# Are Emotion-Expressing Messages More Shared on Social Media? A Meta-Analytic Review

Junhan Chen
University of Maryland, USA
jchen134@umd.edu

Yumin Yan
University of Maryland, USA
yyan1006@umd.edu

John Leach
University of Maryland, USA
jleach@umd.edu

## Abstract

Given that social media has brought significant change to the communication landscape, researchers have explored factors that can influence audiences' information-sharing on social media such as a message feature like emotion-expressing. The present study meta-analytically summarized 19 studies to advance the understanding of the associations between emotion-expressing messages and information-sharing on social media in health and crisis communication contexts. Additional moderator analyses considered social media platform, sampling method, coding method, and emotion valence. Our study showed support for the social sharing of emotion hypothesis on social media; the findings showed that emotion-expressing messages are more likely to motivate audiences' sharing behavior on social media in health and crisis contexts ($r = .09$, $k = 19$, $N = 4,582,823$). Moreover, we found that studies focusing on non-Twitter platforms (vs. Twitter), using nonrandom sampling (vs. using random sampling or all samples), using human coding (vs. machine coding), and focusing on messages expressing positive emotions (vs. negative emotions or both positive and negative emotions) had larger effect sizes. The study suggested implications for the future development of a theoretical framework on emotion-expressing messages and information-sharing. It also informed communication practices of broadening the reach of health and crisis information.

**Highlights**

- A meta-analysis showed that emotion-expressing messages were shared more on social media in health and crisis contexts.
- Social media platform, sampling method, coding method, and emotion valence significantly moderated the effect sizes.
- Studies featuring non-Twitter platforms, positive-emotion messages, human coding, and nonrandom sampling had larger effect sizes.
- The findings supported the social sharing of emotion hypothesis, and revealed methodological issues related to human/machine coding and random/nonrandom sampling.
- The continued discovery of moderators is needed, given the unexplained heterogeneity of findings.
- This study provided a cornerstone for the future development of a theoretical framework focusing on the influence of emotion-expressing messages.
- Communication practitioners may consider using emotion-expressing messages to motivate audiences' information-sharing.

# Content

Social media has transformed the way we communicate since its inception (Hyvärinen & Beck, 2019; Vaterlaus et al., 2015; Yoo et al., 2020). Due to characteristics like intermediacy and interactivity, social media is an increasingly vital channel for individuals to share and obtain information, especially in health and crisis situations that are fraught with uncertainty (Jin et al., 2016; Lu & Jin, 2020; Li et al., 2020). Moreover, sharing information has been found as the most frequently reported reason for individuals' use of social media platforms (Li et al., 2020; Lin & Lu, 2011; Lu & Jin, 2020).

For health and crisis communicators, individuals' information-sharing behaviors on social media can be a double-edged sword that brings benefits and challenges. On the one hand, communicators can reap benefits from individuals' information-sharing because social media enable faster and wider dissemination of information that may result in improvements in individuals' risk awareness and protective action taking (Cohen & Hoffner, 2016; Hyvärinen & Beck, 2019; Sellnow et al., 2017). On the other hand, incorrect or insufficient information shared by individuals makes social media a crowded and noisy place where accurate information combats misinformation and rumors (Liang & Kee, 2018; Lu & Jin, 2020; Mehta et al., 2021; Vosoughi et al., 2018). To facilitate individuals to adopt accurate and instructive information, communicators need to understand what features can make messages stand out and reach a wider audience (Hyvärinen & Beck, 2019).

Researchers suggested that emotion-expressing may be a message feature that motivates information-sharing on social media (e.g., Kramer et al., 2014; Zhu et al., 2020), but studies yielded conflicting findings. There is a need for a meta-analysis to derive conclusions from the findings for two reasons. First, sharing emotions through messages is related to important outcomes in health and crisis contexts, such as obtaining social support (Wang and Wei, 2020) and facilitating coping with crises (Cmeciu & Coman, 2018). This area of research and communication practices will benefit from a theoretical model to predict how emotion-expressing messages will be shared and how they affect message recipients' responses to health and crisis situations. Understanding if emotion-expressing messages are shared more on social media is a vital first step to developing such a framework. Second, theories and empirical studies have suggested primary and secondary social sharing of emotion (Rimé, 2009). However, whether the prediction of social sharing of emotion

can be applied to the social media arena is unclear given the conflicting results (e.g., Zhou et al., 2018; Ali et al., 2019). A systematic assessment of the findings will shed light on the generalizability of social sharing of emotion to a social media context. Therefore, this study uses a meta-analysis approach to test the association between emotion-expressing and message sharing on social media and examine moderators in the relationship.

## Does Emotional Expression Enhance Message Dissemination?

## Social Sharing of Emotion

In 1991, Rimé et al. coined the term social sharing of emotion (SSE) to depict how individuals share emotion-expressing information. In the original conceptualization for the offline settings, SSE occurs when individuals openly communicate with one or more other individuals about significant life events, as well as their emotional reactions (Rimé et al., 1991). In other words, in emotionally charged situations like crises and many health events, sharing emotion-expressing content is an approach for individuals to make sense of the event (Maitlis & Sonenshein, 2010). SSE indicates that emotions should not be seen solely as an ephemeral and intrapersonal phenomenon (Rimé et al., 1991). Rather, emotions as social information can spread among individuals through interpersonal communication (Rimé et al., 1998).

Furthermore, the consequences of SSE can extend far beyond the initial interactants because of information recipients' secondary information-sharing (Rimé et al., 2011). For instance, by assessing participants' offline interpersonal communication, psychologists (e.g., Curci & Bellelli, 2004; Christophe & Rimé, 1997) found that, after exposing to emotion-expressing messages, over three-quarters of participants indicated the propensity of sharing information with others. More recently, Rimé (2009) noted that the information recipients could be tangible and symbolic (e.g., acquaintances in in-person conversations and anonymous users on social media platforms). Moreover, a message's emotional components play a pivotal role in speeding up the social transmission of the message and encouraging engagement among information recipients. The symbolic definition

of information recipients and the social consequences of emotion-expressing messages reveal the potential for SSE online (Rimé, 2009; Stieglitz & Dang-Xuan, 2013; Vermeulen et al., 2018).

However, when discussing social sharing of emotion in the online setting, there are undeniable differences between individuals' communicative behaviors on social media and offline interpersonal interactions, such as fewer nonverbal cues, greater anonymity, more opportunities to form new social bonds and strengthen weak ties, and more information dissemination (Lieberman & Schroeder, 2020; Subramanian, 2017). Moreover, the sharing of emotions only occurs in particular conditions (e.g., right audience, appropriate timing, congruent with existing social norms; Bazarova, 2012; Choi & Toma, 2014, 2021; Vermeulen et al., 2018). Whether the relationship between emotion-expressing and message sharing still holds in the social media setting is a usually assumed yet unanswered question.

Through the lens of SSE (Rimé, 2009), this study employs a meta-analysis approach to assess the association between emotion-expressing and message sharing on social media and to examine moderators in the relationship. Thus, we synthesize empirical findings to understand the following research questions:

RQ1: Are emotion-expressing messages more likely to be shared on social media in health and crisis contexts compared to messages that do not express emotions?

## Moderators Affecting Social Sharing of Emotion

Despite theoretical arguments for the generality of the social sharing of emotion (Rimé, 2009), empirical studies have shown conflicting findings. For example, Kim et al. (2016) found that tweets expressing positive emotion were more likely to be shared, while Lin et al. (2018) did not find significant results for messages expressing negative emotion. The conflicting findings may be explained by the social constraints on emotion sharing. Rimé (2009) has noted three circumstances that can impede social sharing of emotion: first, events or message content elicit affective experiences of shame and guilt; second, events or message content elicit highly intensive affective experience; and third, social environment is not hospitable (i.e., social constraints). In other words, the term "social constraints" means whether individuals perceive the environment to be receptive to the

shared information (Rimé, 2009). Acknowledging that the first two circumstances are undeniably important, this study focuses on social constraints and discusses how social constraints can be reflected through emotional valence and the choice of social media platforms.

### Social Constraints and Emotional Valence

The content that expresses either negative or positive emotions is commonly shared on social media (e.g., Ali et al., 2019; Gurman & Clark, 2016; Hyvärinen & Beck, 2019). For the mechanism of sharing content in negative emotional valence, Schachter (1959; also see Rimé, 2009) observed that individuals experiencing stress would strive to alleviate the triggered anxiety through verbal interaction with others facing the same situation, thereby utilizing others as a gauge for assessing their own emotional status. Based on Schachter's view, content that expresses negative emotions may trigger others' information-sharing intentions to cope with stressful crises and health events. Individuals have the motivation to share content in a positive emotional valence as well. Rimé (2009) argued that content expressing positive emotions might revoke individuals' previous favorable experiences. Furthermore, Langston (1994) demonstrated that sharing positive events with others can generate impacts in ways that go beyond the positive events themselves such as improving individuals' well-being. In sum, sharing content that expresses negative emotion is an approach individuals use to cope with stress; sharing content that expresses positive emotions is a method for individuals to revive favorable experiences.

Although studies note that social sharing of both positive and negative emotions commonly exists, social constraints may be different for sharing positive and negative emotions. Empirical evidence showed that there may be fewer social constraints on sharing content that expresses positive emotions while there may be more social constraints on sharing content that expresses negative emotions. For example, Choi and Toma (2014, 2021) noted that individuals tended to share content expressing negative emotions with a small number of trusted recipients. In addition, Hyvärinen and Beck (2019) found that the higher levels of negative emotion resulted in fewer retweets, while higher levels of positive emotion resulted in greater numbers of retweets. A meta-analysis testing emotion valence as a moderator in the relationship between emotion-expressing and message sharing can pro-

vide summative evidence for the difference in social constraints on positive and negative emotion. Therefore, we asked the following question:

RQ2-1: Does emotion valence moderate association between the degree to which messages are emotion-expressing and the degree to which messages are shared on social media in health and crisis contexts?

## Social Constraints and Social Media Platforms

Social constraints can be reflected by the choice of social media platforms. For instance, because social norms encourage sharing meaningful events, Twitter and Facebook should often be chosen to share highly intense positive events (Choi & Toma, 2014). However, Twitter has often been used to share content expressing positive emotions (Choi & Toma, 2014; Kalandar et al., 2018; Kim et al., 2016), whereas Facebook has often been used to share content expressing negative emotions (Bazarova, 2012; Vermeulen et al., 2018) because boasting was viewed as undesirable on Facebook (Choi & Toma, 2014). The reality can be more complicated than the dichotomy of Twitter and Facebook. Similar social constraints possibly exist for other social media platforms, which would explain the difference in the association between emotion-expressing and message sharing on different social media platforms. Choi and Toma (2014) called for the need to incorporate social constraints (referred to as "norms" in Choi & Toma, [2014, p. 538]) into the social sharing framework to better understand how emotion is shared differently across social media platforms. Therefore, this study proposes the following research question:

RQ2-2: Does sharing platform moderate the association between the degree to which messages are emotion-expressing and the degree to which the messages are shared on social media in health and crisis contexts?

## Method

### Search Strategy

A strategy to ensure a comprehensive search for journal articles, book chapters, conference papers, and dissertations was undertaken. Conference papers and dissertations were included in the search in order to compensate for publication bias. The steps of search and screening are described in Figure 1. First, comprehensive searches of four databases (i.e., EBSCOhost, Proquest, Web of Science, and Pubmed) were done in February 2020 using combinations of four sets of keywords. The first set of keywords was related to emotion, including "emotion", "affect", "narrative", "fear", "anger", "sad", "humor", "guilt", "shame", "pride", "indignation", "pity", "hope", "disgust", "love", "affection", "happy", "joy", "relief", and "sympathy". The second set of keywords was about social media, including "social media", "social networking site", "Twitter", "Facebook", "Instagram", "online", and "microblog". The third set of keywords was about message sharing, including "message sharing", "information sharing", "news sharing", "sharing behavior", "information diffusion", "go viral", "information forwarding", "information dissemination", and "retweet". The last set of keywords was about context, including "crisis", "risk", and "health". The wildcard searching technique was used where possible in order to take into account possible variations of keywords (e.g., forwarding, forwarded, forwards). Titles, abstracts, and subject areas were searched in each database. There was no limit on the year of publication in the search. The search initially produced 732 documents.

Second, 159 duplicate articles were removed, and the remaining articles were screened. Articles needed to meet the following criteria in order to be included in the meta-analysis (a) the study should measure, manipulate, or code the extent to which a message expresses emotions; (b) the study should measure or code message sharing intentions, behaviors, or the actual number of shares; (c) the study should test the association between the two constructs (emotion-expressing and message sharing) and provide proper statistics to compute effect sizes (discussed in more detail in the next section); (d) the article should be a peer-reviewed journal article, or a conference paper, or a dissertation, or a book chapter; (e) the study should be in the contexts of health or crisis; (f) the article should be written in English. For example, articles that focused on political contexts, examined social media users' discrete emotions rather than the message emotion-expressing feature, or did not examine the number of shares or sharing intentions were excluded in this step.

Third, after removing duplicate articles and screening the abstracts and the full texts, the reference lists of the selected articles were searched, and articles that met inclusion criteria were included. This search resulted in 2 additional

articles that were included in the final meta-analysis. One additional study was suggested to be added by the reviewers. We ended with 23 articles.

## Effect Size Extraction and Calculation

The Pearson correlation coefficient, $r$, was used as an effect size indicator. When an $r$ was reported in a study, it was directly extracted from the study. When an $r$ was not reported in a study, it was computed from other statistics such as frequency distribution statistics, chi-square, Cohen's $d$,

odds ratio, Spearman's Rho, and standardized beta coefficients. Chi-squares were converted to $r$ using the method introduced by Rosenthal and DiMatteo (2001). Odds ratios and Cohen's $d$s were converted to $r$ using the online converting tool developed by Lenhard and Lenhard (2016). Spearman's Rho was converted to $r$ using the table provided by Gilpin (1993). In order to include as many relevant studies as possible in the meta-analysis, we decided to convert standardized beta coefficients from regression analysis into $r$, even though it is controversial. Peterson and Brown (2005) showed that the computation generally produces accurate

**Figure 1.** *Searching and Screening Procedure* (back to text)
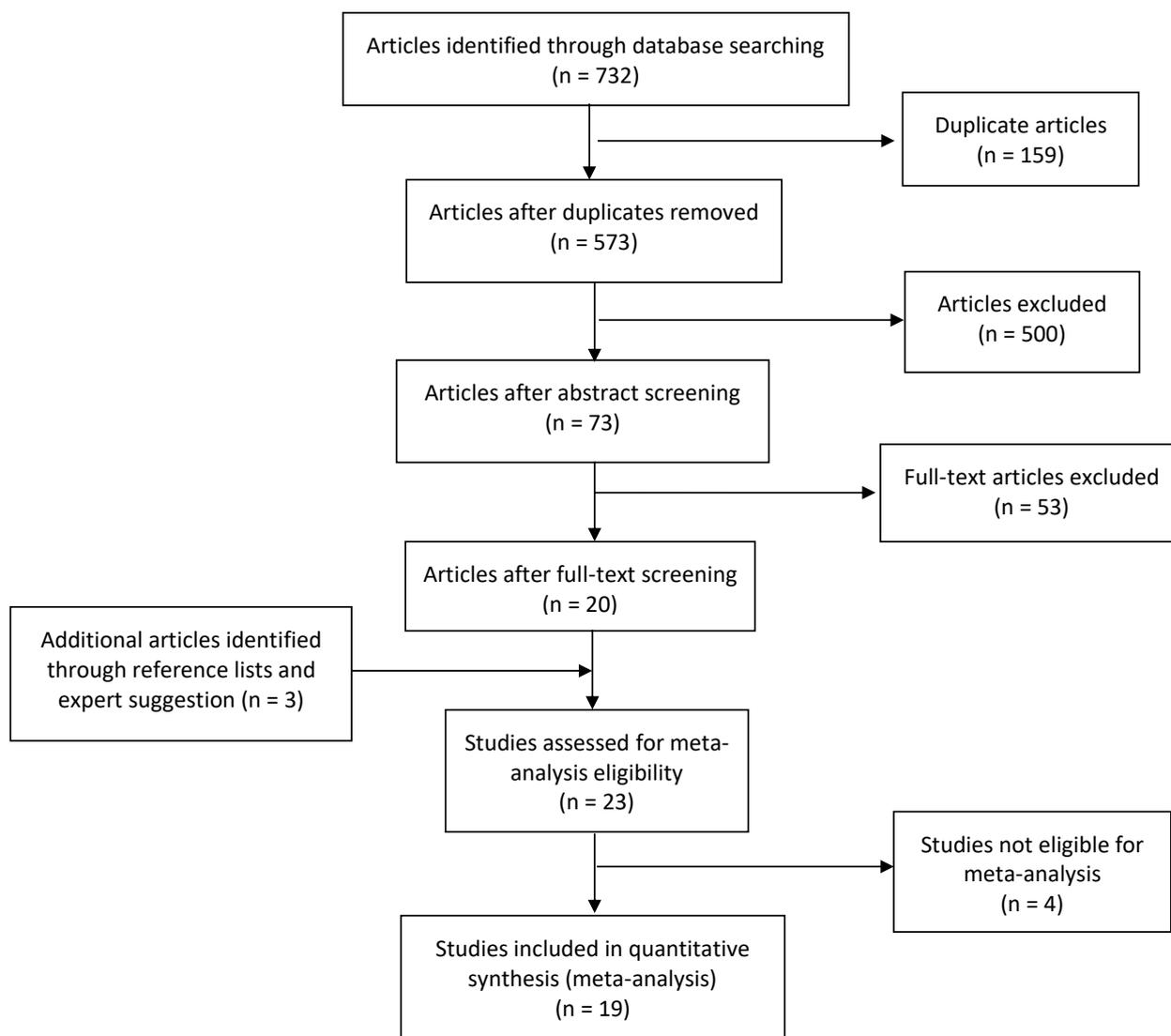
effect size estimates when the standardized beta coefficients are within the interval of -.50 to .50. Because all the standardized beta coefficients reported in the studies met this criterion, we followed Peterson and Brown's method to convert standardized beta coefficients into *r*.

In most cases, only one *r* could be extracted or computed from a study ($k$ = 11). In some cases, more than one *r* could be extracted or computed ($k$ = 8). If the study compared messages which expressed emotions at a low, moderate, and high level (Ali et al., 2009), then the most potent comparison was chosen, that is, the comparison in which the author hypothesized the greatest effect (i.e., the comparison between high and low emotion-expressing messages). If the studies examined both messages expressing emotions in general and messages expressing a specific valence of emotion or specific types of discrete emotion, then the effect size for messages expressing emotions in general was used in the analysis (Wang et al., 2019). Other studies ($k$ = 6) examined messages expressing specific valence of emotion or specific types of discrete emotion. For example, Xu and Zhang (2018) reported effect sizes for four types of discrete emotions. In these cases, one of the effect sizes was randomly picked.

When there were insufficient statistics available to compute *r,* the authors were contacted, and relevant data were requested. Four studies were relevant but could not be included in the meta-analysis because the authors have yet to provide appropriate data for effect size computation. Finally, a total of 19 articles contributing 19 studies were included in the meta-analysis.

## Article Coding

Articles were coded by three independent coders on the following variables: study characteristics (i.e., the year of publication, the name of the journal, context (e.g., health vs. crisis), and theory-based or not), message characteristics (i.e., sharing platform and emotion valence), and methodological characteristics (i.e., sample size, type of design, sampling method, and coding method). Sampling method and coding method were coded for content analysis studies only. In the coding process, we found that researchers used different sampling and coding methods. We decided to use the sampling and coding methods as additional moderators to see if methodological factors affect the results.

Because the total number of studies was small ($n$ = 19), we could not use a subset of the studies for coder training and split the articles into three sets in the formal coding process. Therefore, all the three coders coded the 19 studies. In order to resolve discrepancies in coding timely, the articles were randomly divided into four sets. After finishing coding each set of articles, the coders met to discuss any discrepancies in coding. Coding results of all the 19 studies were used for calculating the intercoder reliability. Krippendorff's alpha and average pairwise percentage agreement were used as indicators of intercoder reliability and were calculated for each coding category using *Recal*, a web service for intercoder reliability calculation developed by Freelon (2010). Krippendorff's alpha ranged from a low of .92 to a high of 1.00. The reliability is satisfactory compared to the .8 criterion (Krippendorff, 2004). The average pairwise percentage agreement ranged from a low of 96.08% and a high of 100%. Overall, the agreement among coders was good.

## Meta-Analytic Approach

Analyses were done using the *metafor* R package (Viechtbauer, 2010). All the correlation *r*'s were transformed to Fisher's *z*'s before calculating the effect size. The computed effect sizes and confidence intervals were transformed back from Fisher's *z* to *r* for results reporting. The effect sizes were weighted by inversed variances. Random effect models were fitted using the Hunter and Schmidt method (Hunter & Schmidt, 2004). The *Q* statistic was used to test heterogeneity among the effect sizes.

## Results

## Description of Studies

The 19 studies included in the meta-analysis are listed in Table 1, along with key moderators, sample sizes, and effect sizes. The 19 studies were published between 2013 and 2020. A total of 17 studies were published in 14 journals in health or communication areas, such as *Journal of Communication, Journal of Health Communication, Computers in Human Behavior, Perspectives in Public Health,* and *Digital Health*. Two studies were published in conference proceedings (Chen & Sakamoto, 2013; Hyvärinen & Beck, 2019).

The majority of the studies featured health contexts ($k$ = 14), while a few studied crisis ($k$ = 3) or both health and

crisis contexts ($k$ = 2; e.g., the Zika outbreak). Most of the studies focused on Twitter as the sharing platform ($k$ = 10) while other papers studied Sina Weibo ($k$ = 2), Wechat ($k$ = 1), Facebook ($k$ = 2), YouTube ($k$ = 1), multiple sharing platforms ($k$ = 1), or did not specify sharing platforms ($k$ = 2). Most studies were content analyses ($k$ = 15), and a few studies were experiments ($k$ = 4). The sampling method and coding method were coded only for content analysis studies. Most content analysis studies used machine coding ($k$ = 9). The rest used human coding ($k$ = 5). In addition, one study used machine coding trained by preliminary human coding data (Wang et al., 2019). Studies used random sampling ($k$ = 4), nonrandom sampling ($k$ = 4), or all the messages retrieved from social media ($k$ = 7). For example, Kim et al. (2016) randomly selected one composite week between August 2011 and September 2011 and captured Twitter talk related to breast cancer for each day. This study was coded as random sampling. Ali et al. (2019) selected a convenient sample of the first 100 English language Facebook posts from the #Zika hashtag search result. This study was coded as nonrandom sampling. Lastly, Gurman and Clark (2016) analyzed all English-language emergency contraception-related tweets from March 2011. This study was coded as using all the message retrieved from social media.

Eight studies did not explicitly report using any theories to justify their hypotheses. The remaining 11 studies reported using one or more theories, including the rumor theory, the risk-as-feelings hypothesis, the heuristic-systematic processing model, the elaboration likelihood model, agenda-setting and priming, the theory of group dynamics, and the theory of diffusion of innovations.

Lastly, 6 studies measured the dependent variable (i.e., message sharing) as being dichotomous (i.e., shared vs. not shared). The other studies ($k$ = 13) measured message sharing as a continuous variable, such as counting the number of times a message was shared or asking participants to rate their intention of sharing the message.

## RQ1: Weighted Effect Size, Publication Bias, and Heterogeneity Test

The first research question was about the magnitude of the effect of message emotion on message forwarding. The inversed-variance-weighted effect size was $r$ = .09 (95% $CI$ = .08, .11, $p$ < .001, $k$ = 19, $N$ = 4,582,823). The result shows that messages that expressed more emotion were significantly more likely to be shared on social media. According to Cohen's (1969) guidelines for the magnitude of effect sizes, an $r$ of .09 is considered a small effect size.

Publication bias was examined by conducting a statistical test and inspecting the funnel plot (Figure 2). Publication bias is the result of relevant trials being published or not, depending on the type and direction of the results (Sedgwick, 2015). For example, a publication bias exists when a study is more likely to be published if the findings are statistically significant. Egger's regression test ($z$ = 6.22, $p$ < .001) suggested that there was a publication bias in this set of studies. The funnel plot suggested a publication bias as well. The funnel plot appeared to be asymmetrical, with many studies falling outside the triangle centered on the estimated effect size. Visual inspection suggested that studies are missing from the lower left portion of the funnel, which is typical when publication bias is present.

Aside from publication bias, the asymmetry may be caused by heterogeneity resulting from differences in study features such as study settings, types of participants, implementation of treatment, etc. (Sterne et al., 2011). The forest plot (Figure 3) and the Baujat plot (Figure 4) showed that three studies had effect sizes deviating from other studies (i.e., Chen & Sakamoto, 2013; Park, 2019; Zhang et al., 2017). This led us to test heterogeneity in the next analysis step.

The heterogeneity test showed that there was significant heterogeneity among the effect sizes ($Q_{18}$ = 2,614.09, $p$ < .001, $I^2$ =89.67%, $\tau^2$ = .001, $se$ = .00). The $I^2$ level suggested that heterogeneity, rather than chance, caused most of the variability of effect sizes across studies. This led us to test potential moderators to explain the heterogeneity of effect sizes.

## RQ2: Moderator Analyses

Moderator analyses were conducted to explore the heterogeneity of effect sizes. The inverse-variance-weighted effect sizes are presented in Table 2. First, we tested the moderation effect of the sharing platform by comparing the effect sizes of studies focusing on Twitter ($k$ = 10) and studies focusing on other platforms ($k$ = 9). We found that sharing platform was a significant moderator ($Q_M$ = 33.889, $df$ = 1, $p$ < .001), accounting for 69.87% of the heterogeneity. Studies focusing on Twitter ($r$ = .065, $p$ < .001) had a significantly smaller weighted effect size than studies focusing on other platforms ($r$ = .124, $p$ <

**Figure 2.** *Funnel Plot of Studies included in the Meta-analysis* (back to text)



**Figure 3.** *Forest Plot of Studies included in the Meta-analysis* (back to text)



**Figure 4.** *Baujat Plot of Studies included in the Meta-analysis* (back to text)
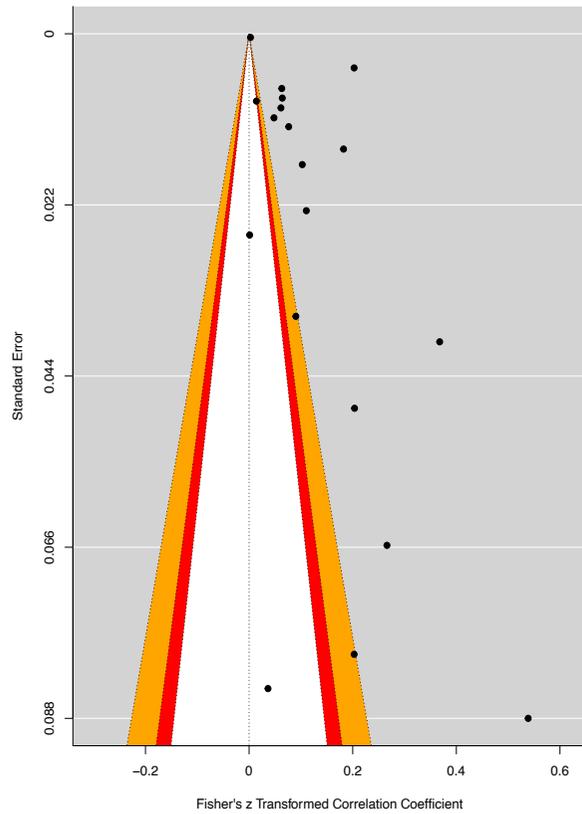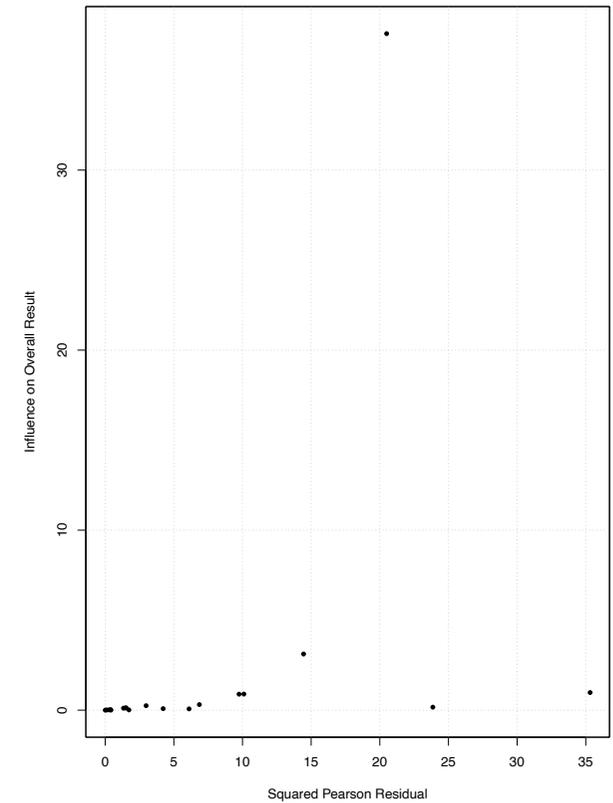


*Note.* The dots represent the studies included in the meta-analysis. The white region corresponds to p-values greater than .10. The red region corresponds to p-values between .10 and .05. The orange region corresponds to p-values between .05 and .01. The grey region corresponds to p-values smaller than .01.
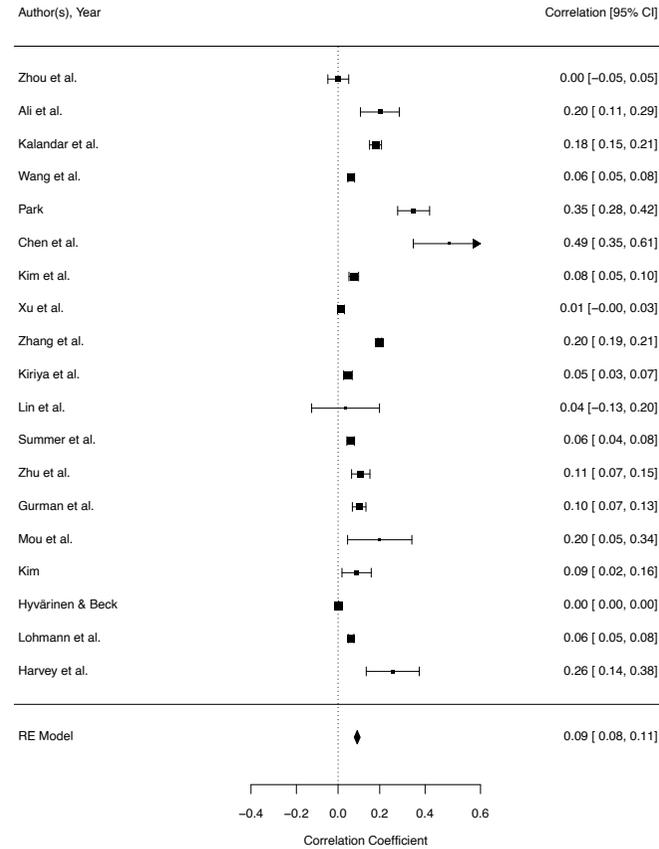
*Note.* The forest plot shows result of the random effect model. The weighted effect size and the effect size of each study is presented as correlational *r* with corresponding 95% confidence intervals.

*Note.* The three dots from right to left represents Park (2019), Chen & Sakamoto (2013), and Zhang et al. (2017). The other dots represent other studies included in the meta-analysis.

.001, $z = -.059$, $p < .001$). The test of residual heterogeneity was significant ($Q_E = 801.008$, $df = 17$, $p < .001$), suggesting that other moderators should be identified to account for the heterogeneity.

Second, we found that emotion valence was a significant moderator ($Q_M = 71.86$, $df = 2$, $p < .001$), accounting for 75.96% of the heterogeneity. Studies that focused on social media posts expressing negative emotions ($r = .044$, $p < .001$) had a smaller weighted effect size than studies that focused on posts expressing positive ($r = .123$, $p < .001$, $z = .079$, $p < .001$) or both positive and negative emotions ($r = .117$, $p < .001$, $z = .074$, $p < .001$). The residual heterogeneity was still significant ($Q_E = 642.84$, $df = 16$, $p < .001$).

Next, the coding method was evaluated for studies that used content analysis to code the degree to which messages were emotion-expressing. The test of moderation suggested that coding method was a significant moderator ($Q_M = 39.02$, $df = 1$, $p < .001$), accounting for 89% of the heterogeneity. The $z$ tests showed that studies using human coding ($r = .186$, $p < .001$) had a larger effect size than studies using machine coding ($r = .070$, $p < .001$, $z = .116$, $p < .001$). However, the test of residual heterogeneity was significant ($Q_E = 2260.444$, $df = 12$, $p < .001$), suggesting the presence of other moderators that would need to be identified to account for the heterogeneity.

Lastly, the sampling method was examined as a moderator for studies whose sampling and analysis unit was single messages. The test of moderators suggested that the sampling method was a significant moderator ($Q_M = 373.252$, $df = 2$, $p < .001$) and accounted for 91.23% of the heterogeneity. The $z$ tests showed that studies that used nonrandom sampling ($r = .210$, $p < .001$) had a significantly larger weighted effect size than studies that used all the messages retrieved from social media ($r = .035$, $p < .001$, $z = .175$, $p < .001$) and studies that randomly sampled social media posts ($r = .084$, $p < .001$, $z = .126$, $p < .001$). Also, studies that used random sampling had a significantly larger effect size than studies that used all samples ($z = .049$, $p < .001$). However, there was still a significant amount of residual heterogeneity ($Q_E = 237.823$, $df = 12$, $p < .001$), suggesting the existence of other moderators.

## Discussion

The aim of this meta-analysis was to examine the association between emotion-expressing messages and information-sharing on social media in health and crisis contexts.

After analyzing 19 studies that yielded 19 effect sizes, we found that the degree to which a message is emotion-expressing is associated with the degree to which it is shared on social media ($r = .09$).

According to Cohen's (1969) standard guidelines, this effect size is small. However, given the context of the study, disparaging the result would be inadvisable (Funder & Ozer, 2019). Some small effect sizes are consequential because they might have important implications over time (Abelson, 1985; Funder & Ozer, 2019). We should understand that emotion-expressing message propagation can grow over time. The accumulation of shares will naturally result in more social media audiences being exposed to the message. Like compound interest, small initial numbers can eventuate in large totals, and for dissemination phenomena, the final tallies are generally more important than the first ones. Because shared information on social media could influence individuals' perceptions and behavioral intentions toward various health issues, as well as crisis events (e.g., Jin et al., 2016; Stellefson et al., 2019), the small effect size found in the current meta-analysis may have a significant practical impact considering the accumulation of shares and shared information's impact on message recipients. This thought needs to be pursued empirically, however.

We believe the evidence of a relationship between emotion-expressing and message sharing on social media across health and crisis contexts has both theoretical and practical implications. Theoretically, the findings provide promising evidence for the theory of social sharing of emotion (Rimé, 2009) in the social media arena and build a cornerstone for a theoretical framework focusing on the influence of emotion-expressing messages. The theory of social sharing of emotion originated in the context of interpersonal communication, supported by evidence of sharing emotion through diaries and face-to-face conversations. After the emergence of social media, many studies tested the idea in the social media context and yielded various findings. This meta-analysis is the first to synthesize findings from these studies, showing that the social sharing of emotion prediction is well-applied to the social media arena. Moreover, evidencing the relationship between emotion-expressing and information-sharing is the first step to building a theoretical model to understand the influence of emotion-expressing messages on social media. Building upon the evidence that emotion-expressing messages are shared more on social media, we envision future studies developing and testing a

theoretical model that predicts if emotion-expressing messages will be secondarily shared to a broader audience, arouse audiences' emotions, and induce behavioral responses to health and crisis threats. Given the above argument on the accumulation of effect, these research inquiries will have more significant implications with the evidence that emotion-expressing messages are shared more in the first place.

Practically, the findings suggest that integrating emotionally charged content is an efficient strategy for communication practitioners to reach a broader range of audiences on social media with health and crisis information and to encourage more audiences to take prevention behaviors. On the one hand, secondary information-sharing (i.e., audiences sharing emotion-expressing messages posted by other users on social media) can broaden the distribution of health and crisis information. On the other hand, secondary emotion-sharing may motivate behavioral changes at a larger scale (Dunlop et al., 2008; Kramer et al., 2014). The emotion-expressing messages may arouse the emotional responses of other audiences on social media, making emotions contagious in an online social network (Kramer et al., 2014). In turn, the emotions aroused may motivate audiences' behaviors to cope with stressful crisis and health situations (Dunlop et al., 2008).

In addition, we were able to identify several potential moderators that should be acknowledged and absorbed into our developing theories of how the emotional content of messages affects their likelihood of dissemination. First, we found that studies focusing on messages expressing positive or both positive and negative emotions had stronger effect sizes than studies focusing on messages expressing negative emotions. The pattern is likely due to impression management on social media. Studies have found that individuals were more likely to disclose positive emotions than negative emotions on social media (e.g., Hall & Caton, 2017; Qiu et al., 2012). This phenomenon has been named "social posturing": people tend to present themselves as more positive to others on social media. Our findings show that social posturing does not only apply to expressing positive emotion as a message generator, but also applies to sharing positive emotion as a message disseminator. Social posturing may have particular significance for individuals in health and crisis contexts. Wang & Wei (2020) found that posts expressing positive or mixed emotions got more social support in the cancer community on Twitter. Also, a meta-analysis showed that the expression of positive and general/nonspecific emotions was related to better social outcomes such as social support, social relationship satisfaction, and social quality (Chervonsky & Hunt, 2017). These social outcomes may support individuals to better cope with threats in health and crisis contexts.

Second, we found that studies focusing on Twitter had a smaller effect size than studies focusing on non-Twitter platforms. The result makes sense given that nearly half of the studies in the review focusing on Twitter examined negative emotion messages; it is possible that people may be more hesitant to share negative emotion messages on a more public platform like Twitter than on a more private social network such as Facebook and WeChat. It is consistent with the implications of previous studies: Twitter may be used more for sharing positive emotion events because it provides accessibility affordances, while Facebook may be more for sharing negative emotion events because it provides privacy affordances (Choi & Toma, 2014, 2021). We also speculate that the length limit of tweets renders the strength of emotion-expression on Twitter weaker compared to other social media platforms such as Facebook and YouTube, and therefore weaken the association between emotion-expressing and message sharing.

We also found that studies using nonrandom sampling had a significantly larger effect size than studies using all the messages retrieved from social media and studies using random sampling. Content analysis studies that investigate social media messages frequently sample a smaller set of social media posts from all the posts that researchers retrieve from social media platforms. The difference in effect size may be due to the way studies selected messages combined with how they measured their dependent variables. Studies that used random sampling or all the messages retrieved from social media primarily used a dichotomous variable to measure message sharing (i.e., assigning "0" to messages that had not been retweeted and "1" to messages that had been retweeted; e.g., Zhou et al., 2018). But studies that used nonrandom sampling mostly measured message sharing as a continuous variable (i.e., the number of reposts of messages). In addition, nonrandom sampling studies may have a large variance in the number of reposts because they selected samples such as the first 100 English language posts (Ali et al., 2019) or a random selection of the most retweeted Tweets and non-retweeted Tweets (Park, 2019), or messages reaching a certain threshold of reposts (Zhang et al.,

2017). Due to these studies' choice of dependent variable measurements and the sampling methods, nonrandom sampling studies' effect sizes may be enlarged. We call for researchers to consider the possible influence of subjective sampling criteria on research findings when interpreting their results.

The coding method deployed in content analyses was found to be a significant moderator as well: studies using human coding had a larger effect size than studies using machine coding. Our moderator analysis showed that the operationalization of emotion-expressing made a difference in effect sizes. The studies deploying a machine coding method applied an established dictionary to texts and classified the messages' words. They operationalized emotion-expressing messages as those including a certain number or percentage of affective words. The studies deploying the human coding method operationalized emotion-expressing messages based on human coders' consensus on how much the messages expressed emotion.

The detected difference in effect sizes may suggest deficiencies in both human and machine coding methods. First, machine coding relies only on the percentage of emotional words in the posts. This approach runs the risk of including posts that do not express emotions. For example, a tweet saying that "I do not feel sad" may be coded as emotion-expressing by machine coding while the message indicates a lack of negative emotion. Such coding deficiency may be the reason why studies using machine coding found a smaller effect size than studies using human coding. Second, human coders may judge based on whether the message induced emotion. It may make the study focus on emotion as a psychological state of message recipients ("emotion-evoking") rather than emotion expressing as a message feature ("emotion-expressing"). However, the emotion expressed in messages does not necessarily translate into emotion experienced by message recipients. It is possible that only messages that express strong emotions induce emotional experiences among human coders. This poses intriguing questions for future studies to investigate: is emotion-inducing a mechanism to explain the positive relationship between emotion-expression and message sharing? Or does emotion-inducing strengthen the positive relationship between emotion-expressing and message sharing? Future studies may test emotion-inducing as a mediator or moderator in the process.

## Limitations and Future Research

First, this study aimed to include all relevant articles, whether published or so-called grey literature (e.g., dissertations, conference papers). However, the authors did not contact researchers in the relevant research areas to request their unpublished studies, which is a prevalent method used in meta-analysis studies to locate grey literature (Conn et al., 2003). There were also four articles that should be included in the meta-analysis, but the necessary statistics were missing for computing effect sizes.

Second, we randomly selected one effect size when studies reported multiple effect sizes. According to Cheung (2019), using multivariate effect sizes is more recommended than using one randomly selected effect size. However, calculating multivariate effect sizes requires information about sampling covariances among the multiple effect sizes reported by the study, which is not available in studies included in our meta-analysis. In this case, the alternative options are randomly selecting one effect size or calculating an averaged effect size, although both methods did not allow utilizing all the available effect sizes and removed valuable information about within-study variations in effect sizes (Cheung, 2019). Scammacca et al. (2014) found that the random selection method had "a somewhat larger estimate of the mean effect and a slightly larger variance" (p. 13) than the average effect size method. Given the small effect size found in our study ($r = .09$), we believe that using the average effect size method will result in an effect size that does not significantly deviate from .09.

In addition, we were unable to explain all the heterogeneity by the significant moderators identified in this study. There is a need for future meta-analyses to explore additional moderators that can explain the heterogeneity in effect sizes across existing empirical studies. Some results may well become clearer as more studies are done, especially if those researchers attend to the moderator issues raised here.

The findings of this study nominate several future research directions. First, using Bartoš and Schimmack's (2020) method, we found that the expected replication rate (ERR) of the included studies was .536. In other words, the success rate of replicating existing significant results under ideal conditions where replication studies are exact copies of the original studies is 53.6%. Future original studies, as well as replication attempts, should consider power-enhancing designs to ensure an adequate power in order to affirm

our knowledge on this topic (Shrout & Rodgers, 2018).

Second, the majority of the studies featured health contexts ($k = 14$) instead of crisis contexts ($k = 3$). Research in crisis communication emphasizes more on the effect of individuals' affective experience of emotions instead of the effect of emotion-expressing messages on individuals' perceptions and behavioral intentions (e.g., Jin et al., 2016), which limited the number of crisis studies included in the meta-analysis. The phenomena under study here, however, apply easily to both health and crisis contexts, and perhaps others as well. Future studies may evaluate the generalizability of the conclusion to other contexts.

Future investigations should continue to explore the role social media platform plays. Most works included focused on Twitter ($k = 10$), which makes sense as Twitter provides platform affordances designed to share information with the retweet function. While there were fewer studies focused on other platforms such as Sina Weibo ($k = 2$), Wechat ($k = 1$), Facebook ($k = 2$), and YouTube ($k = 1$). Although our findings show a difference in effect sizes between Twitter and non-Twitter studies, they do not tell us much about the differences among other platforms. Different social media platforms offer slightly different affordances and may have different functions in health and crisis contexts. Jawad et al. (2015) analyzed a social media campaign about waterpipe smoking and found that different social media platforms allowed different levels of interactivity and attracted different types of audiences. Because of the diversity in social media affordances, understanding how emotion-expressing messages are shared on each platform will allow for analysis of the specific affordances and yielding processes on different social media platforms. New communication technology will continue to challenge the future directions of research literature. We may need to theorize about classes of social media so that our research is not always tied to the media available at the time of the study. For example, the studies included in this analysis focused on the emotional valence of the message text, but many current and future social media technologies may afford the sharing of other possible emotion-expressing elements such as images, videos, and interactive media forms.

Currently, the majority of studies use content analysis ($k = 15$) to understand if emotion-expressing messages are more shared than non-emotion-expressing messages on social media. These studies have provided a snapshot of what is currently happening. Future studies should take these findings and use experimental designs to examine the causal links and potential moderating factors.

## Conclusion

Through meta-analyzing 19 studies, we found that messages that were more emotion-expressing were significantly more likely to be shared on social media ($r = .09$). Although the effect size was small, the association between emotion-expressing and message sharing should be considered seriously, given the potential of accumulated sharing over time. While the heterogeneity in effect sizes was not fully explained, this study identified emotion valence, sharing platform, coding method, and sampling method as significant moderators. The moderation results of emotion valence and sharing platforms indicated that social constraints might exist on social media and possibly influence how individuals share certain types of emotions. The moderation effect of coding and sampling method revealed issues with using machine and human coding and using subjective sampling criteria in this research area. Given the growing saliency of social media as an avenue for information-sharing, this study aimed to provide a cornerstone for future work. Building upon the current findings, future studies may continue theory development on the influence of emotion-expressing messages on emotion-inducing, secondary sharing, and behavioral responses to health and crisis situations. The current findings provide a coalescing of results to display current theoretical implications and suggestions for the upcoming research.

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*Note*. Entries with * were studies included in the meta-analysis.

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**Table 1.** *Study characteristics and effect sizes included in the meta-analyses* (back to text)

| Study | Context | Sample size | Sharing platform | Type of design | Theory-based | Coding method | Sampling method | Emotion valence | r |
|---|---|---|---|---|---|---|---|---|---|
| Ali et al. (2019) | Health & Crisis | 434 | Facebook | Content analysis | Yes | Human | Nonrandom | Negative | 0.2008 |
| Chen et al. (2013) | Crisis | 132 | Not specified | Experiment | No | [1]n/a | [1]n/a | Negative | 0.492 |
| Gurman et al. (2016) | Health | 3535 | Twitter | Content analysis | Yes | Human | [2]All | [3]Both | 0.1023 |
| Harvey et al. (2019) | Health | 234 | Facebook | Content analysis | Yes | Human | Nonrandom | [3]Both | 0.26 |
| Hyvärinen & Beck (2019) | Crisis | 4442261 | Twitter | Content analysis | Yes | Machine | [2]All | Negative | 0.0027 |
| Kalandar et al. (2018) | Health | 4548 | Twitter | Content analysis | Yes | Human | Random | Positive | 0.1803 |
| Kim (2015) | Health | 760 | Multiple | Content analysis | No | Machine | [2]All | [3]Both | 0.09 |
| Kim et al. (2016) | Health | 7000 | Twitter | Content analysis | No | Machine | Random | Positive | 0.0763 |
| Kiriya et al. (2018) | Health | 8553 | YouTube | Experiment | No | [1]n/a | [1]n/a | [3]Both | 0.048 |
| Lin et al. (2018) | Health | 144 | Not specified | Experiment | No | [1]n/a | [1]n/a | Negative | 0.0365 |
| Lohmann et al. (2018) | Health | 20201 | Twitter | Content analysis | No | Machine | Random | Negative | 0.063 |
| Mou et al. (2018) | Health | 160 | WeChat | Experiment | Yes | [1]n/a | [1]n/a | Negative | 0.2 |
| Park (2019) | Health | 640 | Twitter | Content analysis | No | Human | Nonrandom | [3]Both | 0.3521 |

**Table 1.** *Study characteristics and effect sizes included in the meta-analyses* (back to text)

| Study | Context | Sample size | Sharing platform | Type of design | Theory-based | Coding method | Sampling method | Emotion valence | r |
|---|---|---|---|---|---|---|---|---|---|
| Sumner et al. (2020) | Health | 10998 | Twitter | Content analysis | No | Machine | [2]All | Negative | 0.0614 |
| Wang et al. (2019) | Health | 14616 | Sina Weibo | Content analysis | Yes | Human & Machine | [2]All | [3]Both | 0.064 |
| Xu et al. (2018) | Crisis | 13322 | Twitter | Content analysis | Yes | Machine | [2]All | Negative | 0.0141 |
| Zhang et al. (2017) | Health & Crisis | 51855 | Sina Weibo | Content analysis | Yes | Machine | Nonrandom | [3]Both | 0.2 |
| Zhou et al. (2018) | Health | 1496 | Twitter | Content analysis | Yes | Machine | Random | [3]Both | 0.0011 |
| Zhu et al. (2020) | Health | 1934 | Twitter | Content analysis | Yes | Machine | [2]All | Negative | 0.11 |

[1] "n/a" coding method and sampling method were only coded for content analysis studies. The coding method and sampling method refer to how the retrieved social media posts were coded and sampled.

[2] When sampling method was coded as "All", it means that the study used all the social media posts retrieved instead of sampling part of the posts.

[3] When emotion valence was coded as "Both", it means that the study did not differentiate messages that express positive or negative emotion.

**Table 2.** *Results of Moderator Analyses* (back to text)

| Moderator | N | k | r | 95%CI |
|---|---|---|---|---|
| *Sharing platform* | | | | |
| Twitter | 4,505,935 | 10 | 0.065***[a] | [0.053, 0.076] |
| Non-Twitter | 76,888 | 9 | 0.124***[b] | [0.107, 0.140] |
| *Emotion valence* | | | | |
| Positive | 11,548 | 2 | 0.123***[a] | [0.104, 0.131] |
| Negative | 4,489,586 | 9 | 0.044***[b] | [0.031, 0.056] |
| Both | 81,689 | 8 | 0.117***[a] | [0.098, 0.148] |
| *Coding method* | | | | |
| Human | 9,391 | 5 | 0.186***[a] | [0.154, 0.218] |
| Machine | 4,549,827 | 9 | 0.070***[b] | [0.053, 0.087] |
| *Sampling method* | | | | |
| Random | 33,245 | 4 | 0.084***[a] | [0.070, 0.098] |
| Nonrandom | 53,163 | 4 | 0.210***[b] | [0.195, 0.226] |
| All | 4,487,426 | 7 | 0.035***[c] | [0.026, 0.044] |

*Note.* \**p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001.
[a, b, c] Different subscripts show that the corresponding effect sizes within the same moderator variable are significantly different from each another at p<0.05 level or better.

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**Corresponding author**

Junhan Chen

Department of Communication

University of Maryland

0401 Marie Mount Hall

7814 Regents Dr

College Park

MD 20740, USA

jchen134@umd.edu