Tweeting the #flushot: Beliefs, Barriers, and Threats During Different Periods of the 2018 to 2019 Flu Season

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Abstract

Influenza epidemics happen every year, with more than 8 million severe cases in 2017. The most effective way to prevent seasonal influenza is vaccination. In recent years, misinformation regarding vaccines abounds on social media, but the flu vaccine is relatively understudied in this area, and the current study is the first 1 to explore the content and nature of influenza information that is shared on Twitter, comparing tweets published in the early flu season with those posted in peak flu season. Using a quantitative content analysis, 1000 tweets from both parts of the flu season were analyzed for use of Health Belief Model (HBM) variables, engagement, and flu vaccine specific variables. Findings show several promising opportunities for health organizations and professionals: HBM constructs were present more frequently than in previous, related studies, and fewer vaccine-hesitant tweets appear to be present. However, the presence of high barriers to flu vaccine uptake increased significantly from early to peak season, including an increase in the mention of conspiracy theories. Flu vaccine related tweets appear to vary in misinformation level and density throughout the flu season. While this should be confirmed by further studies over multiple flu seasons, this a finding that should be considered by public health organizations when developing flu vaccine campaigns on social media.

Keywords

influenza vaccines, social media, influenza, human, health knowledge, attitudes, practices, prevention

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Introduction

Seasonal influenza, or flu, continues to be one of the more pressing global health issues, with more than 8 million severe cases in 2017.[1] In the United States (U.S.), the 2017 to 2018 flu season set new records for the high numbers of deaths and illnesses, killing around 80 000 people.[2] Potentially life-threatening complications from the flu can often be prevented or lessened through vaccination. After a particularly severe flu season in the previous year, the start of the 2018 to 2019 flu season saw increased rates of vaccination among adults,[3] with around 44% of U.S. adults getting vaccinated—still far less, however, than the U.S. Department of Health and Human Services target flu vaccine uptake rate of 80%.[4]

Flu season varies from year to year, and by world region, but, in the U.S. and Europe, the season generally starts in late fall, around October or November. Peak flu activity usually runs December through February, and the season may end as late as May.[3,5] The Advisory Committee of Immunization Practices (ACIP), which is hosted by the CDC, recommends that individuals get vaccinated before the end of October.[6] Although most individuals who get vaccinated against flu do so earlier in the season, there is a need for ongoing vaccine communication for optimal vaccination rates.[7] As flu season can last well into spring, getting vaccinated during these months can still offer protection, and ACIP recommends that vaccines should continue to be offered in the community throughout the influenza season.[6] There is evidence that late

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reminders, including interactive options along with educational information, can increase late-season vaccination among populations in urban, low-income, and minority communities.[7]

Vaccine Misinformation and Social Media

While a surge in flu severity may have driven increased vaccination rates for 2018 to 2019, increases in misinformation about vaccines may also limit vaccine uptake. Visiting anti-vaccination websites for 5 to 10 min can increase perceptions of vaccination risks and decrease intentions to vaccinate.[8] In addition, a study by Dunn, Surian, Leask, Dey, Mandl, and Coiera showed that HPV vaccine uptake was lower in States where vaccine misinformation and conspiracies made up higher proportions of Twitter exposure, suggesting that negative representations of vaccines on this platform may reflect or influence vaccine acceptance.[9] Finally, a 2019 UK study indicated that the presence of vaccine misinformation may be associated with lower vaccine uptake.[10]

An alarming trend on Twitter suggests that anti-vaccine tweets receive more attention and are shared more frequently than pro-vaccine tweets.[11] Research from large datasets of vaccine-related tweets shows that anti-vaccine tweets are retweeted over 4 times more frequently than neutral tweets, while pro-vaccine tweets are retweeted one-and-a-half times more frequently.[11] Antivaccine tweets more frequently mention the risks or dangers of vaccines and distrust of scientific organizations and government.[11] For pro-vaccine tweets, the most common themes appear to be related to global vaccination efforts, scientific organizations, the efficacy of vaccines, and outbreaks that could have been prevented by vaccines.[11] Recent studies have highlighted the high volume of misinformation that is spread on Twitter and Pinterest regarding vaccines, their alleged link to autism, and perceived severe adverse effects.[12-14]

Currently, online audiences remain polarized on the issue of vaccines, and this polarization leads to active debate strongly for or against vaccines online, often accompanied by echo-chamber effects.[15,16] And studies have shown that this niche exposure to media reinforces specific viewpoints can add to this polarization for flu, such as in the case of swine flu in the U.S.[17] As such, further investigation of the spread of vaccine information through online, social platforms is important. Scholars have called for "a greater need to observe online platforms to better understand the social mechanisms that may contribute to, or reinforce, attitudes and beliefs related to influenza vaccine refusal."[15] Study of social media platforms provides a level of real-time access to individuals' thoughts, beliefs, and experiences regarding vaccination,[18] and platforms such as Twitter offer a glimpse into this conversation. Furthermore, Twitter and other public online platforms provide for a greater reach of vaccine-related messages and may reach audiences that Facebook fails to.[18] Finally, while visuals are not a required component of tweets (compared to digital platforms such as Instagram and Pinterest), vaccine-related tweets that include a visual are more likely to be retweeted.[19] In addition, messages that include visuals are more likely to be remembered, remembered accurately, and remembered for a longer period of time.[20] Twitter visuals are therefore a relevant component of the overall message, particularly when focusing on the topic of vaccines.

With the rampant spread of misinformation on social media platforms, some social media platforms are now looking to block anti-vaccine content on their platforms,[21-23] but these efforts are in the early stages and often do not prevent the portrayal of all vaccine misinformation.

Given the importance of the flu vaccine in prevention and reduction of spread of flu, this study examined communication on social media platform Twitter where misinformation has often been prevalent.[24] While public health organizations define both an early and peak flu season, little research has examined different communication strategies for public health communicators for these 2 stages of the flu season, and more research is needed here to examine how community members and individuals talk about flu vaccines differently during these different seasons. This study will help to fill the gaps by examining the differences in communication during these 2 time periods by asking: (1) what are the differences between flu vaccine-related tweets in the early 2018 to 2019 flu season and the peak 2018 to 2019 flu season and (2) how do users engage with flu vaccine-related tweets in the early 2018 to 2019 flu season and the peak 2018 to 2019 flu season.

Health Belief Model. The Health Belief Model (HBM) is one of the most widely used theories to understand how health beliefs correspond to preventive behaviors.[25] The original model, proposed by Rosenstock,[26,27] was designed to take a practical, applied view to understanding health behaviors. A 1988 revision to the model by Rosenstock, Strecher, and Becker more fully explained conceptual relationships in the model. Health belief variables including perceived susceptibility, severity, benefits, barriers, and self-efficacy work together as independent variables in the model to help predict health behavior, along with health motivations and incentives.[28] The model hypothesizes that if 1 is sufficiently motivated (ie, concerned about their health), believes that they are susceptible or vulnerable, and believes that following recommended health actions will be beneficial (with acceptable costs), then 1 would be more likely to take action. Benefits must outweigh the barriers in this model for action to occur, and individuals must feel the need to make a health behavior change through health motivation and perceived susceptibility/severity of the health threat.[28]

The HBM has been used to understand why some individuals may or may not choose to get vaccinated against flu.

For example, Cheney and John found that perceived severity/susceptibility, barriers, and cues to action all related significantly to future plans to get vaccinated against flu.[29] Individuals who perceived the flu vaccine to be more effective (ie, vaccine efficacy) reported vaccination at higher rates (76% of adults, compared to 43% of overall adults in 2016-2017).[30] Barriers to vaccination included low perceived threat (severity/susceptibility), low perceived vaccine efficacy, potentially risky side effects, lack of health insurance, and a dislike of shots.[30]

Cheney and John's HBM results, however, suggest differences between "accepting" and "resistant" individuals in terms of their beliefs, which requires different types of interventions.[29] For individuals resistant to flu vaccines, the HBM constructs of perceived threat were not present, individuals did not express access barriers, and they did not feel positively toward cues to action.[29] As HBM has been shown to be impactful for examining successful uptake of flu vaccines, presence of constructs of the HBM in communication on Twitter were examined in this study for their influence on engagement with flu messages. This study's final research question was: what extent were Health Belief Model constructs present in flu vaccine-related tweets between the early 2018-2019 flu season and the peak 2018 to 2019 flu season.

Method

A quantitative content analysis of vaccine-related tweets was conducted to address the research questions posed above.

Sample

The sample collected for the content analysis consisted of 500 early-season (U.S. and Europe) flu-vaccine-related Twitter (www.twitter.com) posts and 500 peak-season (U.S. and Europe) flu-vaccine-related Twitter posts. An early season sample of 200 000 was collected in October and November of 2018, and a peak season sample, also consisting of 200 000 was collected in January and February of 2019, both using web-based social media mining tool Netlytic (www.netlytic.org), a cloud-based text and social networks analyzer that can automatically summarize and discover communication networks from publicly available social media posts, using public APIs (Application Programming Interface). The sample was collected using the hashtags "Flu vaccine," "Flu vaccination," and "Flu shot." Using the hashtags "influenza vaccination," and "influenza vaccine" did not yield any additional unique posts, and these hashtags were therefore not included in the sample. Out of these 2 samples of 200 000 tweets each, random sampling was used to collect the final 2 samples for this study, 1 for the early season and 1 for the peak season. Only English-language posts were analyzed.

Coding Protocol

Tweets were coded for engagement variables (retweets, likes, and replies) and account characteristics (type of Twitter user). HBM constructs were also included as variables: the perceived benefits of and perceived barriers to getting the flu vaccine (including specific flu vaccine adverse effects); perceived severity of and perceived susceptibility to the flu virus; perceived self-efficacy to get as well as refuse the flu vaccine; and cues to action to get as well as refuse the flu vaccine. Additionally, coding categories included conspiracy theories (government, medical, and pharmaceutical), as well as visual characteristics: fear visuals (presence of needles, masks, and threat signs), as these categories reflected potential misinformation and rumor regarding vaccines. Lastly, presence of persons (gender and race/ethnicity) was also coded.

Intercoder Reliability

After 5 training sessions, 2 coders coded 10% of posts (n = 100) for intercoder reliability. After pre-testing and subsequent coding protocol changes, intercoder reliability testing showed Krippendorff's alpha was on average 0.73. Individual coefficients were all reliable, with the lowest at 0.70 (complete list is available upon request). Both coders then coded 450 of the remaining posts.

Statistical Analyses

Descriptive analyses were carried out for all variables. In addition, Mann-Whitney U tests were used to check for differences in Twitter engagement between posts with versus without a range of dichotomous variables. Distributions of the engagement frequencies were evaluated and found similar based on visual inspection of a box plot for all variables involved. Finally, differences between the early and peak season tweets were explored via logistic regression.

Results

To determine the differences between flu vaccine-related tweets in the early 2018 to 2019 flu season (52.1%, n = 521) and the peak 2018 to 2019 flu season (47.9%, n = 479), we analyzed tweet source, composition, and flu vaccine context. In regard to source, results revealed that most tweets in both time periods of the flu season were published either by individuals or government entities (eg, the CDC, the WHO) (see Table 1). Of all early season tweets, 64.7% (n = 337) included a visual, while 84.1% (n = 403) of peak season tweets did. Of the early season tweets including a visual, 38.9% (n = 131) consisted of primarily visuals and 31.8% (n = 104) of a mix of images and text; in addition, 10.4% (n = 35) included a fear visual. Of the peak season tweets

Table 1. Flu Vaccine Descriptives for Twitter by Season.

Variable/sub-variable	Early season	Peak season	Direction	Absolute percentage difference	95% CI	*P*-value
Total sample	**52.1% (n=521)**	**47.9% (n=479)**				
Healthcare professionals oppose flu vaccine	.8% (n=4)	1.7% (n=8)	increase	0.9	−0.005, 0.023	.190
Healthcare professionals promote flu vaccine	25.1% (n=131)	18.8% (n=90)	decrease	6.3	−0.115, −0.012	.016*
Mistrust medical professionals	.6% (n=3)	6.5% (n=31)	increase	5.9	0.036, 0.082	<.001*
Mistrust science	.2% (n=1)	3.1% (n=15)	increase	2.9	0.013, 0.045	<.001*
Mistrust government	2.1% (n=11)	7.1% (n=34)	increase	5.0	0.024, 0.076	<.001*
Alternative protection against flu	7.6% (n=38)	4.4% (n=21)	decrease	3.2	−0.058, 0	.025*
Specific target populations flu vaccine	41.5% (n=216)	25.9% (n=124)	decrease	15.6	−0.213, −.098	<.001*
Visual included	**64.7% (n=337)**	**84.1% (n=403)**	increase	19.4	0.142, 0.0247	<.001*
Primarily image	38.9% (n=131)	35.2% (n=142)	decrease	3.7	−0.106, 0.034	
Primarily text	11.9% (n=40)	11.9% (n=48)	None	0	−0.046, 0.047	
Mix of image and text	31.8% (n=104)	34.0% (n=137)	increase	2.2	−0.036, 0.099	
Infographic	3.6% (n=12)	1.7% (n=7)	decrease	1.9	−0.042, 0.005	
Drawing	1.5% (n=5)	2.5% (n=10)	increase	1.0	−0.010, 0.030	
Video	9.2% (n=31)	13.2% (n=53)	increase	4.0	−0.006, 0.085	
GIF	2.4% (n=8)	.2% (n=1)	decrease	2.2	−0.038, −0.004	
Other	.9% (n=3)	1.2% (n=5)	increase	0.3	−0.011, 0.018	
Visual: Person present	**36.1% (n=188)**	**37.8% (n=181)**	decrease	1.7	−0.043, 0.077	.052
Adult	87.8% (n=165)	86.2% (n=156)	decrease	1.6	−0.084, 0.053	
(Pre)teen	12.8% (n=24)	13.3% (n=24)	increase	0.5	−.064, .074	
Toddler/baby	22.3% (n=42)	17.7% (n=32)	decrease	4.7	−0.128, 0.035	
Male	58.5% (n=110)	42.0% (n=76)	decrease	16.5	−0.266, −0.065	
Female	74.5% (n=140)	63.5% (n=115)	decrease	11	−0.203, −0.016	
White	80.9% (n=152)	80.1% (n=145)	decrease	0.8	−.088, 0.073	
Black	18.6% (n=35)	8.8% (n=16)	decrease	9.8	−0.167, 0.028	
Latinx	4.8% (n=9)	1.7% (n=3)	decrease	3.1	−0.067, 0.004	
Asian	8.0% (n=15)	4.4% (n=8)	decrease	3.6	−0.085, 0.013	
Medical professional	28.7% (n=54)	24.9% (n=45)	decrease	3.8	−0.129, 0.052	
Fear visual	**10.4% (n=35)**	**25.6% (n=103)**	increase	15.2	0.098, 0.205	<.001*
Large needle	31.4% (n=11)	35.0% (n=36)	increase	3.6	−0.144, 0.214	
Needle	51.4% (n=18)	66.0% (n=68)	increase	14.6	−0.043, 0.335	
Brightly colored vaccine liquid	5.7% (n=2)	1.0% (n=1)	decrease	4.7	−0.127, 0.032	
Scared facial expression	.0% (n=0)	4.9% (n=5)	increase	4.9	0.007, 0.090	
Mask, gloves	62.9% (n=22)	36.9% (n=38)	decrease	26	−0.445, −0.074	
Visual threat sign (skull, danger)	.0% (n=0)	2.9% (n=3)	increase	2.9	−0.003, 0.062	
Web link	**47.6% (n=248)**	**65.1% (n=312)**	increase	17.5	0.115, 0.236	<.001*
Blog: individual	.8% (n=2)	.0% (n=0)	decrease	0.8	−0.019, 0.003	
Blog: individual, sole proprietor	.4% (n=1)	.0% (n=0)	decrease	0.4	−0.012, 0.004	
Blog: organizational	.4% (n=1)	.0% (n=0)	decrease	0.4	−0.012, 0.004	
Social media	16.1% (n=40)	9.0% (n=28)	decrease	7.1	−0.127, −0.016	
Government/regulatory	39.9% (n=99)	32.7% (n=102)	decrease	7.2	−0.152, 0.008	
Nonprofit website	2.0% (n=5)	.0% (n=0)	decrease	2.0	−0.038, −0.003	
Official medical	5.6% (n=14)	6.4% (n=20)	increase	0.8	−0.032, 0.047	
Healthcare practitioner	.8% (n=2)	.0% (n=0)	decrease	0.8	−0.019, 0.003	

Table 1. (continued)

Variable/sub-variable	Early season	Peak season	Direction	Absolute percentage difference	95% CI	P-value
Other health–focused	3.6% (n = 9)	5.4% (n = 17)	increase	1.8	−0.016, 0.052	
Commercial (not health)	.4% (n = 1)	.6% (n = 2)	increase	0.2	−0.009, 0.014	
Commercial health	3.2% (n = 8)	1.9% (n = 6)	decrease	1.3	−0.040, 0.014	
News	13.3% (n = 33)	17.9% (n = 56)	increase	4.6	−0.014, 0.106	
Academic	4.4% (n = 11)	14.1% (n = 44)	increase	9.7	0.050, 0.143	
Antivaccine organization	2.4% (n = 6)	6.4% (n = 20)	increase	4.0	0.007, 0.073	
Other	5.6% (n = 14)	4.8% (n = 15)	decrease	0.8	−0.046, 0.029	
Broken link	.8% (n = 2)	.6% (n = 2)	decrease	0.2	−0.016, 0.013	
Link to own site	50.4% (n = 125)	45.5% (n = 142)	decrease	4.9	−0.132, 0.034	

Note. Bolded frequencies are totals in group and therefore the denominator for the subgroup in that section.
*Significant at $P < .05$, using Chi Square tests; Fisher's Exact Test if $n < 5$.

including a visual, 35.2% (n = 142) consisted of primarily visuals and 34.0% (n = 137) of a mix of images and text; in addition, 20.6% (n = 103) included a fear visual (see Table 1). The majority of persons portrayed in visuals in both parts of the sample were White (80.9% in the early season vs. 80.1% in peak season). Of all early season tweets, 41.5% (n = 216) mentioned a specific target population for the flu vaccine, while 25.9% (n = 124) mentioned a specific target population for the flu vaccine (see Table 1 for complete descriptives). Chi Square tests showed that healthcare professionals more frequently promoted the flu vaccine in the early season compared to the peak season, while mistrust of medical professionals, science, and government, as well as healthcare professionals opposing the flu vaccine were all more frequently present in the peak season sample (see Table 1).

As users engaged with tweets from the early 2018 to 2019 flu season, the median number of retweets was 1.00 (IQR = 7.00), the median number of likes was 2.00 (IQR = 13.00), and the median number of replies was 0 (IQR = 0).

Mann Whitney U tests were carried out in order to determine whether tweets with specific dichotomous variables were more likely to elicit engagement compared to tweets that did not mention these variables. Table 3 shows that in the early flu season, tweets including a web link, visual, and healthcare professionals promoting the flu vaccine were all significantly more likely to produce Twitter engagement than tweets that did not include these variables. Conversely, mentioning specific flu vaccine target populations in a tweet was significantly less likely to elicit Twitter engagement. In peak flu season, tweets mentioning healthcare professionals promoting the flu vaccine were all significantly more likely to produce Twitter engagement than tweets that did not (see Table 3).

Logistic regression analysis showed that tweets in the peak flu season had greater odds of including a visual and a link, while tweets from the early flu season had greater odds

of targeting specific populations for the flu vaccine (see Table 4).

For Health Belief Model constructs, for the early flu season tweets, 64.5% (n = 336) mentioned perceived high benefits of the flu vaccine, while 11.3% (n = 59) mentioned high perceived barriers to the flu vaccine; 28.2% (n = 147) mentioned self-efficacy to get the vaccine, and 69.1% (n = 360) used a cue to action to get the vaccine. Moreover, 42.0% (n = 219) of the early season sample mentioned the flu's high perceived severity, while 11.9% (n = 62) mentioned high susceptibility to the flu (see Table 2). Of the peak flu season tweets, 54.7% (n = 262) mentioned perceived high benefits of the flu vaccine while 25.3% (n = 121) mentioned high perceived barriers to the flu vaccine; 16.1% (n = 77) mentioned self-efficacy to get the vaccine and 53.2% (n = 255) used a cue to action to get the vaccine. Moreover, 34.7% (n = 166) of the peak season sample mentioned the flu's high perceived severity, while 21.5% (n = 103) mentioned high susceptibility to the flu (see Table 2).

Mann Whitney U tests showed that in the early flu season, tweets mentioning susceptibility to the flu, and those referring to flu vaccine uptake self-efficacy, were more likely to produce Twitter engagement than tweets that did not refer to these variables. In peak flu season, tweets referring to flu vaccine uptake self-efficacy were significantly more likely to produce Twitter engagement than tweets that did not (see Table 3).

Logistic regression analysis showed that tweets from the peak flu season had greater odds of mentioning susceptibility to the flu and barriers to getting the flu vaccine, while tweets from the early flu season had greater odds of mentioning flu vaccine uptake self-efficacy (see Table 4).

Discussion

The current study analyzed content of tweets posted on Twitter between early and peak flu season. We found that

Table 2. Dichotomous Independent Variables and Median Engagement on Twitter.

Engagement variable	Season	Variable	Median present	Median absent	U	P-value
Retweets	Early	Visual	2.00	0.00	41 782.000	<.001
Likes	Early	Visual	3.00	0.00	41 215.500	<.001
Retweets	Early	Web link	2.00	0.00	41 261.500	<.001
Likes	Early	Web link	2.00	1.00	38 827.500	.003
Retweets	Early	Healthcare professionals promote flu vax	2.00	1.00	30 079.500	.002
Likes	Early	Healthcare professionals promote flu vax	4.00	1.00	31 475.500	<.001
Retweets	Early	Specific populations flu vax	0.50	1.00	27 869.500	.002
Likes	Early	Specific populations flu vax	0.00	3.00	24 632.500	<.001
Retweets	Peak	Healthcare professionals promote flu vax	2.00	0.00	20 980.000	.001
Likes	Peak	Healthcare professionals promote flu vax	2.00	0.00	21 267.500	.001
Retweets	Early	Flu susceptibility	4.50	1.00	17 375.500	.003
Likes	Early	Flu susceptibility	6.00	2.00	17 032.000	.009
Retweets	Early	Flu vax uptake self-efficacy	3.00	1.00	32 992.000	<.001
Likes	Early	Flu vax uptake self-efficacy	4.00	1.00	32 687.000	.001
Retweets	Peak	Flu vax uptake self-efficacy	2.00	1.00	18 030.000	.013

Table 3. Flu Vaccine Related HBM Descriptives for Twitter by Season.

Variable/sub-variable	Early season	Peak season	Direction	Absolute percentage difference	95% CI	P-value
Total sample	**52.1%(n=521)**	**47.9%(n=479)**				
Health Belief Model						
Perceived high benefits flu vaccine	64.5% (n=336)	54.7% (n=262)	decrease	9.8	−0.159, −0.037	.002*
Perceived high barriers flu vaccine	11.3% (n=59)	25.3% (n=121)	increase	14.0	0.092, 0.187	<.001*
Perceived high severity flu	42.0% (n=219)	34.7% (n=166)	decrease	7.3	−0.134, −0.014	.017*
Perceived susceptibility flu	11.9% (n=62)	21.5% (n=103)	increase	9.6	0.050, 0.142	<.001*
Cue to action - get flu vaccine	69.1% (n=360)	53.2% (n=255)	decrease	15.9	−0.218, −0.099	<.001*
Self-efficacy - get flu vaccine	28.2% (n=147)	16.1% (n=77)	decrease	12.1	−0.172, −0.071	<.001*
HBM related variables						
Severity: Flu serious	40.5% (n=211)	33.0% (n=158)	decrease	7.5	−0.135, −0.016	.014*
Severity: Flu complications	12.3% (n=64)	15.7% (n=75)	increase	3.4	−0.009, 0.077	.123
Barriers: Flu vaccine deadly	2.5% (n=13)	1.3% (n=6)	decrease	1.2	−0.029, 0.004	.150
Barriers: Flu vaccine does not work	3.6% (n=19)	11.5% (n=35)	increase	7.9	0.008, 0.065	<.001*
Barriers: Mistrust flu vaccine safety	5.8% (n=30)	11.7% (n=56)	increase	5.9	0.024, 0.094	.001*
Barriers: Civil liberties related to flu vaccine	.6% (n=3)	1.9% (n=9)	increase	1.3	−0.001, 0.027	.059
Barriers: Conspiracy	**3.8% (n=20)**	**14.4% (n=69)**	increase	10.6	0.070, 0.141	<.001*
Government	40.0% (n=8)	37.7% (n=26)	decrease	2.3	−0.266, 0.220	
Medical	15.0% (n=3)	46.4% (n=32)	increase	31.4	0.118, 0.510	
Pharmaceutical	30.0% (n=6)	55.1% (n=38)	increase	25.1	0.018, 0.483	
Barriers: Flu vaccine adverse reactions	**3.8% (n=20)**	**7.9% (n=38)**	increase	4.1	0.012, 0.070	.006*

(continued)

Table 3. (continued)

Variable/sub-variable	Early season	Peak season	Direction	Absolute percentage difference	95% CI	*P*-value
Rash	0.0% (n = 0)	5.3% (n = 2)	increase	5.3	−0.018, 0.124	
Shortness of breath	10.0% (n = 2)	2.6% (n = 1)	decrease	7.4	−0.215, 0.067	
Autism symptoms/ diagnosis	.0% (n = 0)	15.8% (n = 6)	increase	15.8	0.042, 0.274	
Paralysis	30.0% (n = 6)	21.1% (n = 8)	decrease	8.9	−0.329, .150	
Death	60.0% (n = 12)	15.8% (n = 6)	decrease	44.2	−0.686, −0.198	
Fever	5.0% (n = 1)	2.6% (n = 1)	decrease	2.4	−0.132, 0.085	
Other	50% (n = 10)	73.7% (n = 28)	increase	23.7	−0.023, 0.497	

Note. Bolded frequencies are totals in group and therefore the denominator for the subgroup in that section.
*Significant at $P < .05$, using Chi Square tests; Fisher's Exact Test if n < 5.

Table 4. Logistic Regression.

Variable	B	SE	Wald X^2	P	OR	95% CI
HBM: Perceived benefits flu vax	0.284	0.207	1.880	.170	1.328	0.885, 1.992
HBM: Perceived barriers flu vax	0.739	0.221	11.164	.001*	2.094	1.357, 3.232
HBM: Flu susceptibility	0.758	0.207	13.476	<.001*	2.135	1.424, 3.200
HBM: Flu severity	−0.050	0.181	0.077	.782	0.951	0.667, 1.356
HBM: Flu vax uptake self-efficacy	−0.615	0.182	11.477	.001*	0.541	0.379, 0.772
HBM: Flu vax cue to action	−0.371	0.213	3.037	.081	0.690	0.455, 1.047
Web link	0.290	0.145	3.975	.046*	1.336	1.005, 1.776
Visual	1.029	0.173	35.429	<.001	2.798	1.994, 3.927
Healthcare professionals promoting flu vax	−0.227	0.172	1.746	.186	0.797	0.569, 1.116
Alternative protection	0.606	0.417	2.114	.146	1.833	0.810, 4.149
Specific populations for flu vax	−0.343	0.173	3.949	.047*	0.710	0.506, 0.995

*Significant at $P < .05$.

tweets in the early season were more likely to be from a health professional and were more likely to target specific populations. Tweets in the early season were also more frequently featured theoretical concepts from the health belief model. Whereas tweets in the peak season were more likely to discuss distrust for medical professionals, science, and government. These tweets were also more likely to feature general visuals, fear visuals, and feature web links. More research is needed to understand if these trends replicate over time. This study provides a contribution to the literature by suggesting that future research should include seasonal variation as an important factor when analyzing vaccine-related social media content. Overall, results provide insight into content of vaccine-related tweets between seasons, and how tweets featured constructs from the Health Belief Model.

Content of Vaccine-Related Tweets in Early and Peak Season

This research explored the differences in content between early and peak season tweets. One interesting finding is that tweets published in the early flu season were more likely to mention positive attributes of the vaccine, including targeting specific populations such as children, the elderly, and those suffering from certain chronic diseases, and were also more likely to be shared by healthcare professionals endorsing the flu vaccine than tweets posted in the peak season. Tweets posted in the peak flu season, however, were more likely to contain high barriers to flu vaccine uptake such as conspiracy theories and include visuals. The potential combination of these 2 findings is problematic particularly because visuals are processed differently than text alone, are more likely to be remembered, remembered correctly and for a longer period of time, and more likely to be acted on.[20] In addition, the presence of fear visuals (visuals likely to elicit fear or anxiety, such as an image of a large syringe) increased from 10 to 20% between the early and peak flu season.

The second research question asked about engagement with tweets between early and peak season. A potentially encouraging finding was that tweets published by healthcare professionals and promoting the flu vaccine in both parts of the flu season were more likely to elicit engagement

in the form of retweets and likes. Also, tweets with visuals and interactive components were more likely to engage users on Twitter. This mirrors prior research findings that vaccine communication with photos, videos, and interactive components is likely to drive online engagement.[31]

The Health Belief Model Constructs

While many recent vaccine-focused social media studies have produced a somewhat alarming picture of a clear majority of anti-vaccine posts on several platforms,[13,32] this study found a much higher percentage of posts discussing the benefits of the flu vaccine as well as discussing the perceived high severity of the flu. According to the Health Belief Model, unless people perceive the flu to be a serious disease and unless they perceive themselves to be at risk of contracting the flu, they are not likely to get the vaccine.[25] This higher frequency of specific HBM constructs in flu vaccine-related tweets is therefore encouraging, since it both appears to point to a lower percentage of vaccine-hesitant or even anti-vaccine tweets in this sample, as well as to a potentially more effective messaging strategy—one in which more people may be convinced to get the flu shot because they are convinced of the flu's threat and the benefit of the flu vaccine.

Barriers: Misinformation and Conspiracy Theories

However, there are some concerning findings as well. The presence of high barriers to flu vaccine uptake increased from 11.3% to 25.3% from early to peak season, a statistically significant increase. This included an increase in the mention of conspiracy theories from just under 4% to close to 15%. The American Medical Association recently called upon Twitter and other social media platforms to limit false anti-vaccine claims.[33] However, even though Twitter and Facebook report actively removing troll accounts,[34] a recent study by Broniatowski et al. found that Russian trolls and sophisticated bots were actively tweeting about vaccines and both posted anti-vaccine as well as divisive content.[12] Addressing vaccine-related misinformation is an issue that will require vigilance and a coordinated approach to identify illegitimate accounts and respond to misinformation appropriately.

Practical Implications

As evidenced by these findings, health communicators should consider providing more information about the flu vaccine and availability of the vaccine early in the flu season to drive engagement. Community health professionals should use the Health Belief Model to strategically guide content that promotes the flu vaccine, including continuing to create social media posts the discuss benefits of the vaccine and the severity of the flu. This content may benefit from interactive components, such as weblinks, quizzes, or other gamification features, and photos and videos; however, more research is needed in this area to understand how these features drive engagement with vaccine-related messages.

As anti-vaccine sentiment was not expressed as strongly on Twitter as has been shown in other recent studies, Twitter should be considered by public health organizations for inclusion in their campaigns against vaccine misinformation on social media. Health communicators looking to address vaccine misinformation surrounding the flu vaccine may find that peak season should be a priority to do so, as findings in this study showed that conspiracy theories were likely to be higher during this part of the flu season. In addition, health communicators may benefit from creating an FAQ page or rumor-dispelling page about vaccines that can be linked to when correcting vaccine misinformation. Trust continues to be an important consideration for vaccine information, and rumor and misinformation correction should come from trusted sources for individuals.[11]

Limitations and Future Directions

The current study had several limitations: This study focused on English-language tweets during the time of early and peak flu seasons in the U.S. and Europe, and excluded parts of the world such as Southeast Asia, where the flu season tends to peak between July and October.[35] Future studies should include or exclusively focus on non-U.S./European regions and languages other than English. In addition, this study concentrated on 1 social media platform, Twitter. Future research might explore early and peak season social media content for a variety of social media platforms where vaccine discussions are present, such as Facebook, Instagram, Pinterest, YouTube, and Reddit. While the inclusion of Twitter visuals is a strength of this study, future studies should add a more qualitative approach to analyze these visuals in order to gain a greater understanding of the visual components of flu vaccine-focused tweets at different timepoints of the flu season. Future research should also look at the interactions between these different actors by analyzing the conversations evolving from each original tweet. Finally, a purpose of the current study was to analyze content that individuals are likely exposed to during early and peak flu season. Total volume of tweets in these time periods was not measured and thus this study only provides information on content without shedding light on post frequency. Future studies should consider analyzing Twitter year-round to see how conversations about the flu vaccine may accelerate or decelerate based on the season. Additionally, future research might examine tweets over a period of several years to examine if these trends hold consistent for multi-year studies.

Conclusion

Flu vaccination remains an important topic for public health communicators to study, particularly in the social media domain where issues like the spread of misinformation affect vaccine beliefs and sharing of vaccine-related information. Frameworks, such as the Health Belief Model, provide a starting point from which to examine factors that may drive engagement with vaccine communication. However, as vaccines remain a polarized issue with strong beliefs on either side of the vaccine debate, HBM constructs alone are often not enough to drive behavior change. Communicators must understand the target audiences and work within and around their worldviews and perspectives, while educating on vaccines. Provided below are some additional recommendations for how to further strengthen flu vaccine-related communication.

Based on the findings from this study, applied communication programs targeting vaccine uptake should include, in the early flu season, information on access and availability to flu vaccines, information about the vaccines themselves, and interactive content including weblinks, photos, videos, and discussion/Q&A with individuals. As vaccine communication overall appears to be more positive during the early season, this may a good time to foster discussion of vaccines and begin the public conversation. Messages should also come from trusted sources that can help to reduce vaccine hesitancy, and findings here showed that messages from healthcare professionals were associated with higher engagement. Finally, communicators should consider being more prepared to address conspiracies and misinformation during peak flu season.

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