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The Picture of #Mentalhealth on Instagram: Congruent vs. Incongruent Emotions in Predicting the Sentiment of Comments

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This study explores the effects of sentiment of Instagram images and captions on the sentiment of comments. All Instagram posts with the hashtag #mentalhealth and the associated metadata were scraped on World Mental Health Day. A mixed-method approach of a sentiment classifier and a quantitative content analysis of Instagram posts ($N = 7{,}078$) was used. Overall, our sample contained more positive sentiment posts and comments than negative ones, indicating a possible connection between mental health-related discourse and positive sentiment on Instagram. Images containing faces elicited more likes, comments and positive comments compared with images without faces. MANCOVA analyses of images with human faces found that emotional contagion from Instagram posts to comments was only observed when considering the sentiment of both images and captions. Congruency effects were seen for posts with both negative captions and images, which elicited more negative comments compared to emotionally incongruent posts. Theoretical implications of emotional contagion and real-life implications for mental health social media campaign design are discussed.

Keywords: emotional contagion, social media, Instagram, sentiment analysis, mental health

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INTRODUCTION

With 72% of American adults using some type of social media, compared with only 5% in 2005 (Pew Research Center, 2021), social media has emerged as a platform for information exchange around mental health issues (Choudhury and De, 2014). Instagram is one of the most popular social media platforms in the United States, with four-in-ten adults and seven-in-ten adolescents having ever used it (Pew Research Center, 2018). Mental-health-related posts are shared daily on Instagram. At the time of this study, ~26,246,131 images were posted with the hashtag #mentalhealth, making it the most used mental health-related hashtag on Instagram.

Emotion, among all other content characteristics, is instrumental in facilitating the popularity and engagement of a social media post (Peters et al., 2009; Stieglitz and Dang-Xuan, 2013). The photo-oriented feature of Instagram makes it an ideal platform for examining emotional content since images convey more emotions and intimate feelings than textual content (Hjorth and Burgess, 2014). Photo-oriented social media such as Instagram also tend to bring about more emotional reactions in viewers, as compared to text-based platforms (e.g., Twitter) or mixed social media platforms (e.g., Facebook) (Pittman and Reich, 2016). Research has shown that exposure to emotional content such as experiences of others can improve the psychological well-being of people with mental health diseases (Park et al., 2021). The current study investigates how the emotions in the discourse of mental health on Instagram may affect viewers' emotional responses.

For the current study, we examined posts that contained the hashtag #mentalhealth and the accompanied users' emotional responses in the comments. #Mentalhealth was the most popular hashtag related to mental health on Instagram, which received over 35 million mentions at the time of data collection. We focused on Instagram posts made on the World Mental Health Day, October 10, 2018. People with different mental health conditions turn to social media to share their personal experiences (Choudhury and De, 2014), including mental health advocates who utilize social media platforms to raise mental health awareness (Koteyko and Atanasova, 2018). Thus, we expected more engagement with mental-health-related conversations would occur on the World Mental Health Day, which in turn would likely elicit sufficient comment-based data for analysis.

Given that previous research on social media discourse of mental health have mainly focused on text-based social media platforms like Twitter and Reddit (Choudhury and De, 2014; Koteyko and Atanasova, 2018), our study's focus on Instagram provides insights on how image-based social media platform can shape mental health discourse. The current study examines the effects of emotions in Instagram images and captions on comments' sentiment and advances the theory of emotional contagion by testing the *congruency effects hypothesis* (Riaz et al., 2018). Specifically, we examined whether the congruence between the emotional valence of an Instagram image and its accompanied post caption would affect the sentiment valence in comments. Because human faces provide non-verbal information such as people's emotional states (Goldman and Sripada, 2005), we focused on images of human faces on Instagram.

Engagement From Images With Face

The human brain has a particular region that is specialized for processing facial information, indicating the importance of faces in people's daily lives (Kanwisher et al., 1997). People's affinity for faces also extends to social media images. Images with human faces are 38% more likely to receive likes and 32% more likely to receive comments on Instagram than images without human faces (Bakhshi et al., 2014). However, the valence of comments to image posts of human faces has not been previously examined. In general, "liking" a post on social media is an indication of preference for the content (Aldous et al., 2019). We hypothesize that image posts with human faces will elicit more likes, comments, as well as more positive comments than images without human faces.

H1: Images with human faces will receive more likes, comments, and more positive comments compared with images with no human faces.

Emotional Contagion Through Social Media

Viewers' emotional reaction to social media posts is important. Those emotions may translate into both positive and negative post-exposure effects (van de Ven, 2016). A growing body of research on the effects of social media from an emotional contagion perspective suggests that people tend to adopt the emotions in others' posts (Kramer, 2012; Kramer et al., 2014; Ferrara and Yang, 2015). *Emotional contagion* is defined as the process in which people adopt and automatically mimic the emotions expressed by others (Hatfield et al., 1993). Laboratory experiments demonstrate that both positive and negative emotions can transfer from one person to other people (Barsade, 2002).

Emotional contagion has also been tested on social media platforms including Facebook and Twitter (Kramer, 2012; Kramer et al., 2014; Ferrara and Yang, 2015). One study found that after a user made a Facebook status update, their friends were significantly more likely to make a status update that was consistent with the user's update in terms of sentiment. Notably, these effects occurred even after 3 days from the initial status update (Kramer, 2012). In another study, people made more positive posts after they were exposed to more positive content in their Facebook News Feed, while the opposite pattern occurred when they were exposed to more negative content in their News Feed (Kramer et al., 2014). Lastly, a study observed a positive relationship between the emotional valence of the posts people were exposed to, and the posts they made subsequently on Twitter (Ferrara and Yang, 2015). In summary, all these studies suggest that emotional contagion occurs through social networks.

We contend that emotional contagion can also occur through the viewing of Instagram posts. Photograms of different facial expressions can also transfer emotions, such that images of happy faces, in comparison to images of sad faces, evoke significantly more happiness, and less sadness, anger, and fear (Wild et al., 2001). Images with people crying (vs. neutral facial expression) elicited more sadness (Hendriks and Vingerhoets, 2006). In addition, Instagram images elicited more feelings of intimacy compared with textual posts, thus suggesting an Instagram picture may be worth more than a thousand words (Pittman and Reich, 2016). However, such a conclusion may ignore the fact that people attend to both images and textual captions simultaneously when they are exposed to Instagram posts. To the best of our knowledge, none of the previous research has examined if Instagram images and captions have a different impact on audiences' emotional reactions. Thus, we posed the following research questions:

RQ1: Is there a difference in comment sentiment for Instagram captions that are positive, neutral, and negative?

RQ2: Is there a difference in comment sentiment for Instagram images (with human faces) that are positive, neutral, and negative?

We also extend the work on emotional contagion by examining if congruency effects occur with the emotional contagion.

Congruent and Incongruent Emotions in Instagram Images and Captions

When people read messages with both visual and textual elements, they tend to actively comprehend both images and text content simultaneously (Schnotz, 2005). The processing of messages with both visual and textual elements is maximized when the visual and textual elements are related (Schnotz, 2005), suggesting that congruency effects may be a moderator in the emotional contagion process.

Congruency effects are widely documented in the literature on selective exposure and information processing. Previous research found that messages that are framed to be congruent with individuals' motivational orientation exert more effects on individuals' behaviors than messages that are incongruent with their motivations (Sherman et al., 2006; Hong, 2012). We extended the theoretical work on emotional contagion by examining whether congruence between the emotional valence in image and post caption would affect the process of emotional contagion from Instagram posts to comments. Thus, while the literature on emotional contagion has demonstrated the polarity of the emotion (e.g., happiness) of a message would elicit the same-valenced emotional response in social media users, and that such corresponding transfers of emotions would be more pronounced when messages contain an intense expression of emotion (Choudhury and De, 2014), we examined whether the matching of emotions from an image and its accompanying post caption would have any effect on subsequent responses in the comments.

The congruence of emotional valence in information has also been studied in interpersonal communication. A study that examined the congruence between facial expression and verbal messages showed that when the facial and verbal information were both positive (i.e., congruent), the speaker was perceived to be a more effective communicator. In contrast, when facial and verbal information were incongruent (i.e., negative facial and positive verbal information), the speaker was given a more negative rating (Newcombe and Ashkanasy, 2002). To the best of our knowledge, none of the previous studies have examined the effects of congruent and incongruent emotions in visual-textual Instagram posts on the sentiment of comments. Based on the above discussion of the emotional contagion theory and congruency effect, we proposed the following hypotheses:

H2a: When positive emotions of images are paired with positive captions, the response comments will be more positive than neutral congruent, negative congruent, and incongruent image-caption posts.

H2b: When negative emotions of images are paired with negative captions, the response comments will be more negative than neutral congruent, positive congruent, and incongruent image-caption posts.

METHODS

Sample and Data Collection Procedure

We used Crimson Hexagon's ForSight social media analytics software to collect all publicly available Instagram posts with the hashtag "#mentalhealth" that was posted on the 2018 World Mental Health Day, which resulted in a sample of 9,512 Instagram posts. Data collection occurred 1 day after the 2018 World Mental Health Day. We limited the data collection to Instagram posts in English only. Next, we removed carousels (multi-image posts) and video posts, resulting in a sample of 7,078 Instagram image posts, along with accompanying metadata such as follower counts. To capture post engagement metrics, we waited 1 week before we used the Python package Pyppeteer to collect post engagement metrics including the number of likes, number of comments, and each of all comments to collected posts. All 7,078 posts were associated with numbers of likes and comments (both can be zero). Three thousand one hundred and six of the 7,078 posts received at least one comment. Overall, 14,015 comments to the 3,106 posts were collected. The study protocol was reviewed by IRB at the authors' academic institution and determined to not pertain to human subjects' research.

Inter-coder Reliability

Four trained coders independently coded the images for the presence of human face and human emotion valence. A codebook with instructions and examples was created for coders during the coding process. Four coders were trained on 50 Instagram images to reach consistency, disputes were discussed and resolved. For inter-coder reliability, coders independently coded 250 randomly selected images. **Table 1** displays the average Cohen's Kappa values as well as the frequency counts for each of the coding variables. Cohen's Kappa values were above 0.7 across all variables, indicating a high level of intercoder reliability (Landis and Koch, 1977).

Images Features: Human Face and Emotion

Coders first coded if the images ($N = 7{,}078$) contained a human face. Because the focus of this study is on the transfer of emotions from Instagram images, emotions were coded for only images with human faces ($n = 1{,}472$). Next, images were coded for the *emotional valence* (negative/neutral/positive) of the person(s) in the image. Specifically, images were coded as positive when the people in the images showed positive emotions such as happiness and excitement. For example, an image of a smiling person would be coded as a positive image. Images were coded as negative when the people in the images showed negative emotions such as sadness, anger, frustration, depression, and loneliness. In addition, an image with a frowning person would be coded as a negative image. Neutral images were coded when the people in the images showed no positive or negative emotions.

Sentiment of Captions and Comments

Sentiment analysis was conducted with VADER 3.3.1 (Hutto and Gilbert, 2014), a parsimonious rule-based model for sentiment analysis of social media text. Research shows that the F1-measure

TABLE 1 | Frequency of coded variables and inter-coded reliability.

	Frequency (Percentage)	Average Cohen's Kappa
Image category		0.92
With human face(s)	1,472 (20.8%)	
With no human face(s)	5,606 (79.2%)	
Emotion of people		0.82
Positive	1,008 (68.5%)	
Neutral	276 (18.7%)	
Negative	188 (12.8%)	

of classification using the Vader lexicon with tested dataset was higher for both positive and negative sentiments (positive: 0.73; negative: 0.72) than four other well-known sentiment analysis lexicons: SentiWordNet (positive: 0.59; negative: 0.42), SentiStrength (positive: 0.71; negative: 0.7), Liu and Hu opinion lexicon (positive: 0.69; negative: 0.67), and AFINN-111 (positive: 0.7; negative: 0.63) (Al-Shabi, 2020). VADER reports a normalized, weighted compound score for each unit of analysis by summing the valence scores of each word in the lexicon after adjusting to the weight rules. The composite score can range from -1 (most extreme negative) to 1 (most extreme positive). Based on the pre-specified rule of the VADER lexicon (Hutto and Gilbert, 2014), a compound score ≥ 0.05 indicates positive sentiment, a score < -0.05 represents negative sentiment, and a score in between -0.05 and 0.05 shows a neutral sentiment.

Sentiment of Post Caption

We analyzed the sentiment of post caption for the 1,472 posts that contained human faces. VADER was performed to analyze the sentiment of each post caption (i.e., the caption associated with each Instagram image). We categorized the sentiment of the caption of a post into positive, neutral, and negative based on the above-mentioned rule of the VADER lexicon (Hutto and Gilbert, 2014). Among all 1,472 Instagram posts with a human face, the average sentiment score was 0.52 ($SD = 0.63$), with 77.6% ($n =$ 1,143) of post captions contained positive sentiment, 4.6% ($n =$ 67) of post captions contained neutral sentiment, and 17.8% of post captions ($n = 262$) contained negative sentiment.

Sentiment of Post Comments

Among the 7,078 posts with the hashtag #mentalhealth, 3,106 posts elicited 14,015 comments. For each of the 3,106 posts, we combined the comments associated with each post to one text unit and then conducted the VADER sentiment analysis of the comment text unit. The average comment count of the 3,106 posts was 1.98 ($SD = 7.06$) and the average comments sentiment score was 0.53 ($SD = 0.47$). 961 of 1,472 images with human faces received comments. The average comment count for the 961 posts was 4 ($SD = 9.88$), and the average comments sentiment score was 0.67 ($SD = 0.43$).

Verification of VADER Performance

To evaluate the performance of VADER in measuring sentiments of posts in the context of mental health discourses on Instagram, we conducted a verification procedure to compare the sentiment results from VADER with our manual coding. First, we randomly selected 50 positive, neutral, and negative posts. Then, the first author and a research assistant who was unaware of the study's objective independently coded the sentiments of 150 posts as positive, neutral, or negative. Coding discrepancies were then discussed and resolved between two coders. Following that, we calculated the Cohen's Kappa value between the manual coding and the VADER results. Cohen's Kappa value was 0.72, indicating a high level of interrater reliability between manual coding and machine classifier (Landis and Koch, 1977).

Congruence Types

Based on the emotional valence of people in the image and sentiment of the post caption, we labeled a post as one of the following four congruence types: positive congruence (+/+), negative congruence (–/–), neutral congruence (n/n), and incongruence [(+/–), (–/+), (+/n), (n/+), (–,n), (n/–)]. For example, positive congruence is the pairing of a positive caption sentiment with a positive emotional valence of people in the image. Negative congruence is the pairing of a negative caption sentiment with a negative emotional valence of people in the image. Neutral congruence is the pairing of neutral caption sentiment with a neutral emotional valence of people in the image. Finally, incongruence is the pairing of any mismatched pairing (e.g., +/–, –/+) of caption sentiment and emotional valence of people in the image.

Data Analysis

For H1, a one-way MANCOVA was performed with all 7,078 posts to determine the effects of human faces on the numbers of likes and comments. The presence/absence of faces in the image was treated as the independent variable, and the numbers of likes and comments were treated as the dependent variables, while the number of followers was controlled in the analysis. Another one-way ANCOVA was conducted with 3,106 posts that received at least one comment to test the effects of human faces on the sentiment of comments. The presence/absence of faces in the image was also used as the independent variable, the sentiment score of comments was treated as the dependent variable, and the number of followers was controlled as a covariate.

For RQ1, we conducted a one-way ANCOVA with the 1,472 images that contained human faces. Image emotion was used as the independent variable (negative, neutral, positive), the sentiment score of comments was treated as the dependent variable, and the number of followers was controlled for the analysis.

For RQ2, we also conducted a one-way ANCOVA with 1,472 images that contained human faces. Caption sentiment was used as the independent variable (negative, neutral, positive), the sentiment score of comments was the dependent variable, and the number of followers was a control variable.

H2a and H2b proposed the congruency effect between image emotions and caption sentiments. We conducted a one-way ANCOVA with the four types of image-caption congruence types (positive congruence, neutral congruence, negative congruence, incongruence) as the independent variable, the sentiment scores of comments as the dependent variable, and the number of followers as a covariate.

RESULTS

Descriptive Results

In all 7,078 Instagram posts that were tagged with "#mentalhealth," 1,472 images contained human face(s). The average like count for all 7,078 posts was 95.38 ($SD =$ 1433.78), and the mean comment count was 1.98 ($SD = 7.06$). The average word count for each of the 7,078 post captions was 87 words. For images with human faces ($N = 1,472$), the average like count was 207 ($SD = 2888.54$), the average comment count was 4 ($SD = 9.88$), and the average word count for each post was 100 ($SD = 91.06$).

Analysis of comments to images with human faces revealed a pattern of encouraging words, with 387 (40.3%) of the 961 posts with human faces that received comments containing the word "love." Complimentary words such as "thank," "beautiful," and "great" were also observed in comments to posts with human faces. A similar pattern of positive words was also shown in comments to all #mentalhelath hashtag posts. **Table 2** displays the top ten most frequent words and emojis in the comments to #mentalhealth posts with human faces and to all #mentalhealth posts. The top ten most frequently used words in all #mentalhealth posts were: "mental," "health," "awareness," "can," "world," "day," "people," "know," "help," and "feel," indicating the overall discourse has a focus on raising awareness toward mental health issues.

The posts and comments were predominantly positive in Instagram posts with the hashtag #mentalhealth. For all the 7,078 #mentalhealth posts, Vader sentiment analysis suggested that the mean sentiment score for captions ($M = 0.44$, $SD = 0.61$) and comments ($M = 0.53$, $SD = 0.47$) were both positive. For the 1,472 posts with human faces, the average VADER sentiment score for caption ($M = 0.52$, $SD = 0.63$) and comments ($M = 0.67$, $SD = 0.43$) were also both positive. Our manual coding of 1,472 images with faces suggested that over half of the people images showed positive emotions (68.5%, $n = 1{,}008$), followed by neutral emotions (18.7%, $n = 276$), and negative emotions (12.8%, $n = 188$).

Faces and Engagement

H1 predicted that images of human faces will receive more likes, comments, and positive comments than images without a face(s). Significant and positive effects were found for the presence of human faces on the number of likes [$F_{(1,7075)} = 8.46$, $p = 0.004$], partial $\eta2 = 0.001$, number of comments [$F_{(1,7075)} = 240.67$, $p < 0.001$], partial $\eta2 = 0.033$, and on the positive sentiment in comments, [$F_{(1,3103)} = 111.43$, $p < 0.001$], partial $\eta2 = 0.035$. H1 was supported.

TABLE 2 | Frequency for top 10 words/emoji in comments to #mentalhealth posts.

Word/Emoji	Comments to posts with human faces that received comments ($n = 961$)	Comments to all #mentalhealth posts that received comments ($n = 3{,}106$)
You	550 (57.2%)	1,318 (42.4%)
❤️	471 (49.1%)	1,225 (39.4%)
Love	387 (40.3%)	927 (29.8%)
Thank	214 (22.3%)	526 (16.9%)
Beautiful	206 (21.4%)	361 (11.6%)
Great	153 (15.9%)	356 (11.5%)
Well	147 (15.3%)	325 (10.5%)
Amazing	140 (14.6%)	266 (8.6%)
Sharing	115 (12.0%)	243 (7.8%)
Important	76 (7.9%)	194 (6.2%)

Emotional Contagion and Congruence Effects

In RQ1 and RQ2, we asked if there are differences in sentiment scores of comments based on the emotional valence in post images and the sentiment of captions. ANCOVA analyses revealed that neither the comment sentiment scores of different image emotions [$F_{(2,951)} = 2.09$, $p = 0.12$, partial $\eta2 = 0.004$], nor the comment sentiment scores of different caption sentiment valence [$F_{(2,951)} = 0.44$, $p = 0.65$], partial $\eta2 = 0.001$, were significantly different.

H2a proposed that positive congruent posts will elicit the most positive comments when compared with neutral and negative congruent posts, and emotionally incongruent posts. H2b proposed that negative congruent posts will elicit the most negative comments compared with neutral and positive congruent posts, and emotionally incongruent posts.

In testing H2a and H2b, we found there is a significant effect of congruence type on the sentiment scores of comments to the posts, [$F_{(3,956)} = 5.57$, $p = 0.001$], partial $\eta2 = 0.017$. Followed up pairwise comparison with a Bonferroni adjustment revealed that positive congruent posts received more positive comments than negative congruent posts with a mean difference sentiment score of 0.26, $p = 0.002$. However, there were no significant differences between positive congruent and neutral congruent posts, as well as positive congruent and incongruent posts. H2a was partially supported. In addition, we found negative congruent posts received more negative comments than emotionally incongruent posts with a mean sentiment score difference of 0.25, $p= 0.004$. H2b was also partially supported.

DISCUSSION

Our study provides an analysis of audiences' responses to Instagram posts that takes into account both the visual and textual elements of this social media platform. Previous research on social media discourses of mental health mainly focused on text-based social media platforms such as Twitter and Reddit (Choudhury and De, 2014; Koteyko and Atanasova, 2018). Moreover, studies on mental-health-related Instagram posts often only analyzed images or captions of the posts (Lee et al., 2020). The accompanied comments with mental health Instagram posts were rarely studied. Our study's focus on Instagram mental-health-related posts and associated comments provide insights on how image-based social media platforms may shape mental health discourse and may potentially influence viewers' emotional states. Our study found that there were no differences in sentiment scores of comments based on the emotional valence in post images or the sentiment of captions. This indicates the importance of incorporating *both* images and captions when analyzing the sentiment valence of an Instagram post and its subsequent effects on audiences. Although there is a common saying that "a picture is worth a thousand words," research suggests that people tend to actively comprehend both images and text content simultaneously when they read messages with both visual and textual elements (Schnotz, 2005).

Although Instagram has a focus on images, users who posted about #mentalhealth also used text in their post captions to convey information. The average word count for each post in the current #mentalhelth dataset was 100, compared to an average of 11 words in #flu-related Instagram posts (Gencoglu and Ermes, 2018), indicating the importance of examining both Instagram images and captions in the context of mental health discourse on Instagram. Our study found that comments to Instagram posts are a function of both the image post and the associated caption, demonstrating that viewers of #mentahealth Instagram posts also pay attention to both post images and captions. Future studies could utilize the eye-tracking approach to learn more about people's Instagram viewing behaviors. Future research of Instagram posts should also consider including both images and captions for analysis since people tend to actively comprehend these two content elements simultaneously (Schnotz, 2005). Importantly, considering the sentiments in both post images and captions, our study supports the notion that emotional contagion can also occur through the viewing of Instagram posts.

Even though emotional contagion has been demonstrated to occur through viewing Instagram posts (Choi and Kim, 2021), little is known about the underlying mechanism by which emotions in posts are transferred to viewers. Compared to text-based platforms like Twitter and Reddit, Instagram contains both a visual and a textual component. By testing the *congruency effects hypothesis* (Riaz et al., 2018), our findings extend the literature on emotional contagion by demonstrating that when the emotion in the image post is congruent with the sentiment of the caption, the emotional contagion effect is more salient in the congruent conditions than non-congruent conditions. The findings of this study may be helpful to practitioners interested in maximizing the emotional reactions from the targeted audience for the communication and prevention of mental health issues. However, congruency effects were only demonstrated for negative congruent posts (posts with both negative images and negative captions), but not for positive congruent posts (posts with both positive images and positive captions). That is, the sentiments of comments for positive congruence were not more positive than incongruent posts, while the sentiments of comments to negative congruent posts were more negative than to the incongruent posts. One possible explanation could be the negativity bias in which people attend to and use negative information more than positive information (Vaish et al., 2008). Extensive research indicates that negatively valenced information is more attention-grabbing and has a processing advantage over positively valenced information (Baumeister et al., 2001). Previous research also found that people automatically attend to negative content rather than to positive content in information processing (Dijksterhuis and Aarts, 2003). Similar to other studies on non-social media, our study also revealed that negative emotions loom larger than positive emotions in viewing Instagram posts with both images and captions. The congruence between emotions of post images and captions was only found to enhance the emotional contagion for negative emotions. Another potential reason why positive congruent posts did not elicit more positive comments than incongruent posts is that the comments were by and large positive. This suggests that congruency effects should be explored for other topics that may garner a more representative range of sentiment.

Aligned with previous research, we also found images with human faces received significantly more likes and comments than images without human faces (Bakhshi et al., 2014). A positive relationship between appearances of faces and positive comments was also found. In addition, we observed that many Instagram images with the hashtag #mentalhealth contain graphic texts expressing social support and inspirational content. Those text images can also convey a wide range of emotions. Future research can look deeper into the effects of those captioned images on viewers' emotional reactions. Our study also suggested that the numbers of likes are not enough to capture viewers' emotional reactions to the posts.

Instagram has become a major platform for people with different mental health conditions to share personal experiences (Choudhury and De, 2014) and for health advocates to raise awareness of mental health (Koteyko and Atanasova, 2018). Overall, our sample contained more positive sentiment comments rather than negative, indicating a possible connection between mental health-related discussions and positive sentiment. Compared to text-based platforms (e.g., Twitter) or mixed social media platforms (e.g., Facebook), Instagram tends to bring about more emotional reactions and a stronger feeling of intimacy to its users (Pittman and Reich, 2016). When designing a mental health social media campaign, health practitioners may take the advantage of the intimate nature of Instagram, and be aware of the emotional reactions they may elicit from the audience.

While research suggests that self-exposure of emotional experience can benefit one's physical and psychological well-being (Smyth, 1998), little research has examined the potential impact of exposure to mental health-related discourse on Instagram. Our analysis of sentiments in comments to Instagram posts with the hashtag #mentalhealth suggested that viewing posts containing others' emotional experiences may have both positive and negative effects on the viewers' emotions (Lin and Utz, 2015). Additionally, people responded the most negative comments to posts containing both negative images and captions. Future research may investigate how emotional contagion from mental health Instagram posts may influence one's perceived emotional states—meta-emotions, at the time of viewing an emotional-charged, mental health-related Instagram post on Instagram (Bartsch et al., 2008). For example, many studies have examined viewers' emotional responses to others' social media posts through the process of social comparison (Latif et al., 2021). It is possible that people can benefit from reading a negatively framed mental-health post since they can relate to such content and emotions. A previous study of mental health discourse on Reddit revealed that negative emotions, along with other post characteristics such as the content of first pronounce, relationships, and death were associated with more comments a post received (Choudhury and De, 2014). Future research may look into the interactions between negative sentiment in posts with other content features to examine what specific negative elements in a post may elicit more reactions. Examining the long-term effects of engaging with negatively valenced mental-health-related Instagram posts on viewers' mental wellbeing is an important direction for future research.

Future investigation can also look into the influence of exposure to negative and positive mental-health-related posts on other important psychological outcomes such as efficacy perceptions—people's perceptions of their capability to perform a behavior (e.g., combating mental health issues) (Cervone, 2000), especially for people who are affected by mental health issues. For instance, a study that assessed efficacy perceptions and attitudes after watching a video of healthy eating found that a positive viewing experience led to stronger efficacy perceptions, which in turn promoted attitudes toward the health eating behavior (Ort et al., 2021). It would be interesting to examine the impact of positive/negative mental health-related Instagram posts on viewers' efficacy perceptions of their own mental health issues and behaviors. In addition, previous research suggests that people perceive emotional social support when they read others' emotional experiences and stories (Park et al., 2021). Future research may investigate if the exposure to emotional content of different valence (i.e., positive and negative) and intensity of emotional content may affect the processes differently. Lastly, while previous sentiment analysis of social media posts has often focused primarily on texts, our study found that images and texts both play vital roles in affecting people's emotions, indicating the importance of incorporating both images and captions for studies of Instagram or other visual social media platforms.

LIMITATION

Some limitations of our study deserve attention. First, there may be a potential for bias toward positive comments as we only analyzed #mentalhealth posts on the World Mental Health Day, a day of awareness and reflection. It is possible that these mental-health-related posts would elicit more positive/supportive comments on World Mental Health Day. Future research should examine the mental-health-related discourse on Instagram over a longer time, as well as the inclusion of other related hashtags. While the reliance on a single hashtag has been used in previous studies (Andalibi et al., 2017; Lee et al., 2020), such an approach can limit the types and nature of discourse. Thus, future research should utilize multiple hashtags related to mental health. For the convenience of analysis, we excluded 512 videos and 1,296 carousels (multiple images or video posts), though it is also important for future research to investigate how videos and multiple images may collectively affect users and their engagements with an Instagram post. In addition, the negative sentiment in comments might be elicited by the topics of the current study, which is mental health (e.g., depression, anxiety disorder). Words such as depression, anxiety, and disorder have all been categorized as negative words in VADER Sentiment Lexicon. So, it is possible that the comments only referred to those mental health diseases without expressing negative sentiment. To address this potential limitation, we searched for the presence of mental health diseases in the comments. Our analysis suggested that only 277 out of all 14,015 comments contained the following selected mental health-related words: "depression," "depressed," "anxiety," "anxious," "stress," and "disorder(s)," suggesting only a small portion of comments' sentiments might be potentially influenced by mentioning these mental health diseases.

Our data is positive in its nature possibly due to the common language pattern of encouragement in the discourse of mental health, as was found with other health issues such as diabetes on social media (Choudhury and De, 2014). Future research may analyze the relationships between the sentiment of posts and comments with other topics that have more mixed sentiments. Lastly, with analyses of variance, such as ANCOVA/MANCOVA, we are unable to demonstrate causality effects for emotional contagion, and the findings of our study should be interpreted as an association instead of causality. Emotional contagion has been demonstrated to occur through viewing social media posts with both experimental studies (Kramer et al., 2014; Choi and Kim, 2021) and analyses of social media observational data (Coviello et al., 2014; Crocamo et al., 2021). While experimental designs can demonstrate causality, unobtrusive social media data provide observational data that can shed light on the emotional contagion effects of real-life social media interactions.

DATA AVAILABILITY STATEMENT

The data underlying this article will be shared on reasonable request to the corresponding author.

AUTHOR CONTRIBUTIONS

This study was directed by TH. TH and JW together designed the study, interpreted the results, and drafted and revised the article. JW collected the data and performed the data analyses. Both authors contributed to the article and approved the submitted version.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.