Journal of Scientometric Res. 2020; 9(3):293-299
http://www.jscires.org

Research Article

Science Map of Cochrane Systematic Reviews Receiving the Most Altmetric Attention Score: A Network Analysis

Jafar Kolahi[1], Saber Khazaei[2], Elham Bidram[3], Roya Kelishadi[4], Pedram Iranmanesh[5], Abbasali Khademi[6], Mohammad H. Nekoofar[7,8], Paul M. H. Dummer[8]

[1]*Independent Research Scientist, Founder and Associate Editor of Dental Hypotheses, Isfahan, IRAN.*
[2]*Department of Endodontics, School of Dentistry, Kermanshah University of Medical Sciences, Kermanshah, IRAN.*
[3]*Biosensor Research Center, Department of Biomaterials, Nanotechnology, and Tissue Engineering School of Advanced Technologies in Medicine, Isfahan University of Medical Sciences, Isfahan, IRAN.*
[4]*Department of Pediatrics, Child Growth and Development Research Center, Research Institute for Primordial Prevention of Non-Communicable Disease, Isfahan University of Medical Sciences, Isfahan, IRAN.*
[5]*Dental Research Center, Department of Endodontics, Dental Research Institute, Isfahan University of Medical Sciences, Isfahan, IRAN.*
[6]*Dental Research Center, Department of Endodontics, Dental Research Institute, Isfahan University of Medical Sciences, Isfahan, IRAN*
[7]*Department of Endodontics, School of Dentistry, Tehran University of Medical Sciences, Tehran, IRAN.*
[8]*School of Dentistry, College of Biomedical and Life Sciences, Cardiff University, Cardiff, UK.*

ABSTRACT

The present study aimed to analyze and visualize the science map of Cochrane systematic reviews (CSRs) with high Altmetric attention score (AAS). On 2020-07-29, the altmetric data of the Cochrane Database of Systematic Reviews were obtained from the Altmetric database (Altmetric LLP, London, UK). Bibliometric data of the top 5% AAS of CSRs were extracted from the Web of Science. Keyword co-occurrence, co-authorship and co-citation network analyses were then employed using VOSviewer software. The random forest model was used to rank the importance of the altmetric resource. A total of 11222 CSRs with AAS were found (Total mentions: 305265), with Twitter being the most popular Altmetric resource. Consequently, the top 5% AAS (649 articles, mean AAS: 204.95, 95% confidence level: 18.95, mean citations: 123.68, 95% confidence level: 13.9) were included. Density mapping revealed female, adult and child as the most popular author keywords. According to network visualization, Helen V. Worthington (University of Manchester, Manchester, UK), the University of Oxford and UK had the greatest impact on the network at the author, organization and country levels respectively. AAS were weekly correlated with citations (r_s=0.21) although citations were moderately correlated with policy document and blog mentions (r_s=0.46 and r_s=0.43). Cochrane systematic reviews received high levels of online attention, particularly in the Twittersphere and mostly from the UK. However, CSRs were rarely publicized and discussed using recently developed academic tools, such as F1000 prime, Publons and PubPeer.

Keywords: Cochrane systematic review, Altmetric, Bibliometric, Twitter, Machine learning, Network analysis, Random forest.

Correspondence
Pedram Iranmanesh
Department of Endodontics, School of Dentistry, Isfahan University of Medical Sciences, Hezar-Jerib Ave., Isfahan, IRAN.
Phone no: + 98-31-36692588
Email: pedram.iranmanesh@yahoo.com

Received: 04-06-2020
Revised: 27-09-2020
Accepted: 15-10-20 20
DOI: 10.5530/jscires.9.3.36

INTRODUCTION

Cochrane is a British charity founded by Iain Chalmers in 1993. The organization was created specifically to manage medical research findings in order to facilitate the evidence-based choices in health interventions faced by health professionals, patients, health policymakers, as well as those interested in health to make informed decisions about health promotion. Cochrane includes 53 review groups from 130 countries.[1]

Alternative metrics, abbreviated to altmetrics, is an emerging academic tool that measures the online attention surrounding scientific research outputs.[2–4] It complements, but does not replace, the traditional citation-based metrics.[5] Altmetric data resources include Twitter, Facebook (mentions on public pages only), Google+, Wikipedia, news stories, scientific blogs, policy documents, patents, post-publication peer reviews (Faculty of 1,000 Prime, PubPeer), Weibo, Reddit, Pinterest, YouTube, online reference managers (Mendeley and CiteULike) and sites running Stack Exchange (Q&A).[6] In comparison with traditional citation-based metrics, altmetric data resources are updated rapidly. A recent bibliometric analysis revealed that only 50% of articles were cited in the first three years after publication.[7] In contrast,

several altmetric data resources are updated in real-time (e.g. Twitter and Wikipedia) or on a daily-basis (e.g. Facebook).

Research funders and charities such as the Welcome Trust and John Templeton Foundation pay attention to altmetric analysis.[8] A study on the influence of the alcohol industry on alcohol policy would be a good example of their engagement.[9] The study was supported by the Welcome Trust, which invests approximately £600 million (US$ 936 million) a year in research, and alleged that several submissions to the Scottish government misrepresented research outputs so as to support policies preferred by the alcohol industry. Three months following this publication in PLOS medicine, it remained without citation. Yet, altmetrics enabled the Welcome Trust to understand that this article had been tweeted by the key influencers, including members of the European Parliament, international non-governmental organizations and a sector manager for Health, Nutrition and Population at the World Bank to reveal its global impact on the policy sphere.[8]

Objectives and Scope of the study

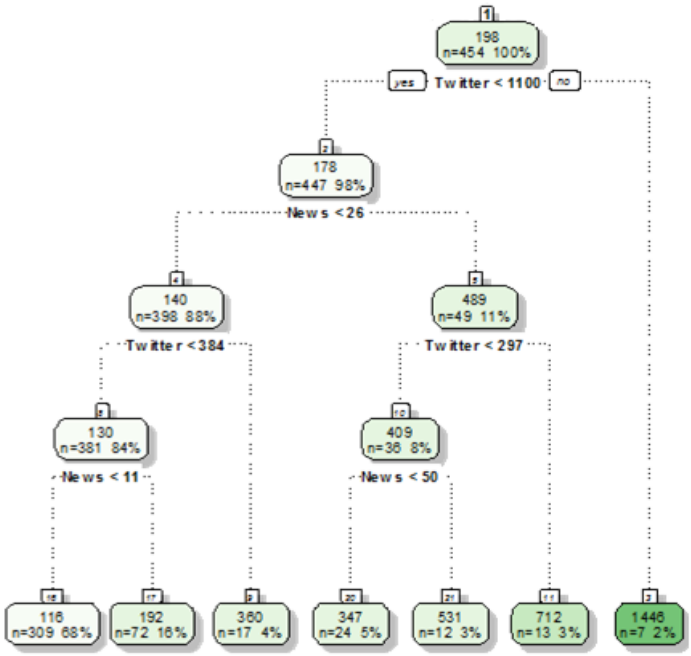
Altmetrics research is a growing field in medical sciences.[10–13] Online attention surrounding medical articles have been assessed in many fields of medical sciences e.g. neurology and cardiovascular sciences.[14,15] It is well-known that the Cochrane Systematic Reviews (CSRs) do a great role in evidence-based medicine. Bibliometrics of CSRs have been analyzed and discussed previously.[16] To our knowledge altmetrics of CSRs has not been analyzed. Here we aimed to analyze and visualize the knowledge structure of CSRs with high Altmetric attention score (AAS) to discover the hot topics and influential researchers, institutions and countries. Furthermore, we planned to assess influential factors regarding AAS and the number of citations via machine learning.

METHODOLOGY

On 2020-07-29, the altmetric data associated with the Cochrane Database of Systematic Reviews (ISSN: 13616137, 1469493X) (CDSRs) were obtained from the Altmetric database (Altmetric LLP, London, UK). The bibliometric data of the top 5% CSRs with the highest AAS were extracted from the Web of Science using their DOI. The bibliometric data were imported as a UTF-8 encoded txt files to VOSviewer 13.6.1 software (http://www.vosviewer.com/, Centre for Science and Technology Studies, Leiden University, Leiden, the Netherlands) for author keyword co-occurrence, co-authorship, co-citation network analyses and density visualization.[17]

The Spearman correlation coefficient was applied to identify any correlation between the main altmetric resources and the number of citations. The source of citation counts was Dimensions database.[18] Principal component analysis (based on a correlation matrix) was used to represent the data in smaller components than the dataset eventually consisted of. Chi-squared tests were used to test the fitness of the model.

The random forest regression (a machine learning algorithm) was conducted to rank the influential factors affecting the AAS and the number of citations. The random forest is made up of several random decision trees which work together like a forest. Each single decision tree is a flowchart-like model in which each internal node represents a "test" on an attribute (e.g. whether the number of tweets < 1100) to make classifications (Appendix 1). The concluding forecasts of the random forest are made by averaging the forecasts of each individual tree.[19]



Appendix 1: Example of a decision tree. In this study to create a random forest model, 500 random decision trees were made by random sampling of training data points and random subsets of features applied when splitting nodes.

Data analysis was carried out using R 3.6.3 software (R Foundation for Statistical Computing, Vienna, Austria). Excel 2016 was used to draw graphs and data-bar visualizations.

RESULTS

A total of 11222 CSRs with AAS were found (total mentions: 305265). Twitter was the most popular altmetric resource (Figure 1) with Tweets originating mainly from the UK (47,897 (18.7%)), Spain (22,953 (9%)) and the US (20,513 (8%)). In addition, @CochraneUK (4,886 total mentions from this Twitter user) was the most active altmetric resource, followed by @CochraneLibrary (1,952 total mentions from

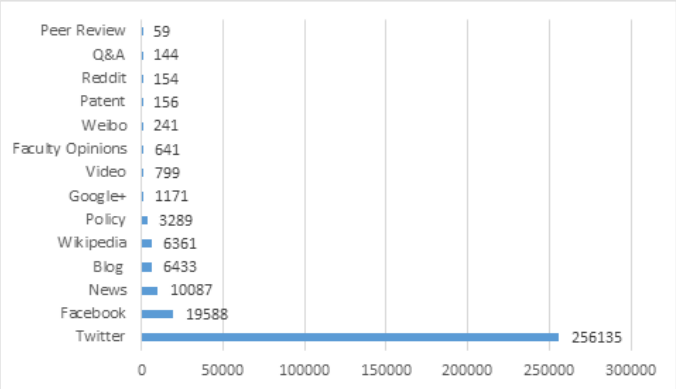


Figure 1:. Sum of scores of various Altmetric data resources among all Cochrane systematic reviews.

(Figure 4 and 5). The co-citation network analysis revealed that the Lancet and CDSRs had the greatest influence on the network (Figure 6).

AAS were weekly correlated with citations (r_s=0.21, 95% confidence interval 0.14 to 0.29, p<0.001) (Figure 7 and 8) but citations had moderate correlation with policy document mentions (r_s=0.46, 95% confidence interval 0.39 to 0.52, p<0.001) and blog mentions (r_s=0.43, 95% confidence interval 0.36 to 0.49, p<0.001). The goodness of fit test confirmed the principal component analysis was used successfully to attribute the main altmetric data resources and citations into three different components (p<0.001) (Figure 7).

Table 1: Data-bar visualization of the top ten Cochrane systematic reviews receiving the most altmetric attention.

Altmetric Score	Title	Publication Date	News	Blog	Policy	Twitter	Facebook	Citations
2880	Vitamin C for preventing and treating the common cold	1/31/2013	353	56	1	1273	110	208
2294	Physical interventions to interrupt or reduce the spread of respiratory viruses	7/6/2011	102	25	10	2517	11	181
1933	Quarantine alone or in combination with other public health measures to control COVID-19: a rapid review	4/8/2020	133	6	2	1400	18	59
1683	Antibody tests for identification of current and past infection with SARS-CoV-2	6/25/2020	90	9	0	1845	24	4
1606	Omega-3 fatty acids for the primary and secondary prevention of cardiovascular disease	2/29/2020	91	16	0	1478	37	106
1501	Prophylactic vaccination against human papillomaviruses to prevent cervical cancer and its precursors	5/9/2018	93	14	0	1620	36	153
1302	Electronic cigarettes for smoking cessation	9/13/2016	144	12	12	415	16	372
1251	Nurses as substitutes for doctors in primary care	7/16/2018	23	1	4	1839	20	93
1246	Portion, package or tableware size for changing selection and consumption of food, alcohol and tobacco	9/14/2015	114	20	2	1032	18	192
1008	Workplace interventions for reducing sitting at work	12/17/2018	98	13	1	464	17	110

this Twitter user) and @CochraneOHG (1,773 total mentions from this Twitter user).

Consequently, the top 5% CSRs (649 articles, mean AAS: 204.95, 95% CL: 18.95, mean citations: 123.68, 95% CL: 13.9) with the highest AAS were included in the study. The bibliometric data of 599 articles found in the Web of Science were further analyzed. "Vitamin C for preventing and treating the common cold" had the highest AAS (score: 2880) among the CSRs (Table 1).

Density visualization indicated that "female", "adult" and "child" were the most popular keywords used by authors (Figure 2). Moreover, the network analysis at author level revealed Helen V. Worthington (Co-Coordinating Editor of the International Cochrane Oral Health Group) had the greatest impact on the network and Lee Hooper (Research Synthesis, Nutrition and Hydration at Norwich Medical School) had a central connecting role in the network (Figure 3). At organization and country levels, the University of Oxford and the UK had the greatest impact on the network

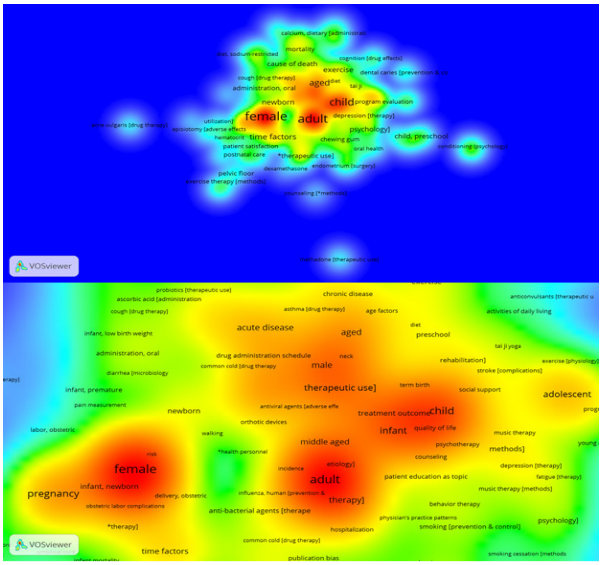


Figure 2:. Hot topics among author keywords of the top 5% Cochrane systematic reviews receiving the most altmetric attention. The lower part zoomed on central hot zones. The distance-based approach was used to create this map, which means the smaller the distance between two terms, the higher their relatedness.

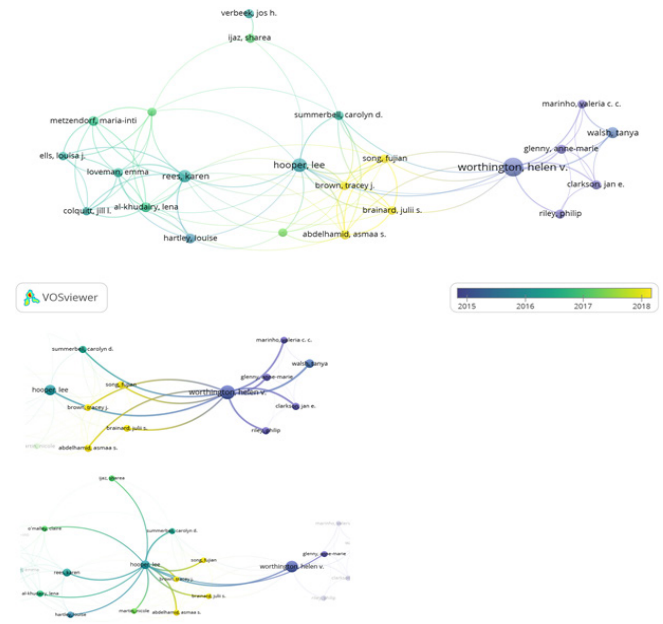


Figure 3: Co-authorship network visualization of top 5% Cochrane systematic reviews receiving the most altmetric attention. The lower parts showed the personal networks of Helen V. Worthington and Lee Hooper. These two people had deep connections with contemporary growing influential authors (yellow nodes).

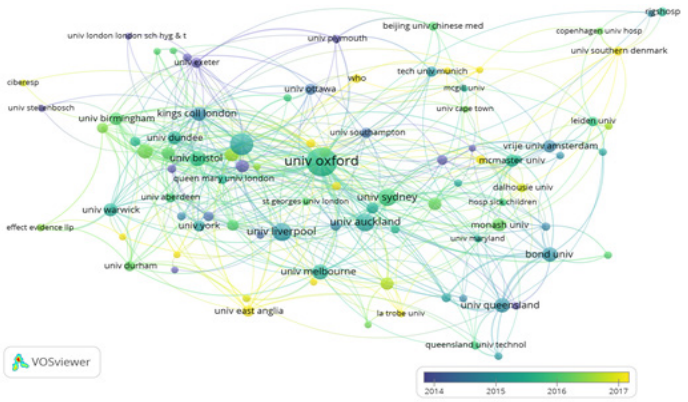


Figure 4:. Organization level co-authorship network visualization of top 5% Cochrane systematic reviews receiving the most altmetric attention.

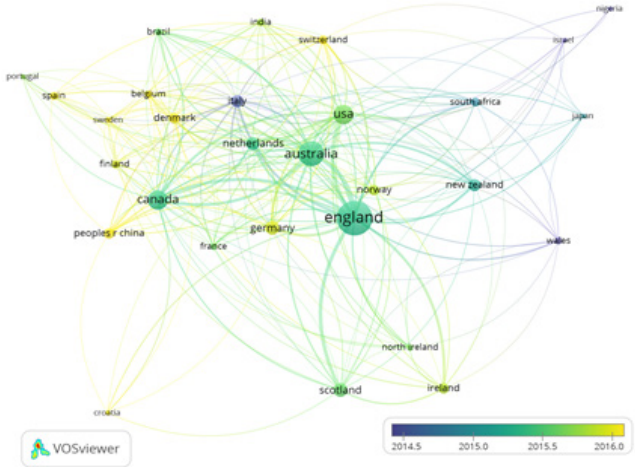


Figure 5: Country level co-authorship network visualization of top 5% Cochrane systematic reviews receiving the most altmetric attention.

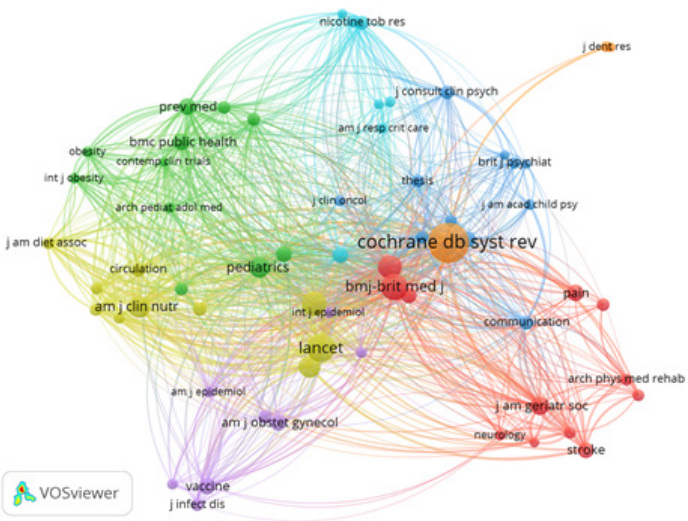
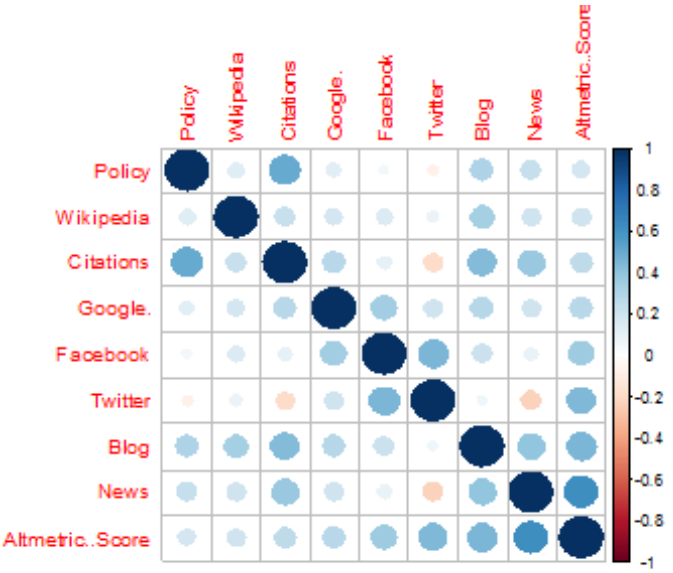


Figure 6: Co-citation network visualization among resources of top 5% Cochrane systematic reviews receiving the most altmetric attention.



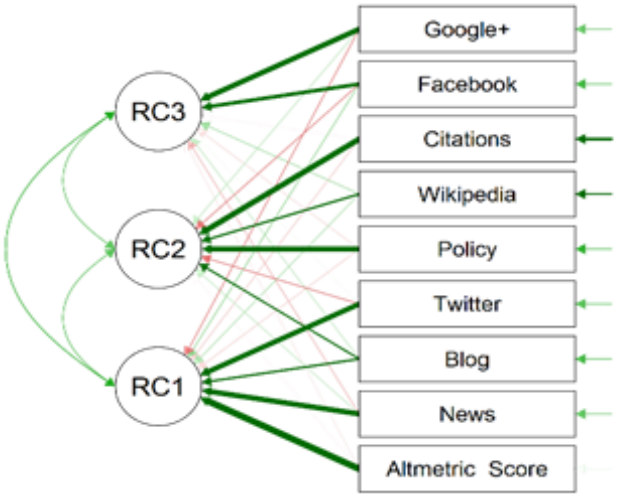


Figure 7:. Correlation matrix visualization among Altmetric score, citations and other important altmetric resources (upper part). Path diagram showed the results of principal component analysis based on the correlation matrix (lower part) (p<0.001). (RC: Related Components)

Results from the random forest model confirmed the importance of policy document mentions regarding citations. News and Twitter were the most influential factors regarding altmetric scores (Figure 9).

DISCUSSION

It is widely believed that CSRs are one of the most important resources in evidence-based clinical decision-making.[20] In the present study, we analyzed the social impact of this reliable medical evidence using altmetrics. The number of social media users has been estimated to escalate to 3.09 billion by 2021.[21] The primary source of altmetric for CSRs was Twitter, a microblogging service with 330 million active users[22] that can act as an important social media to broadcast and find academic information all over the globe.[23–25] Several well-known academic healthcare providers such as the Mayo Clinic also use social media (@MayoClinic with 1.92 million followers and 47600 tweets) to communicate with peers and patients to disseminate trusted medical information.[26] Although the geographical breakdown of Tweets demonstrated they were mainly posted from the UK, the demographic characteristics, social class and occupation of those who Tweeted about CSRs could not be obtained for technical restrictions. In addition, Facebook was ranked the second altmetric resource for CSRs; however; these reviews were not too popular in this social media. Facebook could play an effective role in the rapid distribution of research findings via acknowledgement of substantially active users as well as tools (e.g. chat) that may enable a direct interaction between researchers and target audiences such as peers and patients.[27]

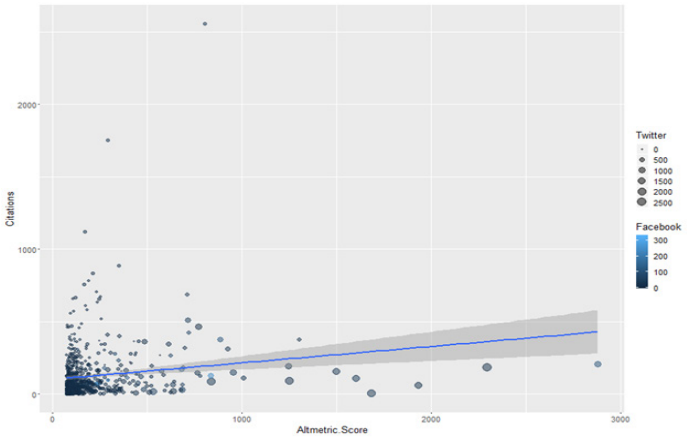


Figure 8:. Scatter plot examining the relationship between Altmetric score and citations. Fitted line represents the linear correlation with 95% confidence interval (r=0.21, 95% confidence interval 0.14 to 0.29, p<0.01 and n=649).

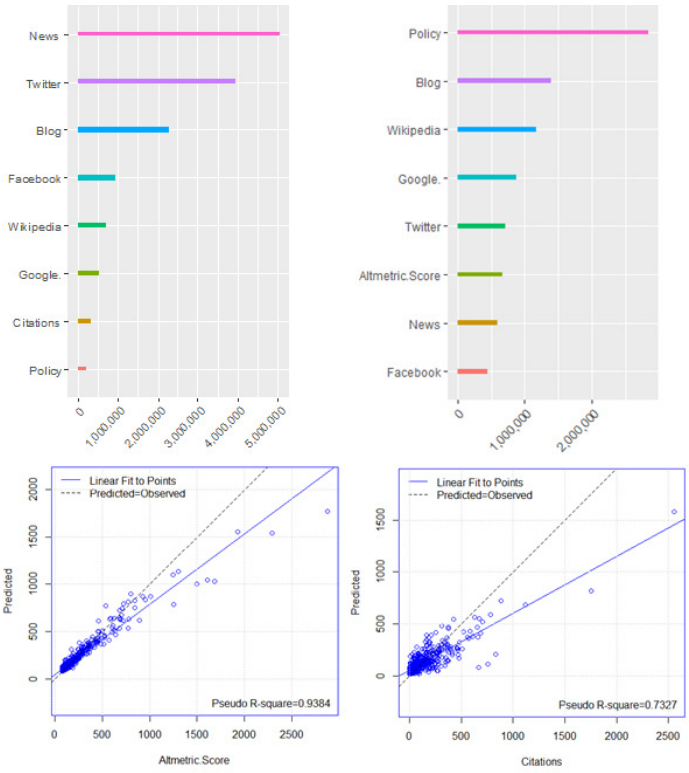


Figure 9: The output of the random forest model showing the relative importance of different altmetric resources considering Altmetric score (left side) and citations (right side) as targets (Number of observations used to build the model: 424, Number of trees: 500). Accuracy of the model is shown in the lower part via predicted versus observed plot.

Despite the popularity of CSRs in the Twittersphere, they were rarely shared and discussed within the emerging academic tools such as F1000 prime, Publons and PubPeer. The post-publication peer review tools allow the scientific community the ability to quickly identify misconduct, fraud, or error in the context of research. F1000 prime recommendations also help scientists to discover key documents in the medical field.[28] Hence, considering the advantages of these new academic tools, both researchers and publishers should pay more attention to this issue. Although the English medical articles on Wikipedia received more than 2.4 billion official visits in 2017,[29,30] the overall Wikipedia mentions among the CSRs were low considering the established partnership between Wikipedia and Cochrane collaboration.[31] Of more interest, CSRs were widely cited among the policy documents, which is promising considering the principles of evidence-based policymaking have an undeviating impact on the health of communities.[32]

It has been reported that journals with their own Twitter account get 34 percent more citations and 46 percent more tweets than journals without a Twitter account.[33] Of more interest, the Cochrane organization and related groups such as @cochranecollab (103.8K followers and 13.7K Tweets), @CochraneUK (54.4K followers and 37K Tweets), @CochraneLibrary (70K followers and 7191 Tweets), @CochraneCanada (5572 followers and 6462 Tweets) were active in the Twittersphere. Among the 11222 Cochrane systematic reviews included in this study, the total number of citations was 80272. With respect to the ratio of number

of Twitter followers (≈233772) to the number of citations (80272), the Cochrane institution must be aware of becoming a Kardashian organization (i.e. overactive in the Twittersphere).[34]

Human knowledge in the medical field is rising incredibly in this information age, so scientists are fronting overloaded information (also known as infobesity, infoxication and information explosion), which needs to be handled carefully. In addition to the enormous data and text analysis methods, science mapping makes it possible to review this abundant amount of data effortlessly. Density visualization map of CSRs revealed the newly emerging and innovative concepts, e.g. genomic medicine, nanotechnology and artificial intelligence, were not included among the hot topics. This finding may be explained by the retrospective nature of CSRs which was also reported in the field of Dentistry,[13,35–37] Endodontology[38] and Iranian medical journals.[39]

Citation analysis is considered an important part of scientometric research. In contrast to the conventional methods of classic citation analysis, which provide limited information, co-citation network analysis can illustrate patterns, trends and association through visualization of a set of multiplex citation data. The co-citation network visualization disclosed numerous well-respected journals in the network, in which the Lancet and CDSRs had the most influence on the network. This finding may be explained by the Lancet-Cochrane collaborate on systematic reviews.[40]

Despite the fact that popular CSRs received a high citation rate, no significant correlation was observed between the number of citations and AAS. Likewise, no significant correlation was reported between the number of citations and AAS for the research articles published in high-impact general medicine journals,[41] the cardiovascular field,[42] radiology[43] and dentistry.[44,45] In contrast, a large-scale survey indicated a significant correlation between six altmetric resources (tweets, Facebook wall posts, research highlights, blog mentions, mainstream media mentions and forum posts) and citation counts.[46] Among the six specialized PloS journals, a significantly positive correlation was found between the normalized AAS and normalized citation counts.[47] Above all, the correlation between AAS and citations is a controversal issue that needs further research and meta-analysis.

In this study, the random forest method was used to find influential factors regarding AAS and the number of citations. This machine learning approach is a newly growing concept in biomedical research. Pubmed query with the term "random forest " revealed 7,177 results. Trendline analysis showed number of articles in this regard are growing fast (Number of articles = $11.379y^2 - 45679y + 5E+07$, $R^2 = 0.94$, y=year). This rapid growth may be explained by advantages of this method such as handling different dimensions (features) of the data, judgements about the importance of the feature, being relatively simple to implement, quick prediction and training speed, low bias, etc.[48,49]

The limiations of the present study should be considered. AAS may fluctuate over time in contrast to conventional bibliometrics. Moreover, altmetric data of some distinguished social media such as ResearchGate, Instagram and LinkedIn could not be retrieved because of technical limitations. In addition, some altmetric resources may be prone to gaming; for example, fake accounts or robots may increase the number of Tweets more than the reality.[50] Lastly, censorship and restrction of some altmetric resources, particularly Twitter, in some countries may limit the estimation of the social impact of CSRs.[13]

CONCLUSION

The top 5% CSRs had a high AAS. Twitter was the most popular resource. Tweets generally originated from the UK. Popular CSRs received a high citation rate; however, there was no significant correlation between the citation counts and AAS.

ACKNOWLEDGEMENT

We would like to thank Altmetric LLP (London, UK), particularly Mrs. Stacy Konkiel for giving us valued support and permitting us to have complete access to altmetric data.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ABBREVIATIONS

AAS: Altmetric attention score; **CSRs:** Cochrane systematic reviews; **CDSRs:** Cochrane Database of Systematic Reviews.

REFERENCES

1. Morley RF, Norman G, Golder S, Griffith P. A systematic scoping review of the evidence for consumer involvement in organisations undertaking systematic reviews: Focus on cochrane. Research Involvement and Engagement. 2016;2(1):36. doi:10.1186/s40900-016-0049-4
2. Konkiel S. What can altmetrics tell us about interest in dental clinical trials?. Dental Hypotheses. 2017;8(2):31-3. doi:10.4103/denthyp.denthyp_12_17
3. Kolahi J. Altmetrics: A new emerging issue for dental research scientists. Dental Hypotheses. 2015;6(1):1-2. doi:10.4103/2155-8213.150855
4. Kwok R. Research impact: Altmetrics make their mark. Nature. 2013;500(7463):491-3. doi: 10.1038/nj7463-491a
5. Butler JS, Kaye ID, Sebastian AS, *et al.* The Evolution of Current Research Impact Metrics: From Bibliometrics to Altmetrics?. Clinical Spine Surgery. 2017;30(5):226-8. doi: 10.1097/BSD.0000000000000531
6. Patthi B, Prasad M, Gupta R, *et al.* Altmetrics: A Collated Adjunct Beyond Citations for Scholarly Impact: A Systematic Review. Journal of Clinical and Diagnostic Research. 2017;11(6):ZE16-20. doi:10.7860/JCDR/2017/26153.10078
7. Wang J. Citation time window choice for research impact evaluation. Scientometrics. 2013;94(3):851-72. doi:10.1007/s11192-012-0775-9
8. Dinsmore A, Allen L, Dolby K. Alternative Perspectives on Impact: The Potential of ALMs and Altmetrics to Inform Funders about Research Impact. PLoS Biology. 2014;12(11):e1002003. doi:10.1371/journal.pbio.1002003

9. McCambridge J, Hawkins B, Holden C. Industry Use of Evidence to Influence Alcohol Policy: A Case Study of Submissions to the 2008 Scottish Government Consultation. PLoS Medicine. 2013;10(4):e1001431. doi:10.1371/journal.pmed.1001431
10. Kolahi J, Khazaei S. Altmetric analysis of contemporary dental literature. British Dental Journal. 2018;225(1):68-72. doi:10.1038/sj.bdj.2018.521
11. Kolahi J, Iranmanesh P, Khazaei S. Altmetric analysis of 2015 dental literature: A cross sectional survey. British Dental Journal. 2017;222(9):695-9. doi:10.1038/sj.bdj.2017.408
12. Serghiou S, Ioannidis JPA. Altmetric Scores, Citations and Publication of Studies Posted as Preprints. Journal of the American Medical Association. 2018;319(4):402-3. doi:10.1001/jama.2017.21168
13. Kolahi J, Khazaei S, Iranmanesh P, Soltani P. Analysis of highly tweeted dental journals and articles: A science mapping approach. British Dental Journal. 2019;226(9):673-8. doi:10.1038/s41415-019-0212-z
14. Punia V, Aggarwal V, Honomichl R, Rayi A. Comparison of Attention for Neurological Research on Social Media vs Academia: An Altmetric Score Analysis. Journal of the American Medical Association Neurology. 2019;76(9):1122-4. doi:10.1001/jamaneurol.2019.1791
15. Patel RB, Vaduganathan M, Bhatt DL, Bonow RO. Characterizing High-Performing Articles by Altmetric Score in Major Cardiovascular Journals. Journal of the American Medical Association Cardiology. 2018;3(12):1249-51. doi:10.1001/jamacardio.2018.3823
16. Shen J, Li Y, Clarke M, Du L, Wang L, Zhong D. Visualization of evidence-based medicine domain knowledge: Production and citation of cochrane systematic reviews. Journal of Evidence-Based Medicine. 2013;6(1):34-42. doi:10.1111/jebm.12022
17. Eck NJV, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010;84(2):523-38. doi:10.1007/s11192-009-0146-3
18. Noorden RV. Science search engine links papers to grants and patents. Nature. 2018. doi:10.1038/d41586-018-00688-0
19. Ali J, Khan R, Ahmad N, Maqsood I. Random Forests and Decision Trees. International Journal of Computer Science Issues. 2012;9(5):272-8.
20. Clarke M. The Cochrane Collaboration and The Cochrane Library. Otolaryngol - Head and Neck Surgery. 2007;137(4 Suppl.):S52-4. doi:10.1016/j.otohns.2007.05.050
21. Clement J. Number of global social network users 2010-2023. Statista. 2020. https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/. Published 2020.
22. Clement J. Twitter: Number of active users 2010-2019. Statista. https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/. Published 2019.
23. Mohammadi E, Thelwall M, Kwasny M, Holmes KL. Academic information on Twitter: A user survey. PLoS One. 2018;13(5):e0197265. doi:10.1371/journal.pone.0197265
24. Pershad Y, Hangge P, Albadawi H, Oklu R. Social Medicine: Twitter in Healthcare. Journal of Clinical Medicine. 2018;7(6):121. doi:10.3390/jcm7060121
25. Kolahi J. Dental research output in twittersphere. Dent Hypotheses. 2017;8(1):1-2. doi:10.4103/denthyp.denthyp_3_17
26. Widmer RJ, Engler NB, Geske JB, Klarich KW, Timimi FK. An Academic Healthcare Twitter Account: The Mayo Clinic Experience. Cyberpsychology, Behavior, and Social Networking. 2016;19(6):360-6. doi:10.1089/cyber.2015.0607
27. Kolahi J. Facebook and contemporary dental researches. Dental Hypotheses. 2017;8(4):85-6. doi:10.4103/denthyp.denthyp_51_17
28. Kolahi J, Khazaei S. Post-publication peer review: A fresh perspective on dentistry publications. Dental Hypotheses. 2016;7(2):29-30. doi:10.4103/2155-8213.183754
29. Murray H. More than 2 billion pairs of eyeballs: Why aren't you sharing medical knowledge on Wikipedia?. BMJ Evidence-Based Medicine. 2019;24(3):90-1. doi:10.1136/bmjebm-2018-111040
30. Kolahi J, Iranmanesh P. Wikipedia and Dental Literature. Dental Hypotheses. 2018;9(4):77-9. doi:10.4103/denthyp.denthyp_75_18
31. Dawson J. The Cochrane-Wikipedia Partnership in 2020: Cochrane. Cochrane. 2020. https://www.cochrane.org/news/cochrane-wikipedia-partnership-2020. Published 2020.
32. Vanlandingham G, Silloway T, Chang V, *et al*. Evidence-Based Policymaking: A Guide for Effective Government. A Report from the Pew-MacArthur Results First Initiative Pew-MacArthur Results First Initiative Senior Advisers External Reviewers. 2014.
33. Ortega JL. The presence of academic journals on Twitter and its relationship with dissemination (tweets) and research impact (citations). Aslib Journal of Information Management. 2017;69(6):674-87. doi:10.1108/AJIM-02-2017-0055
34. Hall N. The Kardashian index: A measure of discrepant social media profile for scientists. Genome Biology. 2014;15(7):424. doi:10.1186/s13059-014-0424-0
35. Kolahi J, Dunning D, Rossomando E. Dental Articles Receiving the Most Online Attention in 2018. Dental Hypotheses. 2019;10(2):25-8. doi:10.4103/denthyp.denthyp_63_19
36. Kolahi J, Dunning D, Rossomando E. Scientific Landscape of Dental Literature in 2018. Dental Hypotheses. 2019;10(3):55-7. doi:10.4103/denthyp.denthyp_104_19
37. Kolahi J, Soltani P. Scientific Landscape of Dental Literature in 2017. Dental Hypotheses. 2018;9(2):29-30. doi:10.4103/denthyp.denthyp_29_18
38. Kolahi J, Khazaei S, Iranmanesh P, Khademi A, Nekoofar MH, Dummer PMH. Altmetric analysis of the contemporary scientific literature in Endodontology. International Endodontic Journal. 2019;13226. doi:10.1111/iej.13226
39. Kolahi J, Khazaei S, Bidram E, Kelishadi R. Altmetric Analysis of Contemporary Iranian Medical Journals. International Journal of Preventive Medicine. 2019;10:112. doi:10.4103/ijpvm.IJPVM_134_19
40. Clarke M, Horton R. Bringing it all together: Lancet-Cochrane collaborate on systematic reviews. Lancet. 2001;357(9270):1728. doi:10.1016/S0140-6736(00)04934-5
41. Barakat AF, Nimri N, Shokr M, *et al*. Correlation of Altmetric Attention Score and Citations for High-Impact General Medicine Journals: A Cross-sectional Study. Journal of General Internal Medicine. 2019;34(6):825-7. doi:10.1007/s11606-019-04838-6
42. Barakat AF, Nimri N, Shokr M, *et al*. Correlation of Altmetric Attention Score With Article Citations in Cardiovascular Research. Journal of the American College of Cardiology. 2018;72(8):952-3. doi:10.1016/j.jacc.2018.05.062
43. Rosenkrantz AB, Ayoola A, Singh K, Duszak R. Alternative Metrics ("Altmetrics") for Assessing Article Impact in Popular General Radiology Journals. Academic Radiology. 2017;24(7):891-7. doi:10.1016/j.acra.2016.11.019
44. Delli K, Livas C, Spijkervet FKL, Vissink A. Measuring the social impact of dental research: An insight into the most influential articles on the Web. Oral Diseases. 2017;23(8):1155-61. doi:10.1111/odi.12714
45. Kolahi J, Seyedhamzeh M, Dunning DG, Kalbasi N. Re-imagining machine learning in dental research: A lesson learned from the COVID-19 pandemic. engrXiv. 2020. doi:10.31224/osf.io/ap6xq.
46. Thelwall M, Haustein S, Larivière V, Sugimoto CR. Do Altmetrics Work? Twitter and Ten Other Social Web Services. PLoS One. 2013;8(5):e64841. doi:10.1371/journal.pone.0064841
47. Huang W, Wang P, Wu Q. A correlation comparison between Altmetric Attention Scores and citations for six PLOS journals. PLoS One. 2018;13(4):e0194962. doi:10.1371/journal.pone.0194962
48. Kho J. Why Random Forest is My Favorite Machine Learning Model. Towards Data Science. 2020. https://towardsdatascience.com/why-random-forest-is-my-favorite-machine-learning-model-b97651fa3706. Published 2018.
49. Breiman L. Random Forests. Machine Learning. 2001;45(1):5-32. doi:10.1023/A:1010933404324
50. Robinson-Garcia N, Costas R, Isett K, Melkers J, Hicks D. The unbearable emptiness of tweeting—About journal articles. PLoS One. 2017;12(8):e0183551. doi:10.1371/journal.pone.0183551