Understanding the Features of Text-Image Posts and Their Received Social Support in Online Grief Support Communities

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Abstract

People in grief can create posts with text and images to disclose themselves and seek social support in online grief support communities. Existing work largely focuses on understanding the received social support of a post in pure text but often overlooks the post that attaches an image in grief communities. In this paper, we first computationally characterize the textual (e.g., theme), visual (e.g., color), and text-image coherence (i.e., semantic and sentiment coherence) features of text-image posts in a grief support community. Then, we conduct regression analyses to systematically examine the effects of these features on their received informational, emotional, esteem, and network support. We find that attaching an selfie image in the post positively predicts received informational and emotional support, while the social image of a post is a positive predictor of network and esteem support. A post is also likely to get more social support if its text is describing the visible content or telling a story depicted in the image or the perceived emotions in the text and image are not conflict. These results supplement existing research on mental health communities and provide actionable insights into assisting grief people to seek social support online.

Introduction

Grief, *e.g.,* for someone's death, a relationship, a job, a pet, a place or an era, affects every person at any time. Online grief support communities offer an accessible place for people in grief to disclose their feelings and seek social support from peers (Robinson and Pond 2019). For example, a support-seeker in the community can create a post in plain text or text with images to express their sadness on the anniversary of the loved person's death. The community members can leave comments to offer social support, *i.e.,* the perception or experience that one is cared for, esteemed, and part of a mutually supportive social network (Taylor et al. 2011). This paper focuses on understanding the features of online grief posts and the received social support of these posts. Understanding how people in grief disclose themselves and receive social support can divert appropriate resources within the community to posts, promote healthy communication within the community, and reduce negative situations where there are no comments or comments do not match needs (Guo et al. 2022; Yang, Li, and Huang 2017; Peng et al. 2021; Wang et al. 2021a). Existing research on general mental health communities has quantified the effects of various textual features, *e.g.,* readability (Pancer et al. 2019), linguistic features (Sharma and De Choudhury 2018), emotions (Kramer, Guillory, and Hancock 2014), of a support-seeking post on its received social support in the comments. However, many grief-related posts (*e.g.,* 30% of the posts in our collected Reddit r/GriefSupport dataset) can contain images, which contribute to support-seekers' self-disclosure and may affect how other members reply to the posts. For example, a #depression post with selfie images in Instagram could attract more informational support than the post without such images (Andalibi, Ozturk, and Forte 2017). If an Instagram #Mentalhealth post's emotions of the text and image are perceived congruent, it is likely to get more likes and replies (Wu and Hong 2022).

Though all these studies shine a light on the various patterns of mental health text-image posts and their relationship with viewers' behaviors, we still know little about how people in grief disclose themselves via a text-image post and how its features affect received social support from viewers. Such an understanding can help to assist grief people in expressing their tough experiences and feelings in multimodal ways to get needed social support. To fill this blank, we model the multi-modal features of text-image posts in an online grief support community and quantitatively examine the effects of these features on posts' received social support. Specifically, we collect 2978 posts that contain text and one image and their received 38100 comments from Reddit r/GriefSupport, a public grief support community with over 87K members up to December, 2023. Our research questions (RQs) are:

- **RQ1:** What are the patterns of the text-image posts' a) textual, b) visual, and c) text-image coherence features in the grief support community?
- **RQ2:** How do the textual, visual, and text-image coherence features of a text-image post impact its received social support in the grief support community?

To answer RQ1, we use existing methods to measure the **textual features** like linguistic accommodation, readability, theme, and sentiment. As for the **visual features**, we exam-

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ine the colors and label 900 images and develop models to classify five image themes (*i.e.,* captioned, selfie, social, pet, and daily; accuracy: 82.2% in the test set) and three levels of image sentiment (*i.e.,* negative, neural, and positive; accuracy: 79.9%). Besides, we model the **text-image coherence features** from the aspects of semantic coherence and sentiment coherence. For semantic coherence, we label 1000 text-image pairs and build multi-modal classifiers (accuracy $\geq 77\%$) to examine if the content of a post's text and image has a visible, subjective, action, story, or meta relation. For sentiment coherence, we measure if the emotions revealed in the text and image are complement, dominant, or conflict with each other.

To address RQ2, we first follow Peng et al. (2020) to build machine learning models to assess the amount (small, medium, large) of four types (*i.e.,* informational, emotional, network, and esteem) of social support provided in the comments. Then, we conduct a series of regression analyses using a post's textual, visual, and text-image coherence features as independent variables and its received social support as dependent variables. We highlight the results about the impacts of visual and text-image coherence features. For example, the selfie images are positively related to informational and emotional support, while the social images positively predict the network and esteem support. When a post's text restates the visible content or tells a story in the image, it is more likely to receive all types of social support. However, if the text describes a dynamic process in which the image is a snapshot (*i.e.,* "Action" semantic relationship) or the perceived emotions in the text and image are conflict, the post is less likely to get social support.

Our contributions are as follows. We unpack the impacts of a post's visual and text-image coherence features on its received amount of social support in an online grief support community. We build computational models to extract the textual, visual, and text-image coherence features of a post and predict its received amount of social support in the online grief support community. Lastly, we extend understandings on the text-image posts that previous work often overlooks in online mental health communities and provide implications to help people in grief.

Related Work

Online grief support communities offer an accessible place for people in grief to anonymously share stories, express feelings, and seek social support at any time. These communities mainly provide four types of social support, *i.e.,* informational, emotional, network, and esteem support (Robinson and Pond 2019). **Informational support** satisfies people's desire of professional support, experiences and stories related to grief, or information on coping with loss and resources such as links to grief support organizations, websites, and online forums. **Emotional support** typically communicates love or caring to help people cope with the pain and sadness of loss. **Network support** provides people with a strong sense of community and companionship. **Esteem support** communicates respect to people and helps rebuild confidence and remember those who have passed away.

To help people with mental health concerns get needed social support in online communities, existing work has examined the effects of various features of the posts on the received social support. For example, Sharma and De Choudhury (2018) categorized 55 mental health communities on Reddit and used the linguistic style matching (LSM) (Gonzales, Hancock, and Pennebaker 2010) approach to quantify the textual posts' linguistic accommodation in the community. They found that the linguistic accommodation in a post positively predicts the emotional or informational support it receives. A post that has higher readability (Pancer et al. 2019), expresses topics related to depression (De Choudhury, Counts, and Horvitz 2013), or conveys positive emotions (Kramer, Guillory, and Hancock 2014) could also increase the amount of social support it receives. Apart from the textual features, researchers have studied the images attached in the posts with disorder tags like #depression and #Mentalhealth in Instagram. For instance, Manikonda and De Choudhury (2017) extracted the visual features (e.g., color), themes, and emotions relating to mental health disclosures on Instagram, indicating the use of imagery for unique self-disclosure need. Wu and Hong (2022) measured the sentiment of the image and text separately for text-image posts tagged #MentalHealth on Instagram and found that posts with congruent sentiment received more positive comments. Nevertheless, these findings on general mental health posts in photo-sharing platforms like Instagram may not adapt to our target community in which the members are exchanging social support about grief issues.

In this paper, we focus more on the post's visual and text-image coherence features, which, as indicated by related work and theories, may affect its received social support. As an example of the visual features, the color of an image can reflect the state of psychological health (Reece and Danforth 2017) of the poster and evoke viewers' emotions (Labrecque and Milne 2012). For the text-image coherence features, inconsistency of a post's visual and textual content for expressing specific ideas or feelings would make readers doubt its authenticity and credibility (Otto et al. 2019). For instance, if the theme (*e.g.,* product) of the post's image fits with its text, it can lead to higher viewers' engagement on Twitter (Li and Xie 2020). The theory of emotional contagion suggests that the congruence between the perceived emotions between the text and image would invoke a stronger emotional response from viewers (Hatfield, Cacioppo, and Rapson 1993). Our work extends these related work and theories by identifying patterns of image-related features in text-image posts and systematically studying their effects on received social support in online grief support communities.

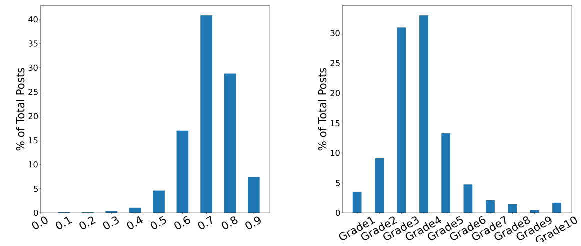
Research Site and Dataset

We aim to understand the patterns of the text-image posts' features and their relationship with the received social support in online grief support communities. In this paper, we focus on grief support communities in Reddit as it offers a wide range of mental health communities that allow people to focus on sharing, talking, and fostering group connections (Balsamo et al. 2023; Jangra, Shah, and Kumaraguru 2023; Chen et al. 2023). Reddit is more suitable for identifying patterns in discussions and conversations surround specific topic (grief in our case) than Instagram and Twitter. The anonymous nature of Reddit allows people to talk about their mental health issues without the fear of being stigmatized. We take several steps to search and filter appropriate grief support communities. First, we query communities with a set of grief-related keywords (*e.g.,* "sad", "grief", "suicide", "bereavemen") via the Reddit community search engine. We explore the associated communities of the search results, which lead to 27 candidate communities. Second, we check the rules and communication of each community. We remove the communities that are not oriented to post-comment interaction (*e.g.,* self-advertisement) and only include those encouraging seeking and providing social support about grief-related issues. After this step, four communities remain. Third, to satisfy our need for sufficient interaction data on text-image posts, we exclude three communities in which there are fewer than 10k members, support-seekers rarely create text-image posts, or the posts seldom receive comments. This process results in one community, the r/GriefSupport with over 87K members as of December, 2023, that is suitable for addressing our research questions.

We collect publicly available posts and comments created between Jan 2018 to Jan 2022 in r/GriefSupport via Pushshift API. We take four steps to pre-process the collected data. First, we remove the posts which contain the "NSFW" (a.k.a., Not Safe For Work) tag for ethical concerns. Second, we delete the posts, and comments whose content is "[removed]" or "[deleted]". Third, we remove the posts (13.4%) without receiving any comment from other members. Fourth, we remove posts (61.5% of the remaining ones) that do not attach any image. After these four steps, we have 2804 support-seekers with 3776 unique thread-starting posts that receive at least one comment. 2978 of the posts contain one image, while the rest 798 posts contain multiple images. The analyses on multiple images would be more complicate because they often create competing relationships (Bigne, Sanchez, and Sanchez 2001). In this paper, we only include the 2978 single-image posts that receive in total 38100 comments and leave the analyses of posts with multi-images for future work.

Ethics and Researcher Disclosure

We shape the work by our experience with and observation on people who have been in grief. The authors have experience of seeking and providing social support online and realize the importance of our topic for mental health communities. Two of the authors have experiences and publications that study the health communities. Our research team obtains IRB approval for broader research projects on patients' and caregivers' practices of healthcare service systems and online communities. We do not include any personally identifiable information such as username, gender, and age in the collected dataset. Besides, we secure the data in firewalled servers, and researchers could download the data only on local machines. Researchers are not allowed to share data and have no interaction with the users.



(a) LSM score (b) Readability score

Figure 1: Distribution of (a) LSM score and (b) readability score of the text in the text-image posts in r/GriefSupport.

RQ1: Features of Text-Image Posts

Textual Features (RQ1a)

Linguistic Accommodation Linguistic accommodation refers to a community's norms reflected by linguistic styles established by its members and has been found to positively related to the received informational and emotional support of text-only posts in Reddit's mental health communities (Sharma and De Choudhury 2018). However, there is a lack of empirical evidence indicating similar results for the text in text-image posts. Following Sharma and De Choudhury (2018), we use the Language Style Matching (LSM) (Gonzales, Hancock, and Pennebaker 2010) to assess the conformance of a post's linguistic style with other posts in our grief support community. It considers the rate of use of function (*e.g.,* prepositions, conjunctions, articles, and other content-free parts of speech) words in an individual's speech (content) to be a proxy for stylistic alignment as they help identify relationships between language and social psychological states (Chung and Pennebaker 2011).

Figure 1(a) presents the distribution of LSM scores in the online grief support community. The histogram shows that most of posts tend to adhere to the linguistic conventions of the online grief support community and imitate the writing styles of other members of the community.

Readability Readability is broadly defined as "the ease of understanding or comprehension due to writing style" and has been showed to positively predict the numbers of the post's like and comments in Facebook (Pancer et al. 2019). It is interesting to check if similar effects occur in the text of text-image posts in the grief community. We use the Dale-Chall Readability Formula (Chall and Dale 1995), a well-established linguistic measure that combines the dictionary-based word lists to measure word familiarity and syntactic complexity, to measure the readability of a post's text. It checks each word of the text against a list of 2,950 words known by at least 80% of fourth graders of primary school. The text with a score below 5 (lower, easier) should be easily read by fourth graders, and the text with a score below 10 should be readable at the college level.

As shown in Figure 1(b), most of the text-image posts in r/GriefSupport have low readability sores, indicating that their text is generally easy to read.

Text Theme The themes of a post can affect how viewers engage with it and are widely explored in literature about analyses of online communities (Chen et al. 2023; Miyazaki et al. 2023). We therefore include it as a predictor of a text-image post's received social support. Following the previous study, we use Latent Dirichlet Allocation (LDA) topic modeling to obtain themes of a post's text (Chen et al. 2023). We obtain themes of the post's text using Latent Dirichlet Allocation (LDA), which involves the following steps. 1) Cleaning: we preprocess the textual content of all the posts (N = 2978) in our dataset by i) removing non-English characters such as emoticon and digit, ii) converting letters into lowercase, iii) removing stop words (*e.g.,* about, the, me), iv) performing stemming for words using the WordNet Lemmatizer from NLTK (https://www.nltk.org/), v) removing words whose length is shorter than 2 or longer than 15, and vi) removing words whose frequency is less than 2 in our corpus. 2) Building: we use the Gensim 3.8 software to build LDA models by setting the metadata parameters "the number of passes" to 100, α to auto, and η to auto, which allow the models to infer the asymmetric theme distribution from the corpora. 3) Evaluation: we use the generated dictionaries and corpora to build 30 separate LDA models with the number of themes ranging from 1 to 30. We select the model with the maximum coherence score, which has 7 themes, as a higher coherence score positively indicates that the themes are human-interpretable (Maier et al. 2021)). 4) Analysis: we make sense of the clustered topics by analyzing the most frequently appeared words and 20 representative posts of each topic. Specifically, for each topic, we rank the posts based on the probability of revealing this topic predicted by our LDA model and select the top-20 posts as the representative ones. Two authors of this paper have multiple rounds of open-coding and discussions on the names and definitions of these clustered themes.

Table 1 presents the themes of the text in the text-image posts, representative words, and definitions. We can found that the text of most text-image posts in r/GriefSupport talks about loss of someone due to a disease (21.12%), followed by the change in life (20.28%), memory of others (17.07%), loneliness (14.50%), hurt (11.64%), anniversary (9.56%), and art (5.81%).

Text Sentiment We assess the sentiment of a text-image post's text via VADER (Hutto and Gilbert 2014), a well-known rule-based model for text sentiment analysis on social media. The score ranges from -1 (most negative) to 1 (most positive). As suggested by the rule in VADER, a score larger than 0.05 indicates positive sentiment of the text, a score lower than 0.05 shows negative sentiment, while a score between 0.05 and 0.05 informs neutral sentiment. We conduct a cross-verification analysis to validate the performance of VADER in sentiment classification in our dataset. Specifically, we first randomly select 50 positive, 50 neutral, and 50 negative posts labeled by VADER. Then two authors independently and blindly code the sentiment of these posts and resolve the disagreement via discussion. The Cohen's κ between the VADER- and human-labeled results is 0.72, indicating a reliable inter-rater agreement.

Table 1: Themes of the text in text-image posts in Reddit r/GriefSupport, representative words, and definitions.

Theme	Representative Words	Definition
Disease Loss (21.12%)	lost, passed, cancer, died, pain, disease, broken, dad, mom, amp	The poster suffers the loss of someone who is ill such as cancer
Change in Life (20.28%)	life, heart, love, time, lost, change, peace, feels, forever, hope	The poster indicates how the grief has had an impact on their lives
Memory (17.07%)	missed, grief, share, remember, waves, pain, memory, story, loved, time	The poster expresses how much they miss what they have lost by sharing stories and memory from the past
Loneliness (14.50%)	feel, alone, loss, miss, died, hard, crying, night, only, sad	The poster conveys a sense of loneliness after a loss or misses the things they have lost
Hurt (11.64%)	lost, hurts, broken, feel, heart, pain, died, cry, bad	The poster shares sad events in the past that hurt him/her
Anniversary (9.56%)	heart, birthday, day, lost, love, anniversary, passed, forever, death, time	The poster talks about anniversary or birthday of the person they lost
Art (5.81%)	lost, poem, loved, tattoo, died, music, left, grief, drawing, cope	The poster associates sadness with art or expresses sadness through artistic means such as drawing

Figure 3(a) shows the distribution of text sentiment in text-image posts in r/GriefSupport. We find that the text of most text-image posts explicitly conveys negative (38.8%) or positive (46.9%) emotion, with only 14.3% posts are perceived neutral based on their text.

Visual Features (RQ1b)

Colors The colors of an image can evoke viewers' emotions (Labrecque and Milne 2012) and therefore affect their provided social support to the poster. We use the HSV (Hue–Saturation–Value) color space, which characterizes a pixel by three numbers: (1) Hue: the color type ranging between 0 and 360 degrees, *e.g.,* 0 is red, 60 is yellow; (2) Saturation: the intensity of the color ranging from 0 to 1, *e.g.,* 0 represents no color and is a shade of gray; and (3) Value: the brightness of the color ranging from 0 to 1, *e.g.,* 0 represents black. We use the OpenCV libraries (https://docs.opencv.org/4.x/) to compute the HSV space of the images in our dataset. The mean of hue is 174.94 (SD = 55.10), which indicates a relatively balanced hue of the images used in the posts. The mean of saturation is 0.29 (SD = 0.14), which suggests that the intensity of colors in the images of the posts is generally low. Lastly, the mean of brightness is 0.54 (SD = 0.14), which indicates that the images of the posts are generally not too dark or too bright.

Image Theme To understand and model the themes of images in the support-seeking posts, we first build an annotated image dataset. Two authors randomly sample 100 images from our dataset of all posts, independently group them into several clusters, and name the theme for each cluster. After that, they meet regularly to compare images and discuss the names of each cluster. After several rounds of iterative clustering and discussion, they agree with the coding scheme on five clusters: Captioned, Selfie, Social, Pet, and Daily Images. Following Manikonda and De Choudhury (2017), the two authors independently apply the scheme to another 800 randomly sampled images. For those that do not fall into the five clusters, the two authors assign a label "Other" to them. The inter-rater metric Cohen's κ is 0.91, indicating a strong agreement (McHugh 2012). We invite another researcher to resolve the disagreement by majority voting, resulting 153 captioned, 225 selfie, 207 social, 162 pet, 151 daily, and 2 other images. Then, we split these labeled 900 images into a training set (60%), a validation set (20%), and a test set (20%). We use the training set to finetune a multi-class classifier that adds a fully connected layer to the standard Inception3 network (pre-trained on the ImageNet dataset), which achieves an accuracy of 83.9% / 82.2% on the validation / test set. We use the model to predict the themes of all images in the dataset.

Figure 2 shows the example image and distribution of each theme. The selfie images (24.3%) are the most frequent theme in text-image posts, followed by social (23.1%), daily (17.6%), pet (17.5%), and captioned images (16.5%).

Image Sentiment We fine-tune the visual sentiment classification model pre-trained on the Twitter for Sentiment Analysis (T4SA) dataset (Vadicamo et al. 2017). Two authors first randomly sample 100 images from our dataset and separately classify their sentiments into the positive, neutral, or negative class. After several rounds of discussion and annotation, they reach a consensus on the annotation scheme. Next, they apply this scheme to another 800 randomly sampled images from our dataset. The Cohen's κ for the 900 images are 0.81, 0.92, and 0.90. We invite another researcher to resolve the disagreement via majority voting. We split these images into a training set (60%), a validation set (20%), and a test set (20%). We train a multi-class image sentiment classifier that adds a fully connected layer to the pre-trained ResNet50. It achieves an accuracy of 81.2% / 79.9% on the validation / test set. We then apply it to all the images in our dataset.

Figure 3(a) presents the distribution of image sentiment. We find that text-image posters attach more positive images (47.7%) than neutral (27.7%) and negative images (24.6%).

Text-Image Coherence Features (RQ1c)

Semantic Coherence Semantic coherence indicates whether the content of a post's text and image has a certain relationship, which could affect viewers' engagement (Li and Xie 2020). Inspired by previous multimodal discourse annotation campaigns (Alikhani et al. 2019), we use an overlapping (*i.e.,* the relations can exist simultaneously) set of high-level relations to represent the semantic coherence between the image and text. The relations adapted from (Prasad et al. 2008; Hobbs et al. 1985; Schiffrin 1980) are: 1) **Visible**, where text presents information that is intended to recognizably characterize what is depicted in the image; 2) **Subjective**, where the text describes the speaker's reaction to, or evaluation of, what is depicted in the image; 3) **Action**, where the text describes an extended, dynamic process of which the moment captured in the image is a representative snapshot; 4) **Story**, where the text is understood as providing a free-standing description of the circumstances depicted in the image; and 5) **Meta**, where the text allows the reader to draw inferences not just about the scene depicted in the image but about the production and presentation of the image itself.

Three authors first randomly select 100 text-image pairs from our dataset and independently label whether they are coherent regarding each of the five semantic relation (1 - yes, 0 - no). They meet, discuss the coding scheme, and refine it for several rounds. Next, they apply the resulting scheme to another 900 randomly sampled text-image pairs. The Kendall consistency coefficients are 0.879, 0.877, 0.893, 0.911, and 0.899 for annotating each type of semantic relations. The disagreement is resolved via majority voting. We use these 1000 labeled text-image pairs to train a multimodal multi-label classifier, which consists of a pre-trained VIT picture encoder, a pre-trained Transformer text encoder, and a late fusion layer that combines the coded picture vectors with the text vectors to learn the inter-modal information. We train several classifiers corresponding to each semantic relation. We choose the best-performed classifier for each relation using 10-fold cross-validation. Next, we use these five classifiers to predict remaining comments from our dataset. One expert annotator manually cross-verifies a random sample of 100 text-image pairs from this machine labeled dataset. This activity yields visible, subjective, action, story, and meta accuracies of 82%, 79%, 77%, 85% and 84% respectively, which is consistent with the performance of the classifier in the 10-fold cross-validation, indicating its robust performance. We apply these classifiers to all text-image posts in our dataset. Figure 4 displays the example post and the distribution of each type text-image semantic relations in our dataset in Reddit r/GriefSupport. We find that most of the text-image posts in Reddit r/GriefSupport have a visible text-image semantic relation (68.0%), followed by meta (64.0%), story (49.4%), action (39.9%), and subjective (38.7%) relations.

Sentiment Coherence Following Wang et al. (2021b), we categorize the sentiment coherence between text and image into three classes: 1) **Dominant**, sentiment of one modality is dominant for expressing the poster's emotion, *e.g.,* a particularly pessimistic picture underneath a very calm quote; 2) **Complement**, two modalities complement each other when people are expressing their sentiment in the post, *e.g.,* a photo showing happy faces and a text expressing happiness; and 3) **Conflict**, the sentiments of two modalities conflict with each other, *e.g.,* a photo showing happy faces and a text expressing sadness. We calculate the text-image sentiment coherence based on the predicted text sentiment and image sentiment by our models as described above. The sentiment coherence is "Conflict" if the sentiments of the text and the image are not congruent (*i.e.,* positive-negative), is "Dominant" if either the sentiment of text or that of image is more to the extremes (*i.e.,* positive-neutral, neutral-negative), and is "Complement" if the sentiments of the text and the image are congruent (*i.e.,* positive-positive, neutral-neutral, and negative-negative).

(a) Captioned Images (embedded text) (491/16.5%)

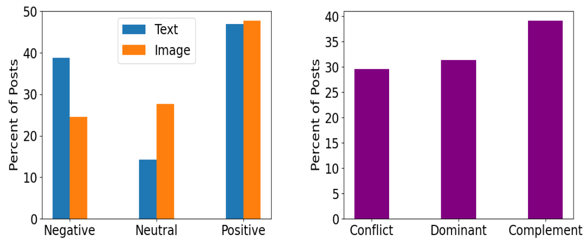
(b) Selfie Images (only one human) (724/24.3%)

(c) Social Images (at least two human) (688/23.1%)

(d) Pet Images (pet or pet with owner) (521/17.5%)

(e) Daily Images (items in daily living) (524/17.6%)

Figure 2: Example images for five image themes and their occurrences/distributions in our dataset of text-image posts in Reddit r/GriefSupport. We decrease the resolution and obscure sensitive information of the images for copyright and privacy concerns.



(a) Text&Image Sentiment

(b) Sentiment Coherence

Figure 3: Distribution of (a) text and image sentiment and (b) text-image sentiment coherence in the text-image posts in Reddit r/GriefSupport.

Figure 3(b) shows that the distribution of three types of sentiment coherence in the text-image posts in Reddit r/-GriefSupport. We find that 39.1%, 31.3%, and 29.6% of the posts have a complementary, dominant, and conflict text-image sentiment relation, respectively.

RQ2: Impact of a Text-Image Post's Features on its Received Social Support

Received Social Support in the Comments

We adapt the classic and nuanced Social Support Behavioral Code (Cutrona and Suhr 1992) to categorize the received social support in the comments. The code groups 23 communication behaviors intended to be supportive into five categories: informational, emotional, tangible, network, and esteem support. However, tangible support such as providing financial support to the posters is not common in Reddit r/GriefSupport [1]. Therefore, we focus on labeling and inferring the amount (1 - small, 2 - medium, 3 - large, following Peng et al. (2020)) of informational, emotional, network, and esteem support as defined at Related Work.

Following Peng et al. (2020), we randomly sample 1000 comments from our dataset. Two annotators who report that they are familiar with online grief support communities first take three rounds of iterations to label the amount of provided social support in 20, 30, and 50 comments, respectively. After each round of annotation, they meet, compare the labels, and refine the coding schemes. They then apply the scheme to the remaining 900 comments. The inter-rater agreement metric Cohen's κ are 0.929, 0.872, 0.925, and 0.876 for informational, emotional, network, and esteem support. In total, the numbers of comments labeled as a small / medium / large amount are 338 / 335 / 328 for informational support, 356 / 321 / 294 for emotional support, 323 / 340 / 317 for emotional support, and 311 / 336 / 333 for esteem support, respectively.

Next, we build classifiers to predict the amount of each type of social support in a comment based on its linguistic features. Inspired by Peng et al. (2020), we employ the well-validated psycholinguistic lexicon, Linguistic Inquiry and Word Count (LIWC) (Tausczik and Pennebaker 2010), to extract the features of a comment. Specifically, we use a set of 50 LIWC categories that closely related to the mental health content on social media (Tausczik and Pennebaker 2010) as input to each classifier. In addition, based on the annotators' feedback, we compile keyword sets "advice" (*e.g.,* URL, advice, suggestion, experience), "encourage" (*e.g.,* encourage, hug, pray), "similar" (*e.g.,* both, similar, too), and "proud" (*e.g.,* beautiful, sweet, proud) as input to classifiers for informational, emotional, network, and esteem support, respectively. Following Peng et al. (2020), for each type of social support, we train several classifiers, including random forest (RF), support vector machine (SVM), multinomial logistic regression (MLR), and multilayer perceptron (MLP). We evaluate the performance of all classifiers using 10-fold cross-validation. RF model achieves the best performance for predicting the amount of informational (accuracy = 0.751) and esteem support (0.675), while the MLP classifier with the adam solver performs the best for predicting the amount of emotional (0.802) and network support (0.659). We then use these best classifiers to predict the amount of four types of social support in the remaining 37100 comments in our dataset. One annotator manually cross-verifies a random sample of 100 comments from this machine-labeled dataset. The classifiers achieve an accuracy of 71% / 77% / 63% / 65% for predicting informational / emotional / network / esteem support, which is comparable

[1] In our coding of 100 randomly sampled comments, only three comments are rated providing a large amount of tangible support.

(a) Missing my big brother **[mask]**
Visible (68.0%)

(b) **[mask]** 5 beautiful angels **[mask]**
Subjective (38.7%)

(c) **[mask]** sorting some clothes **[mask]**
Action (39.9%)

(d) **[mask]** picture after marrying **[mask]**
Story (49.4%)

(e) Keep on dancing **[mask]**
Meta (64.0%)

Figure 4: Example text-image posts and their distribution of (a) visible, (b) subjective, (c) action, (d) story, and (e) meta text-image semantic relation in Reddit r/GriefSupport. We "**[mask]**" text non-related to the relation and blur sensitive content in the image for copyright and privacy concerns.

to the model performances in previous work on social support (Sharma and De Choudhury 2018).

Regression Analyses

We address our RQ2 via a set of regression analyses that treat the textual, visual, and text-image coherence features of a post as independent variables (IVs). Following Sharma and De Choudhury (2018), for each post, we calculate its received amount of each type of social support by averaging the amounts of that type of support in its comments. We use the amount of its received social support in different types as dependent variables (DVs). As the DVs are continuous data, we utilize the linear regression models. All the IVs in the analyses are first standardized for factor comparison, with a mean of zero and a standard deviation of one (Gelman 2008). To ensure the feasibility of this method, we confirm that the pairwise *Pearson* correlation coefficients of IVs are all smaller than 0.6, which suggests the collinearity among the post's features is not severe (Berry and Feldman 1985). We then calculate the variance inflation factors among IVs, which are all smaller than 3, indicating that the multicollinearity issue does not exist (Vatcheva et al. 2016). We thus proceed to conduct regression analyses.

Effects on received informational support Model 1 in Table 3 shows the effects of a post's visual, textual, and text-image coherence features on the amount of its received informational support. As indicated by the coefficients, an attached image with higher hue (β=0.012), higher saturation (β=0.023), or lower brightness (β=-0.030) could improve the received informational support of the post. Community members are more likely to offer informational support to the post whose image reveals the captioned (β=0.090) or selfie (β=0.050) theme. If members perceive that the image conveys negative feelings (β=-0.05), they would also be more likely to offer informational support. When it comes to the textual features, the post's linguistic accommodation revealed by linguistic style matching (LSM) score (β=0.071) and its readability (β=0.014) positively predict the received amount of informational support, while the text sentiment (β=-0.128) negatively predicts the informational support. Members are more likely to provide informational support to the post when its text reveals a theme about anniversary (β=0.019), disease (β=0.027), upset (β=0.057), or art (β=0.030). As for the text-image semantic coherence, if the post's text and image have a visible (β=0.026), subjective (β=0.013), story (β=0.047), or meta (β=0.095) relation, it tends to receive more informational support from the community members. However, if the text describes an extended, dynamic process of which the moment captured in the image is a representative snapshot (*i.e.,* the action relation) (β=-0.016), the post would receive less informational support. Furthermore, the complement (β=0.012) and dominance (β=0.040) relations of the text and image sentiment are positive indicators of the received informational support. Interestingly, if the sentiment of a post's text conflicts with that of image (β=-0.045), it tends to attract less informational support.

Effects on received emotional support Model 2 in Table 3 describes the effects of a post's visual, textual, and text-image coherence features on its received amount of emotional support. As suggested by the model's coefficients, when the post's image is of higher hue (β=0.013), higher saturation (β=0.023), and lower brightness (β=-0.03), it would receive more emotional support. Similar to the case of informational support, the selfie (β=0.01) image could help the post receive more emotional support. However, different from the cases of informational support, the captioned (β=-0.0922) image negatively predicts the amount of received emotional support, while pet (β=0.008) image positively predicts it. As for the textual features, the post with a higher LSM score (β=0.047), higher readability (β=0.026), or lower sentiment (β=-0.032) is likely to receive more emotional support. Members of the community would be more likely to offer emotional support to the post whose text talks about disease (β=0.020), loneliness (β=0.050), or memory (β=0.013) rather than anniversary (β=-0.090), change in life (β=-0.017). Lastly, similar to the impacts on informational support, the visible (β=0.09), subjective (β=0.038), story (β=0.022), and meta (β=0.024) semantic relations as well as the sentiment relations of complement (β=0.022) and dominance (β=0.06) between a post's text and image are positively associated with the received emotional support, while the action (β=-0.13) semantic and conflict (β=-0.034) sentiment relations are negatively correlated to it.

Table 2: Descriptive statistics of variables for predicting seekers' received social support.

		Posts(N=2978)		
	Variables	min/max	mean/std	median
Visual	hue	0/360	174.97/55.10	188.43
	saturation	0/1	0.29/0.14	0.28
	brightness	0/1	0.54/0.16	0.52
	image_sentiment	-1.0/1.0	0.23/0.81	0
	captioned_images	0/1	0.16/0.37	0
	selfie_images	0/1	0.24/0.43	0
	social_images	0/1	0.23/0.42	0
	pet_images	0/1	0.17/0.38	0
	daily_images	0/1	0.17/0.38	0
Textual	linguistic_accommodation	0/1.0	0.79/0.10	0.82
	readability	0/10	4.33/1.48	4
	text_sentiment	-1.0/1.0	0.11/0.58	0
	anniversary birthday	0/1	0.20/0.40	0
	cancer disease	0/1	0.24/0.42	0
	upset sadness	0/1	0.10/0.30	0
	change in life	0/1	0.16/0.36	0
	lonely and miss	0/1	0.10/0.29	0
	art	0/1	0.05/0.22	0
	memory remember	0/1	0.13/0.34	0
Text-image coherence	visible	0/1	0.68/0.46	1
	subjective	0/1	0.38/0.48	0
	action	0/1	0.39/0.48	0
	story	0/1	0.49/0.50	0
	meta	0/1	0.64/0.47	1
	complement	0/1	0.39/0.48	0
	dominance	0/1	0.31/0.46	0
	conflict	0/1	0.29/0.45	0
support	informational support	1.0/3.0	1.88/0.52	1.88
	emotional support	1.0/3.0	2.04/0.32	2.00
	network support	1.0/3.0	1.90/0.47	1.94
	esteem support	1.0/3.0	2.08/0.46	2.00

Table 3: Regression models for predicting the receipt of Informational support (Model 1), Emotional support (Model 2), Network Support (Model 3), Esteem support (Model 4). In the table, $***: p < 0.001; **: p < 0.01; *: p < 0.05$.

	Predictors	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Visual	Hue	0.012**	0.013**	-0.030	-0.018**
	Saturation	0.023**	0.023***	0.040***	0.006
	Brightness	-0.030***	-0.030***	-0.016*	0.005*
	Captioned	0.090***	-0.092***	-0.011	0.008**
	Selfie	0.050**	0.010*	-0.040	0.023
	Social	-0.050	-0.060	0.031***	0.015**
	Pet	0.020	0.08***	0.027**	0.027
	Daily	-0.012	-0.076***	-0.054	0.026
	Sentiment	-0.050**	-0.060**	-0.010*	0.045***
Textual	LSM score	0.071***	0.047***	0.063***	-0.011
	Readability	0.014**	0.026***	0.009*	0.070*
	Sentiment	-0.128***	-0.032***	-0.079***	-0.015**
	Anniversary	0.019*	-0.090*	0.024**	0.022
	Disease	0.027**	0.020**	0.021**	0.008*
	Upset	0.057***	0.040	0.039***	-0.016*
	Change	0.040	-0.017*	-0.018*	-0.014*
	Lonely	-0.020	0.050*	0.024***	0.013*
	Art	0.030**	-0.030	0.010	-0.022
	Memory	0.070	0.013*	0.080*	0.021**
Text-image coherence	Visible	0.026***	0.090*	0.061***	0.027***
	Subjective	0.013*	0.038***	0.031**	-0.080
	Action	-0.016*	-0.130**	-0.029**	-0.023*
	Story	0.047***	0.022***	0.056***	0.030**
	Meta	0.095***	0.024***	0.089***	0.020
	Complement	0.012*	0.022***	0.120***	0.190**
	Dominance	0.040*	0.060***	0.057***	0.028**
	Conflict	-0.045*	-0.034***	-0.017**	-0.032***
	R^2	0.208	0.365	0.240	0.185

Effects on received network support Model 3 in Table 3 describes the effects of a post's visual, textual, and text-image coherence features on the amount of its received network support. Its coefficients suggest that an image of higher saturation (β=0.040) or lower brightness (β=-0.016) could help support-seekers get more network support from the community. The image with a social (β=0.031) or pet (β=0.027) theme would also be helpful for getting network support. For the textual features, members are more likely to offer network support to the post which has a higher LSM score (β=0.063), has higher readability (β=0.009), or is perceived more negative (β=-0.079) in the text. Besides, they tend to provide network support to the post whose text is more about anniversary (β=0.024), disease (β=0.021), upset (β=0.039), loneliness (β=0.024), or memory (β=0.080) but less about change in life (β=-0.018). As for the text-image coherence features, similar to the cases of informational and emotional support, the received network support of a post could be positively predicted by the visible (β=0.061), subjective (β=0.031), story (β=0.056), and meta (β=0.089) relations between its text and image but negatively predicted by the action (β=-0.029) relation. Moreover, a post whose text and image sentiments complement (β=0.12) or dominant (β=0.057) each other is likely to receive a larger amount of network support. However, if the sentiments conflict (β=-0.017) with each other, it tends to get a smaller amount of network support.

Effects on received esteem support Model 4 in Table 3 shows the effects of a post's visual, textual, and text-image coherence features on the amount of its received esteem support. The model's coefficients indicate that when support-seekers use an image of relatively lower hue (β=-0.018) or higher brightness (β=0.005), in their posts, they would receive more esteem support from the community. When they use a captioned (β=0.080) or social (β=0.015) image, their posts are also likely to get more esteem support. Interestingly, different from other types of social support, the received esteem support is positively predicted by the perceived sentiment (β=0.045) of the post's image. As for the textual features, similar to the cases in other types of social support, the post with a higher readability (β=0.070), or more negative sentiment (β=-0.015) tend to receive more esteem support. Besides, the post would attract more esteem support if it is more about disease (β=0.008), loneliness (β=0.013), or memory (β=0.021) but less about upset (β=-0.016) or change in life (β=-0.014). Lastly, for the text-image coherence features, if the post's text and image semantically reveal a visible (β=0.027) or story (β=0.030) relation, it would get a larger amount of esteem support from the community. Similar to the cases in other types of social support, if the semantic relation between the text and image is more about action (β=-0.023), the post would receive less esteem support. Besides, the complement (β=0.190) and dominance (β=0.028) of text-image sentiment coherence positively predicts receiving esteem support, but the conflict (β=-0.032) between text and image sentiment negatively predicts it.

Discussion

The effects of features of the text-image posts on received social support

To our knowledge, our work presents the first quantitative study of how support-seekers disclose themselves via text-image posts and how the features of these posts affect received social support in online grief support communities. Much of the previous research has examined peer support provided to grievers in online grief support communities through qualitative research methods. We build on previous work by taking a more micro-level perspective, extracting textual features, image features, and image-text coherence features of posting content in order to investigate how the features affect the different types of social support received by supporter-seekers. Our RQ2 results indicate that the text's LSM and readability scores are positively associated with all types of social support received by the post, while the text sentiment negatively predicts it. These results validate previous findings about linguistic accommodation, readability, and emotions of textual posts in general mental health communities or social media (Sharma and De Choudhury 2018; Pancer et al. 2019; Harber and Cohen 2005).

The most notable findings of our work lie in the relationship between the image-related features of a post and the amount of its received social support. For example, in table:regression, we can see that a brighter image tends to help the post receive more esteem support but less informational, emotional, and network support. This finding indicates that while brighter colors are more visually appealing and can draw more attention from viewers (Palmer 1999), they do not necessarily lead to more social support offered by the members in online grief support groups. As for the theme of image, we find that the selfie images are positively related to informational support and emotional support (Models 1, 2). This result does not align with the findings on online medical crowdfunding campaigns, in which an image of healthiness narrative with single people tends to get lower first impression ratings, *e.g.,* on empathy and attractiveness (Guo et al. 2022). We also find that social images help the post receive more network and esteem support (Models 3, 4). This verifies findings in Dong et al. (2023) that talked more about social ties, such as friends, family, and affliations, were actually more likely to be impacted. Besides, an image about pet (*e.g.,* lost by the support-seekers) could help the post attract more emotional, and network support (Models 2, 3). This result confirms the positive effect of pet pictures on eliciting viewers' love and sympathy on general social media platform (*e.g.,* Facebook) (Vitak et al. 2017). Moreover, the daily images of the posts are negatively associated with the received emotional support (Model 2). One possible reason is that users posting images related to their own lives could be too personalised to be resonated by the viewers (Burke et al. 2014). Besides, the perceived sentiment of a post's attached image is negatively correlated with its received amount of informational, emotional, and network support but is positively correlated with the received esteem support. This supports previous findings that images of negative emotions can elicit empathy with viewers (Lamm et al. 2007) and inspire them to share advice (Andalibi, Ozturk, and Forte 2015) and experiences that build a sense of community (Phirangee and Malec 2020). Positive images, instead, can enhance one's sense of self-esteem and gain appreciation from others (Burrow and Rainone 2017).

In terms of text-image semantic coherence, we find that if a post's text and image has a visible or story relation, the post tends to get more social support than that without such relation (table:regression). According to the principle of consistency (Thomson 1990), the textual restatement of the image content (*i.e.,* visible relation) could help viewers better understand the ideas conveyed by the post and further support the seekers. When the post's text is telling a story depicted in the image, viewers could better empathize with seekers' experiences and feelings to offer needed support (Capitulo 2004). We also find that if the post's text and image present a subjective or meta relation, it would attract more informational, emotional, and network support. When the text describes the seeker's subjective feeling about the image, the post will be perceived rich in emotion (Hobbs et al. 1985) and elicit emotional support from the viewers. The meta-talk in the text allows viewers to draw inferences about the attached image, which can can promote the members' understanding with each other and lead to positive communication of social support (Rosenberg and Chopra 2015). Besides, we find that when the text describes an extended, dynamic process of image (*i.e.,* action relation), the post tends to get less social support. This could be explained by that the text may not provide sufficient information for the moment of capture to help viewers resonate well with the poster (Zimmermann, Lorenz, and Oppermann 2007).

As for the text-image sentiment coherence, we find that the complement or dominance relation between the sentiments of a post's text and image positively predicts all types of its received social support. On the contrary, the conflict relation between the sentiments negatively predicts the received social support. These findings support the Emotional Contagion theory (Hatfield, Cacioppo, and Rapson 1993), which states that when the words and images are emotionally complementing, readers would be susceptible to the emotions in the post and provide emotional responses. This cognitive load brought by the conflict sentiments, however, may decrease the readers' understanding and acceptance of the post, thus reducing their likelihood of providing social support (Huang et al. 2020).

Our findings provide actionable insights into assisting people in grief online. On the one hand, we can provide support-seekers feedback on the amount of social support that their text-image posts are likely to receive. For instance, if support-seekers want to get informational support, we can suggest them to write a text that expresses a negative emotion and allows the viewers to easily draw inferences from the image (*e.g.,* Figure 4(e)). Nevertheless, the feedback system should not force support-seekers to change their post if they do not feel like to since it may silence them (Blackwell et al. 2017). On the other hand, we can facilitate members, especially those new to the online grief support community, to provide expected social support to the support-seeking post. For instance, when members encounter a post that they would like to offer help, they can get predictions from our models in table:regression on what type of social support the community normally will provide to this post. Our findings could be generalized to other types of online mental health communities whose topics are similar to grief, *e.g.,* those about getting over difficult times, miscarriage, therapy, and so on (Sharma and De Choudhury 2018).

Generalizability

Although this work focuses on the text-image posts of online grief support communities, our findings could be generalized to other platforms or other types of online mental health communities whose topics are similar to grief. The study by Sharma *et al.* clustered mental health sub-reddits based on themes and found that sub-communities under the same broad theme had broadly similar needs for informational support and emotional support (Sharma and De Choudhury 2018), *e.g.,* peer support needs were similar in the Coping type of sub-reddit like r/SuicideBereavement and r/GrifSupport. This suggests that our findings might be generalized to other types of similar mental health communities. We focused on studying recovery-type mental health communities and also encourage other researchers to explore the effects of picture and text features on receipt of social support in other types of online mental health communities.

When naming the themes of the text (table:text theme) and image (fig:image theme) in text-image posts, we borrowed some labels (*e.g.,* Captioned Images) from previous research on online mental health communities (OMHCs) (Manikonda and De Choudhury 2017; Guo et al. 2022; Frison and Eggermont 2016) if they can properly describe the categories. For the categories that could not use the labels in previous work, three researchers determined their names after several rounds of discussions and got another researcher to do the validation. The findings on the impact of these themes of a post on its received social support may generalize to other OMHCs whose posts express similar categories.

Limitation and Future work

Our work has several limitations. First, we do not involve the posts with multiple images or without any image in this work to keep our analyses and modeling process focused on the posts with a single image. Our findings, therefore, may not be directly applicable to the posts with multiple images, without an image, or with other types of materials (*e.g.,* videos). Second, when we label and model the received social support in the comments to a post, we could not avoid that multiple comments under a post may have influenced each other. Future work should examine how to model the structure of multiple comments and how this structure affect the amount of received social support of a post. Third, this research is correlational and uses panel data and lagged dependent variables. We can not show that our results reflect causality between the post's features and its received social support. Fourth, the statistical significance in our RQ2 findings can not stand for practical significance. To learn why the features of a text-image post make a difference on its received social support in practice, future work can be a qualitative interview asking members of the grief support communities how they perceive and respond to the posts with different textual, visual, and text-image coherence features. Fifth, in this study, we primarily focus on the influence of post content on the receipt of support, without accounting for other dimensions such as time and popularity. Sixth, our study considers the effect of the characteristics of the content of the posting on the receipt of social support within a fixed period but does not consider dynamic changes in the amount and type of social support over time. We will examine these factors in future research.

Conclusion

In this paper, we computationally model a post's textual (linguistic accommodation, readability, text theme, text sentiment), visual (color, image theme, image sentiment), and text-image coherence (semantic, sentiment) features and its received social support in an online grief support community. We offer new findings on how people use images to express their grief online and how the used images and their relations with the text would affect their received social support. For example, a text-image post is more likely to receive social support when the sentiments of its image and text are congruent or when the sentiments of one modality dominate the other, and conversely, it was less likely to receive social support if the sentiments of the pictures and words were conflicting. A post is also likely to get more social support if its text is describing the visible content or telling a story depicted in the image. Our work contributes to understandings of online multi-modal mental health self-disclosure and could help people in grief disclose themselves online to seek needed social support. We encourage researchers to explore the importance of different self-disclosure modalities in support-seekers' receipt of social support in the future.

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Ethics Checklist

1. For most authors..

(a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes. We take multiple approaches to protect the privacy as described in subsection "Ethics and Researcher Disclosure". We avoid making any assumptions or conclusions that imply disrespect to societies or cultures.

(b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes. For example, our main claims focus on the text-image posts in online grief communities, which accurately reflect the paper's scope.

(c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes. We provide motivation, goal, or references for each used approach.

(d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes. In section "Research Site and Dataset", we clarify the process of filtering appropriate community used for our analyses. We involve two or more human raters and iteratively refine the rating schemes when labeling data (*e.g.,* subsubsection "Text Theme"). Nevertheless, the used data and labels could not avoid artifacts caused by the background of our authors and human raters.

(e) Did you describe the limitations of your work? Yes.

(f) Did you discuss any potential negative societal impacts of your work? Yes. In the last paragraph of "Discussion", we remind that "the feedback system should not force support-seekers to change their post if they do not feel like to since it may silence them".

(g) Did you discuss any potential misuse of your work? Yes. The example is similar to the answer to previous question.

(h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes. Please check the subsection "Ethics and Researcher Disclosure" for example.

(i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes.

2. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...

(a) If your work uses existing assets, did you cite the creators? Yes. We cite them in reference or urls to the official websites.

(b) Did you mention the license of the assets? No. However, we have confirmed that all the assets in our paper can be used for academic purposes.

(c) Did you include any new assets in the supplemental material or as a URL? Yes. In the supporting file, we describe the detailed approaches for measuring linguistic accommodation and readability of the text in text-image posts.

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? Our curated data of the community is accessible via Pushshift API and may not be feasible to obtain consent from every poster.

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes. Please check the fig:image theme for example.