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Article age- and field-normalized tools to evaluate scientific impact and momentum

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Abstract

The *Field Weighted Citation Index* (FWCI) is an article age- and field-normalized metric to evaluate scientific visibility and impact. The *Topic Prominence Percentile* (TPP) is another parameter that allegedly measures an article's "momentum." Both are available at SciVal and are thought-provoking but have been scarcely used by the community, partially because it is very time-consuming to collect these parameters, paper by paper. In this article, we created and tested a computer code that can efficiently harvest the FWCI and TPP of articles of any chosen researcher, research group, or institution from the Scopus database. After collecting the desired data, our algorithm computes the sum, mean and standard deviation, mode, and median. It also calculates an alternative metric, proposed here, i.e., a normalized parameter that divides each FWCI by the number of authors of that article and then produces similar metrics. We first used the new algorithm to collect an article dataset from a selected researcher, used as an example, who has published 226 articles since 2000. The automated data collection task took 35 min versus 4 h manually. To demonstrate the power of this approach, we present the most relevant results. For instance, 20% of this researcher's papers have achieved very high visibility, an FWCI $\geq$ 2. Surprisingly, however, his articles of the highest FWCI are not the most cited. His 20 oldest papers have a similar FWCI to the 20 newest, showing that his scientific output reached a steady-state long ago. Moreover, we discovered that the papers of the highest FWCI have a higher share (65%) of international collaborators than the articles of the lowest FWCI (< 40%). These results corroborate the well-known trend that international collaboration increases scientific visibility. To generalize these findings, we also successfully compared the FWCI statistics of several senior researchers and young investigators who work in diverse fields, revealing significant differences. This way, we demonstrated that the proposed computer code and resulting metrics provide a new scientometric tool. However, a drawback is that a significant fraction of the "topics" defined by SciVal does not perfectly fit the article's field, which leads to errors in the computation of the FWCI. Therefore, while the FWCI is a handy parameter to evaluate and compare the scientific visibility and impact of researchers of any age and science field, reliable analyses will only be possible using an improved choice of topics.

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Introduction

Research is a fragmented, multi-field complex endeavor. Its outputs vary widely, particularly by the time period and discipline, hence evaluating the research impact of an individual researcher, group, or institution is very challenging (Zanotto 2006; Montazerian et al. 2017, 2019, 2020). Citation statistics play an important role in bibliometric analysis, but traditional measures mainly focus on counting the number of articles and citations. Indeed, evaluation of the scientific output and performance of researchers, institutions, and even countries have been heavily grounded on numerical parameters that (somehow) compute the number of publications and citations. Approximately one hundred such parameters have been proposed in the past two decades (Wildgaard et al. 2014; Waltman 2016), and some—e.g., the *H*-index (Hirsch 2005), and the number of citations per paper (CPP), which are easily obtained from different databases with a click of a button, have achieved global acceptance by the science community and institutions, such as funding agencies and universities (Montazerian et al. 2017, 2019, 2020).

A Scopus search in article titles with the keywords “H-index” or “H index” resulted in approximately 650 papers, including several in 2020, showing that this is still a hot topic. We then selected three of the most recent articles as an example of the pros and cons of the H-index: (Kreinovich et al. 2021; Kaptay 2020; Hu et al. 2020).

It is well-known that article citation statistics are heavily dependent on the article age (the older, the higher the chances of accumulating more citations), and on the discipline or science sub-field, e.g. (Montazerian et al. 2017, 2019, 2020). This is a reflection of research culture, and not performance and quality. This means that, when evaluated by non-weighted metrics, authors or institutions that deal with medicine will likely appear to perform better than their mathematics counterparts. Moreover, in general, for any science field, older, prolific authors obviously accumulate more citations and achieve a higher *H-index* than younger or less prolific authors (Montazerian et al. 2017, 2019, 2020).

Therefore, in addition to article age and field, some authors proposed that scientometric indicators should also be normalized to career time, number of publications or co-authorship (Schubert and Glänzel 2007; Alonso et al. 2009; Egghe 2010; Norris and Oppenheim 2010; Panaretos and Malesios 2009; Waltman 2016), whereas others discussed the pros and cons of normalization using different approaches. As mentioned by one of our colleagues at CeRTEV (Eckert 2020), “The message we need to pass on to our younger colleagues and coworkers is to return to the seemingly outdated view that “what” is more important than “where”. In other words, the quality of the research result is more important than where (high or low impact journal) the article is published.

In any case, it is now widely accepted that the *H*-index and similar metrics can indeed indicate visibility of scientific output, however they are strongly age and field-dependent (e.g., Iglesias and Pecharromán 2007), which creates a serious barrier to a fair evaluation and comparison of the scientific performance of individuals or institutions of different ages working in different fields.

Indeed, some types of modified *H*-indexes have been proposed for across field normalization, for instance (Liang 2006; Sidiropoulos et al. 2007; Iglesias and Pecharromán 2007; Radicchi et al. 2008; Namazi and Fallahzadeh 2010; Claro and Costa 2011; Montazerian et al. 2017, 2019, 2020). However, among dozens of citation-based parameters, only a few normalize citation statistics by article age, number of papers, or science field, and they are quite useful. But most of these normalized parameters require time-consuming extensive collection and manipulation of scientometric data, and thus are unlikely to be widely adopted. Moreover, those parameters that are relatively simple to calculate have severe limitations.

To represent in graphical form the above-described problem about science discipline and number of articles, Fig. 1 clearly illustrates the dependency of the *H-index* to the science field and number of publications. These plots were constructed by taking the average of the 160 most prolific authors of each sub-field and are quite revealing. For instance, an average author of the "Number theory" field, who has published 500 articles, reaches on average a $H = 30$, whereas an average scientist working on Cosmology or Graphene, which has published the same number of articles, easily reaches a $H = 70$!

Luckily, however, a relatively new parameter available from SciVal®, denominated Field-Weighted Citation Impact (FWCI), is intended to solve this problem. The FWCI is defined as the ratio of the total citations received by any given article and the total citations that would be expected based on the average of that particular topic in the same time span. Hence, the FWIC is a normalized index (by article sub-field and age) that is automatically generated by SciVal® and available in the Scopus platform for all articles published since 2000. According to SciVal®, a FWCI ≥ 1 means that the article has been more cited than expected according to the global average for that particular topic during its lifespan since publication. For example, an FWCI = 1.5 means 50% more cited than expected in that period for that topic, which is an excellent performance, whereas an FWCI ≤ 1 means that the output was cited less than the global average of that topic., e.g., Khor and Yu (2016); Huggett et al. (2018).

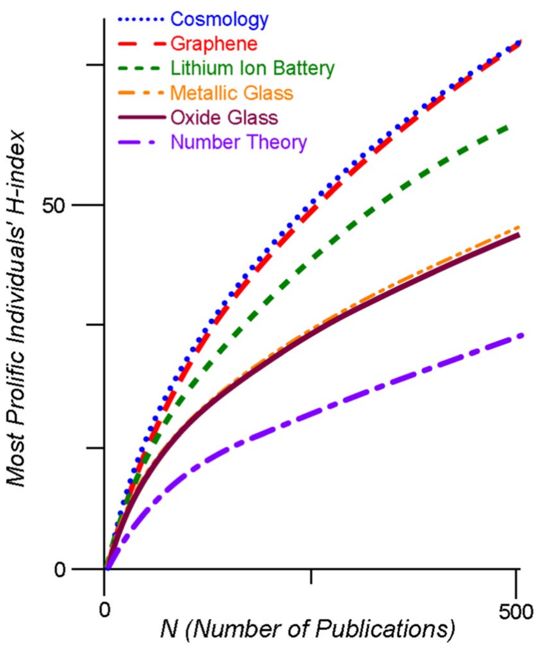

Fig. 1 Average *H-index* versus number of publications of the 160 most prolific researchers in different interdisciplinary fields Adapted from Montazerian et al. (2020), for N = 500 papers. (Color figure online)

Here we should mention that a topic is defined as a collection of documents with a common intellectual interest, which can be of any size, new or old, growing or declining in momentum. Topics are dynamic, they evolve over time. In today's research landscape, many topics are multidisciplinary and certain old topics may be dormant, but they still exist. In addition, researchers work in various areas and thereby contribute to multiple topics. The topics are defined by SciVal® in three keyword sets. For instance, taking our own research specialty, the following topics have been allocated to our papers:

- Glass ceramics/crystallization/lithium disilicate
- Nucleation/vapors/homogeneous nucleation
- Aluminosilicates/glass ceramics/oxynitride glasses
- Bioactive glass/phosphate mineral/glass scaffolds

Therefore, the FWCI takes into account the differences in research behavior across disciplines. It is particularly useful for papers that deal with interdisciplinary research. We will dwell on some possible shortcomings about the definition of these topics in the "Discussion" section.

However, we emphasize from the beginning that while citation metrics can give an important measure of the visibility and interest of scientific articles, they should not be confused with quality (Zanotto 2006; Montazerian et al. 2017, 2019, 2020).

Literature review about the use of FWCI

To our surprise, only a few authors have dealt with the FWIC. This is partially because it is very time consuming to collect this parameter, paper by paper. We summarize below recent findings reported in the literature.

In one of the first papers on the subject of FWCI, Khor and Yu 2016 investigated the effect of international co-authorship on the impact of publications of young universities (<50 years old) and some top ranked old universities (>100 years old). They used several impact indicators: 5-year citations per paper (CPP), the international co-authorship percentage, the CPP differential between publications with and without international co-authorship, and the difference between the percentage of international co-authored publications falling in the global top 10% highly cited publications and the percentage of overall publications falling in the global top 10% highly cited publications ($\Delta\%_{\mathrm{Top10}\ \%}$). Finally, to eliminate the effect of discipline in citation rate, they used an increment of 5 years (2010–2014) in the FWCI of internationally co-authored papers over the 5-year overall FWCI of the institutions. The results show that, for most old institutions, the difference between the CPP of their publications with and without international co-authorship is quite positive, with an increase of up to 5.0 citations per paper over the period of 1996–2003. The $\Delta\%_{\mathrm{Top10}\ \%}$ for international co-authored publications is also generally higher than that for all journal publications of the same institution. The fact that international co-authorship has made a positive contribution to the FWCI of the institution is of special interest. It is also relevant to note that this article has raised significant attention as its FWCI is very high, 6.7 (as of March 20, 2020).

In a subsequent paper, Huggett et al. (2018) discussed field-weighting methodologies. They computed field-weighted readership impact (FWRI) from the Mendeley database and presented comparative analyses of the FWCI and FWRI. They found a strong correlation between the number of papers cited and read per country. Overall, per subject area for the most prolific countries, the FWCI and FWRI values tend to be quite close. The authors concluded that the FWRI is a robust metric that offers a useful complement to the FWCI, because it provides insights into an earlier period of the academic communication cycle.

Kochetkov (2018) used two indicators to analyze a university publication strategy, namely, the Source Normalized Impact per Paper (SNIP) and the FWCI. The author studied the impact indicators using a sample of social and humanitarian fields at the Peoples' Friendship University of Russia (RUDN). His analysis of these metrics revealed a serious problem: high-quality results were often published in low-impact journals that narrowed the results' potential audience and, accordingly, the number of citations.

Purkayastha et al. (2019) reproduced the field-independent citation metric Relative Citation Ratio (RCR) using the Scopus database, and extended it to all subject areas. They compared the RCR to another field-weighted parameter, FWCI, and evaluated correlations to research university benchmarking for both metrics. Their analyses demonstrate that these two metrics correlate with varying strengths across different research fields.

Finally, in a recent article, Chang et al. (2019) introduced a new metric, namely Article Network Influence (ANI), to measure the impact of articles by using broader citation relationships. They used a large dataset from the Web of Science and demonstrated the use of the ANI on an analysis of the statistics research community. These analyses appear in the top-20 influential articles in statistics within every 11 years during 1981–2016. They considered differences between the new metric and other measures, as the impact factor, PageRank, and (FWCI). Unlike FWCI, the ANI does not compensate the biases from the subject difference. The authors comment that this should be an obvious step for future work.

The above articles indicate that the FWCI can be a valuable parameter to distinguish the visibility and impact of research groups from different disciplines, however collecting manually FWCI data can be a very time-consuming operation, especially for publication statistics of research groups and institutions. Moreover, the FWCI has only been scarcely explored.

Another useful indicator: Scival's "topic prominence percentile (TPP)"

Klavans and Boyack (2017) correctly mentioned that stakeholders in the science system need to decide where to place their bets. Key questions include: Which areas of research should obtain more funding? Who should be hired? Which projects should be abandoned, and which new projects should be started? Making informed choices requires knowledge about these research options. In their article, issues of consistency, relevance and demand were addressed by using a model of science consisting of over 90,000 research topics with 58 million documents. They presented a new indicator of "topic prominence"—a measure of visibility, momentum and, ultimately, demand. They assigned several US$ billions of project-level funding data to individual science topics and showed that the "topic prominence" explains much of the funding by topic.

This rare study of the relative importance of science sub-fields can be further followed and developed by using SciVal's topic prominence, which combines three metrics:

- Citation count in year n to papers published in n and $n-1$ (this is equivalent to the well-known "impact factor")
- Scopus view count in year n for papers published in n and $n-1$
- Journal CiteScore for year n

These metrics indicate the short-term impact of the article and journal where it was published. Topics are then ranked by prominence of these citation patterns, which indicates a topic momentum within a field of study.

Objectives

In this article, we significantly simplify the capture of FWCI and TPP sets and extend the applicability of these potentially powerful, but yet scarcely used scientometric parameters. Therefore, the objectives of this article are twofold:

1. To develop and implement an algorithm to automatically collect the FWCIs and TPP of any desired set of papers available at Scopus; and
2. To propose and test different metrics (based on collected FWCI and TPP data) to construct novel parameters to best evaluate the visibility and impact of any chosen researcher, group or institution.

Methods

To collect all the necessary datasets, we used a process automation procedure written in the Python programming language using the selenium library, responsible for communicating with the browser and navigating in web pages. Before running the robot, the user must configure it, defining the author's ID, the number of articles to collect, and the year range to be searched. After configuration, the robot accesses the author's information at the Scopus webpage and downloads a CSV file with all his article's statistics, including URL, year of publication, authors, prominence percentile, journal info, and others. Each article web page is then visited, and the robot finally gets the FWCI and TPP and counts the number of authors, information that is not explicitly included in the CSV file distributed by Scopus. In the end, after all desired article pages are visited, a CSV file containing the collected data is created to generate graphics, and the required statistics (mean, mode, etc.). Furthermore, there is a possibility to compare two datasets in a single figure. For instance, the oldest versus newest articles, the most cited versus the highest FWCI, etc. The generated codes are available at: https://github.com/VinniciusC/FWCI-Scopus-project.

Results

In this session, to test and demonstrate how the proposed FWCI and TPP statistics can be used to evaluate publication output and impact, we compute and analyze different statistical metrics of a chosen researcher. To test the ability of the FWCI to distinguish researchers, we will describe numerous results for several other scholars of a widely different age that work on distinct science fields. We used the new algorithm to collect an article dataset from Scopus of a selected researcher that has published 226 articles since 2000. The data collection task took approximately 35 min versus 4 h manually.

As an example of what information can be obtained, Fig. 2 shows the FWCI statistics for an author of 226 papers in the materials science field in the period of 2000–2019.

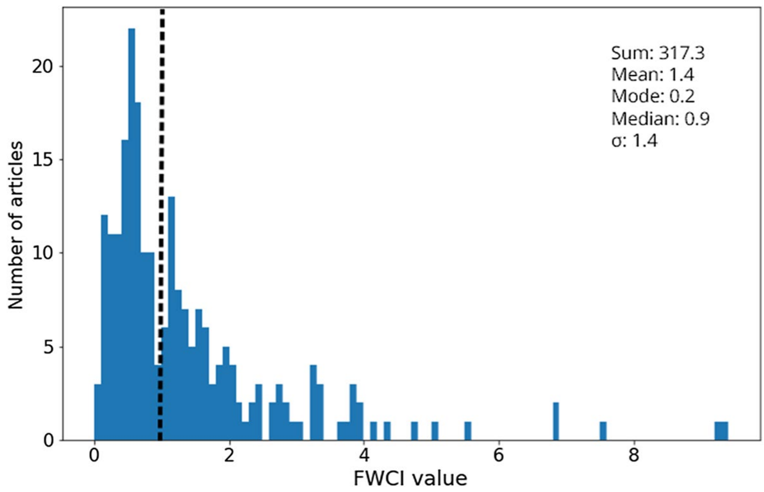

Fig. 2 FWCI statistics for an author of 226 papers in the materials science field published in the period of 2000–2019. The statistical parameters are shown in the inset. The world average, shown by the dashed vertical line, is 1. (Color figure online)

This figure shows a very skewed distribution spanning from 0.1 to 9.5, with mode at 0.2. These statistical metrics are quite revealing, as summarized below:

1. The SUM of FWCIs gives the total output/visibility of that author, which can be used to compare with other authors that have published in the same time period. This metric comprises a mixture of prolificacy and visibility: the higher the number of articles and the individual FWCI of each paper, the larger the SUM.
2. The MEAN FWCI is 1.4. This metric shows that, on average, the articles of this particular researcher have been 40% more cited than the average articles of the same age on his science sub-fields. However, this parameter is heavily biased by the very low and very high values of FWCI. Moreover, the very large standard deviation (SD), $\sum = 1.4$, calls for the use of other statistical measures. We stress here that the SD is almost always very large for FWCI statistics. Therefore, our computer code also calculates other statistical parameters, such as:
3. The MODE of the distribution. In this case, the most frequent FWCI value (10% of the articles) is 0.2. We note, however, that several papers published in 2018 and 2019, which barely had chances of being cited, significantly contribute to this low mode. Therefore, the mode should be best evaluated for older articles. On the other hand,
4. The MEDIAN = 0.9 indicates that 50% of the current articles have FWCI below 0.9 and 50% are above this value. We believe this additional parameter is a useful measure of article visibility because it is not biased by very low or very high values of FWCI.

Other relevant information given by these statistics, and shown in Fig. 2, is about the most visible papers. In this particular case, 45 papers (20% of the total) of this researcher have achieved very high visibility, i.e., a FWCI ≥ 2, whereas 13 have reached extremely high values, FWCI ≥ 4. Any other arbitrary FWCI values could be chosen for this type of analysis, e.g., to compare them with other authors.

Figure 3 shows the statistics for the same author of 226 papers in the period 2000–2019. However, in this case, the FWCI of each article was divided by the number of co-authors. This is a new metric proposed here.

This particular researcher shares his papers with 4 other authors (on average), hence these normalized FWCIs are much smaller than the standard FWCI because they were divided (on average) by 5. This normalized index (=FWCI/#authors) is useful to distinguish the performance of researchers that co-share their papers only with a couple of colleagues from those that usually co-share with dozens or more co-authors. For instance, in the field of high energy physics, papers with over 1000 co-authors are not uncommon. Therefore, most of these physics papers easily surpass many thousands of citations, due to a substantial number of self-citations and cannot be compared with those of other fields.

Figure 4 shows another surprising, yet very clear result. All the articles that have reached an FWCI > 4 have 7 or less authors, except for one "outlier" (FWCI = 9.5, and 15 authors). All the other papers with more than 7 authors have a lower FWCI. Therefore, for this particular researcher being analyzed, his most visible articles have less than 6 co-authors.

Overall, 13 papers have reached an FWCI ≥ 4, whereas 41 papers from this author have reached an FWCI ≥ 2. From these, 59% have co-authors of other nationalities. This percentage of international collaboration is higher than his average, i.e., only 45% of his papers have foreign co-authors. These results corroborate a well-known trend reported in several articles. For instance, Khor and Yu (2016 used the FWCI to demonstrate that international collaboration increases the visibility and impact of universities.

Figure 5 shows a histogram of Topic Prominence Percentile (0–100%) for the chosen author. This is a very interesting result because the mean, mode, and median practically coincide at 85–86%. Hence, most articles by this author have dealt with scientific topics of very high momentum. It should be noted that at least some of the low momentum articles are due to an unproper fit of the topic that is automatically allocated by SciVal to each article. This problem will be further discussed at the end of this section. In this particular case, the 20 most cited articles and the 20 highest FWCI have a TPP > 65%.

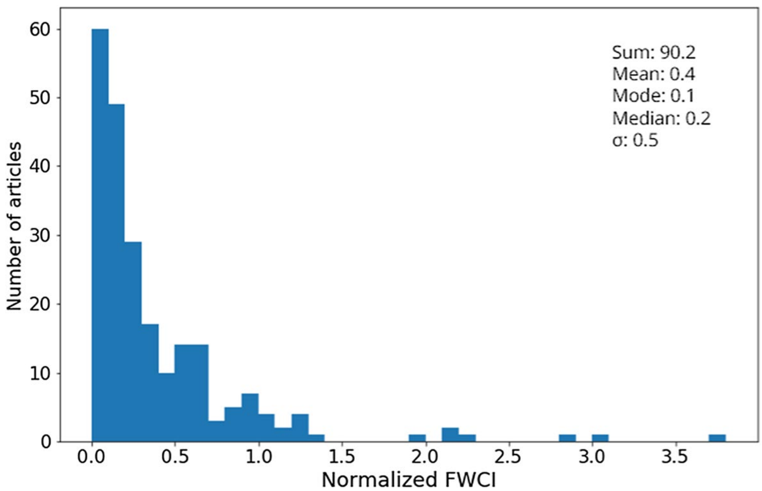

Fig. 3 Overall statistics for an author of 226 papers (in the materials science field) in the period 2000–2019. In this case, the FWCI of each article was divided by the number of authors, hence it is a normalized FWCI. (Color figure online)

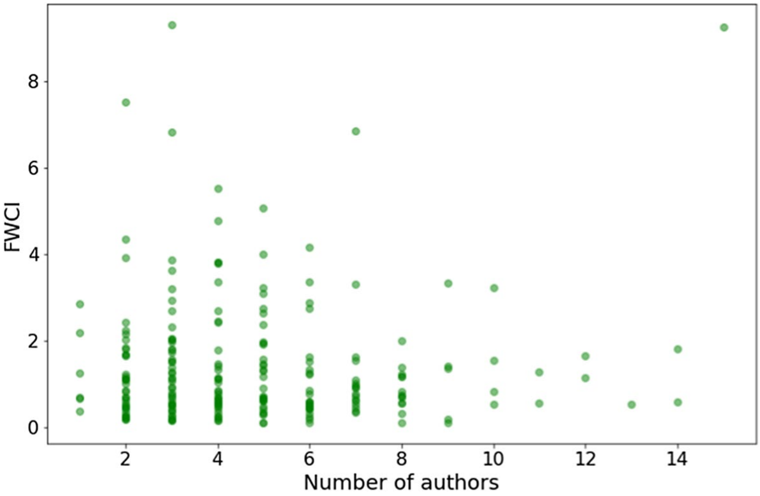

Fig. 4 FWCI versus number of authors per paper. The horizontal dotted line shows the world average, FWCI = 1. (Color figure online)

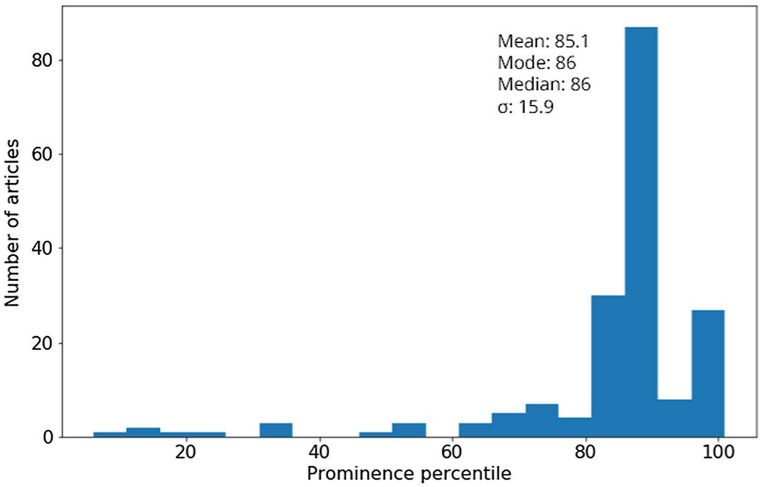

Fig. 5 Histogram of topic prominence percentile (%) for 226 articles of a chosen scientist published between 2000 and 2019. (Color figure online)

In summary, this full set of statistical metrics could be easily used to compare the performance, impact and visibility of individual researchers, groups or institutions. The proposed parameters are much better than traditional indexes and the average FWCI. Moreover, they can be straightforwardly used by individuals or research groups to compare the evolution of their own scientific output, as demonstrated next.

For example, Fig. 6 shows the 20 most cited papers and those that have reached the highest FWCI.

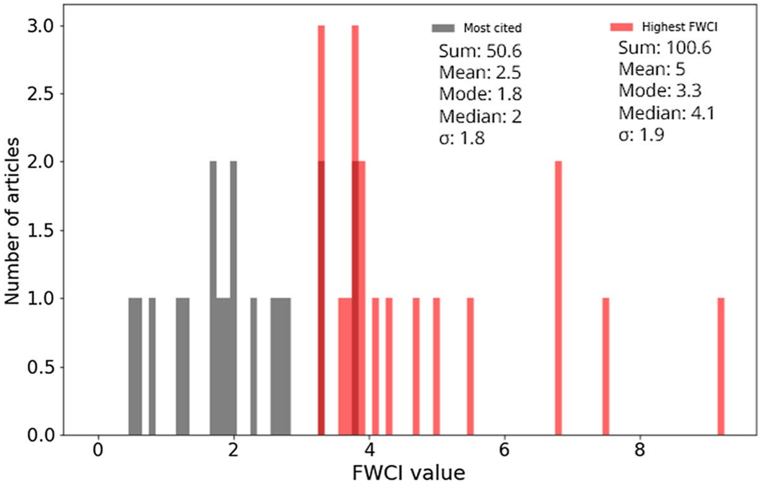

Fig. 6 FWCI statistics for the 20 most cited articles (grey) and the 20 with highest FWCI (light red). The two bars in dark red (FWCI 3.5 and 3.8) refer to overlaps of the gray and red bars. (Color figure online)

Figure 6 clearly demonstrates that, for this particular researcher under analysis, with only two exceptions at the lower bound, there is no overlap of the two groups. Hence, his most visible articles of the highest FWCI are <u>not</u> the most cited, which is a surprising result. The most cited papers accumulated several citations over many years, and have reached very good FWCIs = 1 to 4, with a median value of 2, however, they fall well behind the most visible papers, for which FWCI = 3.5–9.5, with a median over 4.

Figure 7 shows the statistics for the 20 oldest articles (published in the period 2000–2003) versus the 20 newest, published in 2017–2018. In this case, we discarded the

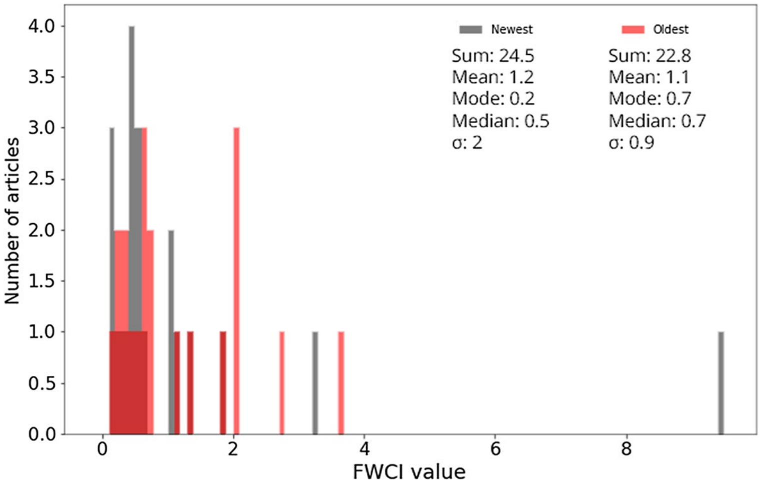

Fig. 7 FWCI statistics for the 20 oldest articles, light red (published in the period 2000–2003) and the 20 newest (gray), published in 2017–2018. The dark red bars refer to overlapping gray and light red. (Color figure online)

papers of 2019 because they barely had a chance to be cited. This is a way to test whether the researcher's impact has been decreasing or evolving over the years or has reached a steady state.

In this case, there is no substantial difference between the two groups of articles, showing that the impact of this analyzed individual reached a steady state long ago. This finding is corroborated by an analysis of the TPP (shown in the Appendix), which is also very similar for both article groups.

Further tests for senior and young authors

To generalize the applicability of the above described FWCI metrics to researchers of diverse seniority that work on different scientific fields, we evaluated 15 investigators—with 30 to 50 years of research experience, all prolific, of high or very high *H*-index, and solid international reputation—and 12 active, but much younger researchers (first paper published between 2003 and 2013). They work on diverse fields, such as chemistry, physics, astronomy, mathematics, biology, geosciences, and construction, materials and chemical engineering,

Figure 8 shows the FWCI statistics for the 15 top-ranked researchers. In the x-axis, the acronyms refer to the nickname, science field, and year of publication of their first paper, which relates to their "scientific age." For instance, Jmed1981 refers to an author nicknamed J, working in medicine, who published his/her first article in 1981. The bars are organized in crescent order of the median (red). Only their most recent articles published from the year 2000 are accounted for; this is a restriction of the FWCI-Scopus.

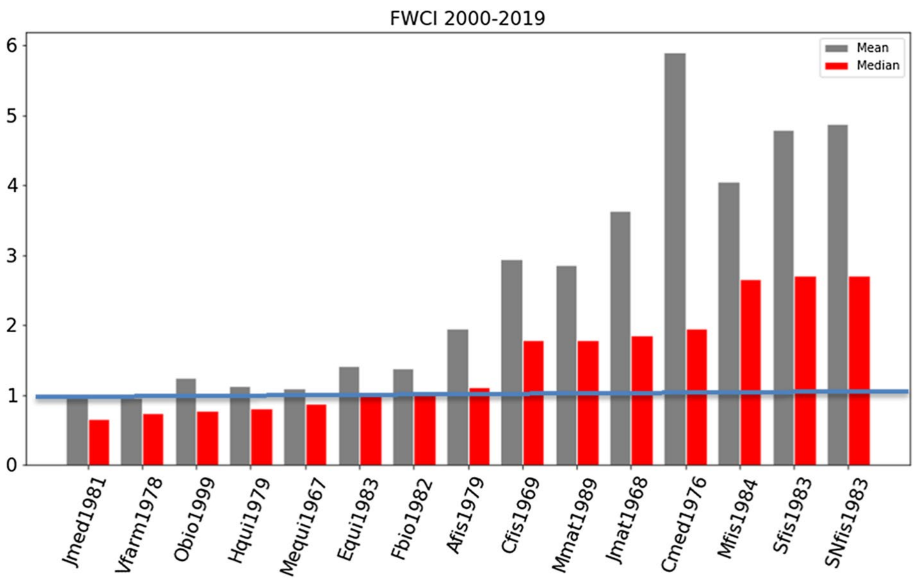

Fig. 8 FWCI statistics for 15 top-ranked researchers that work on diverse fields. In the x-axis, the acronyms refer to the nickname, science field, and year of publication of their first paper, i.e., the scientific "age" of each researcher. The bars are organized in crescent order of the median (red). The horizontal bar indicates the world average of the mean (FWCI = 1). (Color figure online)

Their FWCI values are equal to or larger than the world average (FWCI = 1) in their respective areas. Five FWCIs are close to 1; two are between 1.5 and 2.0 (50–100% above the world average); three have a mean FWCI = 3.0—3.5, whereas, for 5 of them, the mean FWCI lies between 4 and 6, which are very high values!

Figure 9 shows a normalized FWCI. In this second, more rigorous scrutiny, where each article is divided by the number of authors, 3 to 4 individuals stand out clearly. It is interesting, but not surprising, to note that the two high-energy physics (Sfis 1983 and SNfis1983), which share most of their articles with thousands of co-authors, fall to ~ zero for this normalized index.

It is not surprising that these top-ranked senior authors lye at or above their respective fields' world average. However, it would be educational to test the same concept for younger authors, which would be "competing" with other young authors and senior authors.

Young researchers

The results shown in Fig. 10 refer to articles of 12 selected young researchers published since 2013; the youngest in the group started publishing in 2013, and the oldest started 10 years earlier but is still much younger than the scientists highlighted in Figs. 8 and 9. The average and median values of the FWCI are ordered by the scientific age, from the youngest to the most experienced researchers. The x-axis legend (abscissa) uses the same notation as for the senior authors.

In this figure, the mean FWCIs of 9 of the 12 grades lie above the world average (horizontal line, FWCI = 1) in their respective research areas. Moreover, the other three authors are close, with averages between 0.8 and 1. Seven of them stand out, with

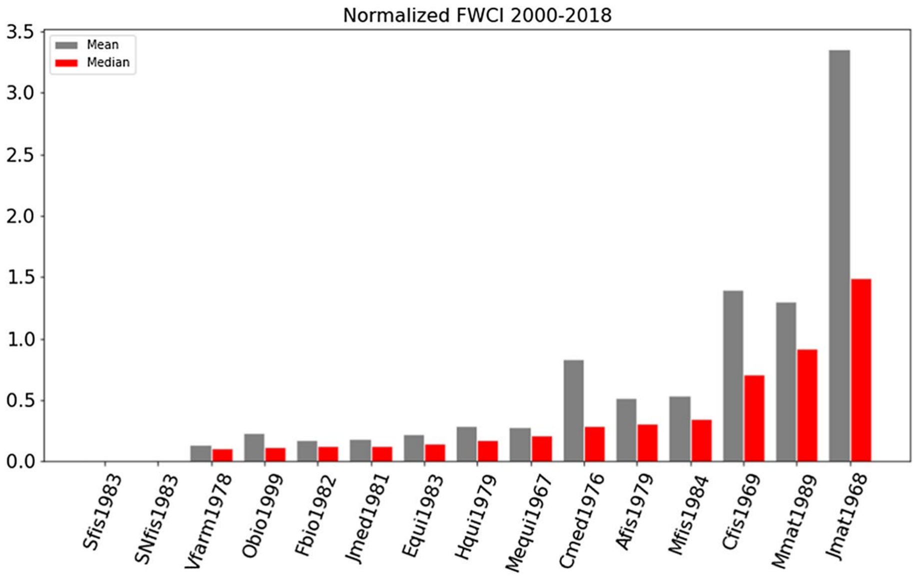

Fig. 9 Normalized FWCI statistics for 15 top-ranked researchers that work on different fields. (Color figure online)

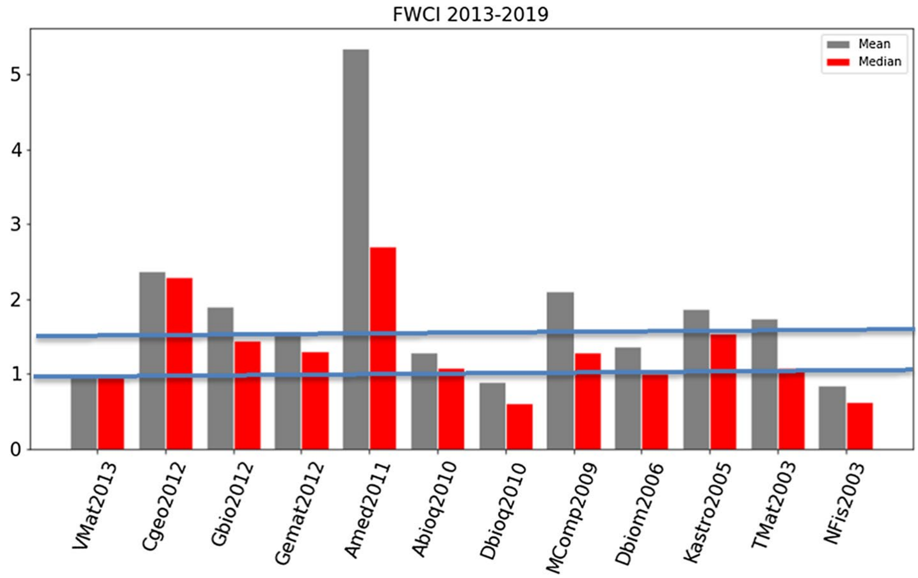

Fig. 10 FWCI statistics for 12 active young researchers that work on diverse fields. (Color figure online)

FWCI approximately 50% above the world average: Cgeo2012, Gbio2012, Gemat2012, Mcomp2009, and Kastro2003, Tmat2003, with particular visibility for Amed2011, with an FWCI 5X above the world average.

Figure 11 was obtained by normalizing the FWCI of each article by the number of authors. Hence the situation significantly changes. The two mathematicians, Vmat2013 and Tmat2003, which share their articles with only one or two co-authors, stand out. And only 2 researchers highlighted in the previous list, Cgeo2012, Mcomp2009 remain in high relief. Nevertheless, the grand champion is still Amed2011. Therefore, these two parameters indicate significant differences between these 12 persons, and corroborate our hypothesis that the FWCI is a good measure of scientific visibility, independent of the science field and age.

Discussion

Article citations are strongly dependent on their age and sub-field, e.g. (Iglesias and Pecharromán 2007). For instance, it is well-known that researchers working in high energy physics, medicine, chemistry, and biochemistry typically produce more output, with many more co-authors and longer reference lists, naturally accumulating more citations, than researchers working in mathematics and education. Therefore, if evaluated by non-weighted metrics, authors or institutions that deal with medicine will likely appear to perform better than their mathematics counterparts. Also, older and prolific authors normally accumulate more citations and achieve a higher *H-index* than younger or less prolific persons (Montazerian et al. 2017, 2019, 2020). Hence, this is not a reflection of performance and quality. Therefore, in addition to article age and field, some authors proposed scientometric indicators that are *normalized* to career time, the number of publications, co-authorship, etc. (Schubert and Glänzel 2007; Alonso et al. 2009; Egghe 2010; Norris and Oppenheim 2010;

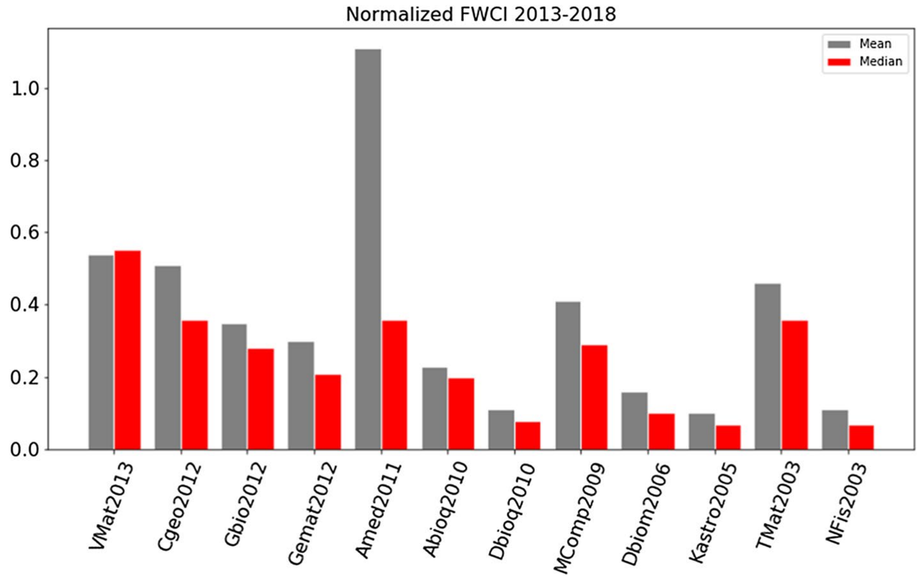

Fig. 11 FWCI statistics for 12 active young researchers that work on diverse fields normalized by the number of authors in each paper. (Color figure online)

Panaretos and Malesios 2009; Waltman 2016), whereas others discussed the pros and cons of normalization using different approaches. For example, Ioannidis et al. (2016), Ioannidis et al. (2018) suggested that citation-based metrics may offer complementary insights, but one should carefully consider their limitations, assumptions, and other factors that underlie their calculation or normalization.

We fully agree and support this view; however, most of these normalized parameters cannot be automatically computed; they require time-consuming extensive collection and manipulation of scientometric data, and thus are unlikely to be widely adopted. Moreover, those parameters that are relatively simple to calculate have severe limitations (Liang 2006; Sidiropoulos et al. 2007; Iglesias and Pecharromán 2007; Radicchi et al. 2008; Namazi and Fallahzadeh 2010; Claro and Costa 2011; Montazerian et al. 2017, 2019, 2020).

For these reasons, we proposed and tested an algorithm that can readily compute different statistical measures of a field and age normalized parameter, FWCI. Our results demonstrate that these new FWCI-based metrics can easily distinguish the visibility and impact of authors independently of age and scientific field. However, there is a serious drawback with the way the FWCI is currently calculated. In many cases, the topics chosen by SciVal are perfectly adequate; however, in other instances, they do not fully match the article's subfield. We selected two of our own papers to demonstrate this drawback.

Example (i) Schmelzer, J.W.P., Abyzov, A.S., Fokin, V.M., Schick, C., Zanotto, E.D.—"Crystallization in glass-forming liquids: Effects of decoupling of diffusion and viscosity on crystal growth". Volume 429, 1 December 2015, Pages 45–53.

FWCI ~ 2, Topic prominence percentile = 82%.

SciVal® topic: Nucleation | Vapors | Homogeneous nucleation|.

This article has no relation whatsoever to "vapors." Hence, we are not sure if the above described inadequacy contributed to increasing or decreasing the prominence percentile and the FWCI.

Example (ii) Montazerian, M., Zanotto, E.D.”A guided walk through Larry Hench’s monumental discoveries” - Volume 52, Issue 15, 1 August 2017, Pages 8695–8732.

SciVal® Topic: Bioactive glass | Carrier transport| Size-quantization regime.

FWCI = 1.2 Topic prominence percentile = 14%.

This paper has no bearing on “carrier transport” and “size-quantization regime”. Perhaps this grave flaw likely explains its relatively low topic prominence?

Statistics with several of our own papers, for which we know precisely the adequate sub-fields, keywords, and topic, have shown that a significant fraction of the SciVal®’s topics does not fit to the article’s main field. In those cases, at least one of the three keywords used to define the topic is inadequate. These unmatched article/topic sets lead to positive or negative errors in both the FWCI and TPP.

To further elaborate on this issue, we selected 22 articles of precisely the same topic (crystal nucleation in glasses) published in the same year (2015) and manually calculated their FWCI. In Fig. 12, we compare their current FWCI (as given by SciVal-Scopus) with our rigorously calculated FWCI.

Figure 12 shows that, overall, the FWCI—Scopus gives a reasonable “ballpark” for the FWCI of many articles; however, it fails for several others. In this particular test, the current FWCI is significantly underestimated in half of the cases. This observation is crucial to optimize this parameter further and will be communicated to the SciVal and Scopus officers.

In summary, this work’s novelty is thus related to developing, implementing, and testing an algorithm that harvests the individual FWCI of any researcher or group registered in the Scopus database. We have then used the bibliometric information retrieved by the algorithm to successfully test different statistical parameters that allow an evaluation and comparision of young and senior researchers’ scientometric performance in different scientific fields. Finally, we unveiled a critical flaw of the current FWCI regarding the three topics chosen by SciVal for each article. They do not always reflect the article’s field.

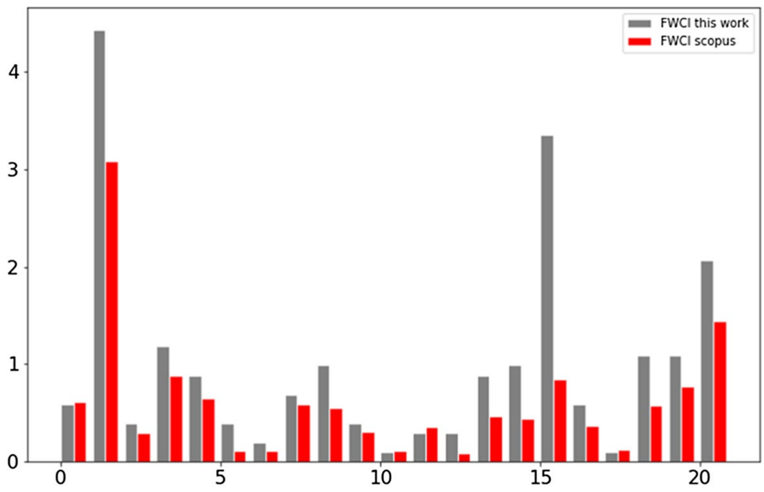

Fig. 12 Comparison of the current FWCI, as given by Scopus, and a rigorously calculated FWCI (this work) for 22 articles of the same topic (crystal nucleation in glass) and publication year (2015). (Color figure online)

Conclusions

We created and implemented an algorithm to automatically collect the FWCIs and TPPs of any desired set of papers available at Scopus from the year 2000. This algorithm is made freely available to the community. Based on some age- and field-normalized parameters, we proposed several metrics to evaluate best the visibility and impact of any chosen researcher or group. We also proposed a normalized parameter, which divides each FWCI by the number of authors of each paper, and which is also automatically harvested and computed by our code. This normalized metric can be particularly useful for comparing authors who share their papers with only a few others with those with many co-authors, hence, naturally accumulating more citations.

Using actual citation data of a selected researcher, as an example, we computed and discussed the following metrics: FWCI and TPP distributions, their sum, mean and SD, mode, and median. Our analysis revealed his standing regarding visibility and impact. We found that 20% of his papers have achieved very high visibility, i.e., an FWCI $\geq$ 2 (twice higher the world average, FWCI = 1). All the articles that have reached an FWCI > 4 have 7 or fewer authors, except for one outlier. His most visible articles, of highest FWCI, are not the most cited, and the 20 oldest papers have similar FWCI as the 20 newest, showing that this researcher's career reached a steady-state long ago.

Moreover, we discovered that the papers of the highest FWCI have a higher share (65%) of international collaborators than the articles of lower FWCI (< 40%). These results corroborate a well-known trend, i.e., international collaboration increases scientific visibility. Finally, the chosen author's TPP statistics are impressive, with mean, mode, and median over 85%. With the new algorithm, all these metrics can be easily computed for any researcher registered at the Scopus database.

To test the method's ability to distinguish researchers among groups, we evaluated 15 senior investigators and 12 younger researchers. The FWCI metrics clearly distinguished the visibility and impact of these scholars. Therefore, this type of analysis is advantageous to compare individual authors or research groups, and could be easily applied for institutions or even countries. However, one drawback is that a significant fraction of the "topics" defined by SciVal does not perfectly fit the article's field. These unmatched articles/topics lead to positive or negative errors in the FWCI.

Taken *in toto*, our analysis shows that the FWCI is a handy parameter to evaluate the scientific visibility and impact of researchers of any age and science field. However, fully reliable analyses will only be possible if the choice of "topics" is improved by SciVal.

Appendix

The generated codes are available at https://github.com/VinniciusC/FWCI-Scopus-project.

What is SciVal's Topic Prominence?

According to SciVal, a topic is a collection of documents with a common intellectual interest, which can be of any size, new or old, growing or declining in momentum. Topics are dynamic, they will evolve over time, and new topics will surface. As with the nature of today's research landscape, many topics are multidisciplinary and old topics may be dormant, but they still exist. In addition, researchers work in various research areas and thereby contribute to multiple topics.

Topic

Topics are based on clustering the citation network of 95% of Scopus content (all documents published from 1996). Each Topic is a collection of documents with a common interest. For example: "Glass ceramics/crystallization/lithium disilicate".

Topics are clustered within SciVal based upon direct citation analysis using document reference lists (a document can belong to only one Topic). As newly published documents are indexed, they are added to Topics using their reference lists. This makes Topics dynamic and most will increase in size over time.

Prominence

Calculating a Topic's Prominence combines three metrics which indicate the momentum of the Topic.

- Citation Count in year *n* to papers published in *n* and $n-1$
- Scopus View Count in year *n* for papers published in *n* and $n-1$
- Average Journa CiteScore for year *n*

Topics are then ranked by Prominence of these citation patterns, which indicates a Topic's momentum in a field of study.

For more information, see Topic Prominence at Elsevier.com.

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