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The Logarithmic Eigenfactor: Solving the Problems with the Normalized Eigenfactor

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ABSTRACT

Since the introduction of the Normalized Eigenfactor as a journal influence factor in 2009, there has been little research into potential problems with this measure. In order to explore and resolve drawbacks associated with the Normalized Eigenfactor, this paper begins by proving that the discriminability realized by this method can be improved upon. By using the JCR2016 mathematics journals as an example, an analysis from the perspective of the discriminative degree and data distribution is performed to compare the Eigenfactor Score with that of the Normalized Eigenfactor. This is done using the Median Maximum Value Ratio, High Score Ratio, Low Score Ratio, Passing Rate, Discrete Coefficient, HHI and Jarque-Bera Test values. The results of the study show that the Normalized Eigenfactor had little effect on the discrimination and data distribution over the Eigenfactor. As such, the published accuracy of Eigenfactor Scores is misleading in claims that the Normalized Eigenfactor can improve the discriminating degree. In reality, it only becomes significant when magnifying the mean value of the Eigenfactor Score by more than 100 times. The Normalized Eigenfactor is a nonlinear transformation, and it will slightly degrade the information captured by the Eigenfactor Score. When the Normalized Eigenfactor is converted, the numerator is the journal's Eigenfactor Score, and the denominator is derived from other journals' Eigenfactors; therefore, the scale of the measurement is not fixed and is at odds with the basic principle of measurement. Furthermore, the divergence between indicator values and evaluation attributes of the Normalized Eigenfactor manifests as data distribution bias, a low Pass Rate, and low sub-area data congestion. On this basis, this paper proposes to replace the Normalized Eigenfactor with the Logarithmic Eigenfactor.

KEYWORDS

Eigenfactor Score; Normalized Eigenfactor; Logarithmic Eigenfactor; Discrimination; Data Distribution; Journal Influence Factor

1 Introduction and Motivation

The Normalized Eigenfactor and the Eigenfactor are very close in nature. The latter was introduced as a bibliometric indicator by Bergstrom et al. (2008). It works to compare the weights of scholarly journals by constructing a citation network and drawing on the PageRank algorithm to evaluate the influence of each. The calculation spans up to 5 years and avoids bias by excluding the influence of self-citing. In 2009, Journal Citation Reports maintained by Thomson Reuters began to use the two indicators: Eigenfactor Score (ES) and Article Influence Score (AIS). These are collectively referred to as the Eigenfactor, and are two important bibliometric indicators after the Impact Factor (IF). In 2015, JCR released the Nor

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malized Eigenfactor (NE), which expresses a relationship between the Eigenfactor and the average value for other journals in the same discipline. For example, an EF score of 2 for a journal means that it is twice as influential as the average journal in the JCR.

It is of great significance to study the characteristics of the Normalized Eigenfactor and its possible problems. Since the publication of the Normalized Eigenfactor, the academic community has been focused on its relationship with other bibliometric indicators, and has done less research on the relationship between the Normalized Eigenfactor and Eigenfactor Score. Further work in this area will help to deepen the understanding and application of the Eigenfactor Score in academic journal evaluation. Specifically, comparing their discriminative ability and data distribution, analyzing their advantages and disadvantages, and working towards resolving problems.

The characteristics of the Eigenfactor score are of great academic research value. Franceschet (2010) proposed 10 reasons in advocating the use of the Eigenfactor method. He believes that it has a solid mathematical background, a well-founded basis of axioms, and an interesting probabilistic interpretation. In summary, Massimo believes that it provides a compelling measure of journal status and shares meaningful relationships with other bibliometric indicators. Ernesto et al. (2018) studied the Radiology, Nuclear Medicine and Medical Imaging journals and found that the Eigenfactor Score (ES), the Article Influence Score (AIS), the cited half-life, and the 5-year impact factor were four significant predictors of 2-year-ahead total citations. Rousseau & Stimulate (2009) studied 165medical journals and concluded that the correlation between the h-index and Eigenfactor score was strong. This was judged on the Pearson coefficient, which between them reached as high as 0.951. The authors went on discuss the feasibility of using ES as an alternative to the Web of Science for evaluating scientific journals. Shideler & Araú jo (2016) examined three different scientific fields (aquatic science, sociology, and immunology), and believed that the Eigenfactor score was the best indicator for the annual advertised subscription price for sociology journals. Of interest, they also felt that differences may vary according to disciplines. The empirical research showed that there was a high correlation between the journal's Eigenfactor, the Article Influence score, and the total citations.

Although the Eigenfactor score is in widespread use, there exist certain problems with the measure. Davis (2008) found that for periodical groups with relatively low overall influence, the difference in Eigenfactor between consecutively ranked journals is smaller, and the degree of dispersion is lower. Because the data for Eigenfactor calculations is often restricted, the accuracy of the calculation is difficult to test. Based on the relationship between the Eigenfactor indicator, the audience factor, and the influence weight indicator, Waltman & Eck (2010) pointed out that the three indicators are insensitive to field differences with low impact. In essence, this is because the Eigenfactor Score indicator does not adequately discriminate appropriately for journals with lower participation. Ren (2009) has pointed out that a low Eigenfactor Score and a low degree of dispersion are common for low-impact journals. Measured in 13 low-influence journals among 76 SCI journals in China, the ES begins to show a difference in the 4th digit after the decimal point. Also, there exist many journals that appear to have heavy values.

From extant research we see that the principle and the characteristics of the Eigenfactor Score is relatively mature, although the primary focus has been on the relationship between ES and other bibliometric indicators, as well as on the application of ES. Given that the Normalized Eigenfactor was only launched in 2015, it is a relatively new bibliometric indicator;

the corresponding research is still in its infancy. This article focuses on the following aspects: Firstly, does the Normalized Eigenfactor improve discrimination of the Eigenfactor Score, in particular for cases of low-partition journals? If so, can we provide a proof?

Secondly, since the Normalized Eigenfactor is based on the Eigenfactor Score, it is important to understand the characteristics and consequences of this conversion. Specifically, what is the relationship between the Normalized Eigenfactor and the Eigenfactor Score?

Thirdly, we seek to establish the difference in discriminative ability and data distribution between the Normalized Eigenfactor and the Eigenfactor score. Is this improvement significant? How does this affect the evaluation of scholarly journals?

Fourthly, given that the Normalized Eigenfactor is an indicator that reflects the influence of an academic journal on a deep level, then, can it accurately suggest the journals' natural influence and gap? If not, how should it be optimized?

Based on the theoretical analysis, this article takes the mathematics journals in JCR2016 as an example. We focus on the comparison between the Normalized Eigenfactor and Eigenfactor in terms of correlation, discrimination, and data distribution. In addition, we make an effort to further analyze problems and possible solutions with respect to the former.

2 Research methods

2.1 Calculation of the Normalized Eigenfactor

Assume that there are n academic journals in a subject, and x_m is the Eigenfactor score for the mth periodical. The Normalized Eigenfactor y_m is:

$$y_m = \frac{x_m}{\left(\sum_{i=1}^{m-1} x_i + \sum_{i=m+1}^{n} x_i\right)/(n-1)} \tag{1}$$

The Normalized Eigenfactor ym is equal to the mean value of Eigenfactor xm, divided by the scores of other journals in the same discipline.

2.2 Proof of increasing the discrimination of the Normalized Eigenfactor

Assume that p and q represent two academic journals having Eigenfactor scores of x_p and x_q, and Normalized Eigenfactor scores of y_p and y_q, respectively. For convenience, we assume the Eigenfactor includes all journals except for p and q. The sum of scores is A.

Assuming that $x_p > x_q$, the ratio between the scores of the two journals' Eigenfactors is $x_p/x_q > 1$. If we can prove that the ratio of Normalized Eigenfactor is greater than the ratio of Eigenfactor scores, that is, $(y_p/y_q - x_p/x_q) > 0$, then we can be confident that the discrimination has improved after the Eigenfactor score is converted to a Normalized Eigenfactor.

According to formula (1):

$$y_p = \frac{x_p}{(x_q + A)/(n-1)} \tag{2}$$

$$y_q = \frac{x_q}{(x_p + A)/(n-1)} \tag{3}$$

$$\begin{aligned} \frac{y_p}{y_q} - \frac{x_p}{x_q} &= \frac{\dfrac{x_p}{(x_q+A)/(n-1)}}{\dfrac{x_q}{(x_p+A)/(n-1)}} - \frac{x_p}{x_q} = \frac{x_p(x_p+A)}{x_q(x_q+A)} - \frac{x_p}{x_q} \\ &= \frac{x_p(x_p+A) - x_p(x_q+A)}{x_q(x_q+A)} = \frac{x_p(x_p-x_q)}{x_q(x_q+A)} > 0 \end{aligned} \tag{4}$$

Thus, we have proved that Normalized Eigenfactor can improve the discrimination of the Eigenfactor. Furthermore, we draw the corollary that the ranking results of the Normalized Eigenfactor are consistent with the ranking of the Eigenfactor.

2.3 The impact of Normalized Eigenfactor conversion in journal influence evaluation

To begin with, the conversion of Eigenfactor Score into Normalized Eigenfactor improves the discrimination, consequently widening the gap of Eigenfactors. This has been proved theoretically, although empirical testing is required in order to determine the degree of effect this has, and importantly, whether the discrimination is significant.

It is important to remember that converting the Eigenfactor Score to the Normalized Eigenfactor is a nonlinear transformation that will destroy the linear relationship between the original data and the target data. As such, there is a certain degree of information loss and this needs to be evaluated. The most commonly used method is to use scatter plots to examine and compare the correlation coefficients.

Furthermore, the nonlinear transformation destroys the original data distribution. This requires that it also be analyzed from this perspective to assess the repercussions.

2.4 Research Methods

1) Methods of comparing the discrimination

Two common discrimination methods are the discrete coefficient and the median maximum ratio. We introduce these methods for use in the comprehensive evaluation of the following attributes: High score ratio, Low score ratio, and HHI (Herfindahl-Hirschman Index). The High score ratio is the proportion of the total of the Normalized Eigenfactors among the top 20% of journals, to that of all journals' Normalized Eigenfactors. Similarly, the low score ratio is proportion of the sum of Normalized Eigenfactors among those in the lowest 20% of journals.

The HHI is a measure of concentration created by Hirschman (1968) to detect monopolies by means of determining market competitiveness. In the domain of journal influence factors, it is used indicate the degree of discrimination, where a larger value means it is less balanced and has a lower degree. The HHI of a Normalized Eigenfactor is the sum of the squares of all journals' Normalized Eigenfactors. The formula is as follows:

$$HHI=\sum_{i=1}^{n}\left[\frac{y_i}{\sum_{i=1}^{n} y_i}\right]^2 \qquad (5)$$

2) Methods of comparing data distribution

Many researchers have found inherent bias in the methods used to evaluate scholarly journals. Vinkler (2009) proved the right-skewed nature of the distribution of citations. The author believed that papers published in journals with a higher impact factor merely provide the possibility of obtaining many citations. It is unreasonable to use this as a measure of a journal's influence, and thus results in a large bias in terms of determining its actual influence. Seglen (1992) found that the distribution of citation analysis is a typical skewed distribution, which does not obey the normal distribution and has a power law characteristic. Adler et al. (2009) believed that the sole reliance on citation data provides and incomplete picture. They outline and provide examples where journals that contain longer papers get more citations. According to the power law, the distribution of citation data is usually right-skewed.

A data distribution test, sometimes referred to as a goodness-of-fit test, checks to see if the data matches a normal distribution. A common method for this is the Jarque-Bera test. Although many bibliometric indicators do not follow a normal distribution, the p-value is usually very low so it is difficult to compare. Alternatively, the size of the Jarque-Bera test value can be used to determine the skew in data distribution is more severe or be optimized when the Eigenfactor Score convert to Normalized Eigenfactor.

3 Empirical research results

3.1 Research data

This paper uses the mathematics journals listed in JCR 2016 as a basis for study. This includes 12 main indicators: Total Cites, Journal Impact Factor, Impact Factor without Journal Self Cites, Impact factor, Immediacy Index, Average Journal Impact Factor Percentile, 5-Year Impact Factor, Eigenfactor Score, Normalized Eigenfactor, Article Influence Score, Cited Half-Life, and Citing Half-life. This paper focuses on the analysis of the relationship between the Eigenfactor Score (ES) and the Normalized Eigenfactor (NE). There are a total of 310JCR 2016 mathematics journals as the data source.

3.2 Comparison of discrimination and data distribution

Comparison between Eigenfactor and Normalized Eigenfactor is shown in Table 1. The Median Maximum Ratio, High Score Ratio, Low Score Ratio, Passing rate, Discrete Coefficient, and HHI of Eigenfactors and Normalized Eigenfactors are all relatively close. In fact, they are all the same after the decimal point, which indicates that the Normalized Eigenfactor has little effect on improving data discrimination and distribution. On average, the mean value of Normalized Eigenfactor is 0.264285, and the mean value of Eigenfactor Score is 0.002305. By observation we see that the Normalized Eigenfactor is simply the Eigenfactor score amplified by 114.66.

Table 1 Comparison between Eigenfactor and Normalized Eigenfactor

Comparative indicators	Eigenfactor Score	Normalized Eigenfactor
Mean	0.004449	0.509824
Median	0.002305	0.264285
Maximum	0.049840	5.711670
Minimum	0.000060	0.007160
Std. Dev.	0.006515	0.746535
Median / Maximum	0.046248	0.046271
High score ratio	0.619839	0.619837
Low scoreratio	0.030801	0.030806
Passing Rate	1.91%	1.91%
Discrete Coefficient	1.464374	1.464299
HHI	0.010120	0.010120
Skewness	3.753054	3.753124
Kurtosis	20.249680	20.250300
Jarque–Bera	4571.119000	4571.423000
Probability	0.000000	0.000000

The scatter plots of NE and ES are shown in Fig. 1. It is clear that the plot depicts almost a straight line, where the correlation coefficient is 1.000000. The means they are highly correlated and almost homogenous.

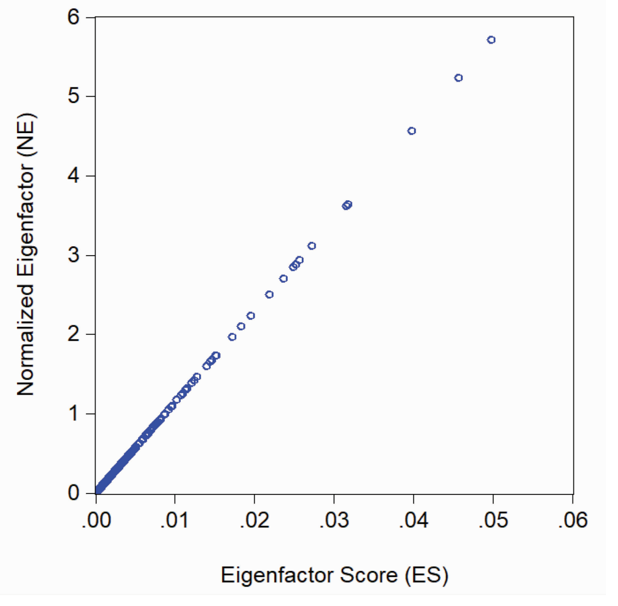

Figure 1 Scatter plots of Normalized versus standard Eigenfactor Scores

From the results we see that when the ES values are accurate to 5 decimal places, there are 69 cases where the values of journals are the same. Comparatively, when the NE values are accurate to 5 decimal places, the values of all journals are different. This suggests that the degree of discrimination has increased significantly.

The mechanism for improving the low segment discrimination of the Normalized Eigenfactor should be made clear by the following three aspects: First, when the Eigenfactor Scores are not equal, the Normalized Eigenfactors can definitely improve the discrimination. This point has been proven within this paper. Second, when the Eigenfactor Scores are equal, the Normalized Eigenfactors must be equal. Third, when the Eigenfactor Scores are equivalent and the Normalized Eigenfactor Scores are not equal, the true reason for the discrepancy is the increase in accuracy of the published score. Simply put, the precision relied upon by the JCR is insufficient. At present, only five digits after the decimal point are presented. If instead this were increased to perhaps the 6th or 7th decimal place, the Eigenfactor Score will reflect the difference. Ultimately, the degree of discrimination will increase.

To summarize, the Normalized Eigenfactor transforms the Eigenfactor to enhance the degree of discrimination. The mean value of the Normalized Eigenfactor is 114.66 times the mean of Eigenfactor score, and thus the difference is reflected in 5 decimal places. Since the score of the Eigenfactor is only published to the 5th decimal place, the discriminative degree cannot be realized. If the score of the low-partition periodical is equal, in fact, it would be necessary to publish up to and beyond the 7th decimal point.

A very important reason for the proposal of the Normalized Eigenfactor is to increase the discrimination for journals with a low partition. However, in summary analysis, the increase to this degree of discrimination is not borne by the contribution of Normalized Eigenfactor.

Rather, simply multiplying the Eigenfactor Scores by 100x, or even 1000x would achieve at least the same results.

4 Problems with Possible Improvements with the Normalized Eigenfactor

4.1 Further discussion on the Normalized Eigenfactor

The Normalized Eigenfactor is debatable, after all, since its conversion is a nonlinear transformation. Although the information conveyed by the Eigenfactor Score is generally not sacrificed, there is actually no improvement, or effective gain, when using the new measure. This is the case not only in discriminative capability, but also with respect to the data distribution. Therefore, it is our opinion that converting the Eigenfactor Score into a Normalized Eigenfactor is of little practical use.

In addition, since the denominator of the Normalized Eigenfactor conversion is the "average impact factor of all other journals", for each journal, the average value is not the same. Given that the Normalized Eigenfactor is supposed to be a measure of journal impact, does it makes sense that the scale can change? Is it still a good ruler? We do not think so.

Due to the reasons above, we feel that there is insufficient reason to convert the Eigenfactor Score into a Normalized Eigenfactor.

Research indicates that the data distribution for the Normalized Eigenfactor is heavily biased. In mathematics journals, such as "ADVANCES IN MATHEMATICS", the highest Normalized Eigenfactor is 5.71167. This is significant given that a perfect score is 100 points, and a passing score is 60. In our investigation we found that there are only 5 journals of the 310, which account for 1.61% of all journals. A result of this type tends to suggest that there is something drastically wrong with the approach. From the perspective of median, the median maximum ratio is 0.046271. That is, in the case of a full score of 100, half of the journals, i.e. 155, scored below 4.63 points. It seems the most likely explanation is due to a biased data distribution.

The Normalized Eigenfactor suffers from bias related to the difference between the evaluation value and its attribute. We suggest that this bias is only a superficial phenomenon. The Normalized Eigenfactor essentially reflects the influence attribute of academic journals. In the evaluation of this material, influence indicators should be close to a normal distribution except in cases of major or original innovations. Clearly, in situations like this, there should be a serious bias distribution. At present, there are few attributes that reflect major or original innovations in the bibliometric indicators. More often, there are indicators to reflect influence and timeliness. Consider the following example: When the Normalized Eigenfactor of the Journal A is 300 times of the Journal B, it does not mean that the influence of the Journal A is 300 times that of the second journal. This is drastically exaggerated. From our research it seems that editors can accept that the Normalized Eigenfactor of their own journal is 1/300 of that of a good journal, but they cannot accept that their journal is 1/300 of the impact of a good journal. It simply does not translate accordingly. Furthermore, the distribution of data based on the Normalized Eigenfactor should be much closer to a normal distribution.

The divergence between the evaluation value and the evaluation attribute is not unique to the Normalized Eigenfactor; the Eigenfactor Score and other bibliometric indicators also suffer from similar drawbacks.

4.2 Further Improvements to the Normalized Eigenfactor

According to the above analysis, the advantage of the Normalized Eigenfactor is that it can increase the degree of discrimination, albeit the level of improvement is almost negligible. There are four disadvantages. Firstly, the conversion of the Eigenfactor score to Normalized Eigenfactor is a nonlinear transformation, and consequently the information will degrade slightly. Secondly, also during the transformation, there is a phenomenon that the "measurement scale" is not uniform. Thirdly, the increase in Eigenfactor score to Normalized Eigenfactor is an illusion. Essentially, it is possible to achieve the same result simply by increasing the accuracy of published Eigenfactor scores. Finally, there is a notable difference between the evaluation value and the evaluation attribute of Normalized Eigenfactor.

4.2.1 Introducing the Logarithmic Eigenfactor

Due to the above problems, we feel that it is necessary to modify or replace the Normalized Eigenfactor to better reflect a journal's influence. In this paper, we introduce the Logarithmic Eigenfactor, which uses the natural Logarithmic scale to convert the Eigenfactor Score. This method has precedent and is used to calculate the population development index in the United Nations Development Programme. In this domain, the national income index reflects the diminishing marginal utility per each dollar increase in income and human development. The linear, dimensionless method is then used to obtain the national income index (UNDP, 2014). Taking the natural Logarithm is a nonlinear transformation, which can effectively reduce the gap between the evaluation objects. Furthermore, it will result in a data distribution closer to a normal distribution.

Since ES is usually very small and ln() is negative, in this paper, we use the following modified positive number:

$$\mathrm{LE} = |\,\mathrm{int}\{\min[\ln(X)]\}\,| + \ln(X) \qquad (6)$$

Where is X is the Eigenfactor Score, int(), ln() and min(), denote the integer component, the Logarithmic function and the minimum of X respectively. We call LE the Logarithmic Eigenfactor.

4.3 Logarithmic Eigenfactor analysis

The Notice that here, the indentation is inconsistent. Please correct this and standardize the formatting before making your final submission to the journal discrimination and data distribution between the Eigenfactor and the Logarithmic Eigenfactor is shown in Table 2. The median maximal value ratio of the LE is 0.561, indicating that the median is still at a slightly lower position. This represents a significant improvement over the ES (0.046). From the perspective of the Discrete Coefficient, the ES is 1.464, while the LE is the greatly reduced value of 0.261. The lower value indicates that the data is more uniform and the degree of discrimination has improved. The High Score Ratio of ES is 0.619, and that of the LE is 0.277. This means that the LE decreases the high score journal value and further unifies the distribution. The low score of ES is 0.031, while the low score of the LE shows improvement at 0.131. With respect to the Passing Rate, the ES is only 1.61%, while the LE reports 40.19%. This is an important advancement that more accurately represents the true influence of the journal.

Table 2 Comparison of Eigenfactor versus Logarithmic Eigenfactor

Comparison Indicators	Eigenfactor Score	Logarithmic Eigenfactor
Mean	0.004449	3.999
Median	0.002305	3.927
Maximum	0.049840	7.001
Minimum	0.000060	0.279
Std. Dev.	0.006515	1.042
Median / Maximum	0.046248	0.561
High Score Ratio	0.619839	0.277
Low Score Ratio	0.030801	0.131
Passing Rate	1.61%	40.19%
Discrete Coefficient	1.464374	0.261
HHI	0.010120	0.003
Skewness	3.753054	0.219
Kurtosis	20.249680	3.427
Jarque–Bera	4571.119000	4.831
Probability	0.000000	0.089

As we have discussed, the Eigenfactor Score does not obey the normal distribution. The Jarque-Bera test, however, calculates the value of the LE at 4.831, and the p value as 0.089, which rejects the null hypothesis of a non-normal distribution and shows that the LE does, in fact, obey one. Figures 2 and 3 illustrate more vividly the improvement of the distribution after the conversion from ES to LE.

In comparing the Logarithmic Eigenfactor to the Normalized Eigenfactor, it is clear that LE is superior in evaluating a journal's influence. In terms of linearity, LE is, indeed, also a nonlinear transformation. However, LE is fundamentally different from NE. The purpose of the nonlinear transformation for LE is to make ES more representative of the journal's influence. Ideally, the relationship between the evaluation indicator value and the evaluation attribute is consistent. While the goal of NE is to improve the degree of discrimination, in reality it does not do so adequately. According to our research it would be easier to simply magnify ES by 100 times, and enjoy similar results.

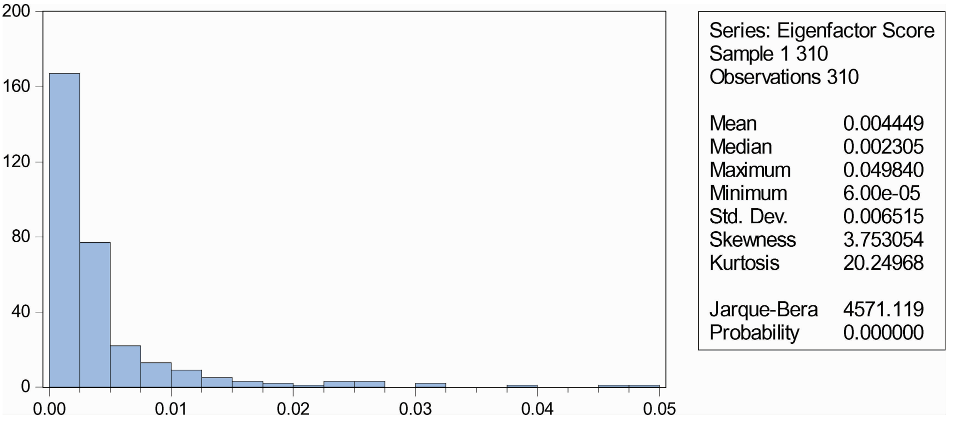

Figure 2 Data distribution of Eigenfactor Scores

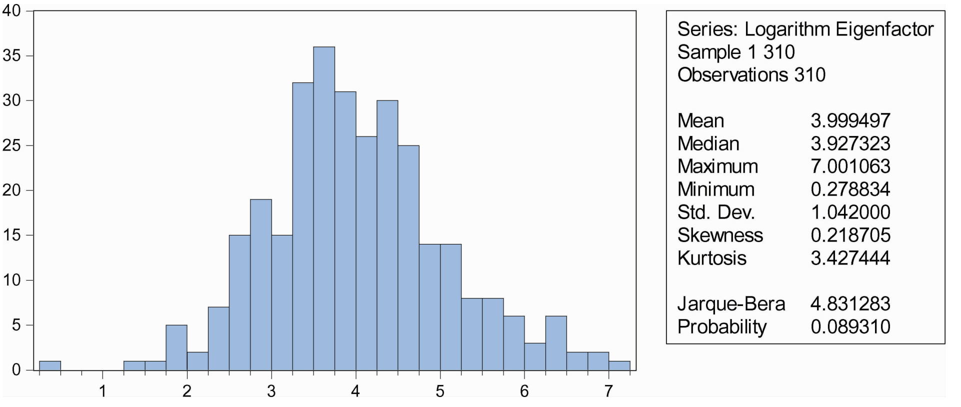

Figure 3 Data distribution of Logarithmic Eigenfactors

5 Research Conclusions

1) The Normalized Eigenfactor has little effect on the discrimination and data distribution of the Eigenfactor

This paper uses the mathematics journals in JCR2016 as an example to comprehensively compare Eigenfactor Scores and the Normalized Eigenfactor using the Median Maximum Ratio, High Score Ratio, Low Score Ratio, Passing Rate, Discrete Coefficient, HHI, and Jarque-Bera Test. The results of the study show that Normalized Eigenfactor had little effect on either the discriminate ability or the distribution of data of the Eigenfactor.

2) The published accuracy of the Normalized Eigenfactor is misleading in that it may cause people to believe that it will improve the discrimination

This paper proves that the Normalized Eigenfactor can improve the discrimination of Eigenfactor Scores in the low-partition of journals, but empirical research shows that it has little improvement. The main reason is that the Normalized Eigenfactor is equivalent to magnifying the mean value of Eigenfactor Score by more than 100 times. Therefore, when the decimal point is accurate to 5 digits, it can reflect the difference in less influential journals. At the same time, however, the Eigenfactor Score cannot highlight the gaps in the low-partition regions. This turns one's attention to the low degree of discrimination offered by NE. It is important to remember that the same discriminative ability can be obtained by increasing the precision of the Eigenfactor Score to7 decimal places, or simply by amplifying the Eigenfactor Score by 100x or 1000x.

3) There are theoretical and practical defects in the Normalized Eigenfactor

There are two theoretical flaws in the Normalized Eigenfactor. First, the conversion of the Eigenfactor Score to the Normalized Eigenfactor is a nonlinear transformation. This causes the loss of some information implicit in ES, although it is relatively minor. Second, when ES is converted into NE, the denominator is the mean of other journals' Eigenfactors. Because this changes dynamically - that is, the scale of the measurement is not fixed - it violates the basic principle of measurement.

From a practical point of view, there are also two major disadvantages. The first is that the Normalized Eigenfactor has neither effectively improved the discrimination of Eigenfactor Scores in the low partitions, nor changed the data distribution. What it has actually done is performed a "data amplification". As such, rather than use the Normalized Eigenfactor, it is more straightforward to simply amplify the Eigenfactor Score accordingly. Secondly, the Normalized Eigenfactor reflects citations of journals on the surface. Essentially, it reports the influence of journals, but fails with respect to identifying gaps because it does not obey a normal distribution of data. In other words, there is significant difference between the indicator values and the evaluation attributes when using the Normalized Eigenfactor.

4) The Logarithmic Eigenfactor is a better indicator

Logarithmic conversion of the Eigenfactor Score into a Logarithmic Eigenfactor greatly improves the discriminative ability, as well as data bias. This study found that the Logarithmic Eigenfactors for JCR2016 mathematics journals are normally distributed and more consistent with the public perception pertaining to the journal in question. Additionally, the distribution of journal influence is closer to normal, which intuitively makes more sense. All things considered, we feel it is necessary to replace the Normalized Eigenfactor with the Logarithmic Eigenfactor. To study the bibliometric indicators, we must analyze not only the data of the indicators themselves, but also to keep the larger picture in mind and consider the results from the perspective of the nature of the indicators.

5) The Logarithmic Eigenfactors of journals in other disciplines need further study

As noted, above, our empirical study was completed using a subset of journals in JCR2016. Our source was comprised solely of mathematical journals, and we are cognizant of the fact that differences in discipline may change LE's degree of discriminant ability, or the distribution of data from normal, or both. This recognition warrants further study, and as such, we feel that exploration through the empirical testing using journals in other fields is an important topic of future research.

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Data Availability

The data used to support the findings of this study have been deposited in the mathematics journals listed in JCR 2016.

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