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Factors Associated With Increased Dissemination of Positive Mental Health Messaging On Social Media

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Abstract

Background: The dissemination of positive messages about mental health is a key goal of organizations and individuals. *Aims*: Our aim was to examine factors that predict increased dissemination of such messages.

Method: We analyzed 10,998 positive messages authored on Twitter and studied factors associated with messages that are shared (re-tweeted) using logistic regression. Characteristics of the account, message, linguistic style, sentiment, and topic were examined.

Results: Less than one third of positive messages (31.7%) were shared at least once. In adjusted models, accounts that posted a greater number of messages were less likely to have any single message shared. Messages about military-related topics were 60% more likely to be shared (adjusted odds ratio [AOR] = 1.6, 95% CI [1.1, 2.1]) as well as messages containing achievement-related keywords (AOR = 1.6, 95% CI [1.3, 1.9]). Conversely, positive messages explicitly addressing eating/food, appearance, and sad affective states were less likely to be shared. Multiple other message characteristics influenced sharing.

Limitations: Only messages on a single platform and over a focused period of time were analyzed.

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Electronic Supplementary Material
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ESM 1. Text and table (.pdf)
Detailed study methods and example words from lexical categories.

Conflict of Interest
We declare no competing interests.

Conclusion: A knowledge of factors affecting dissemination of positive mental health messages may aid organizations and individuals seeking to promote such messages online.

Keywords

social media; positive messaging; depression; suicide; Twitter

From 2001 to 2015, suicide rates increased 28% in the United States (Centers for Disease Control and Prevention, 2017), with the largest increases in suicidal behaviors occuring among youth. Consequently, increased attention is being paid to the influence of new media, such as social media and smartphones, on mental health (Twenge, Joiner, Rogers, & Martin, 2018). Although the area remains understudied, large cross-sectional studies across multiple nations have linked the prevalence of Internet usage to suicide rates (Shah, 2010) and smaller studies in diverse international settings have begun to examine the aspects of online social behavior associated with increased suicidal ideation (Dunlop, More, & Romer, 2011).

To date, leading research using social media data to study mental health has focused mainly on depression and suicide-related messages (Burnap, Colombo, & Scourfield, 2015; De Choudhury, Counts, & Horvitz, 2013; Jashinsky et al., 2014; O'Dea et al., 2015). Fewer studies have examined positive mental health messaging online.

While early research suggests social media-based interventions may hold potential in preventing self-harm (Robinson et al., 2016), little is known about the factors that in fluence dissemination of positive messages about mental health. Interestingly, prior research studying the spread of health-related social media messages has found that factors influencing dissemination of such messages have differed across disease topics (Kim, Hou, Han, & Himelboim, 2016; Mitchell, Russo, Otter, Kiernan, & Aveling, 2017; So et al., 2016). Consequently, in this study we examined characteristics of positive messages about mental health that were associated with greater social sharing.

Method

Data Collection and Outcome Variable

We collected positive messages on Twitter over a 1-week period from August 7, 2017, to August 14, 2017, using a series of 12 tags/keywords commonly employed in such messages (see Electronic Supplementary Material 1 online for list of words and detailed methodological information). Positive messages are defined as messages that attempt to provide support or aid to those with mental health problems through explicit encouragement or the sharing of information about mental health. Seven days following the collection of each message, the number of *retweets* or shares that the original message had was recorded. Given a marked right skew to the number of retweets (most messages experienced no social shares), the number of retweets was classified into a binary variable indicating whether the message was retweeted or not; this served as the primary outcome variable.

Predictors and Statistical Analysis

Characteristics of the account, message, linguistic style, sentiment, and topic were examined as possible predictors of whether a message was retweeted. Characteristics of messages were ascertained from metadata associated with each tweet or computer processing of linguistic and sentiment features (see Electronic Supplementary Material 1). The association of each predictor with the retweet status of a message was assessed using logistic regression. Variables significantly associated with the outcome in exploratory bivariable analyses ($p < .05$) were entered into a multivariable regression.

Results

Nearly 11,000 (n = 10,998) positive messages were collected over a 1-week period. Less than one third of such messages (31.7%) were shared (i.e., retweeted) at least once. In adjusted models (Table 1), accounts that (a) had a greater number of followers, (b) posted a smaller number of messages, (c) included visual media and links, and (d) sent messages in which another user was mentioned had a greater number of messages shared. Linguistically, messages that used a higher proportion of adjectives were significantly less likely to be shared (AOR = 0.4, 95% CI [0.2, 0.7]).

Certain topic areas were strongly predictive of retweets; messages about military-related mental health topics had 60% greater odds of being shared (AOR = 1.6, 95% CI [1.1, 2.1]) as were messages containing achievement-related keywords (AOR = 1.6, 95% CI [1.3, 1.9]). Conversely, supportive messages explicitly addressing eating/food (AOR = 0.6, 95% CI [0.4, 0.9]), appearance (AOR = 0.6, 95% CI [0.4, 0.9]), and sad affective states (AOR = 0.7, 95% CI [0.7, 0.8]) were less likely to be shared.

Discussion

Our investigation into the factors influencing diffusion of positive messages yielded some unique insights. First, although the number of followers of an account is a strong predictor of message spread, we found that the more posts an account had in total, the less likely any single message was to be shared. This suggests that sheer volume of supportive content produced by organizations or individuals may be less important than creating higher-quality messages.

Secondly, our study detected that inclusion of media content in a post increased social sharing. While seemingly intuitive, this finding differs from results of other research in the area of infectious diseases, where inclusion of media content was inversely related to message dissemination (Mitchell et al., 2017). Additionally, in topic areas such as cancer support, investigators found that the degree of positive sentiment in a message is associated with increased message spread (Kim et al., 2016). Interestingly, our study found that while messages containing achievement-related words (e.g., milestone, worthy, conquer, celebration, etc.) were more highly shared, those expressing general positive emotion (e.g., enthusiasm, cherish, happiness, etc.) were not shared to a significant degree. Lastly, of the major content areas examined, military-related mental health messages where shared most often. Positive messages that focused excessively on personal appearance, nutritional health, or personal improvement, as suggested by the eating and appearance topic categories, while well-intentioned, were not widely spread, indicating that such messages may not be having the beneficial effect intended.

Limitations

Limitations of this research include the inability to capture all positive messages and that the study time period was limited. Furthermore, while we assessed dissemination of positive messages on social media, we did not assess how such messages influenced behavior, which is important for future research.

Conclusion

Our results offer some insights to improve health communication via social media. Consistent with social learning theory, which posits that behavior is, in part, learned through environment, observation, and social interaction, suicide-related behaviors are also influenced through the larger social milieu (Lester, 1987). Social media platforms present a novel space where large-scale social interaction and social learning is occurring, particularly in mental health (Colombo, Burnap, Hodorog, & Scourfield, 2016). Consequently, reaching larger audiences with positive messaging about mental health has the very real potential to influence healthy behaviors such as help-seeking. Indeed, early research suggests that positive messaging received online may even help prevent the development of suicidality (De Choudhury & Kiciman, 2017). Continued study of positive messages online may advance opportunities to promote mental health on a broader level than has previously been possible.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1.

Characteristics of social media messages associated with increased sharing online

	Prevalence of element of language (N = 10,998)		Bivariable *OR*			Adjusted *OR*(a)		
Type of predictor	***n***	**%**	***OR***	**95% CI**	***P***	**AOR**	**95% CI**	***P***
Account/media characteristics								
Number of followers								
0–100	2,092	19.0	1.0 (ref)			1.0 (ref)		
101–500	3,118	28.4	1.7	[1.5, 2.0]	< .001	2.2	[1.9, 2.6]	< .001
501–2,000	3,118	28.4	2.6	[2.3, 3.0]	< .001	4.0	[3.4, 4.9]	< .001
≥2,001	2,670	24.3	4.9	[4.3, 5.6]	< .001	8.8	[7.3, 10.7]	< .001
Number of prior posts								
0–500	2,355	21.4	1.0 (ref)			1.0 (ref)		
501–2,000	2,536	23.1	1.3	[1.2, 1.5]	< .001	0.7	[0.6, 0.8]	< .001
2001–10,000	3,528	32.1	1.6	[1.4,1.7]	< .001	0.5	[0.5, 0.6]	< .001
≥10,001	2,578	23.4	1.7	[1.5, 1.9]	< .001	0.4	[0.3, 0.5]	< .001
Media included								
Written text alone	8,208	74.6	1.0 (ref)			1.0 (ref)		
Photo	2,660	24.2	1.6	[1.5, 1.8]	< .001	1.4	[1.3, 1.6]	< .001
Animated GIF	65	0.6	1.4	[0.8, 2.2]	.2500	1.4	[0.8, 2.4]	.1768
Video	65	0.6	2.5	[1.5, 4.0]	< .001	2.3	[1.4, 3.8]	.0016
URL link included in text								
No	2,275	20.7	1.0 (ref)			1.0 (ref)		
Yes	8,723	79.3	1.7	[1.6, 1.9]	< .001	1.2	[1.1, 1.4]	< .001
Message directed at a user (user mentions)								
No	7,525	68.4	1.0 (ref)			1.0 (ref)		
Yes	3,473	31.6	1.5	[1.3, 1.6]	< .001	1.3	[1.2, 1.5]	< .001
Linguistic features								
Emoji used								
No	10,174	92.5	1.0 (ref)					
Yes	824	7.5	1.0	[0.8, 1.1]	.7700			
Number of hashtags used								

Type of predictor	Prevalence of element of language (N = 10,998) *n*	%	Bivariable *OR* *OR*	95% CI	*P*	Adjusted *OR*(a) AOR	95% CI	*P*
0–1	3,392	30.8	1.0 (ref)					
2–6	7,054	64.1	1.0	[0.9, 1.1]	.4000			
≥ 6	552	5.0	0.9	[0.8,1.2]	.5900			
Part of speech[a]	*M* (%)	*SD* (%)						
Nouns	30.6	9.9	1.3	[0.8, 1.9]	.2663			
Pronouns	3.8	4.9	0.3	[0.1, 0.8]	.0100	0.6	[0.2,1.4]	.2384
Verbs	11.5	7.5	1.1	[0.7, 2.0]	.0629			
Adjectives	9.5	7.1	0.4	[0.2, 0.7]	.0017	0.4	[0.2, 0.7]	.0015
Adverbs	3.3	4.7	0.4	[0.2, 1.0]	.0566			
Lexical categories								
Sentiment categories[b]								
Achievement	575	5.2	1.7	[1.5, 2.1]	< .001	1.6	[1.3, 1.9]	< .001
Positive emotion	1,629	14.8	0.9	[0.8, 1.0]	.1206			
Negative emotion	1,159	10.5	0.8	[0.7,1.0]	.0157	1.0	[0.9,1.2]	.6379
Sadness	1,602	14.6	0.7	[0.6, 0.8]	< .001	0.7	[0.7, 0.8]	< .001
Anger	181	1.6	0.8	[0.6,1.1]	.1387			
Topic categories[b]								
Military	189	1.7	1.7	[1.2, 2.2]	< .001	1.6	[1.1, 2.1]	.0043
School	761	6.9	1.2	[1.0, 1.4]	.0495	1.1	[0.9,1.3]	.3816
Science	461	4.2	1.2	[1.0, 1.5]	.0512			
Eating	167	1.5	0.6	[0.4, 0.8]	.0036	0.6	[0.4, 0.9]	.0283
Appearance	142	1.3	0.5	[0.3, 0.8]	.0015	0.6	[0.4, 0.9]	.0294

Note.

[a]Parts of speech variables were calculated as the percent of the total text in a given message that is the part of speech of interest.

[b]Sentiment and topic variables were coded as binary variables indicating whether the message contained the sentiment/topic of interest.