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Quality of the discussion of asthma on twitter

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ABSTRACT

Introduction: Patients obtain a large amount of medical information online. Much of this information may not be reliable or of high quality. We investigated what influences the discussion of asthma on Twitter by evaluating the most popular tweets and the quality of the links shared.

Methods: We used Sympur Signals to extract data from Twitter examining characteristics of the top 100 most shared tweets and the 50 most shared links that included the hashtag #asthma. Information on each site was assessed using an Asthma Content score, and validated DISCERN scores and HONCode criteria.

Results: The top 100 asthma-related tweets were shared 10,169 times and had 16,044 likes. Healthcare organizations posted 49 of the top 100 tweets, non-healthcare individuals posted 20, non-healthcare organizations posted 16 and clinicians posted 14. Of the top 100 tweets, 62 were educational, 11 research-related, 10 political and 15 promotional. The top 50 links were shared 6009 times (median number of shares 92 per link (range 60-710)). Links most commonly (42%) led to educational content while 24% of links led to research articles, 22% to promotional websites, and 12% to political websites. Educational links had higher Asthma Content scores than other links ($p < 0.005$). Overall, all three scores were low for all types of links. Only 34% of sites met HONCode criteria, and 14% were assessed as high quality by DISCERN score.

Conclusion: The top tweets using the hashtag #asthma were commonly educational. The majority of top links on Twitter scored poorly on asthma content, quality, and reliability.

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Introduction

Social media use is widespread in the US, with 72% of the US population using at least one social media site and up to three quarters of users engaging with social media platforms daily (1). Social media usage is even higher in the younger generations, with 90% of Americans aged 18 to 29 years using social media (2). Interestingly, the continued year-on-year growth in social media use can be attributed to increasing usage in those aged older than 65 years (2).

Patients are increasingly turning to social media for medical information. More than half of users report having looked at social media for information regarding their health in the preceding year, and growing numbers of people are turning to these platforms for information about medical treatments and conditions,

recommendations for specialists or institutions, emotional support, peer advice, and coping with health situations (3–10).

These burgeoning interactions have created opportunities for various healthcare stakeholders to engage online. Clinicians and researchers use social media for a variety of reasons such as educating and learning from each other and the patient community at large, advocating for healthcare issues, and conducting research studies (4,11–18). Similarly, healthcare organizations utilize social media to provide educational material, increase awareness, and provide resources to both patients and clinicians (19–24).

However, there is increasing concern about the veracity of information being shared online. While this exponential growth in communications is encouraging, a

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number of studies demonstrate poor or inadequate quality of health information available online (25–30). In order to better understand these conversations, we explored what characteristics drive the conversation surrounding asthma on social media using the popular microblogging platform, Twitter, and to examine the quality of the most commonly shared links.

Materials and methods

We used Symplur Signals (Symplur, LLC), an online analytic tool, to extract data from Twitter. First, we identified the 100 most retweeted tweets containing the hashtag #asthma in the year 2018. The sample size of 100 tweets was arbitrarily decided on prior to starting the study to balance achievability and convenience. We examined the characteristics of these tweets including whether the tweet contained an embedded image or GIF, embedded links, or other hashtags, whether it mentioned other users, and the time and date of each tweet.

We compared tweets by the type of tweet, and by the characteristics of the user tweeting. Tweets were classified into one of four category types: educational, research-oriented, political, or promotional. We classified users into five different stakeholder groups: individuals, clinicians, industry, healthcare organizations (HCOs), and non-healthcare organizations (NHCOs).

Symplur generates 19 different categories of stakeholders using proprietary machine-learning models and algorithms as well as manual human evaluation and quality control (31). We aggregated these categories into five stakeholder groups. We defined Individuals as user accounts classified by Symplur as “caregiver/advocate,” “patient,” or “individual non-health.” We defined Clinicians as user accounts classified as “healthcare provider,” “doctor,” “individual other health,” or “researcher.” Industry was defined as user accounts classified as “organization pharma” or “organization med device.” We defined HCOs to be user accounts classified as “organization advocate/support,” “organization other healthcare,” “organization provider,” or “organization research/academic.” NHCOs were defined as user accounts classified as “non-healthcare organizations.” We excluded the tweets of users identified by Symplur Signals as spam accounts as well as the non-English tweets.

Tweets that were copied and posted multiple times did not count as retweets. Two authors (VK & TSz) collected the data independently and the differences were discussed with a third author (CC) who reconciled any differences. Differences arose from subjective opinion on

categorization of the tweet for 15 of 100 tweets (15%) and link characteristics in 12 of 76 links (16%).

We then used Symplur Signals to collect data on the top 50 links mentioned in tweets containing the hashtag #asthma in the year 2018. Two authors (VK & TSz) independently evaluated each link. For each link, a Health on the Net Code (HONCode) rating, a DISCERN Score, an Asthma Content Score, and an Overall Rating were assigned. In cases of discrepancy in the Overall Rating, a third author (CC) reconciled the scores independently. Numerical scores were averaged unless they were divergent by a significant amount. In those instances, discrepancies were resolved by discussion between CC, TSz and VK.

Health on the Net (HON) is an independent organization that provides guidance on how to assess whether websites provide understandable, accessible, and trustworthy health information (32). Adherence to HONCode principles was evaluated for each video by two authors (VK & TSz), with a score of 1 for adherence and 0 for non-adherence for each of the 8 principles (Supplemental Table S4). This approach was modeled on a methodology used in other studies to assess written, auditory, and visual information provided online (27,28). Possible scores ranged from 0-8 and according to HONCode, scores of 6-8 reflect high quality.

We used the DISCERN instrument, an assessment tool that allows for reproducible results, to assess the quality of written patient information (33) (Supplemental Table S5). The DISCERN instrument has previously been used to assess the quality of information available on the Internet (25,27). DISCERN provides three categories of information: Reliability, Quality, and Overall Rating. Within each section, questions are scored from 1, indicating serious shortcomings in satisfying that information category the link, to 5, indicating minimal to no shortcomings in satisfying that category. The Reliability section has a possible range of scores from 8-40, Quality has a possible range from 7-35, and Overall has a possible range of 1-5. Sites with Overall scores of 4-5 were rated as having a high DISCERN score, while those with Overall scores of 1-2 were rated as having a low DISCERN score.

We developed the Asthma Content Score to quantify the amount of asthma content in tweets. An adult pulmonologist (JP), a pediatric asthma specialist (CLC), and an allergist (DS) on our research team (JP, CLC, DS) created this score using NHLBI recommendations to determine the core asthma content. Content Criteria Scores have been used by other investigators to quantify the amount of disease-specific information in online

Table 1. Characteristics of Top 100 Tweets Using the hashtag #asthma by Category of Tweet (data presented as frequency, or median with 25–75% IQR).

Variable	Gen Ed Tweet (n = 62)	Research Ed Tweet (n = 11)	Political Tweet (n = 10)	Promotional Tweet (n = 15)
Stakeholders Tweeting				
Organization Non-Health	11% (n = 7/62)	45% (n = 5/11)	0% (n = 0/10)	27% (n = 4/15)
Clinician	13% (n = 8/62)	27% (n = 3/11)	10% (n = 1/10)	13% (n = 2/15)
Health Care Organization	68% (n = 42/62)	9% (n = 1/11)	10% (n = 1/10)	33% (n = 5/15)
Individual	8% (n = 5/62)	18% (n = 2/11)	80% (n = 8/10)	20% (n = 3/15)
Industry	0% (n = 0/62)	0% (n = 0/11)	0% (n = 0/10)	7% (n = 1/15)
Tweet Characteristics				
Tweet Contains Image?	65% (n = 40/62)	45% (n = 5/11)	20% (n = 2/10)	67% (n = 10/15)
Users Tagged in Image?	15% (n = 6/40)	0% (n = 0/5)	0% (n = 0/2)	10% (n = 1/10)
Tweet Contains GIF/Video?	23% (n = 14/62)	9% (n = 1/11)	20% (n = 2/10)	7% (n = 1/15)
Contains Other Hashtags?	79% (n = 49/62)	55% (n = 6/11)	90% (n = 9/10)	100% (n = 15/15)
Median number of hashtags	1 (1-4)	2 (1-9)	2 (1-5)	2 (1-10)
Tweet Contains Mentions	11% (n = 7/62)	55% (n = 6/11)	90% (n = 9/10)	100% (n = 15/15)
Median number of mentions	1 (1-1)	3 (1-5)	1 (1-2)	1 (1-3)
Tweet Contains Link?	79% (n = 49/62)	100% (n = 11/11)	50% (n = 5/10)	40% (n = 6/15)
Link Contains Video?	41% (n = 20/49)	9% (n = 1/11)	20% (n = 1/5)	0% (n = 0/6)
Type of Link?				
Gen Education Link	94% (n = 46/49)	0% (n = 0/11)	0% (n = 0/5)	17% (n = 1/6)
Research Ed Link	2% (n = 1/49)	100% (n = 11/11)	20% (n = 1/5)	0% (n = 0/6)
Political Link	0% (n = 0/49)	0% (n = 0/11)	60% (n = 3/5)	0% (n = 0/6)
Promotional Link	4% (n = 2/49)	0% (n = 0/11)	20% (n = 1/5)	83% (n = 5/6)

content (25,26). As per the structure of other Content Criteria Scores, content items were grouped within 6 content areas: definition, symptoms, risk factors, evaluation, management, and outcomes (Supplemental Table S6). Each link was assigned a content score for each of the areas, with a score of 0 indicating an item not addressed in the link, a score of 0.5 indicating an item incompletely addressed, and a score of 1 for an item clearly described in the link. Total possible scores ranged from 0-17. An Asthma Content Score of < 5 (of 17) was defined as a cutoff for low amount of asthma-related content. This score went through several iterations and revisions by this team, but it has not been validated.

An Overall Rating was assigned by the reviewers according to their overall professional assessment of that link. Links were rated as either “relevant”, “misleading/biased” or “irrelevant”. A rating of “relevant” was given to articles that had information that would be potentially be useful to patients and that could be recommended to patients. These links provided education that could help a patient better understand their asthma. A rating “misleading/biased” had significant amounts of information that was factually incorrect or promoted therapies or treatments that were not evidence based. A rating of “irrelevant” was given to links that did not contain information relevant to patient education.

Statistics were performed and data were analyzed using JMP statistical software (version 10.0.1; SAS Institute Inc., Cary, NC, USA) in collaboration with consultation from the Office of Research at the Connecticut Children’s Medical Center. Data are reported as frequencies (%) or as median with 25-75% interquartile range given the non-normal data distribution. Non-parametric

comparative statistics were performed using chi-square and Wilcoxon rank sum tests. To assess correlation between variables, non-parametric Shearman rho test was used. A *p* values less than 0.05 was considered statistically significant. This study was reviewed by the Connecticut Children’s Institutional Review Board and considered exempt.

Results

Top tweets

The 100 most commonly retweeted tweets were collectively shared 10 169 times and collectively received 16 044 likes. The median number of retweets in this cohort of top 100 retweets was 86 (range 59-396 retweets), and the median number of likes was 91 (range 10-842 likes). Of the top 100 tweets, 49 were from HCOs (92% of which were verified), 14 were from Clinicians (86% of whom were doctors), 20 were from Individuals, 16 were from NHCs, and 1 was from Industry (Supplemental Table S1).

Several users had more than 5 tweets in the Top 100. Asthma UK (@asthmaUK), a healthcare organization that provides education and resources on Asthma, contributed 32 out of the 100 top tweets while Dr. David Stukus (@AllergyKidsDoc), a pediatric allergy and asthma specialist, contributed 6. Victoria Browthworth (@VABVOX), an investigative journalist, and the World Health Organization (@WHO) contributed 5 each.

When looking at the content of the top 100 most retweeted tweets, 62 were educational, 11 were research-oriented, 10 were political, 15 were promotional, and 2 tweets were personal in nature (Table 1).

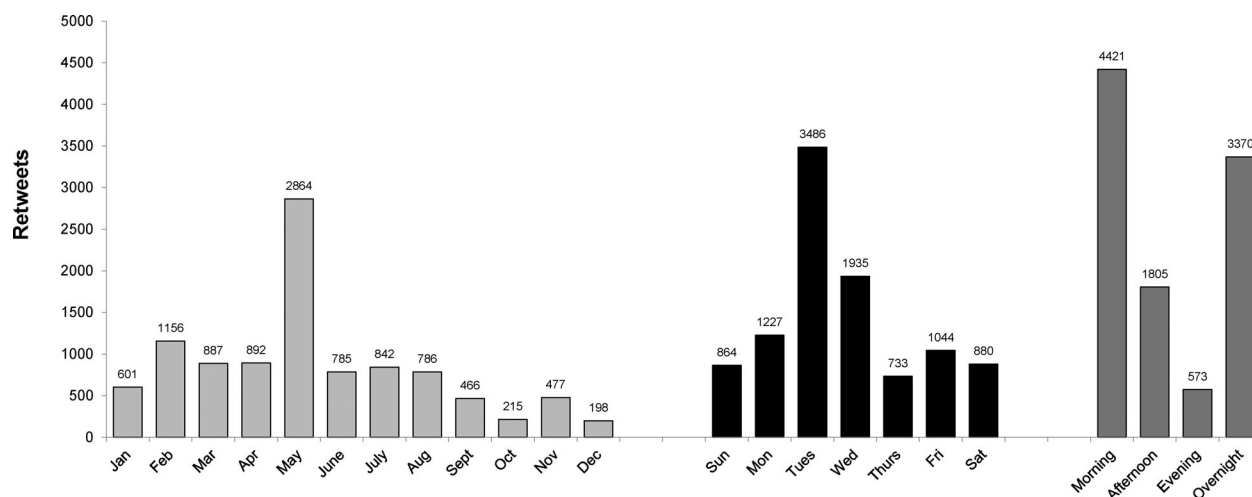


Figure 1. Time trends of the number of retweets for the top 100 tweets containing #asthma in 2018.

Table 2. Qualities of Top 50 Links Related to #asthma in 2018 by Type of Link. (data presented as frequency, or median with 25–75% IQR).

Variable	Gen Educational (n = 21)	Research Article (n = 12)	Promotional (n = 11)	Political (n = 6)
Host of Site				
Healthcare Organization	81% (n = 17/21)	0% (n = 0/12)	9% (n = 1/11)	33% (n = 2/6)
News Media	10% (n = 2/21)	100% (n = 12/12)	18% (n = 2/11)	50% (n = 3/6)
Other Org/Business	5% (n = 1/21)	0% (n = 0/12)	64% (n = 7/11)	17% (n = 1/6)
Industry	5% (n = 1/21)	0% (n = 0/12)	9% (n = 1/11)	0% (n = 0/6)
Provides Relevant Info	76% (n = 16/21)	58% (n = 7/12)	27% (n = 3/11)	17% (n = 1/6)
Asthma Content Score	7 (2-11)	3 (2-8)	2 (0-4)	1 (0-3)
High Asthma Content Score (≥ 5)	57% (n = 12/21)	25% (n = 3/12)	18% (n = 2/11)	17% (n = 1/6)
HONCode Score	6 (4-6)	7 (5-7)	3 (2-4)	4 (2-6)
High HONCode Score	38% (n = 8/21)	58% (n = 7/12)	0% (n = 0/11)	33% (n = 2/6)
DISCERN Score				
Reliability	30 (25-34)	28 (25-33)	21 (17-23)	21 (16-28)
Quality	13 (9-18)	11 (7-21)	9 (7-12)	7 (7-10)
Overall	3 (2-4)	2 (1-4)	2 (1-2)	1 (1-2)
High Overall DISCERN	28% (n = 6/21)	8% (n = 1/12)	0% (n = 0/11)	0% (n = 0/6)
Low Overall DISCERN	33% (n = 7/21)	50% (n = 6/12)	82% (n = 9/11)	83% (n = 5/6)

Most of the educational tweets came from HCOs, and 86% of the tweets of HCOs were educational. Educational & promotional tweets commonly included images (65% & 67%), educational/research-based tweets frequently included links (79% & 100%) and promotional & political tweets regularly mentioned other users (90% & 100%). All types of tweets frequently included other hashtags. Political tweets were most commonly posted by non-healthcare individuals.

When analyzing the top tweets for their characteristics, 15 were part of a thread, 58 contained an image, 19 contained a GIF/Video, 81 contained other hashtags (median 2 other hashtags with range 1-12), and 22 mentioned other users (median 2 mentions with range 1-5). Links to external websites were included in 71 tweets, of which 66% ($n = 47/71$) were educational, 18% (13/71) research-oriented, 4% (3/71) political, and 11% (8/71) promotional content.

May was the most active month (2,864 retweets) while December was the least active (198 retweets).

Within the week, Tuesday was the most active day (3,486 retweets) while Thursday was the least active (733 retweets). In the span of a day, mornings (ET) were the most active time (4,421 retweets) while evenings were the least active (573 retweets) (Figure 1).

Top links

The 50 most shared links tweeted with the hashtag #asthma were collectively shared 6009 times (median number of shares 92, range 60–710 shares) (Table 2). The most common type of links led to educational content ($n = 21$, 42%) and were shared 3111 times, followed by research-oriented links ($n = 12$, 24%) shared 606 times, promotional links ($n = 11$, 22%) shared 1073 times, and political links ($n = 6$, 12%) shared 1219 times (Table 2). In terms of the type of website the links led to, 40% ($n = 20$) were websites of health care organizations, 38% ($n = 19$) were websites

Table 3. Qualities of Top 50 Links Related to #asthma in 2018 by Quality of Link According to the Asthma Content Score. (data presented as frequency, or median with 25–75% IQR).

Variable	High Asthma Content Score (n = 18)	Low Asthma Content Score (n = 32)	p-value (OR)
Type of Link			
General Education	67% (n = 12/18)	28% (n = 9/32)	0.02
Research Article	17% (n = 3/18)	28% (n = 9/38)	0.50
Promotional	11% (n = 2/18)	28% (n = 9/38)	0.29
Political	6% (n = 1/18)	16% (n = 5/32)	0.40
Host of Site			
Healthcare Organization	56% (n = 10/18)	31% (n = 10/32)	0.13
News Media	33% (n = 6/18)	41% (n = 13/32)	0.76
Other Org/Business	6% (n = 1/18)	25% (n = 8/32)	0.13
Industry	6% (n = 1/18)	3% (n = 1/32)	1.00
Asthma Content Score	10 (7-12)	2 (0-3)	<0.0001
HONCode Score	6 (5-7)	4 (3-6)	0.002
High HONCode Score	50% (n = 9/18)	25% (n = 8/32)	0.12
DISCERN Score			
Reliability	32 (29-35)	23 (18-26)	<0.0001
Quality	17 (13-24)	8 (7-12)	<0.0001
Overall	4 (3-4)	2 (1-2)	<0.0001
High Overall DISCERN	39% (n = 7/18)	0% (n = 0/32)	0.0003
Low Overall DISCERN	17% (n = 3/18)	75% (n = 24/32)	<0.0001
Total Number of Shares	3950	2841	

of news media, 18% ($n=9$) were business organization websites, and 4% ($n=2$) were industry websites.

Only 54% ($n=27$) of the links were likely to provide patients with relevant information about asthma as assessed by overall rating. Additionally, the median Asthma Content Score for these 50 links was 3 (25–75% IQR 1–8) out of a possible 17. Using a cutoff of <5 , a majority of the links (64%; $n=32$) contained low amounts of asthma content.

According to HONCode recommendations, a score of 6–8 suggests a high quality of information on the website. Of the 27 links where HONCode Scores were calculated, 44% ($n=12$) scored highly with a median HONCode score of 5.5 (25–75% IQR 4.5–6.5) (Supplemental Table S2).

The median DISCERN score in the aspect of Reliability (possible range 8–40) was 26 (25–75% IQR 21–32) and the aspect of Quality (possible range 7–35) was 11 (25–75% IQR 7–16). The Overall DISCERN score for the links (possible range 1–5) demonstrated a median of 2 (25–75% IQR 1–3.5) (Supplemental Table S3).

General education links had higher Asthma Content scores than other links ($P<0.005$), although overall the scores were low for all types of links (median 7 (25–75% IQR 2–11) vs median 3 (25–75% IQR 0–4)). Research article links had the highest HONCode scores (median 7 (IQR 5–7) vs median 5 (IQR 3–6); $P=0.01$) and were more likely to be highly shared by Clinicians (OR 14; 95% CI 2.6–75.2) compared to other stakeholder groups. Promotional article links had lowest HONCode Score (median 3 (IQR 2–4) vs median 6 (IQR 4–7); $P=0.0004$). There was a strong correlation between DISCERN, HONCode & Asthma Content Scores (Table 3, Supplemental Figure 1).

Discussion

Asthma is commonly discussed on Twitter by clinicians, non-medical individuals, and organizations. In this review, we found that the top tweets using the hashtag #asthma were commonly educational and included images, hashtags, and educational links. However, when we examined the top links shared using the hashtag #asthma, we found that most scored poorly in terms of asthma content, quality, and reliability. Higher quality links more frequently contained general educational information and were mostly shared by healthcare organizations and clinicians. A better understanding of what drives these conversations might provide educators with strategies to improve dissemination of accurate and reliable asthma content.

In addition to the low quantity of asthma-related content on the links most popularly tweeted with the hashtag #asthma, more than a few of these links contained false information as well as recommendations for untested and potentially dangerous therapies. These links to promotional and pseudo-educational sites promise self-labeled “alternative” or “natural” therapies that can “cure” what “traditional” medicine cannot. For example, one of the evaluated links is to an article entitled “6 Natural Asthma Relief Options (That Don’t Require An Inhaler)” (34). This article advises readers that chiropractic care offers symptom relief by allowing lungs, amongst other organs, to “work properly” by realignment of the spine and that “modern scientific studies” support the claim of symptom improvement with chiropractic care. These sites commonly contain links to other similar themed websites. In our review, we found that these links were

more commonly shared by individuals or non-health-care organizations.

Disinformation often seems more novel than factual information and this disinformation can penetrate farther, deeper, and faster than truth in all categories of information (35). A recent study from the MIT found that false news was more likely to inspire replies expressing greater surprise and disgust, leading to increased shares by individuals (35). False information is more readily distributed as compared to factually correct information, and this phenomenon of relatively preferential propagation of false information has been brought to the forefront during the SARS-CoV-2 pandemic (36,37). It is possible that similar forces were at play in this pre-pandemic dataset.

Our study highlights the opportunity for all health-care entities to engage patients in their medium of comfort when communicating, which increasingly appears to be the digital sphere. A significant amount of poor-quality data or frank misinformation is disseminated online with the potential for negative impact on patients and caregivers. This problem can disproportionately affect the over-65 users, who are more likely to suffer from asthma-related problems and who are more likely to share “fake news” on social media (38,39). Understanding patients’ needs and providing the requisite high-quality information and resources can be an impactful way of fulfilling our responsibility to the community. At the same time, spreading awareness regarding availability of objective tools to assess the quality of online information is important to allow users to independently judge the veracity of information before consuming or applying it.

Healthcare clinicians and medical organizations are obligated to play a role in countering disinformation online. By providing factual evidence-based and peer-reviewed information, clinicians and organizations can provide alternatives to those seeking to profit off of disinformation. But to compete in the digital space and on social media, clinicians and medical organizations will need to adopt strategies that utilize some of the aggressive marketing tactics while staying true to facts. The balance between marketing and objective evidence is difficult to achieve, but providing reliable information is crucial if we are to help patients and caregivers navigate through a sea of disinformation. The need for this balance is evident from the fact that a number of tweets in the top 100 tweets for the year 2018 are those from Twitter based journal clubs or “live tweets” from regional and national medical meetings. The Journal Clubs are conducted to encourage

conversations around published articles on social media. Similarly, the live tweets from conferences lead to propagation on scientific information being discussed at these meetings. Both these types of tweets allow for sharing of medical information that is curated and accurate. The engagement with these tweets depicts the potential for wide ranging impact, not limited only to the medical community.

Our approach to analysis was similar to those used by others (25,26), including by Dr. Goobie and colleagues in their analysis of YouTube videos as a source of disinformation in idiopathic pulmonary fibrosis (25). In Goobie’s review, 200 videos were reviewed resulting from a search of “idiopathic pulmonary fibrosis” using HONCode criteria, the DISCERN instrument, and a content score that the authors’ created. We patterned our Asthma Content Score on their methodology of establishing categories of content and having criteria within each category based on NHLBI recommendations with the input of pediatric and adult asthma and pulmonary experts. Although subjective, this provided some measure to gauge the amount of asthma content addressed in each link. Additionally, our cutoff for the level of asthma content was quite low (5 out of 17 criteria met) and still a majority of links had low levels of asthma content.

Our study has several limitations. We chose to collect data for tweets using the hashtag #asthma rather than the keyword “asthma.” A hashtag is a word or a phrase preceded by a pound or hash sign (e.g. #asthma). These hashtags are employed by users as tags on social media, including on Twitter, to easily identify post on a specific topic or theme. Keywords on the other hand are specific words included in a post, in this case asthma, but do not connect to searchable metadata. We previously have found that this methodology results in more actionable data with less viral noise (40), but this methodology may have excluded important aspects of the conversation on Twitter surrounding asthma. While the stakeholder type was assigned by the Symplur data collection platform, we recognize that the veracity of information on a particular profile online is not always verifiable. This can potentially impact the composition of various stakeholder groups. Additionally, there is a potential for subjectivity even when using objective scores, as the HONCode and DISCERN score are not disease-specific. However, this was minimized by having two authors independently collect the data for both aspects of the study (top tweets and top links) with differences mediated by a third author. We haven’t analyzed

correlations between HONCode, DISCERN score, and Asthma Content. We limited our study to the Top 50 links, and performing multiple correlations and regression analysis on a dataset of this size could lead to spurious results from overfitting models. Whilst not statistically evaluated, the majority of links shared similarly low values across all three categories. Finally, a qualitative analysis of the content of the tweet itself was not performed besides categorizing them into the four above-mentioned groups. This is an area for further research and could help understand the minutiae of the communication between stakeholders. Practically, this is difficult to achieve due to the sheer volume of communication online.

Patients and caregivers are increasingly turning to social media for medical information. But that information may not be reliable or relevant and may contain potentially harmful disinformation. In our review of the conversation on Twitter related to asthma, we found that popular tweets using the hashtag #asthma were generally educational, but when we examined the most shared links, most score poorly in terms of asthma content, quality, and reliability. This suggests that highly-shared tweets and links on Twitter are not the best source of information on medical topics and may be helping to spread disinformation. Additionally, a better understanding of what drives these conversations may improve dissemination of more accurate information by healthcare providers and organizations.

Declaration of interest

The authors have indicated that they have no potential conflicts of interest to disclose.

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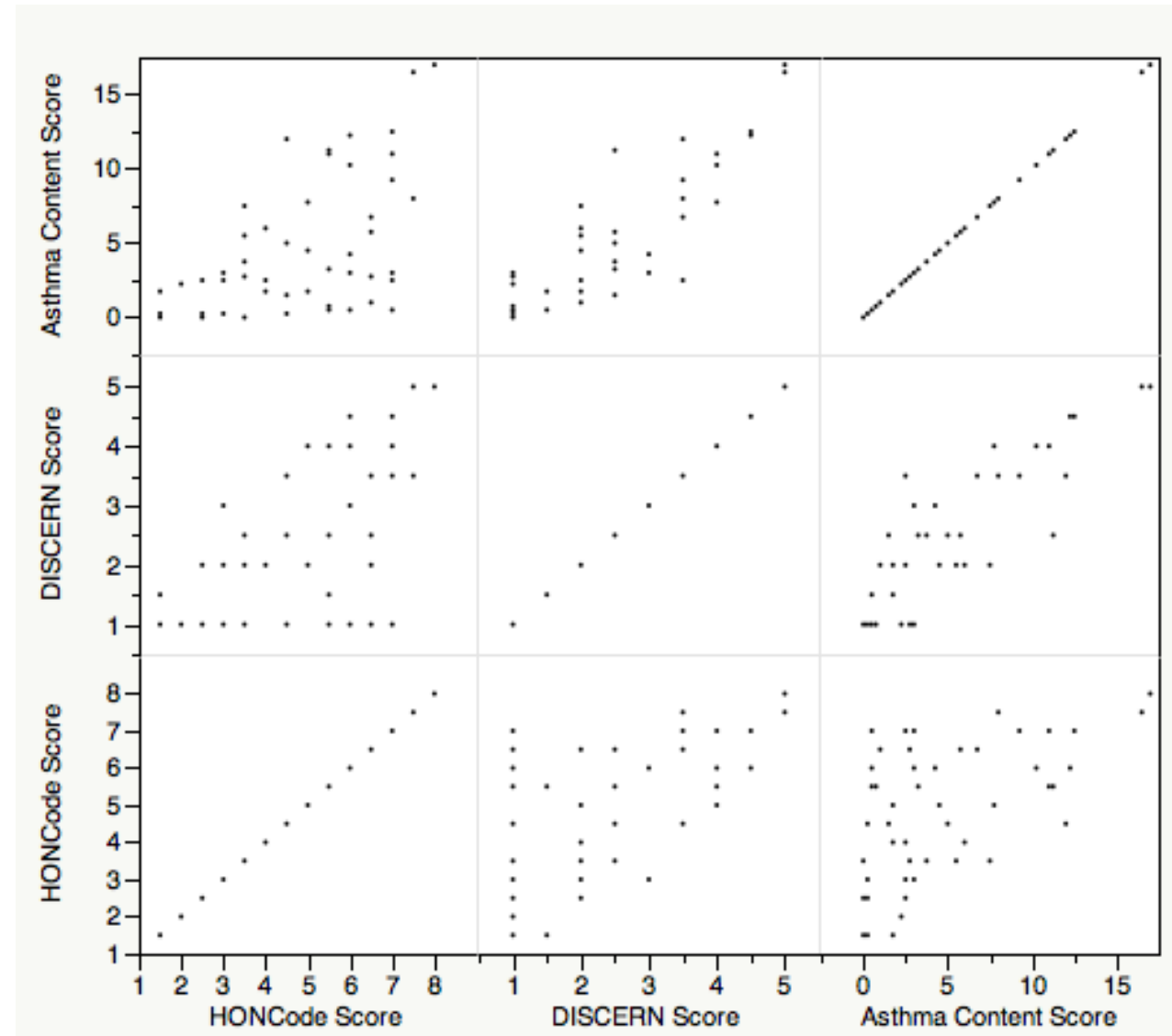
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Supplemental Figure 1: Correlation between HONCode Score, DISCERN Score and the Asthma Content Score.



Supplemental Table S1: Comparisons of Characteristics of Tweets Across Different Stakeholder Types. (data presented as frequency, or median with 25-75% IQR)

	Clinician (n=14)	HCO (n=49)	Individual (n=20)	Org Non-Health (n=16)
Characteristics of Stakeholders Tweeting				
Verified	57% (n=8)	92% (n=45)	25% (n=5)	56% (n=9)
Followers	15,217 (15,217-29,850)	41,255 (14,241-4,641,510)	75,475 (11,501-134,621)	21,040 (7,241-481,353)
Following	660 (608-9,207)	7,727 (2,093-7,727)	2,830 (937-7,022)	339 (126-1,227)
Followers/Following Ratio	23 (3-23)	5 (5-10)	8 (2-27)	162 (42-339)
Tweet Characteristics				
Type of Tweet				
Education Tweet	57% (n=8)	86% (n=42)	25% (n=5)	44% (n=7)
Research Tweet	21% (n=3)	2% (n=1)	10% (n=2)	31% (n=5)
Political Tweet	7% (n=1)	2% (n=1)	40% (n=8)	0% (n=0)
Promotional Tweet	14% (n=2)	10% (n=5)	15% (n=3)	25% (n=4)
Personal Tweet	0% (n=0)	0% (n=0)	10% (n=2)	0% (n=0)
Tweet Part of a Thread	14% (n=2)	16% (n=8)	25% (n=5)	0% (n=0)
Tweet Contains Image	36% (n=5)	76% (n=37)	25% (n=5)	63% (n=10)
Image Tags Users	0% (n=0/5)	16% (n=6/37)	0% (n=0/5)	10% (n=1/10)
Tweet Contains GIF/Video	0% (n=0)	24% (n=12)	20% (n=4)	19% (n=3)
Contains Other Hashtags	86% (n=12)	76% (n=37)	100% (n=20)	69% (n=11)
Median Number of Hashtags	2 (1-10)	1 (1-3)	2 (1-3)	2 (1-4)
Tweet Contains Mentions	50% (n=7)	82% (n=40)	50% (n=10)	88% (n=14)
Median Number of Mentions	4 (1-5)	1 (1-1)	2 (1-3)	1 (1-2)
Tweet Contains Link?	50% (n=7)	82% (n=40)	50% (n=10)	88% (n=14)
Link Contains Video?	0% (n=0)	48% (n=19)	20% (n=2)	7% (n=1)
Type of Link?				
Gen Education Link	57% (n=4/7)	93% (n=37/40)	20% (n=2/10)	29% (n=4/14)
Research Ed Link	43% (n=3/7)	3% (n=1/40)	30% (n=3/10)	43% (n=6/14)
Political Link	0% (n=0/7)	0% (n=0/40)	30% (n=3/10)	0% (n=0/14)
Promotional Link	0% (n=0/7)	5% (n=2/40)	20% (n=2/10)	29% (n=4/14)

Supplemental Table S2: Qualities of Top 50 Links Related to #asthma in 2018 by Quality of Link According to the HONCode Score. (data presented as frequency, or median with 25-75% IQR)

	High HONCode (n=17)	Medium or Low HONCode (n=33)	p-value (OR)
Type of Link			
General Education	47% (n=8/17)	39% (n=13/33)	0.76
Research Article	41% (n=7/17)	15% (n=5/33)	0.08
Promotional	0% (n=0/17)	33% (n=11/33)	0.009
Political	12% (n=2/17)	12% (n=4/33)	1.00
Host of Site			
Healthcare Organization	59% (n=10/17)	30% (n=10/33)	0.0457
News Media	41% (n=7/17)	36% (n=12/33)	
Other Org/Business	0% (n=0/17)	27% (n=9/33)	
Industry	0% (n=0/17)	6% (n=2/33)	
Provides Useful Info	71% (n=12/17)	45% (n=15/33)	0.14
Asthma Content Score	6 (3-12)	3 (0-5)	0.01
High Asthma Content Score	53% (n=9/17)	27% (n=9/33)	0.12
HONCode Score	7 (6-7)	4 (3-5)	<0.0001
DISCERN Score			
Reliability	30 (27-36)	23 (18-28)	<0.0001
Quality	16 (8-25)	10 (7-12)	0.01
Overall	4 (2-4)	2 (1-3)	0.007
High Overall DISCERN	29% (n=5/17)	6% (n=2/33)	0.04 (OR 6.5; 95% CI 1.1-37.9)
Low Overall DISCERN	29% (n=5/17)	67% (n=22/33)	0.02 (OR 0.2; 95% CI 0.06-0.74)

Supplemental Table S3: Qualities of Top 50 Links Related to #asthma in 2018 by Quality of Link According to the DISCERN Score. (data presented as frequency, or median with 25-75% IQR)

	High DISCERN (n=7)	Low DISCERN (n=7)	p-value (OR)
Type of Link			
General Education	86% (n=6/7)	26% (n=7/27)	0.007 (OR 17.1; 95% CI 1.7-168.4)
Research Article	14% (n=1/7)	22% (n=6/27)	1.00
Promotional	0% (n=0/7)	33% (n=9/27)	0.15
Political	0% (n=0/7)	19% (n=5/27)	0.56
Host of Site			
Healthcare Organization	71% (n=5/7)	30% (n=8/27)	0.17
News Media	29% (n=2/7)	37% (n=10/27)	
Other Org/Business	0% (n=0/7)	30% (n=8/27)	
Industry	0% (n=0/7)	4% (n=1/27)	
Provides Useful Info?	100% (n=7/7)	11% (n=3/27)	<0.0001
Asthma Content Score	11 (10-17)	2 (0-3)	0.003
High Asthma Content Score	100% (n=7/7)	11% (n=3/27)	<0.0001
HONCode Score	6 (6-8)	4 (3-6)	0.003
High HONCode Score	71% (n=5/7)	19% (n=5/27)	0.01
DISCERN Score			
Reliability	34 (30-27)	21 (17-26)	<0.0001
Quality	24 (19-28)	7 (7-10)	<0.0001
Overall	4 (4-5)	1 (1-2)	<0.0001

Supplemental Table S4: HONCode Scoring Criteria. One point given for each principle met. Points summed to give total score. Scoring: Low = satisfying 0 to <3 principles; Medium = satisfying 3 to <6 principles; High = satisfying 6-8 principles.

	HONCode Principle
	1. Any medical or health advice given in the video must come from a qualified health professional unless it is clearly stated that the information does not come from a qualified health source.
	2. The information provided in the video must be designed to support the patient's asthma self-management, but it is not meant to replace the patient-physician relationship.
	3. The information in the video maintains the right to confidentiality and respect of the individual patient featured.
	4. Each video contains references to source data on information presented or contains a specific HTML link to source information.
	5. Each video containing claims on the benefits or performance of specific skills/behaviors, interventions, treatments, products, etc., must be supported by evidence through references or HTML links.
	6. The video must provide the viewer with contact information, or a URL to more information.
	7. Any individual or organization that contributes funds, services or material in the posted video must be clearly identified in the video or video description.
	8. If advertisement supports funding to the video or the video's developers, it must be clearly stated. Included advertising must be clearly differentiable to the viewer: There should be a clear difference between the advertising material and the educational material in the video.

Supplemental Table S5: DISCERN Questionnaire. Section 3 Rating: Low = Serious or extensive shortcomings; Moderate = Potentially important, but not serious shortcomings; High = Minimal shortcomings

Section 1 – Is the publication reliable?				
1. Are the aims clear?	No 1	2	Partially 3	4 Yes 5
2. Does it achieve its aims?	No 1	2	Partially 3	4 Yes 5
3. Is it relevant?	No 1	2	Partially 3	4 Yes 5
4. Is it clear what sources of information were used to compile the publication (other than the author or producer)?	No 1	2	Partially 3	4 Yes 5
5. Is it clear when the information used or reported in the publication was produced?	No 1	2	Partially 3	4 Yes 5
6. Is it balanced and unbiased?	No 1	2	Partially 3	4 Yes 5
7. Does it provide details of additional sources of support and information?	No 1	2	Partially 3	4 Yes 5
8. Does it refer to areas of uncertainty?	No 1	2	Partially 3	4 Yes 5
Section 2 – How good is the quality of information on treatment choices?				
9. Does it describe how each treatment works?	No 1	2	Partially 3	4 Yes 5
10. Does it describe the benefits of each treatment?	No 1	2	Partially 3	4 Yes 5
11. Does it describe the risks of each treatment?	No 1	2	Partially 3	4 Yes 5
12. Does it describe what would happen if no treatment is used?	No 1	2	Partially 3	4 Yes 5
13. Does it describe how the treatment choices affect overall quality of life?	No 1	2	Partially 3	4 Yes 5
14. Is it clear that there may be more than one possible treatment choice?	No 1	2	Partially 3	4 Yes 5
15. Does it provide support for shared decision-making?	No 1	2	Partially 3	4 Yes 5
Section 3 – Overall rating of the publication.				
16. Based on the answers to all of the above questions, rate the overall quality of the publication as a source of information about treatment choices.	Low 1	2	Moderate 3	4 High 5

Supplemental Table S6: Asthma Content Score Criteria. If Criteria addressed = 1 point, partially addressed = 0.5 points, not addressed = 0 points

Category	Score	Criteria	Examples
Definition		Chronic Disease	Chronic
		Inflammatory Disease	Neutrophils, Eosinophils, Lymphocytes, Mast cells
		Recurrent	Recurrent, recurrence
		Airways Disease	Airway hyperresponsiveness, Airway remodeling
Signs/Symptoms		Bronchoconstriction	Wheezing, Airway narrowing
		Cough	Cough
		Shortness of breath	Shortness of breath, dyspnea
Risk Factors		Triggers	Allergens, Viruses
		Atopy	Atopy, Eczema, Allergies, Hayfever, Allergic Rhinitis
		Family History	Gene-Environment Interactions
Evaluation		Pulmonary Function Testing	Spirometry
		Allergy Testing	Allergy Testing
Management		Rescue Medications	Albuterol
		Controller Medications	Corticosteroids, LABA
		Asthma Action Plan	Asthma Action Plan
Outcomes		Asthma Control	Control
		Acute exacerbations	Attacks, exacerbations