Normalization of reader impact for Mendeley reader statistics

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Abstract

It is common practice in bibliometrics to normalize citation counts in order to obtain a useful measure for impact of publications. A different number of citation counts is expected for publications of different disciplines and publication years. Also, in the case of Mendeley reader counts, a major influence of publication year and discipline has been observed. Thus, the impact of Mendeley reader counts cannot be estimated without normalization. For the normalization of citation counts, two methods are possible: the cited-side and citing-side normalizations which both can be applied also in the normalization of Mendeley reader counts. In this study, all articles and reviews of the Web of Science core-collection with publication year 2012 are used to normalize their reader counts on Mendeley using both normalization methods. Two new indicators to measure the normalized reader impact are obtained and compared with citation-based indicators. We find that the cited-side and citing-side normalization methods are able to normalize Mendeley reader counts. This enables us to obtain a quantitative measure for reader impact.

Key words

Altmetrics, Mendeley, normalization, cited-side, citing-side, journal usage, reader impact

1 Introduction

The citation impact of scientists, research groups, and institutes in different disciplines and time periods is compared with each other. Both factors – discipline and time period – influence the citation impact of publications independent of the quality of the publications. Normalization regarding both factors started in the mid-1980s (Schubert & Braun, 1986). Only since normalized values were obtained, it became possible to assess the citation impact of entities such as researchers or universities across different disciplines and in different time periods. Since the 1980s, different methods were proposed to create normalized citation impact scores.

Basically, one can distinguish between two levels of normalization: (1) In the case of normalization on the cited side, the total number of citations of the publication to be evaluated (times cited) is counted. This number of times cited is compared to other publications of the same publication year and research field (expectation value of the reference set). (2) In the case of normalization on the citing side, each citation is multiplied with a weighting factor (Zitt & Small, 2008). This weighting factor reflects the citation culture of the scientific field. The number of references in publications reflects the citation habit in the discipline. Therefore, the inverse of this number is usually used as a weighting factor. The sum of all weighted citations is the normalized citation impact of a publication.

In recent years, impact evaluation in scientometric research has been done not only on the basis of citations but also based on alternative metrics (altmetrics) (L. Bornmann, 2014). Altmetrics open the possibility to assess the impact of research faster than with citations. Also, altmetrics seem to be suitable to measure the impact of research in a broader manner than with citations (Lutz Bornmann, 2014). While citations measure only the impact of research on science, altmetrics could be able to measure the impact of research on all aspects of society including science. It is subject of current scientometric research if this hope (especially the broad impact measurement) which is connected with altmetrics is more than a pipe dream.

Data from Mendeley are one of the most important sources for altmetrics: „Mendeley is both a citation management tool and social network for scholars with over two million users” (Rodgers & Barbrow, 2013, p. 12). Since reception of literature by Mendeley readers is captured by Mendeley, these data can be used to answer scientometric research questions. One basic assumption is that a Mendeley reader who adds a publication to his library can be counted as a reader of this publication. Indeed, the results of Mohammadi, Thelwall, and Kousha (in press) show that „82% of the Mendeley users had read or intended to read at least half of the bookmarked publications in their personal libraries.” Therefore, Mendeley counts are seen as a very promising possibility to measure the size of readership of a paper inside as well as outside of science. Furthermore, a Mendeley reader can be seen as a precursor to a citer, as Mendeley users include a publication into their library when they intend to cite this publication in a forthcoming publication. However, this Mendeley user is counted as *one* reader while it is possible that he will cite this publication multiple times or not at all. Therefore, caution should be exercised when interpreting Mendeley reader statistics.

Several studies showed that Mendeley reader impact – similar as citation impact – varies across scientific disciplines (Thelwall & Maflahi, in press; Zahedi, Costas, & Wouters, 2014; Zahedi & Eck, 2014): In one discipline papers are read more often on average (or more literature is included in the user’s Mendeley library) than in other disciplines. Therefore, it is essential to normalize reader impact – similar to citation impact – in order to use Mendeley reader data across disciplines. The aim of this study is to apply established methods for normalization in bibliometrics (methods of cited-side and citing-side) to the field of alternative metrics and propose normalization schemes for Mendeley reader counts.

2 Methods

2.1 Description of the data set

It is common practice in scientometrics to evaluate the impact of articles and reviews. Other document types are usually neglected, although sometimes also letters are included (H. F. Moed, 2005). We retrieved the Mendeley reader statistics for articles and reviews with publication year 2012 (n_A = 1,133,224 articles and n_R = 64,960 reviews) via the Mendeley API which was made available in 2014. The DOIs of the papers were exported from the in-house database of the Max Planck Society (MPG) based on the WoS and administered by the Max Planck Digital Library (MPDL). We used R (http://www.r-project.org/) to interface to the Mendeley API. The DOI was used to identify the paper in the Mendeley API. 1,074,407 articles (94.8%) and 62,771 reviews (96.6%) were found at Mendeley.

In total 9,347,500 readers were found for the articles and 1,335,233 readers for the reviews with a self-assigned sub-discipline. Only 4,924 (0.05%) of the Mendeley article readers and 531 (0.04%) review readers did not share their sub-discipline information. For 118,167 articles (10.4%) and 4,348 reviews (6.7%) we found the paper at Mendeley but without a reader. The papers without any reader could be used in the normalization procedure or discarded. Papers indexed by Mendeley can originate from a former reader, who removed the paper from his library or closed his Mendeley account. If a Mendeley user includes too few bibliographic data for a paper in his library, he doesn't get counted as a reader either, because there is not sufficient information to link this reader to a Mendeley database entry. Also, Mendeley includes Papers into their database without any reader in the first place from publisher feeds. As the origin of a paper without a reader in the Mendeley database is unclear, we dropped the papers without any reader for our study, but we kept the papers where the only reader did not share the discipline. Here, and in the following, we mean Mendeley disciplines when referring to (sub-) disciplines. The requests to the Mendeley API were made between the 11th and 23rd of December 2014.

3 Results

3.1 Differences in reader impact between fields

As known for the citation distribution (Marx & Bornmann, 2015), also the reader distribution is skewed across the subject categories, as shown in Figure 1 for articles and Figure 2 for reviews.

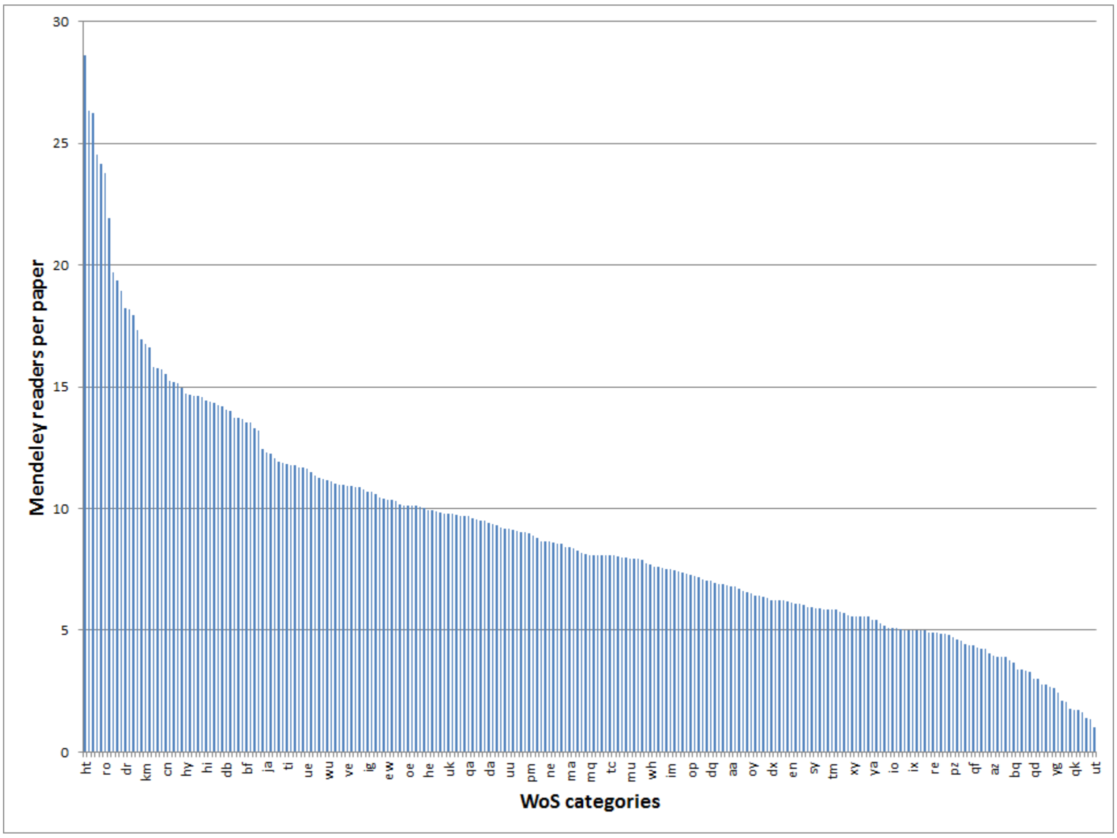

Figure 1: Distribution of Mendeley readers per paper across WoS subject categories for the document type article

The reader spread across the categories ranges from 1 reader per paper in Poetry to 28.61 readers per paper in Evolutionary Biology. The 31 highest populated WoS categories out of 251 (12%) comprise 50% of the readership of the papers studied here.

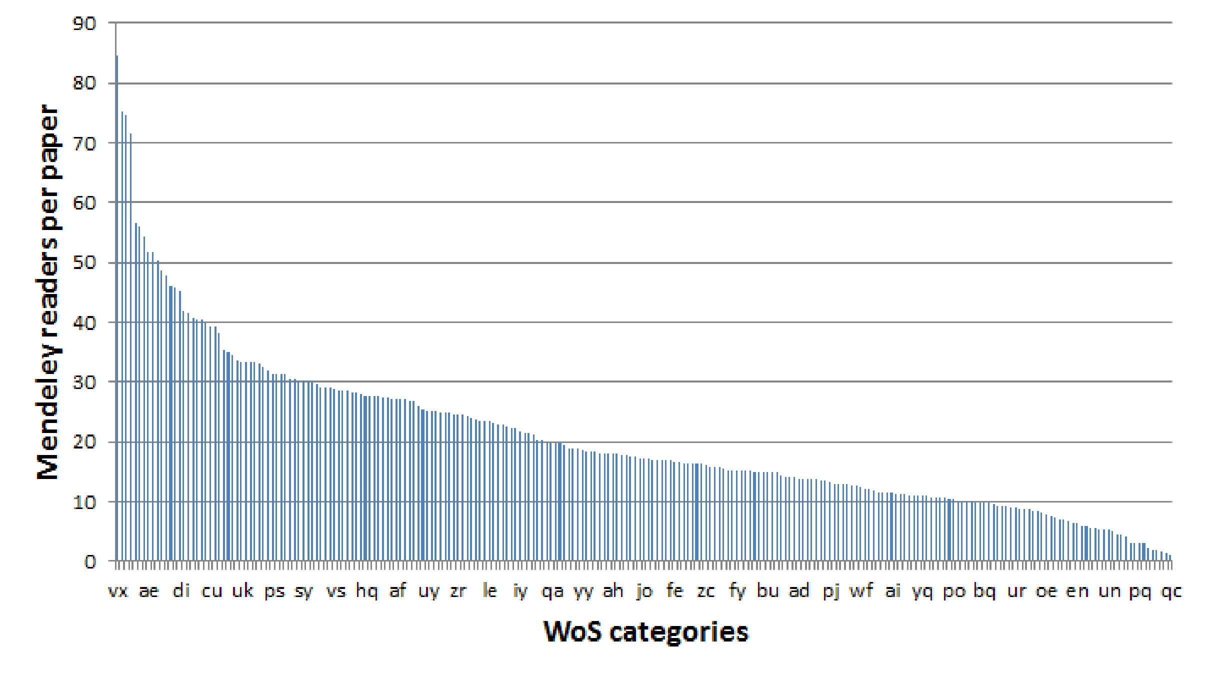

Figure 2: Distribution of Mendeley readers per paper across WoS subject categories for the document type review

For reviews, the highest number of readers per paper with 84.4 is found in the WoS category Psychology, Experimental, while the lowest number is found with 1 reader per paper in Literature, Romance. 50% of the readers are found in the 18 highest populated WoS categories out of 239.

Usually, reviews are cited more often than articles. Therefore, we assume that the reader counts also differ between both document types. Figures 1 and 2 show that reviews are also read more often than articles. The average value of readers per paper across all WoS categories is 9.0 for articles and 20.7 for reviews. Thus, the normalization procedure is done separately for articles and reviews.

3.2 Paper-side normalization of reader impact

In the method of cited-side normalization, the citation impact of a focal paper is compared with the expected citation impact. The expectation value is the average citation impact in the same discipline, publication year, and document type as the paper in question.

This paper set is referred to as reference set. The ratio of observed and expected citations is denoted as Normalized Citation Score (NCS). Currently, the NCS is the standard in bibliometrics to normalize citation impact. A NCS of 1 for a publication indicates an average citation impact as the publications in the reference set. A NCS of 1.5 can be interpreted as a citation impact which is 50% higher than average (Waltman, van Eck, van Leeuwen, Visser, & van Raan, 2011; Waltman, van Eck, van Leeuwen, Visser, & van Raan, 2010). If a paper has been assigned (by a database provider such as Thomson Reuters) to more than one subject category, the average value of all NCS values is used. In the case of aggregations of papers (normalized impact of a researcher or university), the average value of the NCS values of all papers in the set is calculated. This average value is referred to as Mean Normalized Citation Score (MNCS). The MNCS is used in the Leiden Ranking (Waltman et al., 2012), as well as in the SCImago Institutions Ranking (SCImago Reseach Group, 2013) (in SCImago Institutions Ranking the MNCS is referred to as Normalized Impact, NI).

Following the definition of the MNCS, we propose a Mean Normalized Reader Score (MNRS). Our normalization procedure for Mendeley reader impact starts with calculation of the average number of Mendeley readers per paper in each WoS category (c.f. Figure 1). Afterwards, the raw Mendeley reader number is divided by the average number of Mendeley readers per paper of its WoS category. Some papers are assigned to multiple categories. Therefore, in the next step, the average over the categories is calculated for each paper. Finally, the resulting values are scaled so that the average value over all papers is one. Since we include only papers which were published in 2012, the publication year can be neglected during the normalization procedure. If a paper (the journal where the paper is published in) has been assigned to multiple subject categories by Thomson Reuters, as many ratios are calculated as the paper is assigned to subject categories – following the usual procedure for citations.

Figure 3 shows the MNRS broken down by scientific fields (OECD categories).[1] The scores are – as expected – in all scientific fields close to 1 (they vary between 0.94 for Humanities and 1.05 for Natural Sciences). This result shows that the paper-side normalization is able to normalize the reader impact with regard to the subject category.

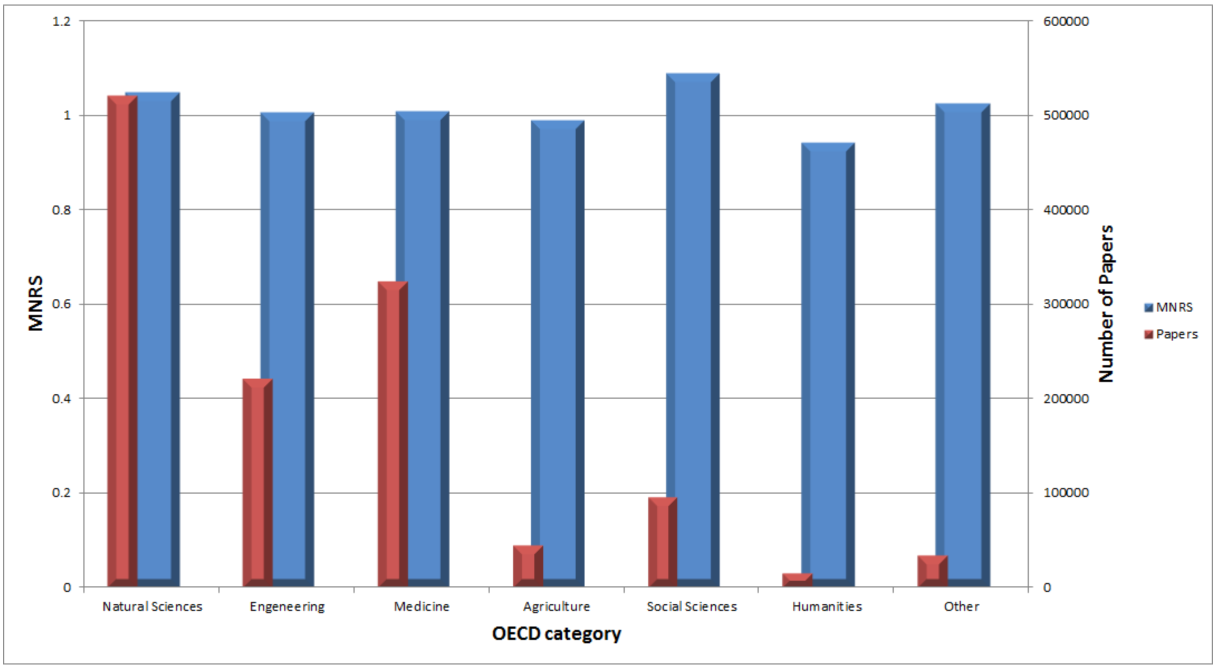

Figure 3: MNRS and number of papers broken down by OECD categories

Table 1 shows the thresholds of MNRS values which a paper has to have at least in order to become a top1% and top10% paper. The differences between the MNRS thresholds between reviews and articles are smaller for top10% than for top1%.

Table 1: MNRS thresholds for top1% and top10% papers

	MNRS threshold	
	articles	reviews
Top1%	5.83	6.66
Top10%	2.12	2.36

[1] The seven broad OECD categories are aggregated WoS journal sets.

3.3 Reader-side normalization of reader impact

The method of citing-side normalization was formulated for the first time in a paper by Zitt and Small (2008). They used the Journal Impact Factor (JIF) modified by fractional citation weighting. The citing-side normalization which is also referred to as fractional counting of citations or a priori normalization (Waltman & van Eck, 2013a) is not only used for journals but also in other contexts. The normalization tries to account for the different citation cultures from where a citation originates from (L. Leydesdorff & Bornmann, 2011; Loet Leydesdorff, Radicchi, Bornmann, Castellano, & de Nooy, in press). Each citation is weighted with regard to its citation culture: A citation from a discipline where many papers are cited has a lower weight than a citation from a discipline where fewer papers are cited. In one of the previously proposed methods of citing-side normalization (A), the number of references is used to weight the citation (Waltman & van Eck, 2013b). That means a citation from a paper with fewer references has a higher weight than a citation from a paper with more references. This method assumes that the number of references in a particular paper reflects the typical number of references. However, this assumption is not always valid. In another previously proposed method of citing-side normalization (B), the average number of references of the papers which appeared in the same journal as the paper in question is used in calculation of the weighting factor. The procedure (B) has a higher probability of estimating the typical citation habits with a higher accuracy than procedure (A) (L. Bornmann & Marx, in press). A combination of both methods is also possible, as described by Waltman and van Eck (2013b). An indicator which is based on the citing-side normalization is referred to as Source Normalized Citation Score (SNCS) by Waltman and van Eck (2013b). Following the citing-side normalization procedures in bibliometrics, we propose a reader-side normalization of reader impact. As this study deals with papers which were all published in 2012, the publication year can be neglected in the normalization procedure.

The Mendeley reader counts broken down by discipline are shown in Table 1. 95.5% of the readers are within 15 of the 25 disciplines while the remaining 4.5% of the readers are in the 10 disciplines with less than 1% each. The disciplines Biological Sciences and Medicine comprise 48.0% of the Mendeley readers of the WoS papers from 2012. The ratio of the percentages of articles and the percentages of reviews is greater than one for 22 of the 25 disciplines. A rather high percentage of reviews compared to the percentage of articles (not shown in Table 2) was published only in the disciplines Medicine and Biology (both show a ratio of 0.7). In Chemistry, this ratio is essentially 1.

Table 2: Mendeley readers of WoS papers (articles and reviews) from 2012 broken down by the different disciplines (sorted in decreasing order)

Discipline	**Mendeley readers**	
	abs. readers	**% readers**
Biological Sciences	3,518,931	32.94
Medicine	1,610,631	15.08
Chemistry	852,261	7.98
Engineering	709,525	6.64
Physics	578,831	5.42
Psychology	567,297	5.31
Environmental Sciences	406,960	3.81
Computer and Information Science	363,337	3.40
Social Sciences	354,877	3.32
Earth Sciences	319,943	2.99
Materials Science	289,464	2.71
Electrical and Electronic Engineering	194,604	1.82
Business Administration	173,815	1.63
Economics	133,370	1.25
Education	133,026	1.25
Management Science	91,340	0.86
Astronomy, Astrophysics, and Space Science	80,713	0.76
Mathematics	77,496	0.73
Sports and Recreation	54,699	0.51
Humanities	45,094	0.42
Design	35,935	0.34
Arts and Literature	30,756	0.29
Linguistics	27,162	0.25
Philosophy	21,121	0.20
Law	11,545	0.11

The average number of Mendeley readers per paper is shown in Table 3. The reader spread across the disciplines is somewhat smaller than for WoS subject categories (cf. Section 3.1), but Table 3 shows that non-normalized reader counts are next to useless. Obviously, one reader count is worth less in Biological Sciences than in Arts and Literature. This holds true for both document types. The average number of Mendeley readers per paper is larger for reviews than for articles in 15 of the 25 disciplines. For the disciplines Arts and Literature, Computer and Information Science, Humanities, Philosophy, Law, and Mathematics the average reader counts are rather similar for both document types. In the case of Business Administration, Education, and Social Sciences, articles have a higher reader count on average than reviews. For the discipline Biological Sciences, an article has to have 15 readers to be among the top-10% and 62 readers to be among the top-1% of the papers, while 8 readers are sufficient to be among the top-10% and 23 readers to be among the top-1% in the discipline Medicine. 7 readers are necessary for an article to be among the top-10% and 24 readers to be among the top-1% in the discipline Chemistry.

Table 3: Average number of Mendeley readers per paper broken down by different disciplines

Discipline	**Reviews**	**Articles**
	Average number of readers	
Arts and Literature	1.14	1.15
Astronomy, Astrophysics, and Space Science	3.06	2.89
Biological Sciences	14.30	6.85
Business Administration	3.11	3.52
Chemistry	5.99	3.42
Computer and Information Science	2.68	2.77
Design	1.33	1.22
Economics	1.78	2.58
Education	1.86	2.17
Electrical and Electronic Engineering	2.67	2.26
Engineering	4.24	2.62
Environmental Sciences	4.66	3.26
Earth Sciences	4.42	3.81
Humanities	1.31	1.38

Law	1.29	1.30
Linguistics	2.33	2.32
Management Science	1.95	2.02
Materials Science	4.13	2.39
Mathematics	1.55	1.54
Medicine	6.81	3.84
Philosophy	1.32	1.47
Physics	4.35	3.46
Psychology	7.41	4.92
Social Sciences	2.54	2.76
Sports and Recreation	2.36	2.16

We use the Mendeley (sub-) disciplines for the reader-side normalization. The sub-discipline "Miscellaneous" is listed in every Mendeley discipline. 76.81% (for articles) and 78.19% (for reviews) of the Mendeley readers assigned themselves the sub-discipline "Miscellaneous" within their specific discipline. Therefore, we normalized the reader counts on the reader-side normalization with respect to the disciplines rather than the sub-disciplines. Table 3 shows that the reader count differs on average between the document types article and review. Thus, the normalization procedure is done separately for both document types.

The procedure is as follows: First, the average number of readers is determined for each discipline (c.f. Table 3). The inverse of the average value is the weighting factor for readers from the different disciplines. Second, the reader count is normalized by multiplication with the weighting factor. Third, the average value of all disciplines is calculated for each paper. Finally, in order to account for the fact that each discipline has a different number of papers without Mendeley readers, the average value has to be normalized by division by the average value over all papers to obtain a normalized reader indicator (discipline normalized reader impact, DNRI) which is around 1 for average, larger than 1 for higher than average, and smaller than 1 for lower than average reader impact. In order to clarify our procedure, we present it in detail using the example of the article with the DOI 10.1111/j.1467-8497.2012.01625.x. We found 9 readers who all shared their discipline: 5 in Medicine, 1 in Psychology, and 3 in Social Sciences. The average reader values for these disciplines are: 3.84, 4.92, and 2.76. Therefore, we obtain the normalized reader values of 1.30 for Medicine, 0.20 for Psychology, and 1.09 for Social Sciences. The average value for this paper is 0.86. The average value over all papers is 0.883 which was used to normalize all papers resulting in the DNRI of 0.98 which indicates an average reader impact for this paper.

Figure 4 shows the DNRI values broken down by scientific fields (OECD categories). The impact values are – as expected – in most scientific fields close to 1 (they vary between 0.76 for Agriculture and 1.16 for Social Sciences). This result indicates that the reader-side normalization based on Mendeley disciplines is able to normalize the reader impact with regard to the subject category, but not as well as the paper-side normalization (c.f. Figure 3) based on WoS categories. Probably, the Mendeley disciplines (n = 25) are too broad to obtain a normalization as reliable as based on the WoS categories (n = 261). Also, problems might arise because the Mendeley disciplines are self-assigned by the reader while the WoS categories are based on journal sets. However, the deviations of DNRI values from 1.0 in Figure 4 could also originate from the different methodology, the reader-side normalization, which is closely related to the citing-side normalization method where similar deviations were observed (Lutz Bornmann & Marx, 2015).

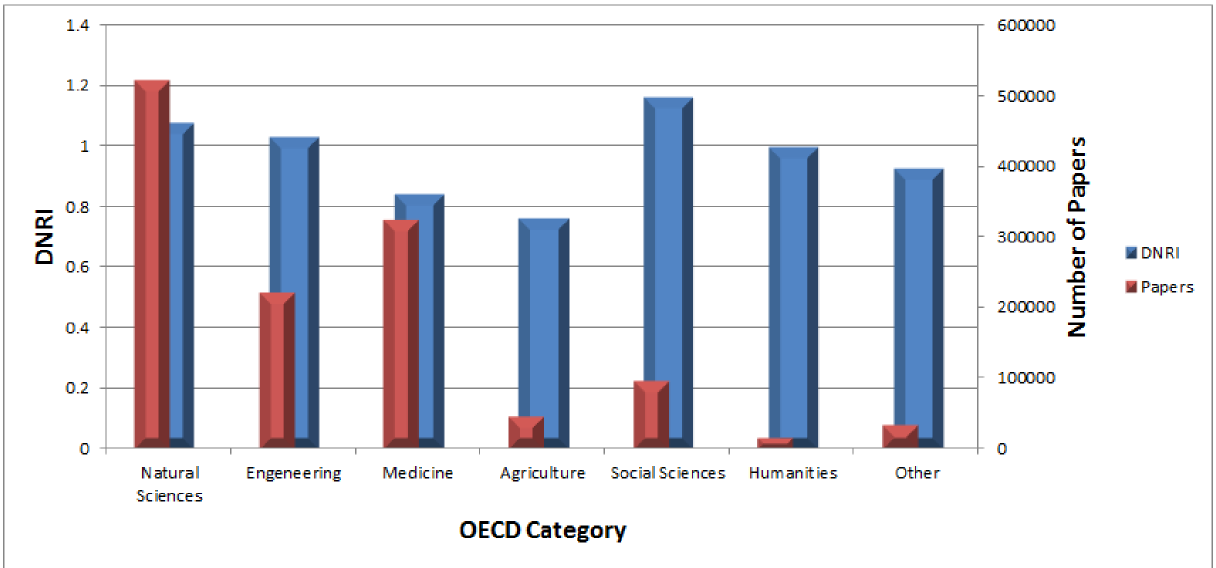

Figure 4: DNRI values and number of papers broken down by OECD categories

Table 4 shows the DNRI values which a paper has to have at least in order to be a top1% and top10% paper. The DNRI values for top10% articles and reviews are very similar. The distinction at the top1% threshold is somewhat more pronounced.

Table 4: DNRI thresholds for top1% and top10% papers

	DNRI threshold	
	articles	reviews
Top1%	4.43	4.63
Top10%	1.95	1.98

In contrast to SNCS, where the number of references of a paper or the average number of references in a journal is used for the normalization procedure, the average number of readers in each (reader-based and self-assigned) discipline is used for the normalization procedure for the DNRI. Therefore, the DNRI is better suited to estimate the field-specific readership cultures than the SNCS.

Normalized readership values can be calculated for different units: single researchers, research groups, institutions, countries, and journals. As examples, we present in the following these values for journals and several German universities.

3.4 Normalized reader impact of journals

Papers from 9,563 journals out of the 12,334 WoS journals in 2012 are covered in the papers found at Mendeley. Table 5 shows the 25 journals with at least 400 papers in 2012 and highest MNRS and Table 6 shows those journals ordered by DNRI. The minimum of 400 papers published in 2012 ensures that a statistically relevant number of indicator values is employed in the calculation of the journal SNRI and MNRS values. Many reputable journals (*Cell*, *Nature*, and *Science*) are also journals with high MNRS. The Journals *Nature Photonics* (10.98), *Nature Biotechnology* (10.82), *Nature Reviews Cancer* (10.75), *Theater* (10.48), *Nature Materials* (9.64), and *Nature Nanotechnology* (9.62) have a higher MNRS than *Cell* but less than 400 published papers in 2012. Interestingly, there is a steep decrease in MNRS from *Nature* to *Science* which is less pronounced for the DNRI.

Table 5: Top 25 WoS journals with a minimum of 400 papers in 2012 sorted by the MNRS

Journal	**MNRS**	**SNIP**	**no. of papers**
Cell	9.47	6.33	415
Nature	7.07	8.81	858
Science	4.73	8.31	826
Nano Letters	4.10	3.74	1066
Advanced Materials	2.81	3.98	864
ACS Nano	2.79	2.73	1189
PLoS Computational Biology	2.70	1.58	504
Journal of the American College of Cardiology	2.62	4.58	417
Circulation	2.57	4.57	587
NeuroImage	2.48	1.92	1217
Plant Physiology	2.47	1.94	459
Cancer Research	2.46	2.04	620
Bioinformatics	2.43	2.14	727
Energy and Environmental Science	2.39	2.63	472
Nucleic Acids Research	2.30	2.40	1417
PLoS Pathogens	2.28	1.79	625
Molecular Ecology	2.24	1.70	445
Journal of Neuroscience	2.17	1.96	1624
Journal of Medicinal Chemistry	2.15	1.76	865
Physical Review - Letters	2.13	2.49	3699
Pediatrics	2.12	3.02	641
Journal of the American Chemical Society	2.11	2.39	3056
Analytical Chemistry	2.08	1.71	1458
Proceedings of the Royal Society of London, Series B : Biological Sciences	2.05	1.87	606
PLoS Genetics	2.02	1.83	691

Table 6: Top 25 WoS journals with a minimum of 400 papers in 2012 sorted by the DNRI

Journal	**DNRI**	**SNIP**	**No. of papers**
Cell	4.52	6.33	415
Nature	4.39	8.81	858
Science	3.58	8.31	826
Molecular Ecology	2.83	1.70	445
Angewandte Chemie International Edition	2.64	2.34	2211
Nano Letters	2.62	3.74	1066
Journal of the American Chemical Society	2.48	2.39	3056
Plant Physiology	2.40	1.94	459
Nature Communications	2.33	2.65	700
Physical Review - Letters	2.32	2.49	3699

PLoS Genetics	2.26	1.83	691
Organic Letters	2.21	1.35	1571
Proceedings of the Royal Society of London, Series B : Biological Sciences	2.18	1.87	606
Earth and Planetary Science Letters	2.11	1.69	513
IEEE Transactions on Power Electronics	2.05	4.13	437
Advanced Materials	2.02	3.98	864
Proceedings of the National Academy of Sciences of the United States of America	2.02	2.69	3637
ACS Nano	1.94	2.73	1189
Physical Review A :: Atomic, Molecular, and Optical Physics	1.88	1.1	2662
Energy and Environmental Science	1.88	2.63	472
Journal of the American College of Cardiology	1.87	4.58	417
Monthly Notices of the Royal Astronomical Society	1.86	1.5	2365
Bioinformatics	1.84	2.14	727
The Astrophysical Journal	1.82	1.74	2653
Organometallics	1.76	0.95	897

Most journals appear in both Tables (5 and 6). In 10 cases, a journal is in the top 25 according to the MNRI but not according to the MNRS. Among those, in six cases the journal is still among the top 50 of the DNRI list. The journals *Cancer Research*, *Journal of Medicinal Chemistry*, *Pediatrics*, and *Analytical Chemistry* are located on the ranks 71, 107, 112, and 122, respectively, out of 9,563 journals ordered by DNRI. However, as the differences of DNRI and MNRS values between close ranks is rather small, we refrain from discussing the journal ranks in more depth.

Many citation-based indicators for journal performance have been proposed. We have added the Source Normalized Impact per Paper (SNIP) (Henk F. Moed, 2010) from 2012 to Tables 5 and 6. The SNIP includes in addition to articles and reviews also conference papers. It is calculated using publications from 2009 – 2011. The MNRS seems to correlate better with the SNIP than the DNRI which was verified by calculation of the Spearman Rank coefficients for both sets (r_s = 0.62 for MNRS vs. SNIP and r_s = 0.42 for DNRI vs. SNIP). A comparison of the correlation coefficients has to be done carefully, as the SNIP is calculated using different publication types and years than the DNRI and MNRS. Papers published in

2012 have had a rather short citation window. Therefore, we compare with the SNIP 2012 which is based on the publication years 2009 – 2011.

Figure 5 shows the MNRS and DNRI values of all WoS journals of the publication year 2012 which were found at Mendeley. Both normalization methods (paper-side and reader-side) seem correlate rather well in the regions with MNRS < 5 and DNRI < 5. This is the region where most journals are located. The linear regression with all journals included resulted in the straight line in Figure 5. The Spearman Rank coefficient was determined as r_s=0.74. Thus, the indicators DNRI and MNRS correlate better with each other than with the SNIP. As they are reader-based rather than citation-based, they seem to capture some of the effects which are included in citation-based indicators, but also seem to measure another kind of impact.

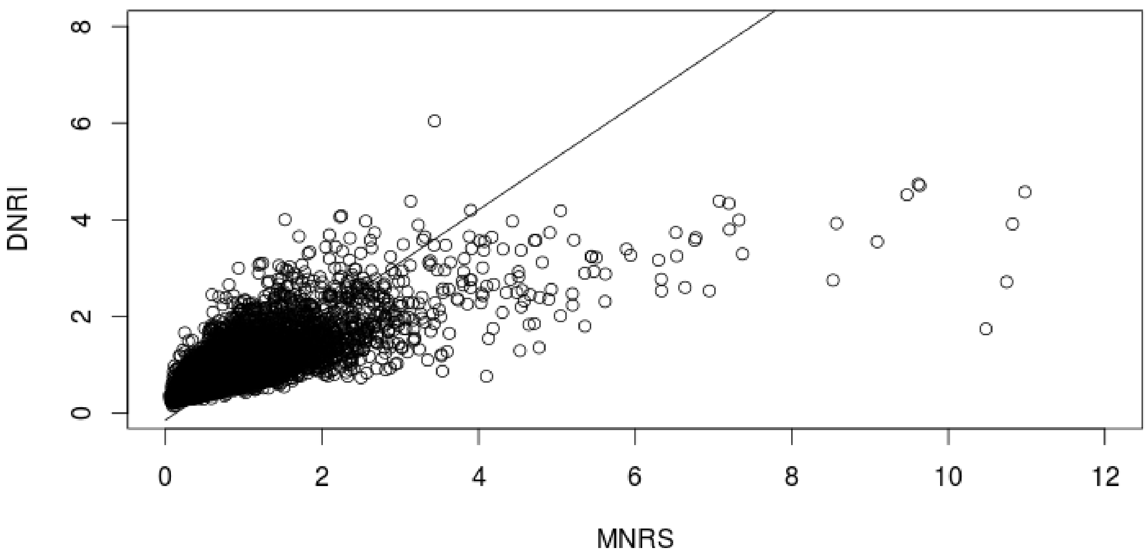

Figure 5: Scatter plot of DNRI and MNRS for 9,563 WoS journals

3.5 Normalized reader impact of universities

Table 7 shows the MNCS, MNRS, and DNRI values as well as papers published in 2012 for the German top 10 universities according to the Leiden Ranking 2013 (http://www.leidenranking.com/ranking/2013) ordered by decreasing MNCS. For comparison, we added a variant of an indicator which is based on the citing-side normalization, namely the SNCS3 (Waltman & van Eck, 2013b). The indicator-specific values of all universities are rather similar. Therefore, we refrain from discussing the ranks of the universities.

Table 7: German top 10 universities with MNCS, MNRS, SNCS3, DNRI values, and papers published in 2012, ordered by decreasing MNCS

University	MNCS	MNRS	SNCS3*	DNRI	Papers in 2012
University Göttingen	1.83	1.33	1.54	1.29	2258
LMU München	1.49	1.32	1.51	1.25	4034
Tech University München	1.47	1.37	1.57	1.24	3027
University Bonn	1.45	1.22	1.60	1.19	2460
University Freiburg	1.42	1.30	1.43	1.20	2307
University Würzburg	1.40	1.30	1.40	1.27	1835
RWTH Aachen	1.40	1.16	1.48	1.16	2229
Goethe University Frankfurt	1.39	1.19	1.41	1.18	2072
Heidelberg University	1.38	1.25	1.40	1.17	3317
University Münster	1.37	1.25	1.49	1.26	1972

* SNCS3 values from 2010

A comparison of the established citation-based normalized indicators (MNCS and SNCS3) with the new readership-based normalized indicators (MNRS and DNRI) shows that the spread of all indicator values within the top 10 German Universities is rather similar, except for one outlier in the case of MNCS, which is discussed in the next section. Therefore, MNRS and DNRI seem to be suitable to serve for a ranking of Universities and other aggregation levels regarding Mendeley readership impact. Although the MNRS and DNRI values of the top10 German universities indicate that they perform about 30% better than average, their MNRS and DNRI average values are still quite far away from the top10% (for MNRS: 2.12 for articles and 2.36 for reviews and for DNRI: 1.95 for articles and 1.98 for reviews) and top1% (for MNRS: 5.82 for articles and 6.66 for reviews and for DNRI: 4.43 for articles and 4.63 for reviews) thresholds, see also Tables 1 and 4.

4 Discussion

Providers of altmetrics (such as Altmetric, Plum Analytics, etc.) only supply raw data counts of the individual altmetrics data. The Directorate for Science, Technology and innovation in Brussels stated that the “use of indicators of social media is relatively well established in advertising and marketing. Some organisations are starting to collect altmetrics on a commercial basis in relation to research publications. In this context, little is known about what individual altmetrics **mean**. This appears to provide a rich set of opportunities for research – though we are probably some time away from being able to think in a precise way about concepts such as a ‘field-normalised tweet’” (COMMITTEE FOR SCIENTIFIC AND TECHNOLOGICAL POLICY, 2014, p. 43). Here, we have proposed field-normalized indicators based on altmetrics. Although we used Mendeley readership counts, a similar normalization procedure as for MNRS can also be performed for tweets from Twitter. However, as Twitter does not provide disciplinary categories for twittered publications, the procedure of the DNRI cannot be used for Tweets.

Our proposed indicators seem to be able to normalize Mendeley readership counts. Successful applications for journal and university rankings have been shown. The MNCS and DNRI values can also be applied for individual researchers and other aggregation units. However, for smaller aggregation units, such as researchers, more publication years should be taken into account. We found a rather good correlation between the DNRI and MNRS values themselves as well as between journal ranks on the basis of DNRI and MNRS values. The MNRS and DNRI values can be interpreted such that a value of 1.5 indicates that this paper has 50% more Mendeley reader counts than average.

The University of Göttingen has rather high values of DNRI, SNCS3, MNRS, and MNCS. However, the difference in the indicators to the next University is much larger in the case of MNCS (ΔMNCS = 0.34) than for MNRS, SNCS3, and DNRI (ΔMNRS = 0.01, ΔSNCS3 = 0.03 and ΔDNRI = 0.02). This is due to a single paper from 2008 which is not included in the data set of MNRS and DNRI (Waltman et al., 2012). The MNCS values are based on papers published between 2008 and 2011 while the MNRS and DNRI values are based on papers published in 2012. Therefore, a comparison of the MNRS and DNRI values with MNCS values should be carried out with caution. Using the newer Leiden Ranking would have introduced another problem: The Leiden Ranking 2014 is no longer based on the WoS categories but on a co-citation cluster algorithm (Ruiz-Castillo & Waltman, 2014), so that those newer MNCS values are hard to compare to the MNRS and DNRI values as well.

Interpretation of Mendeley reader counts themselves is more problematic than interpretation of the normalized value. Scientists do not read papers in the Mendeley application or in the web interface. Usually, scientists add a paper to their Mendeley library when they intend to cite the paper. Therefore, Mendeley reader counts can be interpreted as citation to be. However, a scientist might intent to cite a paper and reconsider it. Also, the scientist might cite a paper multiple times while having this paper in the Mendeley library. In this case the scientist is still counted as one Mendeley reader.

5 Conclusions

We have proposed two different methods for normalization of Mendeley reader counts. The paper-side normalization (yielding the MNRS) is related to the cited-side normalization, while the reader-side normalization (yielding the DNRI) is similar in spirit to the citing-side normalization. Both methods seem to be able to normalize reader counts, although the paper-side normalization seems to be slightly superior, based on a test for OECD categories. A very strong correlation was found between the DNRI and MNRS values themselves as well as journal rankings based on both new reader impact indicators. Less strong, but still significant correlations were found between DNRI and SNIP as well as

MNRS and SNIP. A comparison of the German top 10 universities shows that also University rankings based normalized readership values are possible.

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