Journal of Biomedical Informatics 63 (2016) 390–399

Contents lists available at ScienceDirect

Journal of Biomedical Informatics

journal homepage: www.elsevier.com/locate/yjbin

Healthcare hashtag index development: Identifying global impact in social media

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ARTICLE INFO

Article history:
Received 15 February 2016
Revised 12 September 2016
Accepted 14 September 2016
Available online 16 September 2016

Keywords:
Bibliometrics
Internet
Social media
Family practice
Primary health care

ABSTRACT

Purpose: Create an index of global reach for healthcare hashtags and tweeters therein, filterable by topic of interest.

Materials and methods: For this proof-of-concept study we focused on the field of Primary Care and Family Medicine. Six hashtags were selected based on their importance, from the ones included in the 'Healthcare Hashtag Project'. Hashtag Global Reach (HGR) was calculated using the additive aggregation of five weighted, normalized indicator variables: number of impressions, tweets, tweeters, user locations, and user languages. Data were obtained for the last quarter of 2014 and first quarter of 2015 using Symplur Signals. Topic-specific HGR were calculated for the top 10 terms and for sets of quotes mapped after a thematic analysis. Individual Global Reach, IGR, was calculated across hashtags as additive indexes of three indicators: replies, retweets and mentions.

Results: Using the HGR score we were able to rank six selected hashtags and observe their performance throughout the study period. We found that #PrimaryCare and #FMRevolution had the highest HGR score in both quarters; interestingly, #FMChangeMakers experienced a marked increase in its global visibility during the study period. "Health Policy" was the commonest theme, while "Care", "Family" and "Health" were the most common terms.

Discussion: This is the first study describing an altmetric hashtag index. Assuming analytical soundness, the Index might prove generalizable to other healthcare hashtags. If released as a real-time business intelligence tool with customizable settings, it could aid publishing and strategic decisions by netizens, organizations, and analysts. IGR could also serve to augment academic evaluation and professional development.

Conclusion: Our study demonstrates the feasibility of using an index on the global reach of healthcare hashtags and tweeters.

1. Introduction

Social media use has risen exponentially each year on a global scale [1–4]. As a group of internet-based applications, they allow for the exchange of user-generated content, building on the concept of Web 2.0 [1,5]. These applications include blogs, discussion boards, wikis, and social networking sites [1]. In the medical domain, social media are increasingly used by clinicians and researchers as an efficient way of sharing information, keeping up-to-date with scientific knowledge and collaborating with both peers and patients [1,6–14].

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http://dx.doi.org/10.1016/j.jbi.2016.09.010
1532-0464/

Twitter has particularly gained traction among healthcare professionals and researchers [6–8,10–12,14–18]. While allowing netizens to freely read public messages up to 140 characters ("tweets"), only registered users ("tweeters") can write them, mention other users (by using the symbol @ followed by the username) and mark keywords or topics in a tweet using hashtags (by adding the symbol # before the chosen word).

As healthcare professionals' discussions move onto social media, citations of the literature on Twitter ("tweetations") and quotes of an argument or passage (nanopublications) are becoming increasingly common [2,15,19–21]. With millions of health-related tweets per day, the avalanche of data potentially suffocates healthcare professionals' ability to tap into the learning resources and collaboration opportunities provided by such digital conversations.

Traditional publications have various methods that calculate the influence and reach of medical literature [19,22]. Such a ranking, or impact factor, proves vital by quantifying and comparing a journal's competitiveness and importance to the medical community. Yet, as medical and scientific publication moves to the online world, traditional metrics fail to grasp the full picture - missing communication on social media, like Twitter. Social media-based metrics, also termed "altmetrics", create new ways to assess such communication [19,23,24]. Up until now there is no homologous ranking to gauge the quality or value of the online conversations.

We aim to create a reach index for healthcare hashtags; such index should be filterable by topic of interest; from it we aim to derive the individual impact of participants on those hashtags. Secondarily, the dynamics of the selected healthcare hashtag communities are to be examined and the themes addressed in tweets to be explored. In order to achieve these aims, we perform a proof of concept study on selected hashtags within the context of Primary Care and Family Medicine.

2. Materials and methods

2.1. Hashtag indexation

Hashtags were collated using a participatory approach incorporating the researchers and Twitter users [25]. Such hashtags revolved around Primary Care and Family Medicine, in accordance to the researchers' background. We excluded those which on 03/15/2015 were not part of the Healthcare Hashtag Project [26], the largest publicly available database of healthcare hashtags. The database is maintained by Symplur, a healthcare social media analytics company, while healthcare stakeholders can contribute with hashtags to it. For this study, hashtags for conferences were defined as ephemeral and excluded. Afterwards, Symplur.com was used to find each hashtag's total number of impressions for the immediate past 90 days (12/16/2014 12:00 AM UTC-7 to 03/15/2015 12:00 AM UTC-7). Total impressions are calculated by multiplying the number of tweets per participant by the followers count for that participant, and summing these numbers across all participants during the period under analysis [27].

The five hashtags with the highest total number of impressions were then selected for indexation: #PrimaryCare, #MakeHealthPrimary, #FMRevolution, #FMChangeMakers, #1care. A sixth hashtag, #1carejc, was also indexed as it derived from one of the top five, although it held a lower number of impressions.

2.2. Hashtag analysis

Each hashtag was retrospectively characterized for the last quarter of 2014 ($Q4_{14}$) and first quarter of 2015 ($Q1_{15}$), using Symplur Signals [28]. The studied variables were: (a) number of participants, (b) user locations, (c) user languages, (d) impressions and (e) tweets. Data were independently abstracted by two researchers.

The theoretical framework for the selection of these variables (and later combining them into a meaningful composite indicator, HGR) was based on a fitness-for-purpose principle with the involvement of experts and stakeholders who have participated in a specially run tweet chat [29,30].

2.3. Hashtag Global Reach (HGR)

HGR was calculated using the additive aggregation of weighted and normalized indicator variables [29].

The distance to a reference hashtag was used as the normalization method [29]. For each indicator variable, the reference was established as the leading, best performing hashtag and the relative position of the hashtags were measured vis-à-vis the reference [29]. Hence, for a given indicator variable, the reference hashtag has a value of 1, while other hashtags are given percentage points away from the reference, depending on their distance from the leader; standardized indicator variables that are closer to 1 indicate hashtags with the highest reach.

The five indicator variables were given equal weighting and the index computed as: $HGR = \sum 0.20\, I_i$, where "i" represents the index of summation and indexed variable "I" represents each indicator term in the series; "i" starts out equal to "1" and is incremented by "1" for each successive indicator variable, stopping when "i" equals "5". Equal weighting was chosen with reference to the theoretical framework, after participatory methods that incorporated the team of researchers in such weight negotiations, as previously described [29]. Hashtags were then ranked according to HGR.

2.4. Topic-specific HGR

Topics were established after the selection of keywords, which could either be single terms or sets of quotes:

- Symplur Signals' word frequency reports across hashtags guided the selection of terms: the ten most frequent words were selected by consensus after exclusion of adjectives, words deprived of clinical or scientific meaning and international relevance in the field of Family Medicine [28].
- As for quotes, four researchers used thematic analysis to obtain qualitative themes from textual data (as described in Section 2.6) and then mapped each theme to exemplifying quotes of up to three words. Abstracted quotes were later reviewed and compiled by an independent researcher into sets of keywords for each theme, using the Boolean operator "OR".

Keywords were used to filter each hashtags' database. Data on the indicator variables were independently abstracted by two researchers for each filter and topic-specific HGR calculated.

2.5. Individual Global Reach (IGR)

IGR was calculated for every participant on the six hashtags during the period under analysis, as an additive index of weighted and normalized indicator variables; fitness-for-purpose and equal weighting were adopted, as described for HGR and in the literature [29].

The following formula was used:

$IGR = \sum(R_i + M_i + RT_i) * HGR_i$, where "i" represents the index of summation and "R" stands for number of Replies, "M" for number of Mentions, and "RT" for Retweets during the same timeframe; indexed variables represent each successive term in the series; the index "i" starts out equal to "1" and is incremented by "1" for each successive hashtag, stopping when "i" equals the total number of hashtags to which the specific user has contributed.

We used Symplur Signals to generate the lists of participants by tweets, by replies, by mentions, and by retweets, and filtered them by hashtag and by quarters [28]. For each participant, we found the number of replies, mentions and retweets in each quarter and hashtag. IGR scores were then calculated and ranked.

The process was repeated by weighing in the number of tweets:

IGR per tweet = IGR/t, where "t" stands for the number of tweets during the timeframe the IGR refers to.

2.6. Thematic analysis

Four researchers independently carried out an inductive thematic analysis on a random sample of 500 tweets transcripts obtained using Symplur Signals. The RAND method was used to review, negotiate and revise the themes [31]. Agreed themes were compiled into the final code book.

3. Results

3.1. Hashtag Global Reach (HGR)

HGR, rank position and rank variation for the indexed hashtags in each quarter are shown in Table 1.

In order to clarify what the drivers of composite indicator results are, we profiled hashtag performance at the level of the individual indicator variables. While Table 1 shows the absolute scores, before normalization, in every indicator variable, Fig. 1 depicts the rank position and variation in each of them.

The spider diagram shows that #PrimaryCare and #FMRevolution keep, respectively, the first and second rank untouched in every indicator variable (superimposed solid and dashed lines). #FMChangeMakers showed an overall improvement (solid line outside the dashed line), while both #1care and #1carejc show a negative variation in all indicator variables.

3.2. Individual Global Reach (IGR)

For the six-month period under analysis, the total number of participants across the six hashtags was 8392. The 50 participants with the highest IGR in the last quarter of 2014 are shown in Table 2. IGR adjusted by number of tweets is also in display, together with the respective scores in the first quarter of 2015.

3.3. Thematic analysis

Ten themes were abstracted (Fig. 2). Some of the tweets were comprised of segments that pertained to different themes, and were assigned to more than one theme.

"Health Policy" had the higher number of Tweets, including topics related to access to medical records, human resources, leadership, advocacy and transforming practice:

- "*RT @amcunningham: At #vdgmDublin @June_boulger proposed patients have access to records…definitely the future. Talk to @amirhannan:) #1care*"
- "*No system can replace human effort and commitment in #primarycare, enable PCPs as 'brokers of choice'http://t.co/SSqIKeFOBN @kevinmd*"
- "*RT @Nina__Monteiro: @lygidakis Yes!! And for this we need good leaders, committed to others and not self-centered #fmchangemakers*"
- "*RT @SBRfamilydocs: More than 150 medical students, residents and FPs in the room talking advocacy/pipeline/ACA. FMSummit14 #FMRevolution*"
- "RT @HealthIsPrimary: #Familydoctors want to build a #healthcare system where everyone wins. Let's work together to #MakeHealthPrimary."

The category "Online/Offline Communities and Events" was the second most tweeted. It included Tweets about events in Primary care/Family Medicine worldwide, as showed by the following example:

- "*RT @SeascaleHC: .@BWMedical Looking forward to our next 1st Care Cumbria event in April #timetoworktogether #PrimaryCare #stopworkingforfree*"

The third theme with the most Tweets was "Health and Disease Management". This category included topics related to chronic diseases, lifestyle and behaviors, mental health and the use of evidence in the practice of medicine.

- "*Integrating chronic care and #primarycare to improve #diabetes outcomes in the Philippines http://t.co/oZjryiQbnM @fanhs_national*"
- "RT *@VahabzadehMD*: "*#Primarycare MDs have crucial role in recognizing patients at risk for #suicide, great article by @Suzanne-KovenMD http://t.co/Q4hqVvuOig*"
- "*RT @amccullough104: What can #primarycare do to alleviate #antibioticresistance? We review the #evidence @FrontMedicine @MalenePlejdrup http://t.co/N5kjfWnBtK*".

Table 1
The Hashtag Global Reach Index: aggregated composite indicator, rank position and variation, and decomposed individual indicator variables.

Hashtag	HGR[a]		Rank		ΔRank[b]	Decomposed individual indicator variables[c]									
						Participants		Locations		Languages		Impressions		Tweets	
	$Q4_{14}$	$Q1_{15}$	$Q4_{14}$	$Q1_{15}$	$Q1_{15} - Q4_{14}$	$Q4_{14}$	$Q1_{15}$	$Q4_{14}$	$Q1_{15}$	$Q4_{14}$	$Q1_{15}$	$Q4_{14}$	$Q1_{15}$	$Q4_{14}$	$Q1_{15}$
#1care	0.059	0.075	4	5	**−1**	46	89	9	13	4	4	290,332	723,232	67	142
#1carejc	0.011	0.014	5	6	**−1**	1	2	1	2	1	1	519	15,145	3	2
#FMChangeMakers	0.010	0.190	6	3	*+3*	1	130	1	26	1	9	177	1,846,961	1	1909
#FMRevolution	0.615	0.459	2	2	0	1069	1087	55	52	19	14	14,636,618	13,158,878	6073	4709
#MakeHealthPrimary	0.158	0.171	3	4	**−1**	335	450	21	26	4	5	3,115,313	3,662,209	1408	1506
#PrimaryCare	1.000	1.000	1	1	0	3731	4131	98	103	24	21	21,209,031	31,148,030	8172	10,754

Subtitle: Δ - Delta (variation); HGR - Hashtag Global Reach; $Q4_{14}$ - October 1, 2014 12:00 AM (UTC) to January 1, 2015 12:00 AM (UTC). $Q1_{15}$ - January 1, 2015 12:00 AM (UTC) to April 1, 2015 12:00 AM (UTC).
[a] For clarity the HGR score was rounded to three decimal places.
[b] Figures are positive (italic) for hashtags that improved their rank position, as opposed to negative (bold) for those that worsened it.
[c] The figures refer to the absolute number of participants, locations, languages, impressions and tweets, before data normalization.

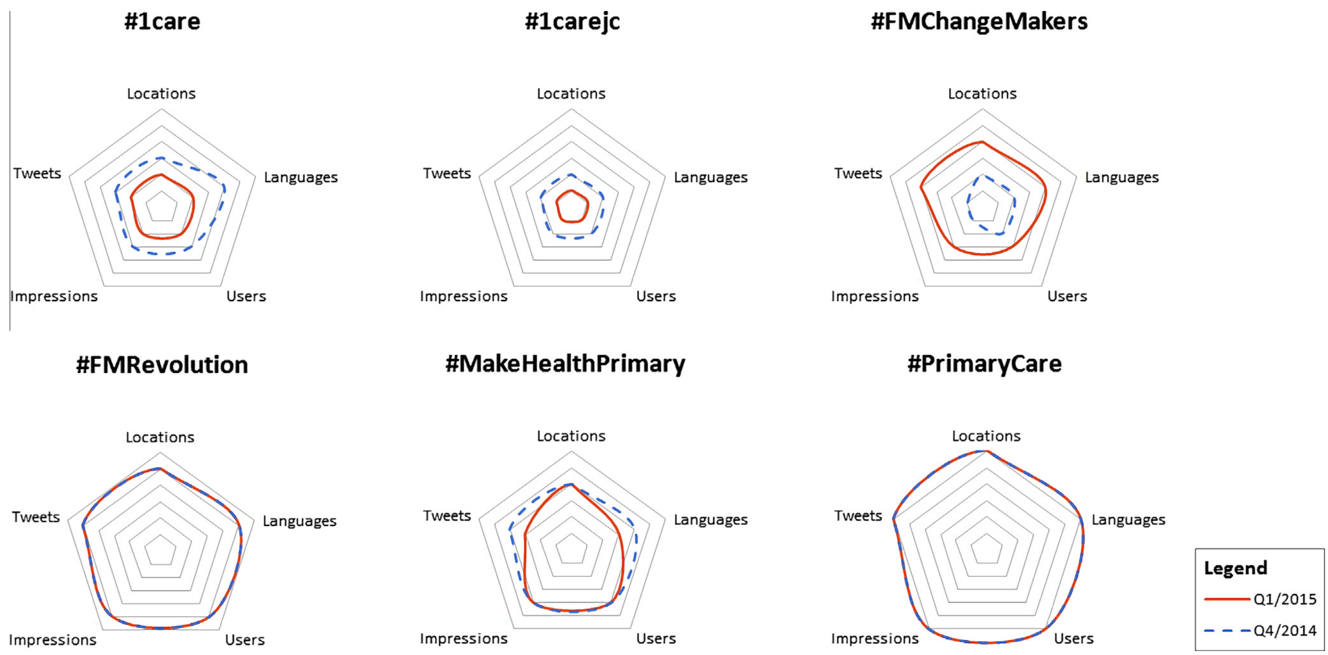

Fig. 1. De-constructing the Hashtag Global Reach (HGR): the contribution of each indicator variable. Spider diagrams for the six indexed hashtags are used to detail the rank position in each indicator variable: proportion of user locations, user languages, users, impressions and tweets. Ranks 1 through 6 are represented from the outer to the inner pentagon. Each of the five indicator variables form individual axes (not shown) which have been arranged radially around the center of the chart; the rank position in each indicator variable is depicted by the intersection of the solid and dashed lines on the respective axis. A dashed line is drawn connecting the rank position for the last quarter of 2014, and a solid line for the first quarter of 2015. Equal performance in the two periods is represented by a single, superimposed solid line. *Subtitle: $Q4_{14}$ - October 1, 2014 12:00 AM (UTC) to January 1, 2015 12:00 AM (UTC). $Q1_{15}$ - January 1, 2015 12:00 AM (UTC) to April 1, 2015 12:00 AM (UTC).*

Another emerging theme was "Family Medicine Competencies and Characteristics". Some examples included the topic of patient-centered care and care coordination.

- *"RT @chasedave: Endemic lack of coordination & communication steals people's quality of life, not to mention $$ http://t.co/uuC6dWXyKC #FMRevolution"*

The theme "Professional Development" ranked fifth within the most tweeted ones and addressed both career opportunities and development:

- "@utpa RT! Have extra time to job search this holiday season? #PrimaryCare careers with #LoanRepayment options: http://t.co/rWbrE1bHqC"

Tweets of "Health Economy" included topics related to health insurance, payment reform and debt of recent graduate physicians. Examples include:

- *"RT @LloydVanWinkle: Price transparency is essential to health care cost reduction #FMRevolution #AAFP2014 #FMbeheard #AAFPCOD"*
- *"@therealTRReid: 'States that focus on primary care have better health and lower healthcare costs.' #MakeHealthPrimary".*

"Medical Training and Education" included tweets related to both undergraduate and graduate training. Related tweets include:

- *"Finding medical schools that invest in #primarycare http://t.co/tBFkR7lyNj "*

Another emerging theme was "Research", either about specific projects or general concepts on the particularities of research in a Primary Care setting:

- *"RT @DrPeterASloane We need to reject research carried out on "pure" populations t/ bear no resemblance to d pts we see in FM #fmchangemakers".*

The theme of "Quality Management" also emerged - and included categories as accountability, transparency and improvement of care:

- *"«Continuity of care was proven to enhance the experienced quality of primary care.» - research from Finland http://t.co/zxnsM1482y #1care".*

Finally, tweets related to "Global Health" were the least common. Issues regarding justice and disparities were among the aspects mentioned.

- "*RT @lygidakis: One Family Medicine for the World! (via Kyle Hoedebecke & @juanrodma) #FMRevolution #primarycare #WONCA http://t.co/cHRIsbXMfg*"

3.4. Topic-specific HGR

The selected terms and sets of quotes (topics) are shown in Tables 3 and 4. 'Care', 'family', 'health' and 'needs' were the most common keywords.

Topic-specific HGR are shown in Fig. 3.

4. Discussion

Our study is the first to describe the use of altmetrics to generate a rank of hashtags. We found that an index of Hashtag Global Reach could be delivered and used to assess the leading hashtags. By filtering for keywords, we have demonstrated the Index holds its consistency at term-specific and theme-specific levels. Furthermore, consistent trends at the individual level could be seen, mak-

Table 2
Overview of individual scores (top 50 by Individual Global Reach [IGR] at the last quarter of 2014, out of 8392 total participants).

#	Screen name	Display name	$Q4_{14}$		$Q1_{15}$	
			IGR[a]	IGR/t[a]	IGR[a]	IGR/t[a]
01	@familydocwonk	Jay W Lee MD MPH	600.8[e]	1.6[b]	231.7[e]	1.7[b]
02	@healthisprimary	Health Is Primary	537.7[e]	28.1[e]	422.5[e]	37.9[e]
03	@notasmedicina	Thebesian veins	500.0[e]	500.0[e]	0.0[b]	0.0[b]
04	@miller7	Ben Miller	377.0[e]	5.8[d]	303.5[e]	8.6[e]
05	@pcareprogress	PrimaryCare Progress	373.2[e]	9.2[d]	480.4[e]	8.5[e]
06	@drkkyu	Kim Yu, MD, FAAFP	367.3[e]	3.2[c]	135.0[d]	4.2[c]
07	@nzdoctor_news	New Zealand Doctor	359.0[e]	4.6[c]	145.0[d]	9.7[e]
08	@drmikesevilla	Mike Sevilla, MD	344.8[e]	3.4[c]	305.8[e]	4.1[c]
09	@pcpcc	PCPCC	334.8[e]	12.2[e]	376.3[e]	23.3[e]
10	@globalmeded	Global Med Education	294.0[e]	3.6[c]	160.0[e]	1.5[b]
11	@aafp	AAFP	220.0[e]	16.5[e]	157.8[e]	22.4[e]
12	@primarycare4um	EUPrimaryCareForum	183.0[e]	3.0[c]	227.0[e]	3.2[c]
13	@mghpsychacademy	Psychiatry Academy	181.0[e]	2.8[c]	103.0[d]	2.2[c]
14	@jackchoumd	Jack Chou	177.8[e]	2.8[c]	70.7[c]	6.3[d]
15	@commonwealthfnd	Commonwealth Fund	177.2[e]	10.0[d]	342.1[e]	17.3[e]
16	@oxprimarycare	OxPrimaryCareSci	158.0[d]	5.3[d]	105.0[d]	4.8[d]
17	@jamainternalmed	JAMAInternalMed	156.0[d]	39.0[e]	1.0[b]	1.0[b]
18	@nhsengland	NHS England	150.0[d]	30.0[e]	53.0[c]	53.0[e]
19	@amorrissinger	Andrew Morris-Singer	143.7[d]	10.2[d]	184.8[e]	7.0[d]
20	@mrsbrull	Jen Brull	136.4[d]	1.4[b]	7.2[b]	4.9[d]
21	@lygidakis	Harris Lygidakis	127.7[d]	5.4[d]	424.4[e]	8.2[d]
22	@cmajblogs	CMAJ Blogs	124.0[d]	7.3[d]	75.0[c]	12.5[e]
23	@vivimbmd	Viv Martinez-Bianchi	123.4[d]	6.3[d]	116.1[d]	3.8[c]
24	@reneecrichlowmd	Renee Crichlow, MD	121.2[d]	4.4[c]	3.7[b]	1.8[c]
25	@aafpfmx	AAFP FMX	117.0[d]	9.0[d]	0.0[b]	0.0[b]
26	@annemont	Anne Montgomery, MD	111.0[d]	2.5[b]	40.4[c]	1.0[b]
27	@drlisarighter	Elisabeth Righter MD	110.5[d]	0.6[b]	63.9[c]	1.0[b]
28	@robertvarnam	Robert Varnam	106.0[d]	4.4[c]	81.0[d]	6.8[d]
29	@kbjones11	Kyle Bradford Jones	103.9[d]	3.1[c]	69.3[c]	2.0[c]
30	@nhscorps	NHSC	102.8[d]	2.1[b]	352.6[e]	3.8[c]
31	@drtomround	Thomas Round	98.0[c]	4.7[c]	459.1[e]	46.0[e]
32	@rliumd	Robyn Liu	96.5[c]	1.2[b]	3.7[b]	0.9[b]
33	@scnosalmd	Sarah Catherine	95.0[c]	0.8[b]	87.3[d]	2.8[c]
34	@umnfamilymed	UMN Family Medicine	94.8[c]	2.3[b]	37.7[c]	3.1[c]
35	@bwerginmd	Robert Wergin	94.7[c]	50.4[e]	1.4[b]	1.4[b]
36	@eastcarolina	East Carolina Univ.	90.2[c]	90.2[e]	8.0[b]	8.0[d]
37	@cafp_familydocs	CA Family Physicians	88.6[c]	12.4[e]	140.1[d]	7.9[d]
38	@grstream	Glen Stream	86.4[c]	72.4[e]	52.1[c]	23.1[e]
39	@bicmay	Bich-May Nguyen	85.0[c]	2.0[b]	76.3[d]	5.0[d]
40	@stfm_fm	STFM	82.9[c]	4.0[c]	110.2[d]	3.5[c]
41	@paul_pcpcc	Paul Grundy	79.6[c]	6.1[d]	136.3[d]	5.8[d]
42	@aafpprez	AAFPprez	79.0[c]	5.4[d]	52.7[c]	6.0[d]
43	@jvalaball	Dr. J. Vidal-Alabll	74.7[c]	2.0[b]	201.1[e]	4.2[d]
44	@erictopol	Eric Topol	71.1[c]	71.1[e]	0.8[b]	0.8[b]
45	@richmonddoc	Mark Ryan	71.0[c]	4.9[c]	59.9[c]	5.8[d]
46	@kennylinafp	Kenny Lin, MD, MPH	70.5[b]	8.4[d]	17.8[b]	2.2[c]
47	@lloydvanwinkle	Lloyd Van Winkle	68.2[b]	1.3[b]	19.6[b]	1.0[b]
48	@brookingsmed	Brookings Health	66.0[b]	5.5[d]	29.0[c]	5.8[d]
49	@drlaurenshughes	Lauren S. Hughes, MD	64.4[b]	3.4[c]	42.4[c]	3.8[c]
50	@jama_current	JAMA	61.0[b]	15.3[e]	21.0[c]	21.0[e]

Subtitle: # - Rank position (ordered by Individual Global Reach at the last quarter of 2014); IGR - Individual Global Reach; IGR/t - Individual Global Reach per tweet; $Q4_{14}$ - October 1, 2014 12:00 AM (UTC) to January 1, 2015 12:00 AM (UTC). $Q1_{15}$ - January 1, 2015 12:00 AM (UTC) to April 1, 2015 12:00 AM (UTC).
[a] For clarity the IGR and IGR/t scores were rounded to one decimal place; percentiles were calculated from the data for the 50 individuals shown.
[b] Below percentile 25.
[c] Between percentile 25 and 50.
[d] Between percentile 50 and 75.
[e] Above percentile 75.

ing it possible to develop the IGR. The analysis was replicated over time, for two consecutive quarters of year. We have also shown that HGR, topic-specific HGR, IGR and IGR per tweet may be used to study and describe the dynamics of activities in a healthcare hashtag community as well as found ten particular themes of interest in the conversations held using the indexed hashtags.

Our measures are a first step to map and evaluate relevant healthcare conversations on social media by communities (hashtags), contributors and topics. Given that the results of this proof-of-concept study suggest that the proposed methods can work in the "real world" conditions they were designed to operate under, a full-scale study is now necessary to assess the reliability of the proposed concept, namely against other methods. In order to guide the planning of such large scale study, a few modifications to improve feasibility are discussed in this section. Additionally, as there is no gold standard to measure the impact of such healthcare conversations on social media, in future studies our measures should be evaluated against stakeholders' relevance scores as well as against traditional metrics (e.g., impact factors in a sub-analysis for journals; University/Faculty/Department rankings in a sub-analysis for institutions), in accordance with previously published methods [38]. Correlations should be measured between such

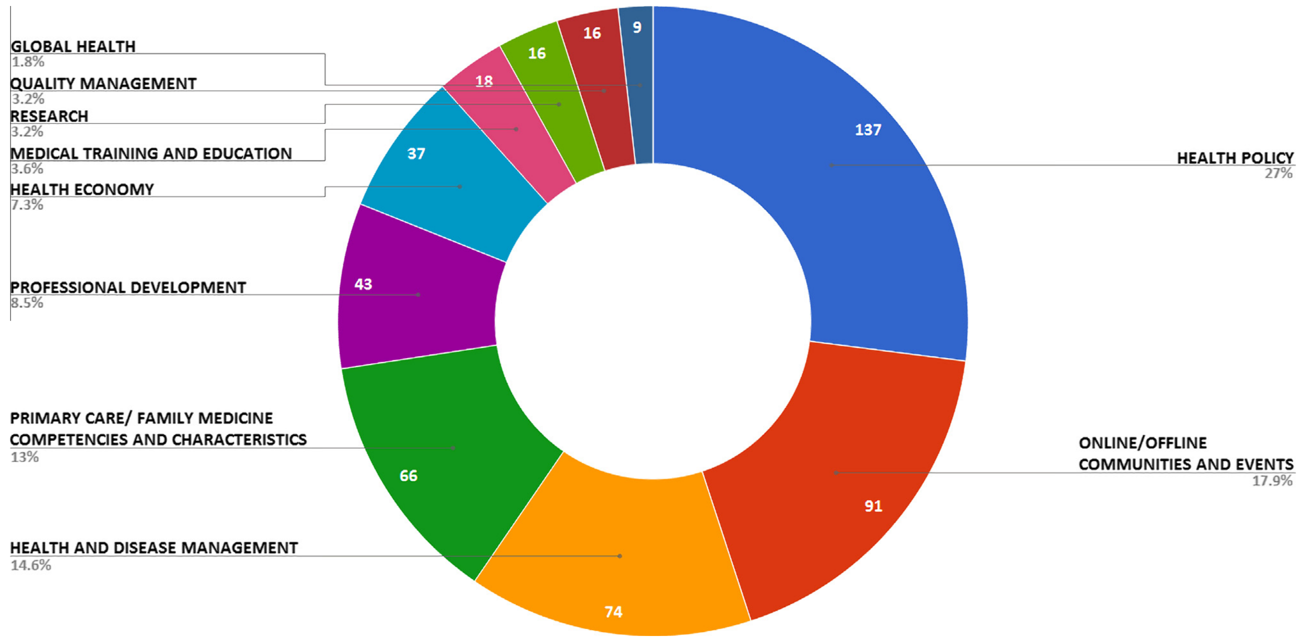

Fig. 2. Themes by tweet frequency. Donut chart for the ten themes that were obtained through an inductive thematic analysis. Absolute frequencies are shown inside each slice, while relative frequencies are shown in the outside next to each theme. 1.4% (7/500) tweets were not coded.

Table 3
Single keywords.

Keywords[a]	Tweets (n)
Care	3409
Family	3080
Health	2863
Needs	2107
Medicine	1890
Primary	1540
Patients	1197
Physicians	903
Need	819
Doctors	735

Subtitle.
[a] Keywords were chosen after the most frequent words in tweets across the six indexed hashtags during the last quarter of 2014 and first quarter of 2015; were excluded: "stop" (n = 1757), "murderous" (n = 1673), "medical" (n = 1152), "time" (n = 973), "week" (n = 959), "AAFP" (n = 931), "great" (n = 924), "good" (n = 749).

scores/metrics and HGR/IGR as well as its componentes. Temporal stability should be determined by determining correlations across time, in the short and long term. Further optimization should be achieved by testing modified versions of our formulas and adjusting the formulas to the best correlations.

Of note, by virtue of the Index construction, a hashtag with a very large number of participants and impressions compared to another can still be surpassed by the latter if the few are more active than the many and/or there is broader transnational communication (eg, #FMChangeMakers outperformed #MakeHealthPrimary in the second period under analysis). Moreover, even the leading hashtag in the overall index can lose to another hashtag in a topic-specific index (eg, on topic "Family" #FMRevolution beat #PrimaryCare, the overall top hashtag). By summarising a complex, multi-dimensional reality, our Index allows another (and easier) way to look at the data compared to ordering hashtags by a battery of many separate variables.

Moreover, the very inclusion of hashtags in low use adds merits to our proof-of-concept study, as it implies that the method can be implemented across the spectrum of hashtag usage.

Considering the dynamics of the indexed hashtags for this study, the unfiltered individual indicator variables showed an overall increase in the hashtag metrics during the second time period ($Q1_{15}$) compared to the first ($Q4_{14}$), Table 1. To properly describe the observed trend, studying these metrics for a longer timeline would have been preferable. Nonetheless, over the stated time period it can be inferred that there was a growth in the activities of the six hashtag communities. This may suggest a typical trend for a new idea with the excitement that accompanies the start of a project or it may actually reflect a growing concern on the issues these hashtags represent. Another possible reason is an increasing sense of connectedness between members, as identified by another study using the Symplur Hashtag Project to identify healthcare hashtags [32]. Notably, growth enablers for hashtag communities seem to include a group of people committed to open discussions, with an understanding of the shared perspectives, a sense of ownership and a common identity [15].

An increase in the number of user languages was not obvious compared to the other metrics (Table 1). This is not surprising since the user language can be chosen of a restrict list (at the time of writing, 34 languages are fully supported and six are in tests). In large health hashtag communities, it is therefore likely that new members have similar settings to those already participating and, as users by default keep their language settings, the variation in the number of user languages should happen at a slower pace than the change of user locations.

At the unfiltered composite indicator level, the performance was higher for the hashtag #PrimaryCare followed by #FMRevolution, which reflects in their HGR. As for #FMRevolution, the HGR actually decreased from $Q4_{14}$ to $Q1_{15}$, Table 1. The negative variation relates to a decrease performance in every indicator except for the participants number. #FMRevolution kept is second place in the ranking but has seen competing hashtags getting closer - risking being surpassed if the same trends persist.

It is clear that these hashtags were quite popular platforms for discussing issues and/or disseminating information of interest to family physicians worldwide. Interestingly, while #PrimaryCare and #FMRevolution hashtags maintained a constant lead, #FMChangeMakers showed the most remarkable increase for

Table 4
Sets of keywords.

Theme	Sets of keywords[a]
Health Policy	*access OR access to records OR advocacy OR agenda OR campaign OR congress OR demand OR democracy OR election OR health system OR health systems OR influence OR lobby OR medical home model OR model OR model of care OR models of care OR political OR politics OR reform OR rights OR senate OR solutions OR sustainable change OR system OR US representative OR vote OR voting*
Online/Offline Communities and Events	*assembly OR attend OR campaign OR celebrate OR conference OR dinner OR event OR facilitation OR forum OR hangout OR meeting OR panel OR presentation OR round table OR speak OR speaking OR speeches OR thesis defense OR webinar*
Health and Disease Management	*alcohol OR alcohol abuse OR antibiotic OR antipsychotic OR asthma OR autism OR behavioral OR cancer OR chronic care OR cognitive assessment OR colon cancer OR comorbidity OR contraception OR COPD OR counseling OR deaf OR decision aid OR depressed OR depression OR diabetes OR diagnosis OR diseases OR drug abuse OR EBM OR EHR OR elderly OR evidence OR fever OR flu OR growth curves OR guidelines OR heart disease OR heart failure OR imaging tests OR lifestyle OR memory loss OR mental OR mental illness OR misdiagnosis OR obesity OR older people OR overweight OR physically active OR pregnancy OR prevention OR prostate OR prostate cancer OR psychiatry OR reproductive health OR screening OR smokers OR statin OR stroke OR suicidal OR suicide OR syndrome OR telemedicine OR treatment OR vaccine OR walk OR walking OR wearables OR weight gain OR wellness OR whole person*
Primary Care/Family Medicine Competencies and Characteristics	*care OR care coordination OR care management OR caring OR collaborative care OR communicate OR communication OR community OR complexity OR comprehensive OR continuity OR continuous OR coordination OR cure OR heal OR improve health OR integrated OR interdisciplinary OR multidisciplinary OR paperwork OR partner OR patient centered OR patient-centered OR referral OR relationship OR satisfaction OR teams OR time OR uncertainty OR work together*
Professional Development	*career OR employment OR international ambitions OR job OR jobs OR practice opportunities OR qualified PCPs OR reentry program OR vacancies*
Health Economy	*$ OR £ OR cash OR co-commissioning OR commissioned OR commissioners OR commissioning OR cost OR costs OR cuts OR debt OR fee OR fee-for-service OR free clinic OR health insurance OR incentive OR investing OR loan OR P4P OR pay OR paying OR payment OR payment price OR return of investment OR savings*
Medical Training and Education	*curriculum OR e-learning OR educational OR exchanges OR learning OR medical boards OR medical education OR medical schools OR preceptor OR residency OR school of medicine OR teaching clinics OR trainees OR training OR webinar*
Research	*fellow research OR publish OR qualitative research OR research OR research committee OR researchers OR study protocol*
Quality Management	*accountability OR best practices OR enhance OR improve OR improve care OR improvement OR indicators OR quality OR quality improvement OR transparency*
Global Health	*disparities OR Global Health OR international OR justice*

Subtitle.
[a] Keywords were chosen after their association with the Themes set by the Thematic Analysis.

HGR and rank in the second quarter. With such an improvement, #FMChangeMakers surpassed #MakeHealthPrimary, #1care and #1carejc. Nevertheless, a performance increase on every indicator variable of all three hashtags was seen (the variation was residual for #1carejc). We speculate participants on the two hashtags with the highest rank also discovered #FMChangeMakers as a viable option for engagement, information dissemination and collaboration, hence a cross utilization of the various hashtags may have occurred or, the users of #FMChangeMakers may have been innovative in their bid to increase their global reach. This is consistent with the desire to properly index a tweet for maximum visibility, confirming what is known about using hashtags to form online communities and also using same to measure the growth of the community [15,17].

We also observed that there were more individuals (27) than organizations (23) in the top 50 Twitter users for the last quarter of 2014 (Table 2), with varying ranks based on IGR and IGR per tweet. The same trend was identified for the first quarter of 2015 (i.e. 22 organizations versus 28 individuals, *data not shown*). Even though previous studies have highlighted organizations' increasing use of Twitter [33,34] the composite index used in this study suggests a trend in favor of more individual-sponsored engagement and information dissemination and confirms that social media, in this case Twitter enables a democratization of access and utilization of health-related data.

Regarding IGR-based ranks, some limitations shall be addressed. First, our metric points out some high-influence players, but may miss many important ones; this shall be tested in future studies. Second, IGR ranks individuals by computing individual variables (e.g. "replies", "mentions" and "retweets") which can be manipulated by excessive tweeting or spamming tools and therefore promote artificially high rankings. Also, the results might be skewed by profiles of organizations with an elevated number of followers; an effect that might or might not reflect actual trends. A possible future approach to further refine this index may consist on the partial adjustment for the number of followers.

The topic-specific HGR scores in general follow similar patterns and trends to those described for the unfiltered composite indicator. #PrimaryCare had the lead in all topics except for two during the last quarter of 2014 and one in the first quarter of 2015. #FMRevolution performance worsened from the first to the second period; nevertheless, it kept the lead position in the topic-specific HGR for "Family" in both periods, well ahead of #PrimaryCare. This seems to indicate selective attrition. Starting from scratch #FMChangeMakers eventually surpassed the other three indexed hashtags for most of the topics - and even surpassed #FMRevolution in the topic-specific HGR for "Research" and "Global Health". This lends further support to the hypothesis that this hashtag community has adopted a strategy that is increasing their global reach.

As shown in Table 3, a secondary finding from our analysis on the tweets' content was that the three most frequent keywords - even before any were excluded - were «Care», «Family» and «Health». Since Family Medicine hashtag communities were used in this study, it is worth noting that the most frequent keywords from their interactions were consistent with the principles of the discipline [35] thus confirming that the indexed hashtags reflected the core issues of the chosen health community.

The most frequent theme in our random sample of tweets was health policy, consistent with previous published literature [36]. Issues of access to care, health systems, models of care and cost

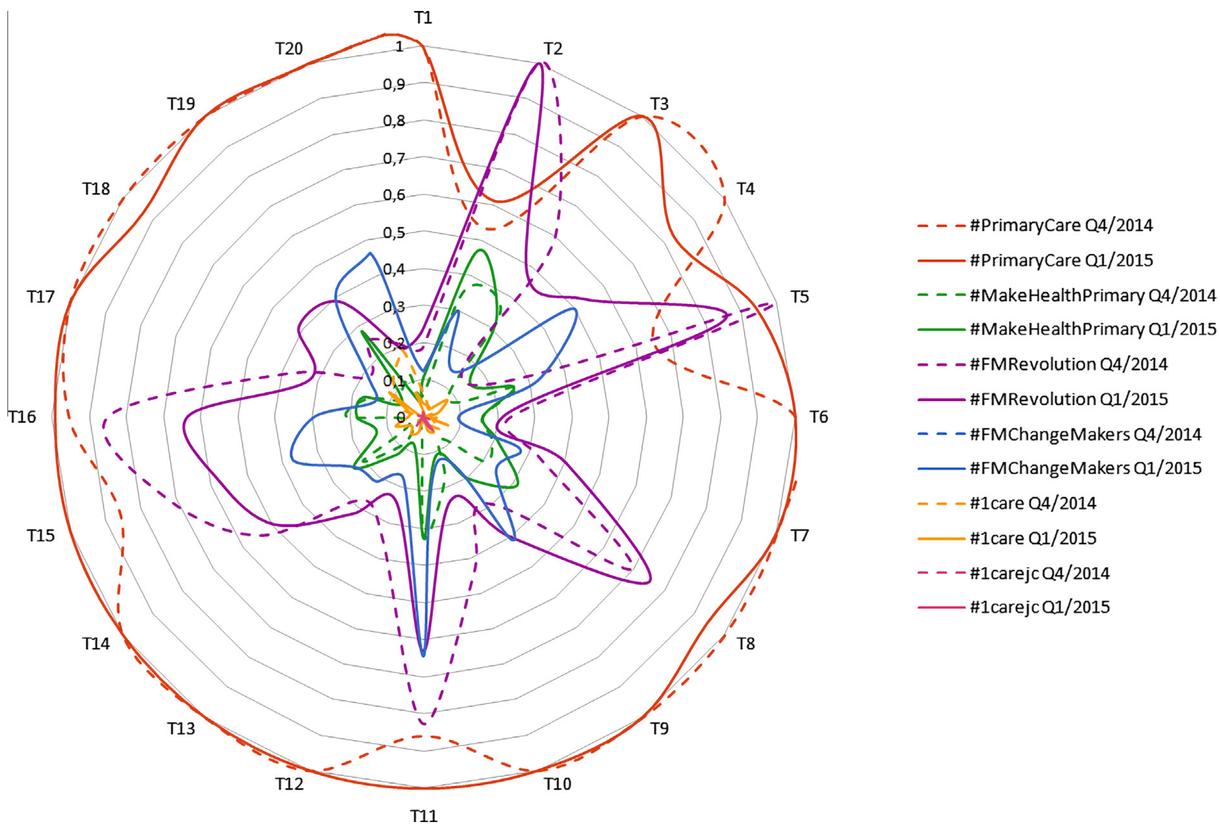

Fig. 3. Spider diagram of topic-specific Hashtag Global Reach (HGR) for the six indexed hashtags. Topics are represented by the letter "T" followed by a number, from 1 to 20; topics 1 through 10 correspond to the top ten terms outlined in Table 3; topics 11 through 20 correspond to the themes outlined in Table 4, by filtering for the respective sets of quotes. The Hashtag Global Reach (HGR) for each topic is depicted by the intersection of the solid and dashed lines on the respective axis. Individual axes have been arranged radially around the center of the chart. A dashed line is drawn connecting the HGR score for the last quarter of 2014, and a solid line for the first quarter of 2015. *Subtitle: $Q4_{14}$ - October 1, 2014 12:00 AM (UTC) to January 1, 2015 12:00 AM (UTC). $Q1_{15}$ - January 1, 2015 12:00 AM (UTC) to April 1, 2015 12:00 AM (UTC). T1 - "Care"; T2 - "Family"; T3 - "Health"; T4 - "Needs"; T5 - "Medicine"; T6 - "Primary"; T7 - "Patients"; T8 - "Physicians"; T9 - "Need"; T10 - "Doctors"; T11 - Global Health theme; T12 - Health & Disease Management theme; T13 - Health economy theme; T14 - Health policy theme; T15 - Medical education & training theme; T16 - Online/Offline Communities & Events theme; T17 - Family Medicine Competencies & Characteristics theme; T18 - Professional development theme; T19 - Quality management theme; T20 - Research theme.*

(from the prevalent theme) trumped those of disparity, justice and even the Ebola epidemic. Looking at the topic-specific HGR (Fig. 3), one may infer that while the indexed hashtags provided a global platform for networking and engagement in this health hashtag community, the predominant themes were a reflection of the influence of the hashtags with the highest HGR and users with the highest IGR. We speculate that Twitter users could be using other hashtags for their conversations on Global Health related issues.

As discussed above, the HGR, IGR and IGR per tweet are composite indicators built upon an explicit conceptual framework and data on indicator variables are sound, relevant and readily available, with no missing values, following previously described guidelines [29]. While there is wide range of methodological approaches to build composite indicators, we relied on fitness for the intended purpose and in peer acceptance (from experts and stakeholders). Experts and stakeholders who participated in a specially run tweet chat considered the individual indicators suitable for inclusion in a composite formula to calculate HGR and IGR; as the single indicators were found equally important, equal weighting was chosen to combine them into a meaningful composite indicator. Of note, given that impressions are the total number of times tweets have been delivered to users' Twitter feeds during each period, not everyone who receives a tweet will read it. Impressions are therefore a metric of the size of the potential audience, complementary to sheer activity metrics (number of tweets and of participants), transnational communication metrics (participant's countries and language) and engagement metrics (like retweets, mentions and replies). Moreover, we have carried normalization to render the indicator variables comparable and made use of clearly defined methodologies for data weighting and aggregation, along the lines of the underlying theoretical framework, in accordance to the norms in place [29]. However, we did not perform a multivariate analysis prior to the aggregation of the individual indicator variables, nor a sensitivity analysis to assess the robustness of the composite indicator. We acknowledge such limitations and argue that the index should be seen as a first step, one which should bring attention to the matter at hand and therefore persuade for more resources and efforts to be put in preparing an improved tool - rather than abandoning the exercise of developing it. In addition, although there we found no gold standard which could serve as a ground truth for evaluating the computed scores, the Index performance seems fair according to the author's best knowledge about the analyzed hashtags and the leading participants. Assuming the analytical soundness is proven, we hypothesize that the index should hold and be generalizable to hashtags pertaining to other health professions and healthcare fields. However, it is important to note that this was a first exploratory attempt to implement a healthcare hashtag index and further studies are needed to assess its generality in health-related topics. Future studies should also address the scalability of the model, specifically regarding its administrative scalability (the ability to accommodate an increasing number of users) and its load scalability (the ability to adapt in order to accommodate higher or lower number of inputs). We argue that by programming artificial intelligent algorithms HGR and IGR could be computed in real time. This would make the index generalizable to any number of hashtags and users on any timeframe. Topic curation should also be scalable thanks to customized search filters using Boolean operators and regular expressions search patterns. As for theme coding and analysis, it's increasingly common to process text corpora into themes using automatic unsupervised clustering methods, allowing for the analysis of millions of entries [37]. Such strategies would unravel the full potential of the proposed Index.

Although the data coverage for each hashtag was complete, and thus we had no missing data on any of the variables, we did exclude "unknown locations" when counting the number of user locations. Yet, it seems unlikely this should affect the hashtags in a differential way or significantly impact the composite indicators.

In addition, more precise measurements on indicator variables will be needed to confirm the topic-specific HGR scores. Due to the inner workings of Symplur Signals, the search feature works upon tweets which are sometimes truncated. As it happens, Signals can convert short links/symbols into lengthier links/symbols and also adds the expression "RT by @username:" at the beginning of every retweet. By doing this however, tweets may exceed 140 characters and get truncated for search purposes. If keywords are left out, the corresponding tweets will therefore be missed by the search feature, creating bias on the individual indicator variables and, consequently, the topic-specific HGR scores. As such, the analytics tool will have to be reprogrammed in order to search for the complete/original tweet. Only then will it make sense to pursue this line of research and develop the corresponding topic-specific IGR.

Furthermore, for the current exercise we arbitrarily chose a quarter year as our time frame of analysis and comparison. Nevertheless, shorter time frames might be of use depending on one's needs. We foresee the index could be released as a periodical publication but also as a real-time business intelligence tool. The latter should allow users to customize the timeframe of analysis and obtain real-time information on HGR and IGR, perform direct comparisons and trend analysis. It should also allow customization of topics that are important to the user, by making it possible to run personalized search filters using Boolean operators and regular expressions search patterns.

Simultaneously, efforts should be made to expand the number of indexed hashtags. We yearn for the progressive inclusion of hashtags present at the Healthcare Hashtag Project (over 7000 at the time of writing) [26]. The indexation should prioritize hashtags with high activity metrics. In the opposite direction, the Index could inform on hashtags that should be added to the Healthcare Hashtag Project. This could be achieved by running analysis on the hashtags used by the indexed participants as well as hashtags co-occurring with the indexed hashtags. These procedures would help identify frequently occurring hashtags still not indexed.

Similar to the Impact Factor for medical journals, our results seem to implicate that the HGR could be used as a quantitative tool to assess, rank and run comparisons on hashtags. However, this allows for such objective analysis to go even further and be replicated over different topics (that could be made customizable) and allowing for the evaluation, ranking, and comparison of individual contributions (via IGR).

Thus, netizens could potentially use it to curate and make rational decisions on how to manage and prioritize their Twitter hashtags' reading list as well as discover the most relevant hashtags on given topics. Conceivably, organizations and movements could use HGR and IGR to better understand the reach of their own hashtags and/or accounts, identify threats and opportunities, and review their overall strategy. Additionally, specialists in bibliometrics/webometrics could track trends and patterns allowing for strategic decisions. Intuitively, the index could be used in a horizontal (across topics and individuals), vertical (for topics or individuals) and longitudinal (over time) way. In addition, we speculate the derived individual scores could also serve the purpose of academic evaluation and professional development when the evaluation criterion is the international reach of the user's digital footprint.

5. Conclusion

This study proves the concept feasibility of creating an index of healthcare hashtags based on altmetrics around global reach as well as using it to describe the dynamics of the activities in healthcare hashtag communities. Studies are needed to confirm the analytical soundness of the composite indicators.

Conflicts of interest

All authors declare no competing interests: no support from any organization for the submitted work, no financial relationships with any organizations that might have an interest in the submitted work, no other relationships or activities that could appear to have influenced the submitted work.

Free access to Symplur Signals social media analytics platform was awarded to the researchers as a reward for being selected as a semi-finalist for the "2015 Stanford MedX | Symplur Social Media Analytics Research Challenge".

Acknowledgements

We thank the multiple contributors during the tweet chat brainstorming that became the cornerstone for our research project, and Jay W Lee and Mike Sevilla for disseminating such event to the legion of their followers on Twitter. We also thank Harris Lygidakis for his contributions to writing the study protocol and drafting the Thematic Analysis protocol. Finally, we would like to thank Anne-Marie Cunningham, Viviana Martinez-Bianchi, Canan Tuz and Seda Coskun for their input during the development of the study protocol.

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