Normalization of the Article Influence Score Between Categories

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***Abstract*—This study introduces a normalized article influence score. The main objective is to show that the article influence score obtained in different categories is not equivalent and it is necessary to normalize it when comparing journals form different categories. Several methods are suggested including a normalization that divides the article influence score by the average and another approach that normalizes the results in [0, 1] inside the same category in order to be able to compare between different fields. The results show that each category have different results and it is necessary to develop a normalization process in order to compare the journals. The article analyses a case study in engineering.**

***Index Terms*— Article influence score, Bibliometrics, Web of Science, journals.**

I. Introduction

The article influence score is an indicator that measures the average influence of the articles of a journal during the first five years of publication. It was developed in 2007 by Carl Bergstrom and Jevin West at the University of Washington [4]. Currently, it is available in the Web of Science (WoS) through the Journal Citation Reports (JCR) as one of the representative bibliometric indicators for measuring the journals quality.

In the literature, there are many different approaches that analyse the journal quality and influence [1,6,12]. However, there is no single method that unifies all the approaches providing one single result. The main problem is that the data can be considered under different perspectives. Therefore, each analyst may give different importance to each of the variables considered so each analyst may interpret the data in different ways. In bibliometrics [5], a very typical example is the comparison between productivity and influence of an author or an institution [11]. Some analysts may give more importance to one of the variables and vice versa, so it is difficult to get a single result. Although there are methods that could partially solve this issue through consensus, still there could be differences because scientific research is dynamic and evolves throughout time.

The aim of this paper is to present a new approach for measuring the article influence score by using a normalization process between categories. The main reason for doing so is because the results obtained in different categories are substantially different [13]. Therefore, when comparing journals from different categories, it is not easy to compare them. This question is a complicated one that may also be considered under different perspectives. However, our objective is to improve the knowledge in this field by providing new approaches for representing this indicator.

First, we analyse the average article influence score by calculating the average of the article influence scores of all the journals of the category. Next, we recalculate the article influence score by dividing it by the average article influence score of the category. The result is the normalized article influence score. This approach permits to compare better the results between categories. However, there are still limitations in the analysis because many other issues could produce deviations including the degree of interdisciplinary of the journals in the category and some journals that do not fit with the usual profile.

The work also analyses other approaches including a normalization of the article influence score in the [0, 1] interval and through a ranking process in [0, 1] inside each category. The results indicate an improvement in the analysis but we see that the comparison between categories may favour different journals depending on the specific approach considered. Some numerical results are presented in order to understand the new approach.

The rest of the paper is organized as follows. Section 2 briefly reviews some basic preliminaries. Section 3 presents the normalized article influence score and some other related extensions. Section 4 develops some numerical examples and Section 5 summarizes the main findings and conclusions of the paper.

II. Preliminaries

All the data is assessed with the WoS database. However, it is also possible to consider other databases including Scopus and Google Scholar. Currently, Web of Science divides scientific research in 251 categories. The journals of each category are studied through the JCR. One of the indicators considered is the article influence score. It is calculated as follows:

$$Article\ \ Influence\ \ Score = \frac{0.01 \times EigenFactor}{X}, \tag{1}$$

where X is the division between the 5-year journal article count and the 5-year article count from all journals. Note that the eigenfactor is calculated based on the number of citations received a specific year from the journals of the JCR by articles published during the last five years in the journal. Additionally, it also considers the current value of the journal so citations from a highly cited journal influences more the results. Note that self-citations are excluded.

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In this study, in order to calculate the normalization process we use the arithmetic mean which is formulated as follows for a set of arguments (a_1, a_2, …, a_n):

$$AM(a_1, a_2, ..., a_n) = \frac{1}{n}\sum_{i=1}^{n} a_i \ , \qquad (2)$$

where a_i is the ith argument of the set.

Note that in the literature there are many other averaging aggregation operators [19]. For further reading, see for example [2-3].

III. Normalized article influence score

The normalized article influence score measures the influence of a journal considering the results obtained in its WoS research category. This approach is useful in situations where we want to compare journals between different categories because it equilibrates the results from categories with higher results versus categories with lower results. It can be formulated as follows:

$$Normalized \ \ AIS = \frac{AIS}{Average \ \ AIS \ \ category} , \qquad (3)$$

where AIS is the article influence score of the journal and it is divided by the average AIS of the category where the journal belongs in WoS.

The average article influence score of the category is calculated as follows:

$$Average \ \ AIS = \frac{1}{n}\sum_{i=1}^{n} a_i \ , \qquad (4)$$

where a_i is the ith journal of the category which has a total of n journals.

Note that some journals appear in several categories, so their normalized results may change depending on the category considered. Generally, the assumption is to consider the journal in the category where it fits better in the specific problem considered.

Observe that Eq. (3) calculates the normalization with the arithmetic mean of all the journals of the category. However, the importance of the journals is not the same in the category according to a wide range of assumptions. Therefore, a better approach to calculate the normalization process is through the weighted average. However, the problem here is how to weight each journal because different issues could be considered. For example, we could weigh the journals according to the number of papers published although from a technical point of view we should also consider the number of pages and words. Another alternative would be to weigh the journals according to the number of citations received. And so on. In this case, we could call this indicator the weighted article influence score (WAIS) and formulate it as follows:

$$Weighted \ \ AIS = \sum_{i=1}^{n} w_i a_i \ , \qquad (5)$$

where w_i is the weight given to the ith journal a_i of the category considered.

When we do not know how to weight the journals, an alternative approach may be the use of the ordered weighted average (OWA) [7,15,18]. Thus, we could present the ordered weighted average article influence score (OWAAIS) as follows:

$$OWA - AIS = \sum_{j=1}^{n} w_j b_j \ , \qquad (6)$$

where b_j is the jth largest article influence score of the journal a_i according to Eq. (5).

Note that usually, when we do not know the weights, the easiest choice is to use the arithmetic mean which is obtained from the OWA when all the weights: $w_j = 1/n$. However, it is worth noting that there are many other particular types of OWA operators that could be considered including the step-OWA, the olympic-OWA, the window-OWA and the centered OWA [16].

Observe that the OWA operator under or overestimates the data according to a degree of optimism or pessimism which can be represented with the following measure $\alpha(W)$:

$$\alpha(W) = \sum_{j=1}^{n} \frac{n-j}{n-1} . \qquad (7)$$

The closer α to the top, the more optimistic the analyst is in the analysis and vice versa.

Sometimes, the numerical values, may bring additional difficulties in the analysis so the reordering process is more complex. In these cases, an alternative approach is the induced OWA operator [10,17] which generalizes the OWA operator by using order inducing variables in the reordering process of the information. Thus, we get the induced OWA article influence score which is formulated as follows:

$$IOWA - AIS = \sum_{j=1}^{n} w_j b_j \ , \qquad (8)$$

where b_j is the article influence score of the journal a_i, ordered according to the values of the order inducing variables u_i in the pair [u_i, a_i] of the set ({u_1, a_1}, {u_2, a_2}, …, {u_n, a_n}).

Note that many other extensions and generalizations could be developed following the OWA literature [9,14,18]. The objective is to use the aggregation operator [8] that better fits to the specific problem considered.

IV. Normalization in [0, 1]

The normalized article influence score provides a better equilibrium between categories. However, there are many other issues that should be considered when comparing categories. First, the categories are not equally important. Second, different persons may have different preferences between categories. And third, the publication style regarding productivity, number of words per article and other related issues, is not the same between categories. Additionally, note that we follow WoS approach for classifying the categories but many journals are interdisciplinary and many times a category can be divided and merged with others.

An alternative approach is to evaluate all the journals inside the category and give them a score between 0 and 1 where the score of 1 would be given to the journal with the highest result. In order to do so, there are different alternatives. First, we can normalize in [0, 1] by dividing all the article influence scores of the journals by the maximum one. Thus, the journal with the highest result would get a score of 1 while the other ones would get a score between [0, 1]. It is formulated as follows:

$$Normalized \ \ AIS \ \ [0,1] = \frac{AIS_x}{Maximum \ \ AIS} , \qquad (9)$$

where AIS is the article influence score of the journal *x* and Maximum AIS is the article influence score of the journal with the highest result in the category.

This alternative is a useful approach in order to identify the top journal of the category. However, it has several important weaknesses. First, if the top journal can be seen as an outlier, it strongly distortions the results of the rest of the journals. And second, the value of each category is not always the same so the top journal in a small category may be less influent than the top journal in a huge category.

The second limitation can be solved by weighting the value of each category. Thus, the formulation would be as follows:

$$Normalized \;\; AIS \;\; [0,1] = C_i \left(\frac{AIS_x}{Maximum \;\; AIS} \right), \qquad (10)$$

where C_i is the weight given to each category. Note that in order to use a [0, 1] scale, $C_i \in [0, 1]$. However, it is also possible to use a different scale. Eq. (10) could be an alternative for comparing categories but the problem is that different points of view should be considered so the weights may be different according to the person that analyzes the categories. In other words, some people may think physics is more important, but some other may think chemistry, economics, and so on.

The first limitation may bring important differences in the results so an alternative measure is needed. Another approach may be obtained by using the ranking position of the journal in the category. Here we would obtain the ranked normalized article influence score. This is formulated as follows:

$$Ranked \;\; normalized \;\; AIS \;\; [0,1] = 1 - \frac{(i-1)}{n}, \qquad (11)$$

where *i* is the ranking position of the journal in the category according to the article influence score (or the impact factor) and *n* is the total number of journals in the category. Note that we could develop an equivalent indicator for the impact factor and for the 5-year impact factor as follows:

$$Ranked \;\; normalized \;\; IF \;\; [0,1] = 1 - \frac{(i-1)}{n}. \qquad (12)$$

As we can see, the journal with the highest result obtains a result of 1 while the journal in the last position obtains 0. This approach avoids the problem of outliers and is reasonably useful. However, we could also consider other issues including the distribution of journals in the category. Eq. (10) assumes that all the journals are equally distributed but this is not always the case. For example, if in a set of one hundred journals, there are five top journals well above the rest, these five journals should obtain results substantially higher than the rest. For doing so, we should weight the distribution of the journals. Note that this has many difficulties but from a general perspective, we could formulate it as follows:

$$Weighted \;\; rank \;\; normalized \;\; AIS \;\; [0,1] = 1 - \frac{(z \times i - 1)}{n}, \qquad (13)$$

where *z* is a weight that corrects the numerical number of the position when the value of the journals are not equally distributed in the category. Note that many questions may arise in order to understand *z*, but here let us simplify this with Eq. (13). For example, z should be 1 for the first and last journal if we want to keep the results in [0, 1].

Eq. (11) and Eq. (12) should also be studied taking into account that the value of different categories is not the same. Therefore, following Eq. (10), we could reformulate Eq. (11) as follows:

$$Ranked \;\; normalized \;\; AIS \;\; [0,1] = C_i \left(1 - \frac{(i-1)}{n} \right), \qquad (14)$$

where C_i is the weight given to each category and in order to use a [0, 1] scale, $C_i \in [0, 1]$.

Note that these indicators and those developed before by other authors improve our knowledge on how to value journals and may work well in specific situations. The key is to use the method that better fits the specific problem considered. However, there are still many open questions in order to find a final method. The main problem is that we may always consider different perspectives so the interpretations by one analyst may be different than another one. Therefore, the conclusion is that depending on the specific situation we are analyzing, we should select a different approach. In order to find a single method is quite complicated because there should be an agreement between all the specialists regarding how important is each criteria.

V. Numerical Example

In order to understand better the equations presented in the previous sections, this section analyses two numerical examples.

In the first example, let us look into a specific category and see how we can calculate the indicators mentioned in the previous sections. The example focuses on the WoS category of Industrial Engineering. Table 1 presents the results of all the journals in this category.

As we can see, the average article influence score is 0.448. This is a very low result because the average article influence score of all science is 1. Thus, when normalizing the scores of the journals in this category, the results increase significantly. In this context, it is interesting to see that categories with low values may increase they result significantly and vice versa. This issue is useful between categories because the indicator normalizes the results so we can compare better the results.

Next, let us look into the results found in different categories in order to see which ones tend to obtain a higher article influence score. Table 2 presents some WoS categories with their average results.

There are significant differences between categories. From the set of categories considered, we see some that obtain an average article influence score around 0.5, while some other categories obtain up to 1.5. Thus, when comparing journals between different categories, it is important to consider this issue in order to make a fair comparison. However, many additional questions may arise about the value of a journal. For example, the value of each category could also be different so the normalization should take into account this issue. And so on. But from a general point of view, the normalized article influence score tends to obtain more representative results because it eliminates significantly the differences between categories.

The article influence score integrates all sciences being 1 the average score. But since each category has different degrees of citation, it is necessary to consider the average article influence score of the category and from here establish some values.

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Table 1. Journals in Engineering: Industrial

R	Name	IF	5IF	AIS	NIF	N5IF	NAIS	IF[0,1]	5IF[0,1]	AIS[0,1]
1	Computers & Operations Research	1,861	2,454	0,962	1,134	1,600	2,146	0,814	0,854	1,000
2	J. Quality Technology	1,152	2,096	0,907	0,702	1,367	2,024	0,488	0,756	0,976
3	Technovation	2,526	3,636	0,878	1,539	2,371	1,959	0,953	1,000	0,951
4	J. Product Innovation Management	1,696	2,926	0,821	1,034	1,908	1,832	0,744	0,927	0,927
5	Reliability Engineering & System Safety	2,410	2,693	0,817	1,469	1,756	1,823	0,930	0,902	0,902
6	Int. J. Production Economics	2,752	3,069	0,806	1,677	2,001	1,798	1,000	0,976	0,878
7	IIE Transactions	1,371	1,582	0,760	0,835	1,032	1,696	0,605	0,561	0,854
8	J. Materials Processing Technology	2,236	2,660	0,753	1,363	1,735	1,680	0,907	0,878	0,829
9	CIRP Annals-Manufacturing Technology	2,542	2,971	0,743	1,549	1,938	1,658	0,977	0,951	0,805
10	Computers & Industrial Engineering	1,783	2,412	0,700	1,087	1,573	1,562	0,767	0,829	0,780
11	Human Factors	1,694	2,037	0,678	1,032	1,328	1,513	0,721	0,683	0,756
12	Safety Science	1,831	2,210	0,612	1,116	1,441	1,365	0,791	0,805	0,732
13	Applied Ergonomics	2,023	2,143	0,589	1,233	1,398	1,314	0,837	0,780	0,707
14	Ergonomics	1,556	1,804	0,535	0,948	1,176	1,194	0,674	0,634	0,683
15	Research in Engineering Design	1,233	1,906	0,527	0,751	1,243	1,176	0,558	0,659	0,659
16	IEEE Trans. Engineering Management	1,103	1,526	0,488	0,672	0,995	1,089	0,465	0,512	0,634
17	J. Manufacturing Systems	1,682	2,078	0,449	1,025	1,355	1,002	0,698	0,707	0,610
18	Quality and Reliability Engineering Int.	1,191	1,217	0,446	0,726	0,794	0,995	0,512	0,415	0,585
19	J. Engineering and Technology Management	2,060	2,081	0,430	1,255	1,357	0,959	0,860	0,732	0,561
20	Int. J. Production Research	1,477	1,770	0,410	0,900	1,154	0,915	0,651	0,610	0,537
21	Probability in the Engineering and Information Sciences	0,460	0,565	0,403	0,280	0,368	0,899	0,140	0,171	0,512
22	J. Construction Engineering and Management	0,842	1,363	0,399	0,513	0,889	0,890	0,326	0,439	0,488
23	Industrial Management & Data Systems	1,226	1,544	0,350	0,747	1,007	0,781	0,535	0,537	0,463
24	J. Management in Engineering	0,928	1,474	0,349	0,566	0,961	0,779	0,395	0,488	0,439
25	Int. J. Industrial Ergonomics	1,070	1,366	0,328	0,652	0,891	0,732	0,442	0,463	0,415
26	Quality Engineering	0,553	0,807	0,325	0,337	0,526	0,725	0,209	0,317	0,390
27	Research Technology Management	1,017	0,966	0,316	0,620	0,630	0,705	0,419	0,390	0,366
28	IEEE Industry Applications Magazine	0,352	0,628	0,303	0,215	0,410	0,676	0,093	0,195	0,341
29	Proc. Institution of Mechanical Engineers Part O-J. Risk and Reliability	0,860	0,907	0,292	0,524	0,591	0,652	0,372	0,366	0,317
30	Production, Planning & Control	1,466	1,733	0,280	0,893	1,130	0,625	0,628	0,585	0,293
31	Quality Technology and Quantitative Management	0,583	0,550	0,255	0,355	0,359	0,569	0,233	0,146	0,268
32	Systems Engineering	0,700	0,793	0,240	0,427	0,517	0,535	0,279	0,268	0,244
33	Issues in Science and Technology	0,508	0,516	0,234	0,310	0,337	0,522	0,163	0,098	0,220
34	European Journal of Industrial Engineering	0,736	0,866	0,220	0,449	0,565	0,491	0,302	0,341	0,195
35	Industrial Robot: An International J.	0,635	0,750	0,193	0,387	0,489	0,431	0,256	0,220	0,171
36	Travail Humain	0,533	0,775	0,182	0,325	0,505	0,406	0,186	0,244	0,146
37	Engineering Economist	0,844	0,795	0,176	0,514	0,518	0,393	0,349	0,293	0,122
38	EMJ-Engineering Management Journal	0,319	0,542	0,102	0,194	0,353	0,228	0,070	0,122	0,098
39	Int. J. Industrial Engineering: Theory, Applications & Practice	0,396	0,404	0,054	0,241	0,263	0,120	0,116	0,073	0,073
40	R&D Magazine	0,180	0,142	0,042	0,110	0,093	0,094	0,047	0,049	0,049
41	South African Journal of Industrial Engineering	0,061	0,112	0,022	0,037	0,073	0,049	0,023	0,024	0,024

Abbreviations: R = Rank; IF = Impact Factor; 5IF = 5-year Impact Factor; AIS = Article Influence Score; NIF = Normalized Impact Factor; N5IF = Normalized 5-year Impact Factor; NAIS = Normalized Article Influence Score; IF[0,1], 5IF[0,1], AIS[0,1] = Impact Factor, 5-year Impact Factor and Article Influence Score normalized in the scale [0, 1].

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Table 2. General results of some WoS categories

R	Web of Science category	TP	Ref	Ref/Art	NJ	Art/J	IF	5-IF	AIS
1	Behavioral Sciences	6.521	294.638	45,2	51	127,9	3,189	3,749	1,329
2	Business	5.466	294.076	53,8	115	47,5	1,747	2,491	1,001
3	Business, Finance	4.067	136.220	33,5	88	46,2	1,319	1,569	1,138
4	Communication	2.918	59.123	20,3	76	38,4	1,080	1,398	0,654
5	Computer Science, Artificial Intelligence	11.450	301.413	26,3	123	93,1	2,134	2,076	0,712
6	Computer Science, Cybernetics	1.388	31.156	22,4	24	57,8	1,628	1,883	0,580
7	Computer Science, Information Systems	12.341	215.071	17,4	139	88,8	1,563	1,712	0,636
8	Computer Science, Interdisciplinary Applications	12.038	277.789	23,1	102	118,0	1,886	1,895	0,645
9	Computer Science, Software Engineering	8.064	145.665	18,1	104	77,5	1,241	1,402	0,690
10	Computer Science, Theory & Methods	7.396	146.450	19,8	102	72,5	1,327	1,387	0,661
11	Dentistry, Oral Surgery & Medicine	8.944	264.119	29,5	87	102,8	1,807	1,884	0,510
12	Economics	17.305	549.769	31,8	333	52,0	1,283	1,526	1,253
13	Education & Educational Research	9.654	164.498	17,0	224	43,1	0,922	1,256	0,533
14	Engineering, Industrial	4.297	115.582	26,9	43	99,9	1,641	1,533	0,448
15	Environmental Studies	6.910	170.028	24,6	100	69,1	2,224	2,208	0,840
16	Ergonomics	1.381	33.838	24,5	15	92,1	1,566	1,572	0,439
17	Geography	3.921	90.013	23,0	76	51,6	1,661	1,710	0,640
18	Health Care Sciences & Services	8.511	243.476	28,6	89	95,6	2,288	2,320	0,904
19	Industrial Relations & Labor	863	19.192	22,2	26	33,2	0,849	1,378	0,844
20	International Relations	3.218	49.128	15,3	85	37,9	1,067	1,102	0,704
21	Law	4.008	90.357	22,5	140	28,6	1,099	1,077	0,514
22	Management	7.886	409.409	51,9	185	42,6	1,749	2,408	0,955
23	Mathematics	24.456	379.152	15,5	310	78,9	0,741	0,806	0,953
24	Mathematics, Applied	23.307	407.233	17,5	255	91,4	1,098	1,123	0,830
25	Mathematics, Interdisciplinary Applications	9.570	219.614	22,9	99	96,7	1,461	1,474	0,906
26	Nutrition & Dietetics	10.606	386.204	36,4	77	137,7	3,006	2,928	0,833
27	Operations Research & Management Science	8.073	230.262	28,5	81	99,7	1,721	1,683	0,717
28	Planning & Development	2.941	69.086	23,5	55	53,5	1,420	1,753	0,719
29	Psychology	7.051	341.667	48,5	76	92,8	2,836	3,475	1,287
30	Psychology, Applied	3.569	157.011	44,0	76	47,0	1,663	2,170	0,885
31	Psychology, Multidisciplinary	8.196	316.413	38,6	129	63,5	2,091	2,333	0,937
32	Public Administration	1.701	33.181	19,5	46	37,0	1,047	1,240	0,556
33	Public, Environmental & Occupational Health	18.710	650.853	34,8	162	115,5	2,392	2,206	0,778
34	Social Sciences, Interdisciplinary	4.808	89.264	18,6	95	50,6	1,163	1,112	0,469
35	Social Sciences, Mathematical Methods	2.231	113.723	51,0	46	48,5	1,397	1,769	1,553
36	Sociology	5.251	153.457	29,2	142	37,0	1,018	1,370	0,738
37	Statistics & Probability	8.399	302.912	36,1	122	68,8	1,130	1,497	1,265
38	Transportation	2.153	48.309	22,4	29	74,2	1,969	2,112	0,704

Abbreviations: TP = Total publications; Ref = Total references; Ref/Art = References per article; NJ = Number of journals; Art/J = Articles per journal.

Note that in Table 1 we also present a normalization scale in [0, 1] which is useful for comparing journals between categories because a value of 1 indicates the best journal in the category and so on. Additionally, if the journal has a result above 0.75, is in the first quartile, between 0.5 and 0.75 in the second quartile, between 0.25 and 0.5 in the third quartile and below 0.25 in the fourth quartile.

VI. Conclusion

This article has presented the normalized article influence score. This normalization process has been developed under several perspectives. The main objective is to develop an indicator that can compare journals from different categories. Several approaches have been studied including the normalization through the average influence score of a category and the normalization in the [0, 1] scale inside a category. The average article influence score has been studied by using a wide range of averaging aggregation operators including the weighted average, the OWA operator and the induced OWA operator. Each of them becomes useful under specific situations. An alternative approach has been suggested by using a [0, 1] scale inside the category. The main reason is that here we can equilibrate the results of different categories because the journal with the highest result always obtain 1. This approach has been considered with the article influence score and with the impact factor.

These indicators have been tested in a numerical example. First, a particular case has been considered. We have focused on the WoS category of Industrial Engineering which is discipline with low results in the article influence score. Therefore, by applying the normalized article influence score, the results have more than doubled showing more similar results compared to other fields. A second example has analysed the general results of some representative categories. We have seen their annual volume of publications and references, and their average results in the impact factor, 5-year impact factor and article influence score. There is huge dispersion between categories having some categories three times higher result than other ones.

This study introduces a new version of the article influence score that provides a better comparison between categories. In future research, we will study further improvements trying to adapt better to the specific necessities that may occur between categories or when comparing other factors. Other aggregation operators will be considered and also other WoS categories. Finally, it is worth noting that this study has focused on the normalization between journals, but it is also interesting to mention that future research should also look into normalization processes between different fields that compare authors, universities and countries.

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