2017). Academic journal comprehensive evaluation: Improving PLS weight based on the entropy value method. *Journal of Intelligence, 36* (6), 192–196+201.

Xu, X. J. (2020). Application of Z–index in periodical network transmissibility. *Journal of Academic Libraries, 38* (6), 111–117. doi: 10.16603/j.issn1002–1027.2020.06.015.

Yang, G. & Gao, X. H. (2017). A comparative analysis of the role of Scopus and JCR in discipline evaluation: A case of mathematics discipline in university. *Journal of Shanxi University (Philosophy and Social Science Edition), 40* (6), 93–99. doi: 10.13451/j.cnki.shanxi.univ(phil.soc.).2017.06.013.

Zhai, L. L. (2017). Academic journals? Influence evaluation research based on altmetrics [M.A. Thesis]. Wuhan: Wuhan University.

Zhao, R., & Wang, X. (2019). Research on impact evaluation of academic journals from multidimensional per–spective: Taking international multi–disciplinary journals as an example. *Library Hi Tech, 38* (2), 458–478. doi: 10.1108/LHT–03–2019–0067.

Zhai, S. S., Ye, D. L., Hu, P., & Xu, X. (2020). Evaluation of the Academic Impact of Data Papers Fused with Altmetrics and Citation Analysis. *Journal of the China Society for Scientific and Technical Information, 39* (7), 710–718. doi: 10.3772/j.issn.1000–0135.2020.07.004.

Zhou, M. X. (2020). Research on multidimensional evaluation of journal influence based on Altmetrics [M.A. Thesis]. Wuhan Textile University. doi: 10.27698/d.cnki.gwhxj.2020.000310.

Zhang, M., Yu, J., Wang, Q.Y., Zhang, J.C., You, X. T., Yao, M. J. & Ma, C. J. (2021). Evaluation and classifi–cation for physicohemical quality of vine tea on entropy method and grey relation analysis. *Food & Machin–ery, 37* (1), 186–192. doi: 10.13652/j.issn.1003–5788.2021.01.031.