# Modeling and Understanding Visual Attributes of Mental Health Disclosures in Social Media

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## ABSTRACT
Content shared on social media platforms has been identified to be valuable in gaining insights into people's mental health experiences. Although there has been widespread adoption of photo-sharing platforms such as Instagram in recent years, the role of visual imagery as a mechanism of self-disclosure is less understood. We study the nature of visual attributes manifested in images relating to mental health disclosures on Instagram. Employing computer vision techniques on a corpus of thousands of posts, we extract and examine three visual attributes: visual features (e.g., color), themes, and emotions in images. Our findings indicate the use of imagery for unique self-disclosure needs, quantitatively and qualitatively distinct from those shared via the textual modality: expressions of emotional distress, calls for help, and explicit display of vulnerability. We discuss the relationship of our findings to literature in visual sociology, in mental health self-disclosure, and implications for the design of health interventions.

### Author Keywords
social media; mental health; Instagram; visual attributes

### ACM Classification Keywords
H.4 Information Systems Applications: Miscellaneous

## INTRODUCTION
Social media platforms have emerged to be conducive means of social exchange and support seeking around stigmatized concerns like mental health. The benefits of such practices are situated in the literature on self-disclosure—*the "process of making the self known to others"* [11]. Self-disclosure can be an important therapeutic ingredient and is linked to improved physical and psychological well-being [30]. Moreover, since many social media platforms, like Instagram, Tumblr or Reddit allow anonymous or semi-anonymous discourse, they have come to be adopted widely in helping cope with mental health challenges [13, 4]; conditions known to be associated with high social stigma.

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Self-disclosure can happen via the adoption of many diverse interaction modalities. For instance, expressive writing is identified to play a prominent role in supporting mental health therapeutic processes [43]. In fact, recent research has studied mental health disclosures through the lens of social media [3, 10, 14], and has largely explored the ways in which linguistic attributes, such as affect, cognition, and linguistic style may reveal cues about one's psychological state. We note that other modalities of mental health disclosure, such as visual imagery shared on social media, are under-explored.

The rich literature in visual sociology situates imagery to be a powerful means of enabling emotional expression related to mental illnesses, especially those feelings and experiences that individuals may struggle to express verbally or through written communication [45]. It has been found that the parts of the brain that process visual information are evolutionarily older than the parts that process verbal information [33]. Thus, visual imagery are likely to evoke deeper elements of psychological consciousness than do words or writing. Mental health disclosures based on words alone utilize less of the brain's capacity than do those in which the brain is processing imagery as well as words. Given these considerations, sharing and reflecting on visual narratives are a known psychiatric approach to tackle mental illness [26].

Extracting and characterizing the expressive meanings conveyed in the imagery shared around mental health disclosures on social media can provide rich information grounded in individuals' everyday experiences and interactions. Thus these approaches could raise the quality of language-only studies of mental health disclosures. We leverage the recent uptake of photo sharing practices on different social media platforms, such as Instagram and Tumblr to investigate this research problem [15]. We are observing a shift in online user-generated content from predominantly text-based data to richer forms of image-based media. As Tifentale and Manovich [51] rightly noted, these image sharing practices open up fascinating opportunities for the study of "digital visual culture". Our broad research goal in this paper revolves around investigating *how social media disclosures of mental health challenges could be characterized via shared visual imagery*. Specifically, we address the following three research questions:

**(RQ 1)** What *visual features* characterize images of mental health disclosures shared on social media?

**(RQ 2)** What are the kinds of *visual themes* manifested in these images, and what is the nature of *emotional expression* associated with these visual themes?

**(RQ 3)** How do visual themes of mental health images complement and contrast with themes manifested in the language of these social media posts?

To address these research questions, we leverage a large dataset of over two million public posts associated with ten mental health challenges shared on Instagram. We present some of the first quantitative insights into the nature of visual features, themes and emotion expressed in these images. For the purpose, we employ computer vision techniques of image analysis and unsupervised machine learning methods to identify visual and linguistic themes.

Our findings indicate the prominence of a visual channel supporting candid and disinhibited social exchange around mental health. Specifically, we find that the visual and emotional markers of mental health images capture unique characteristics of self-disclosure, beyond those expressed via the sharing of linguistic content. These include, expressions of distress, personal struggles, explicit graphical content, as well as calls for help, and supportive advice toward improved well-being. We find that many of these markers align with forms of self-disclosure reported in the psychology literature.

We situate our findings in literature on visual sociology and the role of visual narratives in mental well-being. We discuss how our work can inspire further research on visual cues of mental health disclosures on social media. We also present design and ethical considerations toward building human-centered technologies and tools to provide support and scaffolding around this new self-disclosure medium.

## BACKGROUND AND RELATED WORK

### Self-Disclosure and Mental Health

Goffman posited the importance of "sympathetic others" in helping people cope with difficult experiences, as well in enabling self-disclosure [22]. Self-disclosure has been widely investigated both in the psychology and the computer mediated communication (CMC) literature. This body of work has argued self-disclosure to be beneficial: having been linked to trust and group identity, as well as playing an important role in social interactions by reducing uncertainty [2, 11, 30].

In the context of mental health, Ellis [16] reported that discourse on emotionally laden traumatic experiences can be a safe way of confronting mental illness. Jourard [32] also reported that self-disclosure was a basic element in the attainment of improved mental health. This is because, painful events that are not structured into a narrative format, may contribute to the continued experience of negative thoughts and feelings that underlie many mental illnesses. Self-disclosure facilitates a sense of resolution, which results in less rumination and eventually allows disturbing experiences to subside gradually from conscious thought. A seminal work [42] found that participants assigned to a trauma-writing condition showed immune system benefits. Self-disclosure has also been associated with reduced visits to medical centers and psychological benefits in the form of improved affect [48].

Our work builds on these observations and examines the manner in which individuals might be appropriating the photo-sharing capability of social media platforms like Instagram to self-disclose about mental health challenges.

### Visual Methods and Visual Sociology

Visual methods have widely been employed in the study of psychosocial aspects of health and well-being [25, 45]. According to Harrison [26], 'visual methods' describe any research design, which utilizes visual evidence, including the use of photographs, video recordings, drawings, and art. Often, these approaches connect "core definitions of the self" to society, culture and history via the examination of imagery. In fact, Harrison [26] distinguished between the visual as *topic* (i.e. the visual itself as the subject of investigation) and the visual as *resource* (i.e. the visual as a means of accessing data about other topics of investigation).

Visual methods have been found to be very powerful, since certain emotions, thoughts, feelings, experiences, events, and relationships are more easily or variously expressed in a visual, rather than verbal form (see Gillies et al. [21]). They can also act as a tool for an individual's identity and communication [47]. In particular, positive affect manifested in visual imagery can be indicative of an individual's well-being, as well as provide insight into their social, cognitive, and behavioral tendencies and responses [33]. Imagery is also known to help portray stories or narratives relating to the intimate dimensions of the social—family, or one's own body [47].

In our work, we leverage the observation that vulnerable individuals might be taking on to social media platforms to engage in mental health self-disclosure via visual imagery. We aim to examine some of the complexities typically explored through qualitative visual methods, via large-scale characterization of such mental health imagery shared on social media.

### Social Media Imagery Analysis

Users of social media platforms are sharing large volumes of images around their daily lives, personal life events, or opinions, often in the form of personal photographs, selfies, memes, gifs and so on. Recently, a growing body of research has examined and characterized such imagery to identify sentiment and emotion [31], societal happiness [1], geographic landmarks [34], abusive behaviors such as alcohol use [41], public health challenges such as obesity [19], and fitness [52].

Many of these works combine both text and imagery features toward the problem domain under consideration. For instance, Pang et al. [41] mined markers of underage drinking by first inferring age and gender of users from their Instagram profile pictures, and then analyzing the associated hashtags to discover the existence of drinking patterns in terms of time, frequency and location. Similarly, Abdullah et al. [1] developed a measure of population-scale happiness, known as Smile Index, by analyzing the visual cues of Instagram images, and then went on to validate it against text-only measurements as well as self-reported happiness. Another interrelated line of research [6, 39] has also examined visual features present in these images, for instance, color palettes, and their relationship to social engagement. In this paper, we borrow several computational social media image analysis methodologies employed in the above body of research, in order to extract and characterize visual cues relating to mental health disclosures on Instagram.

### Social Media and Mental Well-being

Recently, a growing body of research has focused on understanding how large-scale social media activities can be used to understand, infer, and improve the wellbeing of people, including mental health concerns [12, 13, 27]. A common thread in this research is how computational techniques may be applied to naturalistic data, that people share on today's online social platforms, to make sense of their health behaviors and related experiences.

However, these works have primarily focused on the computational analysis of text and language for the purpose: including psycholinguistic analysis, topic modeling, and supervised and unsupervised language modeling. As noted earlier, many social media platforms today allow sharing of rich media objects, such as images, beyond text. We extend current state-of-the-art by examining the nature of mental health related visual cues manifested in Instagram posts.

Another complementary line of research has also examined how content, primarily text, shared on social media and online communities may enable self-disclosure and help seeking, specifically toward facilitating wellbeing [17, 29, 18]. In this light, approaches to community building have been proposed [53], and the role of participation and self-disclosure in such communities toward promoting health recovery and coping has been examined in domains as cancer, diabetes, and drug abuse [37, 38, 46]. In the mental health domain, Balani and De Choudhury [7] developed a classifier to automatically infer levels of self-disclosures in different mental health forums, whereas in [13], the authors found that self-disclosure around a stigmatized condition like mental illness tends to be higher in platforms that allow anonymity.

Close to our work are the works of Andalibi et al. ([3, 4]) and Reece et al. ([44]). In the former work, Instagram images shared on #depression were analyzed through qualitative coding and did not study the visual cues of the images. In the latter work, Instagram user profile data collected through responses to a standardized clinical depression survey were utilized to reveal predictive markers of depression. However, these works did not characterize mental health disclosures facilitated uniquely by the visual modality. We employ computational methods to examine themes emerging out of the visual content of images spanning different mental health disorders. Thus our work extends this larger body of work by characterizing a form of online content, visual imagery, hitherto under-investigated in the context of mental health.

## DATA

### Data Collection

We utilized Instagram's official API[1] to obtain the dataset used in this paper. Each post in this dataset is public and contains post-related information, such as, the image, caption, likes, comments, hashtags, filter and geolocation, if tagged.

[1]https://www.instagram.com/developer/

| | | |
|---|---|---|
| anxiety | depression | mentalillness |
| bipolar | bpd | schizo |
| selfharm | paranoia | anorexic |
| depressed | bingeeatingdisorder | thinstagram |
| socialanxiety | unwanted | blades |

Table 1: Sample tags used to obtain our Instagram dataset.

Referring to prior literature [10], we adopted an iterative approach to first identify a set of appropriate, distinguishing hashtags around different prominent mental illnesses prevalent in social media. With the seed tags, we performed an initial data collection of 1.5 million posts shared on Instagram between Dec 2010 and Nov 2015. Then by leveraging an association rule mining approach, we compiled the top $k$ ($k$ = 39, frequency $\geq$ 5000) co-occurring tags in the 1.5M posts, and then appended them to the original seed tag list for further data collection. Table 1 lists a sample set of tags used to crawl the dataset.

This final list of 45 tags was thereafter passed on to a psychiatry researcher to be categorized into different disorder types. For tags that described experiences or symptoms cross-cutting across different conditions (e.g., "anxiety"), they were counted toward each disorder type. Table 2 gives a list of the ten different disorders identified in our data. We additionally consulted the Diagnostic and Statistical Manual of Mental Health Disorders (DSM-V [5]), that indicates these disorders to be prominent mental health challenges in populations. This categorization of the mental health challenges was conducted to ensure that our data used in the ensuing analysis focused on well-validated and clinically recognized conditions. At the same time, it allowed us to focus on a diverse range of disorders expressed on social media, rather than specific ones studied in prior work [12, 13, 27]; thus enabling us to discover generalized patterns in visual disclosures of mental health challenges in social media. Our final crawl included 2,757,044 posts from 151,638 users spanning these disorders.

| | | |
|---|---|---|
| Anxiety Disorder | Depressive Disorder | PTSD |
| Bipolar Disorder | Panic Disorder | Suicide |
| Eating Disorder | OCD | Schizophrenia |
| Non-suicidal Self-injury | | |

Table 2: Disorder Categorization.

### Data Reliability

Next, we assessed the suitability and reliability of our collected corpus of Instagram posts and users for our later analyses. For the purpose, we extracted $n$-grams ($n$=3) from the profile biographies of users. The top 10 *uni*-, *bi*- and *tri*-grams are shown in Table 3. They show that users are appropriating Instagram to seek and provide social and emotional support around different mental health concerns ("need someone talk", "feel free dm"). There are also explicit mentions of specific psychological challenges around mental health ("depression anxiety", "telling suicidal kids"), including warnings for profile visitors ("trigger warning"), and personal experiences of the condition ("alone alone alone").

We corroborated these observations with a licensed psychiatrist, and concluded that the users in our dataset are engag-

| Trigrams | Bigrams | Unigrams |
|---|---|---|
| need someone talk | days clean | love |
| just another depressed | report just | follow |
| ever need talk | self harm | like |
| depression self harm | secret account | account |
| telling suicidal kids | stay strong | days |
| feel free dm | mental health | need |
| one dat time | depression anxiety | one |
| dm need talk | need talk | years |
| report just unfollow | just block | depression |
| mine unless stated | trigger warning | dm |

Table 3: Top mentioned tri-, bi- and uni-grams of bios extracted from user profiles sharing mental health posts.

ing in genuine mental health disclosures, tend to demonstrate disinhibition towards sharing their mental health experiences, and are appropriating the platform specifically for this purpose via the chosen account.

## METHODS

**Visual Features.** Towards our first research goal RQ 1, to examine the visual features of images relating to mental health disorders, we employ the extraction of color profiles, i.e., *grayscale histograms* [50]. Grayscale histograms provide us intuition about the brightness, saturation, and contrast distribution of images. In these histograms, images with high contrast pixels are binned in bins with lower numbers (near 0), whereas images with brighter pixels are binned in higher number bins (near 255). We utilize the OpenCV library[2] to extract these color histograms of images in our dataset.

We also assess the *visual saliency* of images (using OpenCV) – a distinct subjective perceptual quality that makes some images stand out from their neighbors [24]. A typical image in our dataset is of size 612px × 612px, so by using a saliency metric, we obtain a $612 \times 612$ grid matrix. For each image in these three visual feature categories, we obtain an empirical threshold that ensures $1/3^{rd}$ of the pixels will be greater than this value, when sorted based on their saliency.

**Visual Themes.** Identifying meaningful themes from images is known to be challenging as they contain richer features compared to text [23]. To examine the themes manifested in different mental health images that is posed as RQ 2, we used a 2-step human-machine approach. The first step employed automated computer vision techniques to perform initial clustering. The second step involved human raters to refine and label the automatically generated clusters, wherein they independently reorganized the clusters to obtain coherent descriptor labels. Our human-machine methodology is motivated by two observations: Human coding can help extract semantically meaningful and contextually relevant image themes, but is difficult to scale in the face of datasets as large as ours. Automated clustering techniques can address the issue of scalability, but, on their own, may not provide reliable or meaningful themes. We describe our two step method below:

*Step I.* In the first step, we used OpenCV to extract the Speeded Up Robust Features of the mental health images (SURF: [8]). SURF is a speeded-up local feature detector and descriptor that is good at handling images with rotation and blurring. More elaborately, the method uses a blob detector based on the Hessian matrix to find points of interest. It then develops a unique and robust description of an image feature, e.g., by describing the intensity distribution of the pixels within the neighborhood of the point of interest. It is typically used to locate and recognize objects, people or faces, to make 3D scenes, to track objects and to extract points of interest. Thus, these are likely to be helpful in characterizing the visual attributes of our mental health image data.

The extracted SURF vectors for all images are of 64 dimensions. Following the standard image vector quantization approach (i.e., SURF feature clustering) [8], we obtained the codebook vector for each image[3]. Finally, we used the $k$-means clustering algorithm (with Euclidean distance metric) to obtain 20 clusters, where we determine $k$ in an empirical data driven manner, that improves cluster consistency.

*Step II.* Next, with the help of two researchers familiar with mental health content on social media, the images in the 20 clusters and the affinity of themes were independently examined, so as to refine the clusters, as well as develop semantic descriptors characterizing them. The researchers adopted a semi-open coding approach, borrowing from the literature on mental health self-disclosure [30, 2, 11] and recent work in characterizing mental health images shared on different social media platforms [3, 4]. The annotators first independently coded all of the 20 clusters. Then following mutual discussion and resolution of inconsistencies, they merged the 20 clusters and readjusted them (shifting some images to other appropriate clusters) to eventually identify six major visual themes of mental health images.

**Linguistic Emotions of Visual Themes.** Next, we employ the psycholinguistic lexicon LIWC (http://liwc.wpengine.com/) on the text associated with our mental health images spanning the different visual themes. We use the following five emotional attributes, motivated from prior work on mental health and social media [13, 7] – *anger, anxiety, sadness, positive affect* and *negative affect*, and a measure of attributions to loss of life, indicated by the *death* category.

**Linguistic Themes.** Finally, to complement the visual themes (our research goal RQ 3), we identify themes from the captions and hashtags (textual data) associated with the Instagram images in our dataset. We refer to these latent topics as *linguistic themes*. Existing literature [42] emphasizes the importance of studying language, since it reflects a variety of thoughts, functions as a signal of identity, and emphasizes the social distance. We believe the linguistic themes may therefore help us contrast the visual themes around how individuals engage in mental health disclosure on Instagram.

We used TwitterLDA[4] to extract these linguistic themes. This method was developed for topic modeling of short text cor-

[2]https://opencv-python-tutroals.readthedocs.io/en/latest/

[3]For a given image $I$, it can have 96 SURF features corresponding to the different segments of an image. These features are expressed in terms of the codebook vector (of size $n$) as $I = <C_1 : f_1, C_2 : f_2, C_3 : f_3, dots, C_n : f_n>$ where, $C_1$ is the cluster of all features about specific characteristic of an object in the image.

[4]https://github.com/minghui/Twitter-LDA

| | Anxiety | Bipolar | Depression | ED | NSSI | OCD | PD | PTSD | Schizophrenia | Suicide |
|---|---|---|---|---|---|---|---|---|---|---|
| Proportion of High contrast images | 0.101 | 0.113 | 0.12 | 0.08 | 0.122 | 0.073 | 0.104 | 0.092 | 0.106 | 0.116 |
| Proportion of High saturation images | 0.58 | 0.644 | 0.577 | 0.669 | 0.481 | 0.751 | 0.601 | 0.733 | 0.63 | 0.577 |
| Proportion of High brightness images | 0.32 | 0.243 | 0.30 | 0.25 | 0.396 | 0.175 | 0.295 | 0.1743 | 0.263 | 0.306 |

Table 4: Proportion of different mental health category posts belonging to the three color (pixel) distributions. Here ED=Eating Disorder; NSSI=Non-suicidal Self-injury; PD=Panic Disorder. All columns sum to 100%.

pora for mining the latent topics. As typically done in topic modeling, we pre-processed the data by removing a standard list of stop words, words with very high frequency (> 0.25× datasize), and words that occur fewer than five times. Since LDA is an unsupervised learning approach, identifying the correct number of topics is challenging. We used the default hyper-parameter settings and 10 topics, which we determined based on the value of average corpus likelihood over ten runs.

These 10 topics constituted what is known as lifted forms of linguistic vocabulary [54]. On these extracted linguistic vocabulary, to arrive at interpretative descriptions (we call them linguistic themes), we adopted a similar semi-open coding approach as the visual themes that involved the same two researchers as above. The raters referred to the mental health literature [2, 11, 30], and identified the best possible description that characterized the tokens in the linguistic vocabulary corresponding to each of the 10 linguistic topics.

To characterize and represent each of these visual and the linguistic themes, we propose a measure of visual diversity. This measure estimates how coherent images are with respect to the each other in a theme. To measure the diversity in terms of the latent visual features, images are expressed in terms of their principal components within a theme. In the component space, distance between a pair of images are computed by employing the cosine theta similarity function. To perform these set of operations, we utilize the Python *scikit-learn* library[5].

## RESULTS

### RQ 1: Visual Features

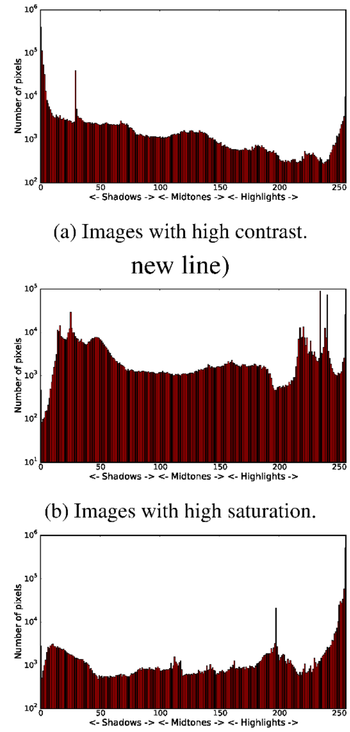
Toward our first research goal, we examine a variety of visual features manifested through the mental health imagery shared on Instagram. First we explore the types of color profiles (grayscale histograms) of the mental health images. In Figure 1 we show histogram plots associated with three categories: images of high contrast, those with high saturation, and those with high brightness.

| | Contrast | Saturation | Brightness |
|---|---|---|---|
| saliency | 45302 (45340) | 59500 (55027) | 41995 (42650) |
| hashtags | 13 (13.4) | 6 (10.2) | 10 (12) |

Table 5: Median (and mean) values of saliency and hashtag counts of images associated with the three color categories.

Next in Table 4 we show the proportion of posts belonging to the three color categories. We observe that a large number of images across the disorders are of high saturation (48-75%), i.e., these images contain different types of colors. However a considerable fraction *does* belong to the extreme ends as well, i.e., the high contrast and high brightness categories (25-52%). Thus, unlike prior findings where 90% of Instagram images were observed to *not* have dominant colors [39], in our case, we observe a contrasting pattern.

We further find that (Table 5) the high saturation mental health images have higher saliency compared to the other categories ($\chi^2(2) = 19.7; p < 10^{-15}$; eta-squared estimate of effect size $E_r^2 = .52$, based on a Kruskal-Wallis test). This implies that these mental health images are likely to trigger greater cognitive and perceptual stimulus to viewers [24]. Further, high contrast and high brightness images tend to have more hashtags attached ($\chi^2(2) = 13.6; p < 10^{-15}; E_r^2 = .35$), indicating that the authors of these posts attempt to engage with the Instagram audience by associating their posts with a wide range of topics and content indicators. We conjecture this might be a way for the authors of these posts to increase their likelihood of discoverability and visibility on Instagram.




(a) Images with high contrast.

new line)

(b) Images with high saturation.

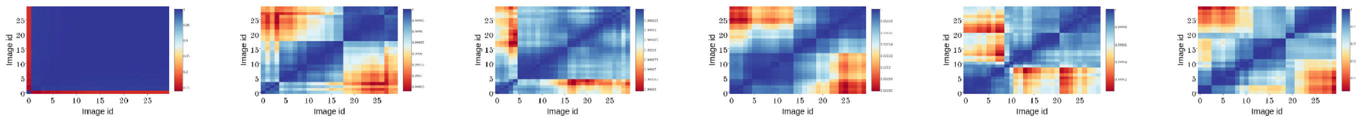
(c) Images with high brightness.

Figure 1: Example images corresponding to the three color categories obtained by extracting grayscale histograms of mental health images.

### RQ 2a: Visual Themes

Next, per RQ2, we examine the types of visual thematic content present in mental health images in our Instagram dataset. Figure 2 gives heat map visualizations of all images that were clustered into six different visual themes; the heatmaps were generated from a dimensionality reduced (via Principal Component Analysis) representation of the images in each visual cluster. Specifically, we considered each heatmap as a symmetric matrix with the row and column corresponding to two images from a given visual theme. The pixel value to a given row and a column represents the visual diversity value between the two images that are marked on the axes. For a given set of images, visual diversity is thus computed for all possible combinations of image pairs in a visual theme. Alongside the heatmaps, we also include the manually curated labels of the themes, and their percentage representation in our Instagram dataset. We find that within the themes themselves, there is

[5]http://scikit-learn.org/stable/



(a) **Captioned Images** (images with embedded text, motivational words and quotes) [52%]

(b) **Selfie Images** (self-portraits; only one human face is present in the image) [17%]

(c) **Social** (users posing with others; at least two human faces are in the image) [11%]

(d) **Food** (images about food, recipes, diet, drinks etc.) [10%]

(e) **Physical Perceptions** (images of explicit body parts in high detail) [5%]

(f) **Graphic Images** (images with explicit, self-destruction or self-harm content) [2%]

Figure 2: Heatmap representations of images in the six visual themes. We use an RGB scale, meaning that red indicates high visual diversity, whereas blue indicates the reverse. Percentage of images belonging to the theme are provided in square brackets.

| Visual Theme | Top Tags |
|---|---|
| Captioned Images | depression, anxiety, depressed, suicide, suicidal, sad, anorexia, selfharmmm, ana, alone, bipolar, worthless, bulimia, broken, anorexic, selfhate, ptsd, pain, schizophrenia, lonely, recovery, killme, sadness, love, death, hurt, help, quotes, suicidalthoughts, emo, depressionquotes |
| Selfie Images | depression, anxiety, depressed, suicide, suicidal, bipolar, anorexia, selfharmmm, ana, bulimia, ocd, schizophrenia, fat, ptsd, mia, ugly, anorexic, grunge, recovery, panicattack, love, blithe, ednos, secret_society123, bulimic, emo, ed, mentalillness, mentalhealth, eatingdisorder |
| Social | depression, anxiety, depressed, suicide, suicidal, anorexia, ocd, panicattack, ana, ptsd, bipolar, bulimia, mia, worthless, recovery, anorexic, emo, love, eatingdisorder, ednos, mentalillness, blithe, schizophrenia, grunge, mentalhealth, depressing, bulimic, skinny, ed, death |
| Food | depression, anxiety, depressed, suicide, sad, bipolar, suicidal, ptsd, ana, ocd, anorexia, schizophrenia, mentalhealth, alone, mia, broken, mentalillness, fat, ugly, bulimia, recovery, panicattack, anorexic, eatingdisorder, bulimic, calories, help, emo, sue, fitness |
| Physical Perceptions | depression, depressed, suicide, suicidal, anorexia, anxiety, ana, bulimia, sad, mia, anorexic, fat, bulimic, eatingdisorder, ed, worthless, skinny, ugly, blithe, lonely, broken, purge, mentalillness, ednos, pain, emo, ptsd, hurt, thin, workout |
| Graphic Images | depression, depressed, anxiety, suicide, suicidal, cutting, selfharmmm, blithe, cuts, suicidalthoughts, cut, starve, sad, blood, secret_society123, triggerwarning, f4f, fat, pathetic, empty, blades, numb, depressing, bruise, brain, razors, alternative, boyscanbedepressedtoo, scared, hated |

Table 6: Top 30 tags associated with each of the six visual themes.

low visual diversity, as expected, based on a cosine similarity metric ($CS$) $\geq 0.98$. Among the visual themes, *Social* has lowest ($CS \geq 0.99$) and *Captioned images* has highest ($CS \geq 0.90$) visual diversity with $H = 1254$, $p < 10^{-15}$.

What kind of textual cues characterize these visual clusters? In Table 6 we present the top 30 tags associated with each of these themes. We do not observe as much difference across them. For instance, inspection of the content of these tags across the visual themes reveals that many of these top tags include the tags we used to collect our data around the 10 mental health disorders ("depression", "anxiety", "eating disorder", 'suicide"). Moreover, tags like "pain", "broken", "lonely", "'death" appear consistently across multiple themes, likely because the content associated with the different themes relate to the topic of mental health concerns. Our observations can further be quantified through the high value of the mean Spearman rank correlation ($\rho$=.21 ($\sigma$=.19), $p < .001$; ref. Table 7) between the tags and their frequency ranks in each visual theme.

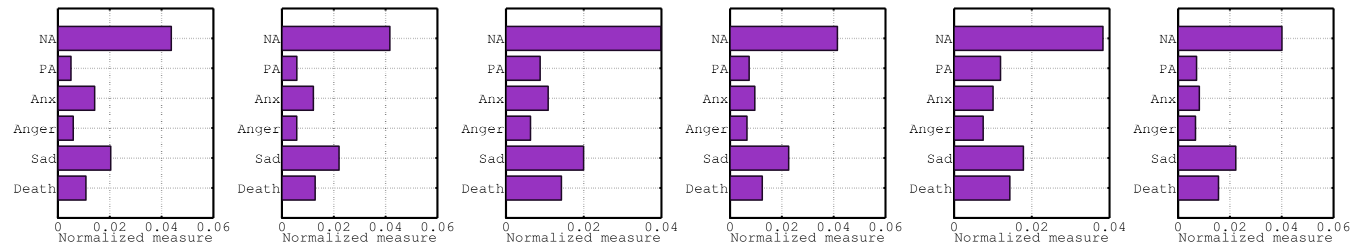
We now present a descriptive analysis of the visual themes:

**Captioned Images.** First, we find that more than half (52%) of the mental health images contain embedded textual data. We conjecture that individuals use this medium as a way to share motivational and encouraging thoughts, quotes and ideas, such as calls for support. One such embedded text image says: *Life is way too short to spend another day at war with yourself.* Additionally, use of tags like "warrior" and "dontgiveup" in images of this theme indicate individuals' desire to express their opinions and thoughts relating to tackling mental health challenges.

Nevertheless, we do also observe people to share confessions in this theme, or as a way to converse with or reach out to an audience: *It is starting to hurt, too much again*; *You killed what was left of the good in me.* The tags associated with this theme include "broken", "lonely", "help". Our inspection of images in this theme reveals high self-focus and self-preoccupation i.e., most of the embedded text are in first person singular pronouns and concern one's personal thoughts and experiences. These observations align with prior work that analyzed social media language relating to mental health [14].

**Selfie Images.** Next, although selfie images are observed to be a visual theme in our study, they span less than a fifth of all types of mental health images (17%). On the contrary, in generic Instagram images, prior work reports selfies to be one of the most notable types [28].

Marwick [40] found that selfies shared by Instagram users show glimpses of their lives to others, connect with audiences, and receive instant feedback. While these motivations are likely still present in the mental health communities on Instagram, the images in this visual theme tend to share considerable negative perspectives or signs of distress: e.g., tags like "ugly", "mentalillness", "anxiety", "fat", "selfharmmm". These tags contrast the typical tags appearing in generic self-




(a) Captioned Images (b) Selfie Images (c) Social (d) Food (e) Physical Perceptions (f) Graphic Images

Figure 3: Distribution of emotions for each of the six visual themes extracted in this study.

| | Captioned | Selfie | Social | Food | Phys Perc | Graphic |
|---|---|---|---|---|---|---|
| Captioned | 1 | 0.189 | 0.272 | 0.107 | 0.282 | 0.217 |
| Selfie | | 1 | 0.674 | 0.091 | 0.260 | 0.247 |
| Social | | | 1 | 0.249 | 0.141 | -0.165 |
| Food | | | | 1 | 0.161 | -0.056 |
| Phys Perc | | | | | 1 | 0.459 |
| Graphic | | | | | | 1 |

Table 7: Spearman rank correlation coefficients $\rho$ comparing the most frequent tags across all pairs of visual themes.

ies [28]. Further, Tifentale and Manovich [51] noted that by sharing their selfies, Instagram users construct their identities and simultaneously express their belongingness to a certain community. Hence, usage of the variety of mental health tags in the images of this theme might be a mechanism for individuals to find communities that relate to similar difficult to disclose experiences, or as a way for them to define their identity around stigmatized conditions.

**Social Images.** The third largest visual theme (11%) in our dataset is found to visualize social settings in people's everyday lives. The post images associated with this theme all tend to have more than one human face present in the same frame. This indicates that some individuals in our data may be choosing to share public information about their social contexts or their association with friends or family. Our conjecture stems from observing tags like "happy", "support" and "people" that appear frequently in images of this theme. It is known that feelings of social isolation and loneliness are predominant in individuals with mental health concerns [48].

**Food.** The fourth visual theme spans 10% of the image posts, and revolves around aesthetic visuals of plated food. While many generic mental health tags tend to be associated with this theme, we observe the presence of distinctive tags relating to dietary practices and physical health ("fat", "fitness", "calories"). Some of the mental health disorders we consider in this paper relate specifically to unusual or dangerous dietary habits, such as eating disorders and anorexia. This may explain the presence of diet or ingestion specific tags. Contrastively, tags like "recoveryfood", "healthyfood", "highprotein", "plantstrong", "foodisfuel" in the images associated with this time may indicate recovery trajectories or intentions to cope with these mental health challenges.

**Physical Perceptions.** Next, the visual theme around "physical perceptions" (5%) includes content that elucidate detailed perspectives about one's own body. Tags in this cluster include "skinny", "ugly", "thin". It is known that mental health conditions like eating disorders and anorexia are associated with manifestation of a desire to be unusually skinny, by adhering to normative perceptions of body image [20]. Thus, certain individuals might be appropriating the visual communication channel of Instagram to craft, reinforce, advocate or share particular body image perceptions. This observation is further supported in the usage of various tags that illustrate injurious attitudes and beliefs about one's body, such as "face", "fatfatfatfat", "notskinnyenough", "fatty", "overweight".

**Graphic Images.** Finally, despite being a smaller share (2%), we observe a noted visual theme of highly graphic images, wherein individuals share images of damaging their own body. Tags like "cut", "blood", "blades", "bruise" uniquely appear in the images associated with this theme. While the specific intent behind the sharing of these images needs further investigation, usage of tags like "pathetic", "empty", "numb", "hated" does indicate the range of self-deprecating thoughts that characterize images in this theme. The visual expressivity of Instagram may be providing individuals with an outlet to showcase and release their emotional pain [35].

### RQ 2b: Emotions Manifested in Visual Themes

Next, we present the expression of emotions in the mental health images spanning the six visual themes. Figure 3 summarizes the distributions of the measures of six emotions across each visual theme described above.

Broadly, the different visual themes express diverse emotions. Expectedly, levels of Negative Affect (NA), Anger, Anxiety, Sadness and Death are relatively higher in all themes, compared to Positive Affect (PA). However, we observe notable differences in how specific emotions are expressed in the different visual themes. We discuss them below:

First, NA is consistently the largest emotion expressed in all the six visual themes ($H(1433663, 6) = 5.7; p < .001$ based on a Kruskal Wallis test). It is highest in the Graphic Images visual theme (+8.7%), followed by Captioned Images (+8.0%). We note similar trends for Sadness; it is higher by +28% in the Captioned Images theme, compared to others. As observed earlier (also see Table 6), the images associated with the Captioned Images tend to act as an outlet of deep-seated feelings and emotional distress—this can explain the high measures of NA and Sadness in it.

Anxiety is the highest in the Social theme (+60%; $H(1433663, 6) = 6.4; p < .001$); its second highest value is observed for the Graphic Images theme (+48%). Since per Table 6, many of the tags associated with Graphic Images relate to self-injurious behaviors known to be commonly associated with anxiety challenges [35], we see that manifested via the Anxiety measure.

Next, we find that Anger is highest in the Food and Social themes (+18% and +12% respectively; $H(1433663, 6) = 2.7; p < .01$). Recall that our data consists of images associated with the topics of eating disorders and anorexia; hence the manifested anger in the Food theme may indicate self-conflicting thoughts about diet and food. On the other hand, high Anger in the Social theme may be attributed to limited access to social support; an aspect that characterizes many mental health related content on social media [14].

Somewhat surprisingly, we observe that the Food theme also includes the highest manifestation of PA (+108%; $H(1433663, 6) = 10.5; p < .0001$). This shows that, for some individuals, sharing Food related content may relate to a desire to adopt healthy and functional dietary habits, and positive perspectives towards physical health. Moreover, many individuals in mental health recovery tend to share diet images as a way to identify with this behavior change process (ref. tags in Table 6). This might also be the underlying reason behind high PA. Next, PA is lowest in the Graphic Images (-52%; $H(1433663, 6) = -5.9; p < .001$). Due to the large volume of images in the Graphic Images theme relating to deliberate harm to one's bodies, the emotion expressed in these images tends to be of largely negative tonality (and thus low PA). Finally the theme of Physical Perceptions stands out from the rest of the themes with respect to the expression of Death related emotions (+50%; $H(1433663, 6) = 6.2; p < .001$).

### RQ 3: Linguistic Themes

As a final analysis (per RQ 3), we present and contrast the observations gleaned from the visual themes and their emotions, with linguistic themes obtained from the same set of mental health images. The extracted 10 linguistic themes and their associated vocabulary is presented in Table 8.

All of the linguistic themes are highly semantically coherent within themselves, as noted from the themes' annotations in Table 8. Further, none of the linguistic themes overlap conceptually with any of the visual themes, as noted in the human annotations. In fact, mean Spearman rank correlation between the top 100 tags of each linguistic and visual theme is only .14 ($p < .01$), indicating that the sets of themes provide complementary perspective in understanding the different mental health disclosures of individuals on Instagram.

Going deeper into specific linguistic themes, we notice two themes (7 and 8) specifically expressing positive and negative emotion respectively. Example tags for the two themes include "sadness", "emo", "emogirl" and "good", "happy", "fun", "beautiful" respectively. Expectedly, two themes (2 and 5) relate to specific mental health challenges, ranging from anorexia and self-harm (tags like "blithe", "selfhate", "anorexia") to expressions of suicidality ("cutting", "worthless", "killme"). (Table 7).

At the same time, we find the presence of a few linguistic themes that do not particularly relate to mental health issues. For instance, theme 6 spans content shared with the typical

| Topic | Top Words |
|---|---|
| 1 | [non-English posts] con, amo, por, para, feliz, dia, pra, mais, meu, minha, mi, na, nao, los, amor, vida, em, como, narcissist, mas |
| 2 | [anorexia and body image] suicide, anorexia, ana, bulimia, mia, anxiety, anorexic, sad, fat, blithe, worthless, selfhate, sue, ugly, ednos, scars, skinny, ed, secret_society123 |
| 3 | [fitness and workout] mentalhealth, ptsd, health, fitness, motivation, thinstagram, inspiration, workout, fitspo, veterans, fit, healthy, awareness, gym, support, weightloss |
| 4 | [everyday feelings and updates] feel, people, life, time, day, me, make, today, good, hate, anxiety, make, back, things, it, love, sad, fucking, mentalhealth, im, hope, hard, school |
| 5 | [self-hatred, self-harm and suicidality] sad, cutting, worthless, selfharm, broken, selfhate, lonely, ugly, cut, scars, fat, sadness, scars, pain, killme, death, hurt, dead |
| 6 | [general Instagram audience oriented content] love, instagood, follow, followme, photooftheday, tagsforlikes, beautiful, picoftheday, girl, cute, instadaily, fashion, happy, smile |
| 7 | [negative emotion] grunge, emo, sad, bands, tumblr, scene, ana, selfharm, music, softgrunge, punk, alternative, goth, bmth, sadness, pastel, ptv, pale, piercetheveil, emogirl |
| 8 | [positive emotion] love, happy, day, lol, good, birthday, tbt, time, night, fun, beautiful, family, baby, work, great, cute, snow, morning, selfie, friends, miss, home, made |
| 9 | [art, poetry, memes] art, dankmemes, drawing, memes, anime, fnaf, poetry, emo, bipolar, autism, sketch, filthyfrank, artist, kidzbop, sad, selfharmmm, feminism, love, dank, lol |
| 10 | [mental health recovery] depression, anxiety, recovery, anorexia, bulimia, ednos, eatingdisorder, edrecovery, ed, ana, hope, suicide, staystrong, anorexiarecovery, mia |

Table 8: Linguistic theme distributions generated using the Latent Dirichlet Allocation (LDA). The human annotations of the topics are included inside the square brackets.

Instagram audience [28] (note tags like "instadaily", "smile", "bestoftheday", "instamood", "selfie", "tagsforlikes"). Another example is theme 4 that expresses feelings and thoughts around everyday activities and experiences (example tags include "life", "people", "today", "good", hope", school"). Together, these themes indicate that despite primarily maintaining mental health focused accounts on Instagram (ref. Table 3), certain individuals do involve themselves in generic discourse as well. Again, this is in contrast to the visual themes, where we observed some mental health challenge manifested in every theme.

Finally, we find two linguistic themes that relate specifically to more uplifting content, such as relating to fitness (theme 3) and mental health recovery (theme 10). The former consists of tags like "workout", "healthy", "support", "motivation", "gym", "exercise" and "mentalhealthawareness". This indicates that the posts associated with this theme encourage and promote behaviors around improved physical health, known to bear links to better mental well-being [49]. Theme 10 includes majority of content around recovery from eating disorder behaviors, as observed through tags like "anorexiarecovery", "eatingdisorderrecovery" and "staystrong". By sharing the posts associated with this theme, individuals may be aiming to seek and provide emotional support, or to share their personal stories and experiences. Further inspection reveals that some of the posts associated with these two themes (3 and 10) tend to also be generated by a range of mental health support groups on Instagram. We note that such recovery related information was not discoverable through the visual themes.

## DISCUSSION

### Relationship of Findings to Visual Sociology

Our work indicates the adoption of the visual modality of photo-sharing social media platforms for mental health disclosure. In fact, many of the shared mental health images bear specific visual signatures, such as with high brightness or high contrast pixels. To explain this finding, we draw on Berger [25]: *"black-and-white photography is paradoxically more evocative than colour photography. It stimulates a faster onrush of memories because less has been given, more has been left out"*. Individuals might be choosing these minimalist visual techniques to draw attention to their psychological state. The specific visual signatures may also indicate that the individuals want their emotions and experiences to be *visible* to others [45], beyond linguistic descriptions, although displaying these emotions can make them susceptible to both judgment and encouragement.

Further, through the analysis of visual themes, we found that images with a variety of distinct visual cues serve as a vehicle of expression of distress, helplessness and social isolation to certain individuals. From the theme "Physical Perceptions", we can learn that shared visual imagery on Instagram may be allowing some individuals to seek feedback on atypical perceptions of their own physical image [20]. Further, we observed the use of imagery in sharing graphic content (theme: "Graphic Images"). Research identifies many underlying reasons behind such physically damaging graphic expression, such as normalization of behavior as a way to deal with emotional distress [9].

At the same time, we observed mental health images on Instagram also being mobilized to seek and provide psychosocial support and as "safety valves" [21]. This is observable in the theme Captioned Images, that includes explicit calls for help. Goffman [22] posited the desire of individuals with socially stigmatized experiences to look for "sympathetic others". Adopting the visual modality, individuals may be intending to bond around mental health topics.

One of our less expected findings is that the visual and the linguistic themes were considerably distinct. These differences can be ascribed to the ways that the themes capture not just different forms of mental health disclosures on Instagram. They also capture the disinhibiting nature of people's discourse with their audiences, as well as in expressing aspects of their experiences that may not be easily communicated via either of the modalities. For instance, the presence of the visual themes, Graphic Images and Physical Perceptions indicates that individuals are taking to the photo-sharing affordance of Instagram as a way for emotional release around a distressful experience. As Keltner noted, such tendencies of emotional expression via the visual modality are a known attribute of many mental health sufferers [33].

At the same time, linguistic themes provide us with contextual groupings around the shared visual imagery. We found the presence of a linguistic theme around mental health awareness and recovery, and others around specific positive and negative emotions. Together, the two modalities provide us a comprehensive picture of the characteristics of social media based mental health disclosure practices.

### Implications for HCI and Design

An important goal of this paper has been to open up new discussions in the social media and mental health research communities about the role of image-sharing behaviors on social media in addressing mental health challenges. Can we develop mechanisms that can sense, based on one's shared visual imagery, their vulnerability, and extend timely, tailored and helpful support to those in need? We discuss HCI and design implications relating to intervention tool development, technologies for emotional self-reflection, and capabilities that enable access to social and emotional support, in the light of mental health challenges.

**(Semi)-automated intervention tools**, or automated tools that use domain expert help, can be built leveraging our visual theme extraction method. These tools can trigger a warning, in a privacy-honoring way, to individuals when imagery with visual signatures related to unusual physical and mental vulnerability are shared. This can include imagery relating to the themes "Physical Perceptions" or "Graphic Images", that contained many vulnerable tags ("selfharmmm"), and expressed high negative emotion. Note that the role of visual cues is critical here, since the usage of linguistic cues alone may not reveal the nuances of one's mental health disclosure—the tag "depression" can appear in a variety of posts, ranging from the naïve to those that can describe potentially dangerous behaviors. In fact, combining the characteristics of the visual and linguistic cues, psychologists can assess the gravity or severity of the mental health disclosures made on social media platforms, including understanding their temporal trends in the larger community.

Although Instagram and other social media platforms have put in place some intervention policies to bring help to those users who engage in mental health disclosure, at best, they can be called "blanket" strategies. This is because the interventions are neither tailored to the individual or the context, nor do they leverage nuanced and subtle cues manifested in shared content. For instance, Instagram bans certain mental health tags (e.g., 'suicide', 'thinspiration'), whereas Tumblr issues a public service announcement for all searches on a set of terms (e.g., "depressed", 'proana'). Our methods can help improve such efforts by discovering, analyzing, and characterizing the diverse range of information shared in visual imagery, aside from textual data.

**Technologies for self-reflection.** Leveraging our methods of characterizing visual and linguistic attributes of mental health disclosures, we believe that social media platforms can provide individuals with capabilities for emotional self-reflection. These capabilities can include personal visualizations and displays: individuals can analyze historical trends of the different visual themes manifested through their shared social media content, and associated linguistic constructs. For instance, temporal patterns of themes like "Physical Perceptions", "Graphic Images", or "Selfies" can be shown to end users, alongside the associated tags and the expressed levels of PA, NA, Anger, Anxiety, Sadness and Death, derived via our emotion extraction method. Interpretable summaries of the visual features of shared images can also be included in these self-reflection enabling systems—such as, color or saliency based information that compare one's social media visual signature with typical Instagram content. Those intending to cope with or manage mental health challenges can especially benefit from such self-awareness.

**Capabilities to avail social and emotional support.** Exclusive mechanisms to seek support around mental health issues can also be developed utilizing our visual and linguistic content characterization framework. Individuals who engage in consistent sharing of imagery with negative body image perceptions, graphic images or content associated with extreme negative emotion can be algorithmically recommended to access recovery related content shared on the same platform, that may be residing outside of their "echo chambers". Additionally, pointers to help resources can be incorporated, such as ways to avail online therapy, pop-ups to reach out to a friend, or a self-care expert.

### Ethical Considerations

Due to the sensitivities around the topic of investigation in this paper, there are many important ethical implications to consider. For this work, we used public posts shared on Instagram, and we did not have any interaction with the users. Therefore our work did not qualify for approval from the relevant Institutional Review Board.

Nevertheless, we acknowledge that employing our proposed methods and approaches in the design of the above outlined interventions presents some ethical challenges. How can these automated approaches, that are themselves prone to errors, be made to act fairly, as well as secure one's privacy, their rights on the platforms, and their freedom of speech? Further, how can we address potential risks of these automated approaches misinterpreting and misrepresenting any of the shared visual or linguistic cues? To address these ethical challenges we propose the following guidelines to be incorporated in the design and deployment of the above proposed interventions and tools: a) Seeking voluntary consent from the population being studied and those likely to benefit from the technologies. b) Partnership with a trained domain expert, e.g., a clinical psychologist or a psychiatrist so as to ensure that the tools bear potential to extend help and support to individuals engaging in significant mental health disclosures. c) Including extensive privacy and security protocols to protect the individuals being studied, starting from collection of social media data, to its analysis and modeling, and then during the development of the interventions and tools. And d) Adoption of user centered design approaches in intervention and technology development, to investigate specific needs and constraints of the target users, as well as their acceptability, utility, and interpretability.

### Limitations and Future Work

We acknowledge that there are some limitations to our work, as the analysis and the inferences obtained are purely data-driven and relied on public posts shared on Instagram around mental health challenges. Specifically, to obtain disclosures of mental health issues, we utilized tags attached to posts. We presume self-selection biases in users who make public posts and link them to different mental health hashtags. We caution against applying our methods to arbitrary contexts.

Moreover, although users might be voluntarily relating themselves to one of the mental health disorder categories, it is unclear to what extent this constitutes an online identity construction activity. Importantly, it is challenging to assess the gravity of a given user's health condition using these posts or images alone, or more specifically if they are actually experiencing a clinical mental health concern. On a related note, although the tags we employed for obtaining our mental health data were verified through consultation with a licensed psychiatrist, we do not claim our methods reveal symptoms or diagnostic markers of mental illness in individuals. Therefore the methods we developed in this paper were not evaluated for their effectiveness in discovering mental health concerns, but rather as a principled and quantifiable way to understand the nature of mental health disclosures shared on social media. Putting it together, our findings should not be interpreted to be diagnostic claims about one's mental health. To do so, we advocate for collaboration between clinicians and HCI researchers, along with voluntarily consenting patients. This constitutes one of our future research directions.

Finally, qualitative methods would lend a deeper understanding of the motivations behind appropriating a public social media outlet for vulnerable and sensitive exchange. We also emphasize that the analyzed visual and linguistic patterns on Instagram are not the only patterns that can help study self-disclosure. Indeed, current advancements in machine learning approaches like deep learning [36] have created a new thread of research in image classification, where image classification problems once difficult to solve, can now be solved very efficiently. We believe such methods can be incorporated to study mental health imagery shared on social media.

## CONCLUSION

In this paper, we presented one of the first quantitative analyses of visual imagery shared on the photo-sharing social media Instagram around a variety of mental health challenges. We characterized different forms of self-disclosure as enabled via the visual imagery medium, and contrasted them with that enabled via linguistic expression. We found that individuals were appropriating photo-sharing affordances of Instagram to vent their discontentment around mental health challenges, seek support, and to disclose sensitive and vulnerable information about their emotional distress. We believe our approach and findings can influence the design of new health interventions that leverage the rich information embedded in visual imagery of mental health disclosures.

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