Norms Matter: Contrasting Social Support Around Behavior Change in Online Weight Loss Communities

Stevie Chancellor
Georgia Tech
Atlanta, GA USA
schancellor3@gatech.edu

Andrea Hu
Georgia Tech
Atlanta, GA USA
ahu35@gatech.edu

Munmun De Choudhury
Georgia Tech
Atlanta, GA USA
munmund@gatech.edu

ABSTRACT
Online health communities (OHCs) provide support across conditions; for weight loss, OHCs offer support to foster positive behavior change. However, weight loss behaviors can also be subverted on OHCs to promote disordered eating practices. Using comments as proxies for support, we use computational linguistic methods to juxtapose similarities and differences in two Reddit weight loss communities, r/proED and r/loseit. We employ language modeling and find that word use in both communities is largely similar. Then, by building a word embedding model, specifically a deep neural network on comment words, we contrast the context of word use and find differences that imply different behavior change goals in these OHCs. Finally, these content and context norms predict whether a comment comes from r/proED or r/loseit. We show that *norms matter* in understanding how different OHCs provision support to promote behavior change and discuss the implications for design and moderation of OHCs.

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social media; weight loss; online health communities; social support; behavior change; Reddit

INTRODUCTION
Across health conditions, online support offers advice and personal motivation to promote agency for individuals to manage these challenges [20, 33, 46, 47]. Social support is linked to positive behavior change – support from online health communities (OHCs) encourages behavior tracking and often the achievement of desired well-being goals [32, 63].

One such behavior change is weight loss. Weight loss OHCs provide accountability through weekly weigh-ins, advice on navigating challenging situations, and celebration when hitting a new weight loss low [43]. Clinical research has overwhelmingly shown that OHCs help individuals lose weight with health outcomes comparable to offline groups [42, 64, 80]. On social networking sites, research has examined how different kinds of users engage with others [58] and how support influences future weight loss [24].

Because of the prevalence of obesity and its risks on health outcomes [10], many conceptualize weight loss to be a universally positive health choice. However, weight loss can be used in less positive contexts where individuals appropriate online communities and social media platforms to encourage disordered eating behaviors [15, 73]. These communities outwardly discuss weight loss, but for physically destructive purposes; they share content promoting extreme calorie deficits, abuse of laxatives and prescriptions, and excessive exercise [7]. In fact, prior work on online eating disorder communities has found that content is *not* unanimously supportive for recovery even in recovery communities [14], and in some cases users fight for pro or anti-recovery sentiments [27, 90].

These two forms of online support for weight loss goals – one toward healthy behavior change [43] and the other towards harmful or "subversive behavior change" [15] – have surface similarities but are motivated by radically different intentions manifesting as distinct behaviors. To understand how support in different OHCs encourages behavior change around complex issues like weight loss, we must unravel the underlying intentions and motivations characterizing these communities.

To understand these intentions, we are motivated by a rich body of work in psychology [22], sociology [30], and HCI [50, 78], offering a helpful theoretical lens to study community behaviors and intentions – its set of *norms*. This research situates norms as contextual and embedded in community language [39, 53, 54, 66], both in deciding what behavior is appropriate [30] as well as identifying outsiders to communities [18, 50]. In this paper, we bring methods from the field of computational linguistics to understand norms and language of support in weight loss OHCs to tease apart differences in how they encourage healthy and subversive behavior change.

Our work is a case study juxtaposing norms in two weight loss OHCs: the subreddits r/loseit and r/proED on the social media platform Reddit. r/loseit is a subreddit that promotes "sustainable methods of weight loss" [83]. Conversely, r/proED defines itself as a "support subreddit for those who are suffering with...disordered eating behaviors but are not ready for recovery" [84]. Both subreddits discuss techniques that facilitate weight loss but have different intentions, and therefore different norms driving why participants want to lose weight.

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Using comments on these communities as a proxy for support, we address three research questions in this paper:

RQ1: *What **content** differences in norms characterize social support on r/loseit and r/proED?*

RQ2: *What **context** differences in norms characterize social support in these two communities?*

RQ3: *Can we algorithmically predict support to be healthy or subversive, that is, characteristic of the norms prevalent in r/loseit or r/proED, based on their content, context, or both?*

We develop a novel computational framework to address these RQs and explore differences in linguistic norms. Our framework uses several probabilistic language modeling techniques derived from deep neural networks to understand support. We distinguish between *content*, or the specific linguistic cues in support, from *context*, or the meaning and use of these cues in specific ways. Surprisingly, we find that these two communities show similarity in their linguistic content. However, by exploring the context of these linguistic cues, dramatically different behaviors around the seemingly common goal of weight loss emerge in the two communities. Finally, we show that these content and context norms predict with high accuracy (78%) if a comment is supportive of healthy behavior changes as promoted in r/loseit, or subversive ones as in r/proED.

Our results show that *norms matter* in how different OHCs direct support for health and well-being goals, and also in understanding how support encourages healthy or subversive behavior change. We discuss the implications of our work in informing the design and moderation mechanics of OHCs.

RELATED WORK

Norms and Online Communities

According to Hogg and Reid, norms are "regularities in attitudes and behavior that characterize a social group and differentiate it from other social groups" [44]. Social scientists use various conceptualizations of norms as both implicit or explicitly defined [22], as well as signaling understanding of norms through subtle cues and signs [30, 40, 44]. In online communities, stakeholders constantly negotiate norms; this includes users, moderators, and other interested parties [51].

Research in online communities has explored how norms play out online. Norms promote behaviors that help the community achieve its goals [50], whether that be writing content on Wikipedia [9] or promoting negative health behaviors [11]. Design theories in HCI facilitate norm construction in online platforms [50]. Norms have been analyzed from the perspective of undesirable interactions like trolling [18], aggressive harassment of newbies [74], and handling vandals on Wikipedia [38]. Not all work on online norms is motivated by deviant behavior [8]. For example, norms influence newcomer participation [3, 9, 79]. On Slashdot, for example, Lampe and Resnick examined how distributed moderation systems harnessed community norms to find high-quality content [55].

In particular, we rely on language to measure and understand community norms. Sociolinguist William Labov observed that persistent language "signatures" are linked with accumulation of local accommodation effects in communities [53] reflecting commitment to the community's norms. Other work in sociolinguistics has situated language as a primary mechanism through which a community's norms are established, exchanged, and propagated [39, 53, 66]. In the absence of "assessment signals" in Donath's terms [30], these observations have been validated in the online context as well [25]. For instance, researchers have studied how norms relate to language socialization online [41, 54, 69], language choice and user lifespan [26], and how community feedback influences future posting patterns of members [17].

Although some work has examined norms in OHCs via qualitative methods [2, 73], to our knowledge, no work quantitatively analyzes how norms tie to social support. Our work demonstrates how norms of support relate to healthy and subversive behaviors by studying weight loss OHCs on Reddit.

Behavioral Change and Online Social Support

Kaplan defines social support where "an individual's needs for affection, approval, belonging, and security are met by significant others" [49]. Social support is known to positively influence health [45], and ample research confirms that online communities encourage healthy outcomes for specific illnesses [20, 46, 62]. Communities offer an always-available source of information and advice, discussions of uplifting news, and provide support during times of struggle [46].

Research has explored OHCs and their role in promoting positive behavior change. Using personal and health informatics frameworks, researchers considered how to facilitate social support for positive behavior changes [32, 63] as well as critical ways to evaluate these technology's effectiveness [52]. Newman et al. explored the ways people strategically choose what health information to disclose on online social platforms to achieve behavior goals [65]. Other work on positive behavior change has looked at topics like support and its relationship to language on social networking sites [82], smoking cessation [6, 85], and improving sleep [19]. Related to our work is Chung et al., who interviewed food "journalers" on Instagram to understand their healthy eating habits and receive support to continue better eating behaviors [21].

The majority of quantitative text analyses on behavior change in OHCs examine disease or addiction, and the vast majority focus on support. MacLean et al. map text cues to stages of behavioral change in an online prescription drug addiction recovery forum [57]. There has been a particular focus on breast cancer sites in prior work, some of it combining human-machine hybrids to identify types of support [87], inferring support satisfaction [86], as well as computational content analysis to understand support dynamics [88]. Additionally, Yang et al. used linguistic patterns to understand self-disclosure behaviors when users are seeking support [89]. De Choudhury and De found that users offer many kinds of supportive information to users who disclose mental health challenges [28]. Finally, Park et al. use linguistic analysis to understand whether someone receives support with higher linguistic homophily [71].

We build on prior work and explore weight loss, a behavior that can be used for healthy or subversive intentions. Through our use of community norms to explore these intentions, we provide the first quantitative exploration of this space.

Communities Oriented Around Weight Loss

Finally, in this section we discuss work related to weight loss communities and their presence on social media platforms.

Weight Loss Communities. These communities focus on supporting and promoting weight loss – some encourage specific protocols or methods, like low-carbohydrate diets, while others are more general purpose. In these communities, members share personal stories and weight loss victories and reach out to others for support and advice to help them succeed with losing weight [56]. Research across medical and psychological venues has robustly shown that weight loss communities facilitate weight loss efforts [42, 64, 80] and different patterns of user behaviors on these communities [43, 48, 58].

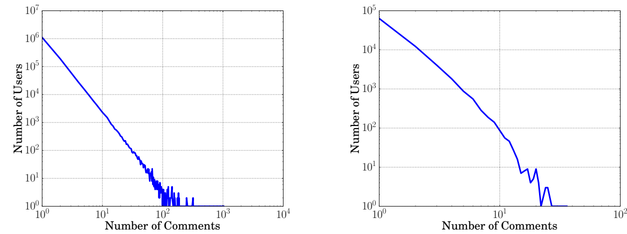
Social media sites and apps have been deliberately developed for and appropriated by weight loss communities to facilitate these behavior change goals. For instance, MyFitnessPal is a hybrid food tracking and weight loss community app and has been examined to understand success rates of users' weight loss [29]. Researchers have also studied the impacts on engagement of cross-posting eating and exercising status from updates on MyFitnessPal to Twitter [72]. Even when used independently, Twitter has been shown to be effective at promoting weight loss [68]. Two recent studies led by Cuhna examined r/loseit, and they showed that social support and feedback directly link to new members returning [23] as well as more self-reported weight loss [24].

Our work also focuses on the weight loss community r/loseit; however, in contrast to prior work, we provide a first study of support norms around behavior change in this community.

Eating Disorder and Pro-ED Communities. Eating disorders are a genre of psychosocial and behavioral disorders characterized by both obsessions with weight and body image as well as abnormal behaviors and preoccupations with eating and exercise [4]. According to DSM-V, symptoms include food restriction, binging, purging, avoiding certain foods, obsession about weight and body image, and other extreme emotional responses to eating, exercise, and body image [4].

Pro-eating disorder, or pro-ED communities, are communities that normalize eating disorders as alternative lifestyle choices [13]. Users share restrictive dieting plans, techniques to conceal their symptoms or behaviors, and exchange "thinspiration" to maintain their disordered behaviors [7, 27, 73]. Research has begun to understand pro-ED communities and the kinds of content they share [73], how they blend into communities at large [13], the conflict between pro-ED and pro-recovery communities [90], users' reactions to banning policies of pro-ED content [15], and community moderation strategies to curb the sharing of pro-ED behaviors [11]. While behavior change in these communities has not been studied directly, Chancellor et al. [14] found these communities to be less encouraging of recovery on Tumblr.

Overall, these insights show that weight loss OHCs may provision support towards practices which serve different behavior change goals, some healthy and others more subversive. Our



(a) Number of comments made by users of r/loseit

(b) Number of comments made by users of r/proED

Figure 1: Descriptive statistics of acquired Reddit data.

	r/loseit	r/proED
Total posts	164,745	8,468
Post authors	60,599	1,423
Total comments	2,301,766	123,407
Comment authors	172,685	4,067
Total users	184,109	4,253
Average comments per user	1.601	1.472
Median comments per user	1.0	1.0
Std. dev. of comments per user	3.174	1.233
Average score per comment	2.944	3.036
Median score per comment	2.0	2.0
Std. dev. of score per comment	10.066	3.346

Table 1: Summary statistics of r/loseit and r/proED data.

work unpacks this by juxtaposing two weight loss communities with similar surface goals, and examining how language around support connects to behavior change goals.

DATA

Overview of Reddit Weight Loss Communities

Reddit is an online content curation and social media site. Posts are organized into communities of interest called *subreddits*, which span a variety of topics ranging from news, politics, hobbies, and health. Users can submit text posts or links to subreddits for discussion through *comments* to the original post that are voted on by the community.

r/loseit. r/loseit [83] is a subreddit focused on facilitating weight loss. Founded in July 2010, the description of the community in the sidebar reads: "A place for people of all sizes to discuss healthy and sustainable methods of weight loss." Community members discuss topics related to weight loss, include weight loss achievements (scale victories), achievements to changes in lifestyle (non-scale victories), struggles with their weight loss, and questions they have. Users can also update "flair" with their starting, current, and goal weights. As of August 2017, r/loseit has over 600,000 subscribers [59].

r/proED. r/proED [84] is "a support subreddit for those who are suffering with an ED or disordered eating behaviors but are not ready for recovery." Members discuss advice for maintaining disordered eating habits, share their daily food diaries and calorie counts, congratulate others for meeting their weight goals, and share "thinspiration" albums with photos of underweight people. Users can also update their flair with their starting, current, and goal weights, and many users choose to include their goal BMIs. As of August 2017, r/proED has over 13,500 subscribers and was founded in May 2015 [59].

r/loseit
You look amazing. Congrats on the hard work and success.
Fantastic progress. I can totally see the difference! Keep it up and please never stop! You are my inspiration.
I had a really similar problem with progress pictures, and it took me until I'd lost 80-100 lbs to really see any difference.
r/proED
How often do you binge? Ive been thinking about doing this.
Yes!!! I don't judge, but I imagine those calories in my system and it freaks me out! Not so much food as I do with liquid calories. Liquid calories actually scare me.
I do this too. I buy a food with really safe numbers and macros, and then I outsmart myself by inhaling the entire thing at once

Table 2: Example (paraphrased and de-identified) comments from r/loseit and r/proED.

Data Collection Strategy

To gather data from r/loseit and r/proED, we queried archived Reddit data through Google's BigQuery in October 2016. BigQuery is a cloud data warehouse where third parties can access publicly available datasets using SQL-like queries.

From r/loseit, we gathered over 2.3 million comments from July 2010 to September 2016, shared on over 164K posts. r/proED had over 123K comments that ranged from May 2015 to September 2016 from nearly 8.5K posts. Summary statistics for this data are given in Table 1. In Figure 1, we show the distribution of comments in r/loseit and r/proED. In Table 2, we present some paraphrased, de-identified examples of comments shared in the two communities.

METHODS

RQ1: Characterizing Content

RQ1 characterizes the content of support (comments) shared in r/loseit and r/proED. In the past, word matching approaches like the psycholinguistic LIWC [76] have been employed to study the language content of OHCs [28, 75]. However, for communities around specialized topics, open vocabulary approaches are preferred because they capture words unique to the communities not included in typical lexical dictionaries [81]. Second, for communities like r/proED, community members often appropriate word or linguistic variations that may not map to standard dictionary words [15]. Our computational linguistic framework uses two approaches described below. To prepare the data for this analysis, we first employ *n*-gram language modeling to tokenize all lowercased comments, followed by stopword and punctuation removal.

TF-IDF Analysis: Rather than use raw counts to identify important linguistic tokens that overly bias for frequently used operational or function words ("the," "is," etc), we use the term frequency-inverse document frequency metric (TF-IDF). TF-IDF is a statistical measure that balances for the appearance of the word in a document to its overall frequency in the entire corpus. The importance of a token increases proportionally as its frequency in a document (comment) increases, but is offset by the frequency of the token in the entire corpus (all comments in a community).

Log Likelihood Ratio (LLR) Analysis: Log likelihood ratios (LLR) takes word analysis a step further and teases out the most distinctive and the most similar words between two corpora. For our comments from r/loseit and r/proED, LLR is calculated as the logarithm of the ratio of the probability of a word's occurrence in r/loseit to the probability it appears in r/proED. LLRs range from -1 to 1. Therefore, large positive values imply that the word is more frequent in r/loseit, whereas negative values show the word appears more frequently in r/proED. A value of 0 shows the word is equally frequent in both sources. We normalize the LLRs by the raw number of words in each dataset to prevent r/loseit's larger comment corpus from skewing our ratios.

RQ2: Characterizing Context

To examine the context of specific linguistic tokens, our computational framework borrows from recent advancements in deep neural probabilistic language modeling [61], specifically through word embedding analysis [60]. Word embeddings capture the idea that "a word is characterized by the company it keeps," popularized by Firth [36]. Based on deep neural network architectures, word embeddings quantify semantic similarities between linguistic tokens from their distributional properties in large corpora of language data [60].

Taking an unsupervised learning approach, word embeddings have seen tremendous success in natural language processing tasks in recent years [77]. Unlike traditional vector space language models, word embeddings go beyond simple linguistic co-occurrence analysis and reveal latent contextual cues of language use not observable directly in the data. They do so by projecting similar words into a continuous vector space of lower dimension. Similar deep learning techniques used on community language [89] and multimodal data [11] are beginning to appear in HCI research, especially in quantitative studies of OHCs. In understanding the norms of r/loseit and r/proED, these latent contextual signals are particularly insightful for our purposes.

We use a popular, well-validated implementation of word embeddings, known as word2vec [60] – we use the skip-gram neural network architecture to best model word associations to nearby words, with a minimum count of 50 for all words to remove most misspellings. Although word2vec provides pre-trained embeddings, we built and trained our embeddings from scratch due to the uniqueness of our comment data.

RQ3: Prediction Task

For RQ3, we investigate the role of content-based features, context-based features, and their combination to distinguish between comments in r/loseit and r/proED. This provides an algorithmic mechanism to predict if a comment suggests support for healthy or subversive behavior change.

We use supervised learning by training regularized logistic regression models. Prior work has shown that these models, due to their high interpretability and ability to handle collinearity and sparsity in data, are well-suited for problems like ours [12]. We fit three models with different predictor variables:

`Content Model`: This model uses the top 1000 linguistic tokens TF-IDF weights as the independent variables.

`Context Model`: This model uses the outcomes of the word embedding analysis performed on the linguistic tokens with the largest TF-IDF weights. They specifically include the 50 most similar words (based on cosine similarity) given by the embeddings corresponding to the 600 largest TF-IDF tokens, taken from both communities, duplicates excluded.

`Content+Context Model`: This final model combines the independent variables of the above two: the top 1000 TF-IDF weights (from the `Content Model`) and the top 50 most similar words corresponding to the 600 tokens with the largest TF-IDF weights (from the `Context Model`).

Our response variable for all models is a binary variable, indicating whether a post belongs to r/proED (0) or r/loseit (1).

In all cases, we balance the class sizes of our r/proED and r/loseit datasets by randomly sampling from r/loseit to match the total number of comments from r/proED. After removing deletions and removals, our class size is 115,921 with 231,842 total examples. We use 80% of the data for training, parameter tuning, and reporting goodness of fit; the remaining 20% were heldout for testing and assessing model performance. Note that, we experimented with adding more TF-IDF unigram features and similar words from the word embedding model, but our models experienced worse performance due to sparsity.

RESULTS

RQ1: Content Analysis

In this section, we analyze the *content* of comments in r/proED and r/loseit using two methods: TF-IDF and LLR analysis.

TF-IDF Analysis

First, we show the top 25 linguistic tokens sorted by their TF-IDF weights from both communities in Table 3. Examining these results, there is very little discernible quantitative or qualitative difference in the most frequent tokens of either community. To begin, across the tokens listed in Table 3 we find 3%-80% (mean: 26.4%) difference in use across the two communities from the TF-IDF weights; this difference is not found to be statistically significant based on a two-tailed Mann Whitney U-test ($U = 311; z = 0.48, p = 0.63$).

Qualitatively, we see the use of similar function words across both communities, such as “like,” “good,” “really,” and “make.” Because functional words indicate linguistic style of text [76], stylistically speaking, support through commentary in the two communities is not noticeably different. We also observe that words related to weight loss are used very similarly in both communities. For instance, we see the appearance of tokens about regulating food intake, like “calories,” “eat,” “eating,” “food,” and “diet” in the comments of both r/loseit and r/proED with nearly the same TF-IDF weights. We also see similar use of the word “weight” as well as “lose,” referring to weight loss, in both communities. Overall, analysis of TF-IDF indicates that support in these two communities use similar words with similar frequencies to discuss weight loss topics despite the communities having different norms and intentions.

Log-Likelihood Ratio (LLR) Analysis

Next, we report the outcomes of our log-likelihood ratio (LLR) analysis. Table 3 shows three categories of tokens and their associated LLR values. Recall that tokens with an LLR closer to 1 are more frequent on r/loseit, an LLR closer to -1 are more frequent on r/proED, and values close to 0 show that the token occurs similarly in both communities. We set a minimum threshold that the token must appear more than 10 times to filter for common misspellings and typos. We do not show LLRs closest to 0 because the results from this analysis align with and repeat our findings from our TF-IDF analysis.

r/loseit		r/proED		r/loseit > r/proED		r/proED > r/loseit	
Token	Weight	Token	Weight	Token	LLR	Token	LLR
weight	0.307	like	0.358	faq	0.927	lw	-0.997
just	0.292	just	0.314	myfitnesspal	0.885	thinspo	-0.995
like	0.241	really	0.186	logging	0.766	bronkaid	-0.990
calories	0.186	feel	0.174	wife	0.753	ugw	-0.990
day	0.178	weight	0.168	victory	0.75	wl	-0.986
eat	0.175	eat	0.163	paleo	0.747	hw	-0.970
good	0.165	day	0.154	journey	0.746	eds	-0.969
really	0.145	think	0.146	guide	0.744	ec	-0.968
time	0.136	know	0.146	lifestyle	0.741	purge	-0.954
eating	0.126	good	0.127	action	0.731	purging	-0.948
food	0.115	calories	0.126	cheat	0.716	expression	-0.946
think	0.112	food	0.125	5k	0.710	ephedrine	-0.937
know	0.112	want	0.122	concerns	0.683	ed	-0.934
going	0.110	eating	0.121	jogging	0.670	stack	-0.906
people	0.109	people	0.121	wiki	0.670	restricting	-0.897
want	0.108	time	0.115	fitness	0.667	binged	-0.846
make	0.106	make	0.097	program	0.647	restrict	-0.840
week	0.102	going	0.090	index	0.643	105	-0.831
work	0.102	look	0.086	machines	0.637	idk	-0.811
feel	0.101	way	0.085	sustainable	0.637	disordered	-0.784
lose	0.100	lot	0.083	wagon	0.635	broth	-0.778
way	0.095	try	0.080	tracking	0.629	binges	-0.767
fat	0.095	love	0.080	discouraged	0.629	underweight	-0.764
great	0.090	fat	0.080	success	0.622	binging	-0.755
diet	0.088	water	0.074	trainer	0.619	anorexia	-0.750
look	0.087	body	0.074	mfp	0.618	gender	-0.747

Table 3: Left two columns: top 25 most frequent linguistic tokens and their weights in descending order from our TF-IDF analysis. Right two columns: top 25 linguistic tokens with the most positive (left column), and most negative (right column) LLR values across the comments in both communities. Tokens are filtered by minimum probability of presence of 10^{-6}.

Tokens with an LLR close to 0 align with our findings from our TF-IDF analysis (not shown in Table 3). However, tokens more frequent in r/loseit (positive LLR) discuss the methods and techniques of weight loss. Users talk about strategies for food tracking (“myfitnesspal,” “logging,” “paleo,” “cheat,” “program”) as well as new fitness and exercise habits they may be adopting or promoting to others (“5k,” “jogging,” “fitness,” “machines,” “trainer”). They also seem to discuss weight loss as a struggle with lifestyle changes (“journey,” “guide,” “discouraged,” “lifestyle,” “action,” “sustainable,” “wagon”) as well as celebrating their own or others’ achievement of desired weight loss targets and goals (“victory,” “success”). Finally, we see more frequent use of meta-moderation comments in this community (“wiki,” “faq”).

Conversely, in r/proED with tokens with negative LLR, we see an emphasis on weight loss goals suggesting extreme or dangerous approaches. This includes the use of appetite suppressants (“ec [short for ephredrine/caffeine],” “ephredrine,” “bronkaid,” “stack,” and “broth [commonly used to suppress appetite during fasting]),” and symptoms of eating disorders (“purge,” “purging,” “binged,” “restrict,” “binging”). r/proED comments are more likely to discuss low body weights and idealized goal weights ("lw (low weight)," "ugw (ultimate goal weight)", "hw (high weight)," "105," and "underweight").

Although many linguistic tokens appear with the same frequency in both communities from the LLR and TF-IDF analysis, the LLR ratios show there are several tokens that are more likely to appear in the support provided in r/loseit or in r/proED. These differences highlight distinctive norms around weight loss embedded in the two communities, prompting deeper exploration into these contextual differences in RQ2.

RQ2: Context Analysis

In this section, we present the results of our word embeddings analysis for r/loseit and r/proED. Recall that we assembled a word embedding for each community from the comments, one for r/proED and one for r/loseit.

Table 3 has the outcomes of this word embedding analysis. In r/loseit, our vocabulary size is 1,348,160 unique tokens and in r/proED, 1,353,241 unique tokens. With this data, we looked up selected tokens that appear in either the TF-IDF top 25 analysis or our LLR analysis closest to 0. For each token, we show the 20 most similar tokens in the embedding, based on cosine similarity. Cosine similarity measures the similarity of the angle between two vectors and ranges from -1 (absolute opposites) to 1 (identical).

These embeddings show distinct differences in the linguistic context of tokens in the comments. To understand these differences further, we present a discussion of selected quotes from comments where the tokens and similar words from the word embedding analysis are both present. To select comments for consideration, we use the following inclusion criteria. First, the quote must contain a token from our top 25 lists for TF-IDF or LLR close to 0. Second, to analyze high-quality quotes the community endorses as good behavior – a signal of the community's norms – the quote must have a score of `median score + stdev`. For r/proED, the comments have a score of +6 or higher, and in r/loseit, +12 (ref Table 1).

We explore two tokens in-depth: *fat* and *diet*. Quotes and scores have been lightly edited to protect privacy. The numbers after the quotes indicates the net votes (upvotes minus downvotes) it received in its community.

Fat. The first token we explore is "fat." Fat appears in both TF-IDF lists as well as having an LLR near 0 (LLR=0.091). Although both communities use this token at similar rates, the contexts are very different between the two communities, signaling the differences in their underlying norms.

Beginning with r/loseit, "fat" is strongly associated with physiological representations or biological processes of body fat. This is reflected in words like "adipose," "visceral," "glycogen," "catabolization," and "subcutaneous."

> You got the stretch marks when you tore your dermis, since your skin couldn't expand quickly enough to accommodate the subcutaneous *fat* you were putting on. (r/loseit, +45)

In this quote, the user is describing what causes stretch marks as a biological response to gaining weight.

Another way that "fat" is used in the comments of r/loseit is discussing "fat" in its relation to bodyweight change, like "mass," "deposits," "percentage," "bodyfat," "muscle," "stored," "lbm (lean body mass)," and "lean." In this context, users of r/loseit look to discuss how their or others' body composition changes, what percentage of body fat they or others have compared to muscle mass, and similar discussions.

> What exercise is really awesome for, is making sure that your weight loss is *fat* loss and not muscle loss. (r/loseit, +15)

In the above quote, "fat" again is being described in a dispassionate way to describe how to prioritize fat loss over muscle loss during weight loss through exercise.

> Go for protein rich foods that will help you maintain muscle mass and signal your body to burn *fat* mass instead. Good luck! (r/loseit, +25)

In r/proED, a distinctive category involves comments about negative physical/visual appearance of fat. Words related to "fat" in r/proED include "squishy," "flab," "curvy," "jiggly," "doughy," and "firmer." In many cases, these tokens are used to self-deprecate and insult their own or others' bodies:

> I looked in the mirror this morning and noticed that my squishy *fat* wings on my back were gone! (r/proED, +8)

This is a subjective judgment about the negative physical appearance of fat going away. Other such comments reflect this negative and visceral disgust at the presence of body fat.

> One day i can be thinspo to all the other short girls out there.... one day... but that day isn't today because i still get stupid rolls of *fat* and flab when i lean over (r/proED, +16)

There are also users who insult the bodies and health of others or glorify thinness as a positive ideal to boost their own disordered eating behaviors. This sometimes appears as "meanspo," or mean inspiration, on r/proED.

> I find *fat*, jiggly bodies to be just...the token symbolism of everything wrong with society. Thinness is a virtue, therefore my ED has a moral piece to it. (r/proED, +11).

In the case of this comment excerpt, fat is paired with "jiggly" in a strongly negative, moralistic way.

> While everybody is complacent with their lard-ass, doughy *fat* bodies, we work hard to be better than that. We shove in their face that CICO is an undeniable fact. (r/proED, +12)

Overall, these differences in "fat" illustrate the divergence in norms around what is encouraged as good behavior on both r/loseit and r/proED.

Diet. We also saw similar occurrence of the token "diet" between the comments of r/loseit and r/proED, per their respective TF-IDF weights in both the communities. However, this implied similarity of usage in content is not supported by the word embeddings.

In r/loseit comments, "diet" refers to two meanings. The first is specific dietary choices or plans. This is captured in words like "vegetarianism," "lowcarb," "keto," "highcarb," "ketogenic," "veganism," "vlc [very low calorie, a medically supervised extremely low calorie diet]," "slowcarb," and "paleo."

> Where I worked about 5 years ago, I started doing a low-carb *diet*. I basically ate grilled chicken and broccoli all day (and lost over 100 lbs). (r/loseit, +39)

The other use of diet in r/loseit is an abstracted notion of diet, closer to an overall theory of nutrition. This is captured in

Word	r/loseit	r/proED
weight	20-30lbs (0.63), poundage (0.62), wt(0.62), 10-20lb (0.60), 1kg/week(0.59), mass (0.58), 2lb/week (0.57), pounds/week(0.57), weightloss(0.57), 115lbs(0.57), 30lb(0.57), 60lb(0.57), 40-50lbs (0.57), 120lbs (0.57), 2lbs/week (0.56), 10lbs (0.56), 10-15lbs (0.56), lbs/week (0.56), 5lbs (0.56), 100lbs (0.56)	50lbs (0.70), 10lb (0.69), 40lbs (0.68), 12lbs, (0.67), steadily (0.67), fluctuation (0.67), 8lbs (0.66), 10lbs (0.66), 70lbs (0.66), 30lbs (0.66), rapidly (0.66), 88lbs (0.64), 5lbs (0.64), reassess (0.64), maintained (0.64), 20lbs (0.64), 95lbs (0.64), 25lbs (0.64), 10kg (0.64), 15lbs, (0.64)
calories	cals (0.89), kcals (0.84), kcal (0.81), cal (0.74), calorie (0.71), 500cals (0.67), calories/day (0.64), 100cals (0.63), 1312 (0.63), grams (0.63), 500kcal (0.63), 200kcal (0.63), 300-500 (0.62), 3400 (0.62), net (0.62), 2000cal (0.62), kj (0.62), carbs (0.62), 400cal (0.62), cal/day (0.62)	cals (0.86), kcals (0.84), totals (0.71), 500cal (0.70), calorie (0.70), cal (0.69), estimated (0.68), grams (0.68),calories/day (0.68), 2400 (0.67), 1900 (0.67), 650 (0.67), kcal/day (0.67), 2k (0.67), 750 (0.66), 2100 (0.66), cals/day (0.66), 7000 (0.66), 300-400 (0.66), guesstimate (0.66)
fat	mass (0.65), adipose (0.64), visceral (0.62), deposits (0.62), percentage (0.61), subcutaneous (0.61), bodyfat (0.61), stored (0.60), muscle (0.58), lbm (0.58), lean (0.57), saturated (0.57), fats (0.56), monounsaturated (0.56), trans (0.56), lard (0.55), tissue (0.55), estrogen (0.54), glycogen (0.54), catabolize (0.54)	squishy (0.64), flab (0.63), adipose (0.62), muscle (0.62), distributed (0.60), deposits (0.60), curvy (0.60), denser (0.59), mass (0.59), recomposition (0.59), saturated (0.58), nourished (0.58), builder (0.58), jiggly(0.58), doughy (0.57), firmer (0.57), implants (0.57), muscley (0.57), visibly (0.57), tissue (0.57)
eat	consume (0.74), ate(0.70), eating (0.68), overeat (0.66), ingest (0.64), graze' (0.63), devour (0.60), eaten (0.60), eats (0.59), snack (0.58), gorge (0.57), crave (0.57), cram (0.56), munch (0.56), indulge (0.55), prelog (0.55), snacked (0.54), overindulge (0.54), restrict (0.53), ration (0.53)	eating (0.71), ate (0.71), consume (0.71), overeat (0.69), graze(0.68), indulge (0.67), nibble (0.66), cram (0.66), gorge (0.65), devour (0.65), restrict (0.65), forgo (0.64), deviate (0.64), hearty (0.64), grazing (0.64), modify (0.63), spoil (0.63), consist (0.63), craved (0.63), compensate (0.62)
eating	consuming (0.69), eat (0.68), overeating (0.66), binging (0.63), intaking (0.61), ingesting (0.60), ate (0.59), snacking (0.59), restricting (0.57), grazing (0.56), eaten (0.55), dieting (0.54), exercising (0.54), undereating (0.54), munching (0.53), drinking (0.52), feeding (0.52), nibbling (0.52), bingeeating (0.51), eater (0.51)	eat (0.71), bingeeating' (.66), overeating (0.65), undereating (0.65), consuming (0.63), limiting (0.62), doubtful (0.62), restricting (0.62), aggressively (0.62), compensating (0.62), binging (0.62), ate (0.61), indulging (0.61), grazing (0.61), bping (0.61), feeding (0.61), 1200-1500 (0.61), sneaking (0.61), binging/purging (0.61), unheard (0.61)
food	foods (0.68), junk (0.64), takeout (0.64), fast (0.60), junk (0.60), homecooked(0.59), highcalorie (0.57), takeaway (0.56), convenience (0.55), takeaways (0.55), dining (0.54), prepackaged(0.54), restaurants (0.54), preprepared (0.54), processed (0.53), meals (0.53), junky (0.53), calorieladen (.53), garbage (0.53), cafeterias(0.53)	junk (0.68), foods (0.65), takeout (0.64), kfc (0.57), takeaway (0.57), buffets (0.57), nutrientdense (0.57), housemates (0.56), mindlessly (0.56), gelato (0.55), temptations (0.55), tossing (0.55), tempt (0.54), rubbish (0.54), compulsions (0.54), dinnertime (0.54), appetizers (0.54), junky (0.54), temptation (0.53), drawer (0.53)
look	looked (0.70), looking (0.69), looks (0.65), lookin (0.59), radiant (0.58), daaaam (0.57), handsome (0.55), marvel (0.55), wowza (0.55), stunning (0.55), yowza (0.54), dayum (0.54), swoon (0.53), gorgeous (0.53), gurl (0.53), unrecognizable (0.53), transformation (0.53), hubba (0.52), photo (0.52), smokin (0.52)	looked (0.73), looks (0.71), looking (0.70), fashionable (0.64), muscly (0.64), accentuate (0.64), frumpy (0.64), uggs (0.64), skeleton (0.63), resemble (0.63), proportione (0.62), boney (0.62), glimpse (0.62), elegant (0.62), tats (0.62), lithe (0.62), minnie (0.62), tattooed (0.62), unfamiliar (0.62), drawings (0.61)
lose	losing (0.72), gain (0.69), maintain (0.65), drop (0.65), shed (0.65), regain (0.64), lost (0.62), relose (.59), loss (0.58), sustainably (0.54), breastfeed (0.53), gaining (0.52), conceive (0.52), regained (0.52), gained (0.51), shedding (0.50), loses (0.50), succeed (0.49, pound/week (0.48), attain (0.48)	gain (0.80), losing (0.78), lost (0.71), gained (0.68), fluctuate (0.66), projection (0.66), loss (0.66), maintain (0.65), regain (0.65), drop (0.64), restrict (0.64), surely (0.63), healthily (0.63), sustain (0.63), predict (0.63), rapidly (0.63), disappear (0.62), succeed (0.62), funnily (0.61), kilos (0.61)
diet	calorierestricted (0.69), regime (0.66), regimen (0.64), diets (0.64), dieting(0.64), dietary (0.63), vegetarianism (0.62), lifestyle (0.62), keto (0.59), lowcarb (.58), fad (0.57), highcarb (0.57), ketogenic(0.57), restriction(0.56), veganism (0.56), vlc (0.56), slowcarb (0.56), intake (0.56), paleo (0.56)	coke (0.79), 7up (0.69), pepsi (0.67), sodas (0.67), dew (0.66), fad (0.66), cola (0.65), soda (0.65), cranberry (0.65), tonic (0.64), dp (0.63), dr (0.62), mt (0.62), zevia (0.62), sport (0.62), ketogenic (0.61), rum (0.61), elimination (0.61), abc (0.61), lacroix (0.60)
know	understand (0.73), think(0.71), idk (0.67), dunno (0.67), realize (0.65), wonder (0.64), realise (0.63), tell (0.63), guess (0.61), mean (0.59), believe (0.59), knowing(0.58), assure (0.58), exactly (0.57), assume(0.57), suppose (0.56), clue (0.56), say (0.56), knows (0.56), explain (0.55)	think (0.78), understand (0.72), mean (0.70), dunno (0.69), realize (0.69), realise (0.68), illogical (0.67), interpret (0.67), dishonest (0.66), agh (0.66), rank (0.66), idiots (0.66), resonate (0.66), approve (0.65), fathom (0.65), untrue (0.65), derail (0.65), guess (0.64), bd (0.64), imply (0.64)

Table 4: Top 20 word embedding tokens most similar to tokens with the 10 largest TF-IDF and LLR values. Numbers in parentheses represent the cosine similarity value between the tokens. Two embedding models were built for r/loseit and r/proED.

related words like "calorie-restricted," "regime," "regimen," "dietary," "lifestyle," "fad," "restriction," and "intake."

> It's a crappy cycle. You are overweight and struggling, and in order to succeed you need to change your life, your lifestyle, your *diet*. Everything! (r/loseit, +15)

In comments on r/proED, however, the token "diet" is used very frequently with low or no-calorie drinks, especially sodas – "coke," "mountain dew," or "doctor pepper":

> Dinner: Strawberries and cream (44), chicken alfredo lean cuisine (250), *diet* coke, tootsie roll (22) =316 (r/proED, +7)

In these two highly upvoted comments, diet soda choices are discussed mostly for the daily food logging threads that happen on r/proED. In these threads, users are encouraged to state a daily calorie goal and report the food they eat. Diet sodas are frequently discussed because of their low-to-no calorie status as well as the appetite suppressing qualities of caffeine.

> Always have a *diet* soda or bottle of water in your hands so your holding something. (r/proED, +17)

Here, the comment author is advising someone to have a drink in hand at social events to appear normal in eating patterns.

In summary, we highlighted the importance of context in interpreting linguistic tokens from r/proED and r/loseit. This analysis illustrates the importance of the distinctive norms in these communities, and how they influence different behaviors and motivations for weight loss, both healthy and subversive.

Model	Deviance	df	χ^2	p-value
`Null`	128560	0		
`Content`	106320	999	22240	$< 10^{-15}$
`Context`	93449	1849	35111	$< 10^{-15}$
`Content + Context`	87309	2849	41251	$< 10^{-15}$

Table 5: Summary of model fits. Comparisons with the `Null model` are statistically significant after Bonferroni correction for multiple testing ($\alpha = \frac{0.05}{3}$).

Actual/Predicted	Class 0	Class 1	Total
`Content Model`			
Class 0	16362	6715	23077
Class 1	8080	15212	23292
Accuracy	68%	68%	68% (mean)
Precision	.68	.68	.68
Recall	.69	.67	.68
F-1	.68	.68	.68
AUC	.681		
`Context Model`			
Actual/Predicted	Class 0	Class 1	Total
Class 0	17030	6065	23007
Class 1	5907	17367	23292
Accuracy	75%	75%	75% (mean)
Precision	.74	.74	.74
Recall	.74	.75	.74
F-1	.74	.74	.74
AUC	.747		
`Content + Context Model`			
Actual/Predicted	Class 0	Class 1	Total
Class 0	17529	5548	23007
Class 1	4968	18324	23292
Accuracy	78%	79%	78% (mean)
Precision	.78	.77	.78
Recall	.76	.79	.77
F-1	.77	.78	.78
AUC	.779		

Table 6: Performance of the classifiers on 20% heldout dataset.

RQ3: Classification Tasks

Finally, for RQ3, we ask if content and context signals, separately or together, can help predict whether a comment is indicative of the normative behavior of r/loseit or r/proED, or in other words, supportive of healthy or subversive behavior change. Recall (ref. Methods) we created three models: the `Content Model` with TF-IDF weights of the comment tokens as independent variables/features, the `Context Model` with token similarities given by the word embeddings models, and the `Content+Context Model` combining both variable/feature sets. We report results on all three classifiers, and provide an extended analysis of our most successful classifier, the `Content + Context Model`.

First, we present the goodness of fit measures of all three models in Table 5. Compared to the `Null` models, all three models provide considerable explanatory power with significant reductions in deviances. Our best fitting model, the `Content + Context Model` fits out data the best. The difference between the `Null` and the deviance of this model approximately follows a X^2 distribution: X^2(2849, N=263K) = 128560 - 87309 = 41251, $p < 10^{-15}$. Expectedly, we find the second best model to be the `Context Model` that gives $\chi^2 = 3.5 \times 10^4$.

Next, we analyze performance of the models on the 20% heldout dataset, beginning with the results of the `Content Model`. The `Content Model`'s confusion matrix and results are given in Table 6. Using the TF-IDF weights as features, this model has an overall accuracy of 69%, and an average precision/recall/F-1 at 69%. The performance of this model is very good, with a 19% improvement over baseline, a chance model where all test data points are labeled with the larger class's label. Next, our results for the `Context Model` are given in Table 6. It outperforms the `Content Model` noticeably. The accuracy of this model is 75%, 6% higher than the `Content Model`. It also gives precision/recall/F-1 values as .74/.74/.74, respectively, which are an improvement over baseline by 25% and over `Content Model` by 6%.

Next, we present an extended analysis of the `Content+Context Model`. This model's confusion matrix and results are given in Table 6. We observe that this final model outperforms both the `Content Model` and `Context Model` substantially and expectedly with a mean accuracy of 78% and precision/recall/F-1 of .78/.77/.78, respectively.

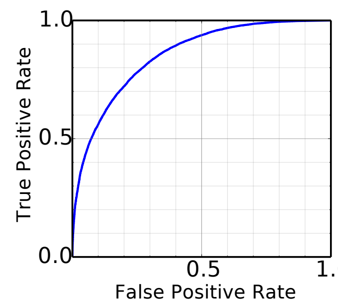


Figure 2: ROC curve for the `Content + Context Model`.

In Figure 2, we report the receiver operating characteristic (ROC) curve of this model that illustrates the false positive and true positive rate at various settings of the model; the area under the curve (AUC) is .779. Overall, this model improves over baseline by 28%.

Feature	β	Feature	β
myfitnesspal	5.01	restricting	-10.86
journey	4.89	thinspo	-9.59
c25k	4.38	purge	-6.30
counting	3.95	bronkaid	-5.37
logging	3.67	laxatives	-5.35
success	3.40	underweight	-5.27
diet	3.36	restriction	-5.01
moderation	3.30	electrolytes	-4.17
wagon	2.92	idk	-4.05
healthier	2.92	free-embeds	-3.84
cardio-embeds	2.63	mean-embeds	-3.81
learning	2.51	broth	-3.47
confidence	2.47	pants-embeds	-3.44
started	2.34	thin	-3.37
self-embeds	2.31	fast	-3.36
12-embeds	2.27	bmi	-3.25
5k	2.19	boyfriend	-3.15
sustainable	2.19	anxious	-2.98
eaten-embeds	2.16	treatment	-2.97
1200-embeds	2.12	gap	-2.97
110-embeds	2.09	cal	-2.93
victory	2.05	recommend-embeds	-2.74
overweight	2.04	world-embeds	-2.63
awesome	2.02	watch-embeds	-2.63

Table 7: Selected features with the largest positive/negative coefficients (β) given by the `Content+Context Model`.

Finally, we present an analysis of 20 of the top 50 independent variables/features with the largest positive and negative coefficients (β weights from the logistic regression `Content+Context Model`) – see Table 7. Here, positive β

values indicate that the presence of the corresponding token in a comment increases its likelihood of belonging to r/loseit (Class 1). Negative β values increase the likelihood that the comment will be from r/proED (Class 0).

The positive variables most predictive of whether a post will promote healthy support, *i.e.* come from r/loseit, overwhelmingly relate to behavior changes associated with long-term weight loss. This includes "myfitnesspal," "counting," "moderation," "c25k [Couch to 5K, a beginner running program]", and "5k." We also see the appearance of the contextual meaning of words like "cardio" being more predictive for healthy lifestyle changes. In contrast, beta values that increase the likelihood of a post containing subversive support, or coming from r/proED, match to behaviors related to disordered eating. We see words related to binging and purging cycles, such as "restricting", "purge," "laxatives," and "electrolytes." We also see a preoccupation with thinness and low bodyweight throughout, in words like "underweight," "bmi," "thin," "thinspo," and "gap [referring to a gap between the thighs]."

DISCUSSION

We provided a computational linguistic approach to examine norms in social support for behavior change in different online health communities (OHCs). To our knowledge, this is one of the first works that uses a quantitative, at-scale approach to unravel how linguistic community norms encourage healthy or subversive behavior change outcomes around weight loss.

Our approach highlights the importance of considering *both* content and context of social support language, and how this reinforces norms about behavior change. We offer a few observations. First, in RQ1, the similarity in content between the comments in r/loseit and r/proED was unanticipated and therefore somewhat surprising. Drawing from prior social computing and health research [15, 73], we know that weight loss and disordered eating behaviors present very differently, both clinically and behaviorally. Yet, the comments on r/loseit and r/proED used very similar linguistic cues while engaging with support seekers. Summarily, linguistic content measures like TF-IDF and LLR by themselves did not capture the differences in norms in support in the two communities well.

However, the deep learning-based word embedding technique in RQ2 allowed us to delve deeper into *how* these linguistic cues were used in context in the comments. We found that the support practices in the two communities, despite similar surface goal of weight loss, actually perpetuated distinct norms and behavior change goals. In fact, content and context features of comments together automatically predicted whether they encouraged healthy or subversive behavior change in RQ3. In essence, our work emphasizes the need to go beyond quantitative approaches that use lexicon matching techniques to decipher community norms, social support, and the role of support in behavior change. Thus, we extend conversations initiated by biomedical and clinical researchers underlining the limitations of off-the-shelf natural language processing tools when applied to online health data [70].

Although surprising to us, our observations are supported by the literature in clinical psychology [5]. For eating disorders, preoccupation with body shape and its visual appearance promote and encourage dietary restrictions [34]. When users of r/proED use "fat" to shame themselves and others with negative language, they reinforce disordered thoughts and behaviors. This is in contrast to successful weight loss behaviors, where r/loseit users make moderate changes to their overall nutrition strategy indicated by "diet" [31]. Examining these highly contextual pieces of information help us understand how OHCs with similar surface goals perpetuate distinctive normative behaviors. In sum, we argue that *norms matter* in understanding how support in different OHCs promotes healthy or subversive behavior change goals.

Implications for Social Computing and Health Research

In the context of weight loss, we find that while the assumptions of healthy support are valid for certain OHCs, like r/loseit — for other communities like r/proED with very similar surface goals, this premise does not hold. By exploring the underlying norms in these communities using our computational linguistic framework, we can understand how the language of support aligns with and promotes both healthy and subversive goals.

This work opens up research directions towards more comprehensive consideration of subversive behavior change in OHCs, which unpack the complexities in how unmet health needs are encouraged and addressed by OHCs, whether for achieving improved health or fulfilling subversive goals. With the proliferation of online and social media platforms for health and well-being [33], these investigations can help craft a typology of OHCs as well contribute to assessments of community "health" or "success" in promoting improved wellness.

Our computational methods can also augment current methods to improve understanding of desirable normative behavior in communities. Examples of existing methods include distributed scoring/voting systems [55]. However, for scoring moderation systems in communities like r/proED, scores may perpetuate norms of subversive behavior change [12, 13], not of "high-quality" or "good" support. While qualitative insights are important to characterize normative support behaviors, scaling these insights to large, dynamic, or growing OHCs may be challenging. Using the methods we propose, health and social computing researchers can both understand community norms and support, but also understand the complex ecosystem of healthy and subversive behavior change.

Design Implications

Our understandings of norms in support on Reddit weight loss communities also offers design implications for tracking and understanding deviant behaviors, community moderation strategies, and supportive content delivery for OHCs.

Tools to Track Social Support Norms in Deviant OHCs. Our computational linguistic methods provide a new suite of tools to community managers to track support behaviors on OHCs. Our techniques can assess which OHCs advocate support toward subversive behavior change, allowing a systematic and tractable way to recognize communities promoting these norms. Advising, banning, and blocking have been adopted to manage deviant behaviors on online communities more broadly with mixed success in curbing deviant behaviors [15, 16]. With our methods in their toolboxes, stakeholders can understand and measure how subversive behavior change responds to these strategies to reduce deviant behavior.

Human-in-the-Loop Distributed Moderation. As noted above, distributed moderation techniques like voting may not adequately address online support that advocates subversive behavior change. We envision our techniques providing behind-the-scenes moderation and triaging of support in OHCs. In weight loss communities that may not advocate dangerous behaviors, disordered eating advice can appear on the site. Moderators are challenged by these behaviors, both because of increased moderator load as well as the difficulty in moderating these behaviors [35]. To identify these comments before they can affect others' behavior or lead to cascading effects, our classifier in RQ3 could be used as a tool by community moderators to detect the subtleties in support around healthy weight loss behaviors versus subversive use of techniques to promote eating disorders.

They use of human versus automated moderation systems presents tradeoffs for social platforms to consider. Not all normative behaviors ought be negotiated exclusively through automated systems like our classifier – the same system that encourages an individual to count calories on r/loseit could be appropriated to encourage disordered calorie manipulation techniques by those suffering from eating disorders on r/proED. Moreover, no classification system will work at 100% accuracy, and there is always the risks for false positives and negatives in an automated moderation system. In spite of the risks of automated moderation systems, human moderation of all content is impractical for many communities who struggle with the volumes of user-generated content. Especially with sensitive or graphic content like disordered eating behaviors in r/proED, moderators may have challenges dealing with that content themselves [2, 11].

We maintain that any automated systems should be tempered by human sensitivity or "human-in-the-loop distributed moderation techniques" of support in OHCs. Prior work has indicated the importance of human curation with automated attempts at managing content shared in online communities [11]; we strongly believe that delivering moderation suggestions should be accompanied with the same sort of care. "One-size-fits-all" approaches to supporting healthy behavior change goals like weight loss across different OHCs are short-sighted — norms are complex and unique to the communities that they belong to. We believe our work will encourage social media researchers, practitioners, designers, domain experts in psychology and behavior change, and other interested parties to deal with these challenging yet critical issues.

Limitations and Future Directions

We note some limitations in our work. Here, we provide a comparative analysis of support in two specific Reddit OHCs. We caution against generalizing our results to other OHCs on other social media sites, and encourage others to use our methods to understand the interplay of norms and support. We also do not measure or account for the evolution of norms on either community, where communities shift support practices to new behaviors over time. Pro-ED communities are transient and clandestine [15], and their temporal comparison can be challenging. Future work can investigate these patterns.

We also acknowledge a positive survivorship bias in our dataset, where we only analyzed comments available when we collected our data. At the time of analysis, we saw about 8-10% of our comment data was removed or deleted; prior work over larger and older datasets shows these removal rates even higher on other social networks [12]. Unfortunately, we do not have access to the content that moderators remove for breaking subreddit rules or those that users remove for personal reasons. We miss the "worst of the worst," or the most non-conforming comments shared in these communities. Relatedly, we considered all comments to be a proxy for positive or subversive support in the communities we study, which is also an established method employed in prior work [37]. We do not disentangle content supportive of healthy behaviors on r/proED and visa versa on r/loseit that are also highly upvoted. On manual inspection, we find that the vast majority of upvoted content align with the stated goals of the community. However, there could alternative ways to assess support in OHCs, such as machine learning techniques to assess levels of emotional or informational support in comments [87] or mixed methods approaches, and future work could examine them in studying community norms.

Amidst the new quantitative methods we develop, we also advocate for partnerships between qualitative and quantitative researchers. Methods such as interviews [48] and inductive analyses of data [1] can be powerful to complement analyses like ours. Domain expertise can also provide necessary background that explains the motivations of support norms.

CONCLUSION

In this paper, we proposed a computational approach to understand norms of social support around behavior change for two weight loss communities, r/loseit and r/proED. We analyzed the comments in the communities using language models, and found that the tokens they use were surprisingly similar. Then, we explored the context of use of these tokens in the comments of the two communities with word embedding models, and observed that the context of word use implied substantially different support practices. Finally, we developed and evaluated logistic regression classifiers to identity the community a comment comes from, thereby distinguishing between healthy and subversive support behaviors. Overall, we found that norms of support in these two communities facilitated healthy as well as subversive behavior change around weight loss. Our work suggests strategies and solutions with our methods and insights toward improving online health communities.

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