It's Not Just About Sad Songs: The Effect of Depression on Posting Lyrics and Quotes

Lucia Lushi Chen, Walid Magdy, Heather Whalley and Maria Klara Wolters

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Lucia Lushi Chen[1], Walid Magdy[1], Heather Whalley[2], and Maria Wolters[1]

[1] School of Informatics, University of Edinburgh, Edinburgh, United Kingdom
[2] Centre for Clinical Brain Sciences, University of Edinburgh, Edinburgh, United Kingdom {lushi.chen, wmagdy, heather.whalley, maria.wolters}@ed.ac.uk

Abstract. When studying how mental illness may be reflected in people's social media use, content not written by the users is often ignored, because it might not reflect their own emotions. In this paper, we examine whether the mood of quotes posted on Facebook is affected by underlying symptoms of depression. We extracted quotes and song lyrics from the feeds of 781 Facebook users from the MyPersonality database who had also completed the the CES-D depression scale . We found that participants with elevated depressive symptoms tend to post more song lyrics, especially lyrics with neutral or mixed sentiment. By analysing the topics of those lyrics, we found they center around overwhelming emotions, self-empowerment and retrospection of romantic relationships. Our findings suggest removing quotes, especially lyrics, might eliminate content that reflects users' mental health conditions.

Keywords: social media · quotes · lyrics · depression

1 Introduction

Social media records provide psychologists with a novel way of examining mental illness symptoms [5, 4]. Existing studies often focus on the emotional content written by the social media users themselves, which we refer to as "self-created Content" (SC)[15]. Non-self created content, such as reposts, music and videos, is seen as reflecting indirect emotions of the user and thus receives less attention in the analysis [18] .

There are two types of non-self created content: *repost* (e.g. shares and retweets), and *copy-and-paste quotes* (e.g. song lyrics, religious verses, and famous quotes). A repost is easy to identify, since it is a functionality on social media platforms to share a post from another user. However, quotes are more complicated to identify, since usually there are no quote marks or references to the source. Furthermore, sometimes quotes and lyrics are posted from memory, which can introduce distortions. There are only a few studies that examine reposts (e.g., [17]), while, to our knowledge, quotes have not been studied yet.

There is extensive work on how affective disorders, especially depression [5, 4, 15, 17], are reflected in social media data. However, existing studies in this line of research focus on self-created content only. To the best of our knowledge, this study is the first that examines whether quotes and lyrics in social media are associated with users' emotional state. This is surprising, because music is associated with mood regulation. [6, 9, 14].

Our research questions are:

1. Is posting lyrics and quotes associated with levels of depression symptoms?
2. What are the themes and emotions conveyed in the lyrics and quotes posted by people with high symptoms of depression, and how might they relate to symptoms?

We analysed a set of 93,378 posts from 781 Facebook users who consented to take part in the myPersonality study [1] and who completed a measure of depressive symptom levels (CES-D) in addition to the personality scales. Potential quotes and song lyrics were detected using an automatic classifer, and logistic regression was used to examine links between the emotions expressed in quotes and lyrics and depressive symptom levels. Topic modelling was used to identify the themes of lyrics that are posted by people with high versus low depressive symptoms.

We found that quotes account for more than 10% of the content in 12.6% of participants [3]. Users with higher depressive symptom levels tend to post more lyrics with neutral sentiment. Our findings suggest that lyrics are used as an agent for users to communicate their emotions indirectly. Therefore, not all the non self-created content should be regarded as noise.

2 Background

Social Media Behavior and Depressive Symptom Level Experiencing negative emotions can increase the amount of social interaction and sharing of emotions, both of which are part of the mood regulation process that leads to mood improvement [7]. Posting patterns on social media and the mood of posts may reflect symptoms of depression [4, 15, 17]. To study the emotions expressed in text, researchers often use sentiment analysis that categorizes affect or opinions expressed in the text. Several studies have shown that users with depressive symptoms use more negative affective words (e.g., sad, cry, hate) in their text than those who do not [5, 17].

Effects of lyrics and quotes on depression A recent study by Chen et al. [3] on a subset of the current data set found a potential association between posting quote on Facebook and users' depressive symptom levels, but they did not examine the sentiment expressed in the quotes. Surprisingly, the link between the content of quotes and symptoms of depression has not been examined in the existing literature, even though music is strongly linked to emotions.

People often choose music that is in congruence with their mood. Listening to songs centered around hurt, pain, and grief is part of the mood regulation

[3] for distribution details, see Figure 1 (Appendix))

process for coping with adverse life events [6]. Retrieving nostalgic memories from music may enhance the mood, especially when these memories are related to meaningful moments in life [13]. Listeners may find some consolation in lyrics when they realize they are not alone in dealing with the painful situations [6, 14]. Quotes, especially song lyrics, may induce congruent emotions [6, 9, 14].

3 Data Collection and Preparation

3.1 myPersonality dataset

We used the myPersonality data set [1]. myPersonality collected Facebook posts from 180,000 participants from 2010 to 2012, with the consent from Facebook users. The data collection process complied with Facebook's terms of service, and we obtained the required permission to use the data. Ethical approval for the secondary data analysis was obtained from the Ethics Committee of the School of Informatics, University of Edinburgh.

781 participants over the age of 18 also completed the Center for Epidemiologic Studies Depression Scale (CES-D). We extracted all posts that these participants posted during the year before completing the CES-D ($N = 93,378$). On average, participants posted 120 posts during this time window. Most participants are young ($M = 26$, $SD = 11.7$) female ($N = 448$, 57%) and White American ($N = 309$, 39%). Detailed demographics are provided in Table 5.

Depressive Symptom Screening Test The 20-item CES-D scale is a widely used tool that measures the presence of depressive symptoms in the general population [12]. It has high internal consistency, test-retest reliability [12, 11], and validity [11]. Scores range between 0 and 60. Following common practice, we adopted 22 as a cutoff point to divide participants in our dataset into high symptom (P_{HS}, $N = 478$) and low symptom groups (P_{LS}, $N = 303$) [5, 17].

3.2 Identifying quotes in user timelines

For each post, we retrieved the first page of search results via the Google search API, which included the link, title, and snippet. Since we observed that quotes often contain misspellings or small variations, we created a rule-based classifier outlined in 1, which assigns each post to one of three classes: 1) Lyric, 2) non-lyric quote (NL-quote), and 3) self-created content (SC).

In order to calculate the cosine similarity between post and snippet, we created document embeddings for each by converting each word to word embedding using the pre-trained word embeddings from Python Package Spacy [8], and summing the word embeddings into a single document embeddings. The first author (LC) annotated a subset of 750 posts for the quote classifier to determine the values of the thresholds in Algorithm 1 $\{X, Y, Z, N, N_l\}$ using grid search, and to test the performance on a separate test set. Of those 750 posts, 523 were used as validation for threshold optimisation and 227 were used for testing. The final

Algorithm 1 Quotes identification algorithm. $\cos(\theta)$ is the max cosine similarity between post and each of the retrieved snippets. C_q and C_l are the counts of search results that contain the word "quote" or "lyric" respectively

$\cos(\theta) = argmax(cosine(post, snippet))$
$C = C_q + C_l$
if ($\cos(\theta) > X$) OR ($X > \cos\theta > Y$ and $C > 0$) OR ($Y > \cos\theta > Z$ and $C > N$) **then**
  label ← Quote
  if ($C_l > N_l$) **then**
    label ← Lyric
  end if
else
  label ← Self-create
end if

Table 1: Result of Quotes and Lyrics Classifier shown in Algorithm 1

	validation			test		
	F1	Recall	Precision	F1	Recall	Precision
NL-quote	87.8	88.3	87.2	89.1	85.3	94.0
Lyrics	76.6	78.0	80.3	79.6	80.0	82.2

values for the threshold are: $X = 0.998$, $Y = 0.975$, Z = 0.85, $N = 3$, and N_l = 2. Table 1 shows the classifier performance on the validation and test sets for detecting quotes and lyrics.

Of the 93,378 Facebook status updates in our data set, 3,722 were p classified as quotes or lyrics. They were posted by 305 (39%) of our 781 participants. 1,488 (40%) of the 3722 posts were song lyrics, posted by 102 (13%) of the participants.

Figure 1 (Appendix) shows the percentage of posts which were quotes or lyrics for those 305 participants. For roughly a third ($N = 99$), 10–40% of their posts were quotes.

4 Quotes/Lyrics and Depressive Symptom Levels

4.1 Frequency and sentiment of quotes and lyrics

When considering all 781 participants, 198 (41%) of the P_{HS} (high symptoms) share quotes compared to 107 (35%) of P_{LS} (low symptoms). (P_{HS}) also share significantly more quotes and lyrics on their timeline ($M = 5.55, SD = 14.07$) than those with low symptoms (P_{LS}, $M = 3.52$, $SD = 9.12$) (t-test, t(2.4) = 778.61, p = 0.015).

The sentiment of quotes was analyzed based on the sentiment scores calculated by SentiStrength, which has been validated and adopted by researchers [16]. Posts that are dominated by a polarised sentiment score were labeled accordingly as Positive or Negative, while posts with no dominant polarised sentiment (neutral or equivalent magnitude of positive and negative words) are labeled as Neutral/Mixed. Table 2 shows the full distribution of sentiment in the quote posts shared by participants for each P_{HS} and P_{LS}.

Table 2: Sentiment distribution in identified quotes for P_{HS} and P_{LS}

	High symptoms (P_{HS})				Low symptoms (P_{LS})			
	total	pos	neg	neut/mix	total	pos	neg	neut/mix
Lyrics	1056	422 (40%)	253 (24%)	381 (36%)	432	172 (40%)	117 (27%)	143 (33%)
NL-Quotes	1597	655 (41%)	399 (25%)	543 (34%)	637	261 (41%)	140 (22%)	236 (37%)
Total	2653	1061 (40%)	663 (25%)	929 (35%)	1069	428 (40%)	256 (24%)	385 (36%)

Notes: NL-quote: non-lyrics quotes

4.2 Sentiment of Quotes

Since P_{HS} are more likely to post quotes than P_{LS}, we now examine the relationship between the sentiment of those quotes and level of depressive symptoms more closely. We use logistic regression, with symptom group (low versus high) as the dependent variable, frequency of lyrics and quotes (expressed as ratios), and sentiment of lyrics and quotes as independent variables.

We derived 13 relevant metrics of lyric and quote sentiment, which are listed in Table 3. Most variables are weakly correlated ($r < 0.25$) with each other, and all the correlations are significant ($p < 0.001$; see also Fig. 1). However, the magnitude of sentiment variables are moderately correlated with ratio of lyrics and quotes ($r > 0.40$).

We constructed two general linear models, one with all 13 metrisc as independent variables (Model 1), and one excluding variables that have high collinearity with others (Model 2).

Model 1 (AIC = 1028) and Model 2 (AIC = 1021) are not significantly different from each other (ANOVA, F(2,6) = -4.86, $p > 0.05$). Both models are shown in Table 3. We see the strongest association between symptom level and the ratio of lyrics to total post count. People with higher symptom levels are more likely to post lyrics, and when they post non-self created content, lyrics are somewhat more likely to be of mixed or neutral content. Non-lyric quotes may also be somewhat more likely to carry a negative sentiment.

4.3 Themes in quotes

We have seen that people with higher levels of depressive symptoms are more likely to post quotes, in particular lyrics. Now, we investigate whether there are differences in content between quotes and lyrics posted by P_{HS} versus P_{LS} We used LDA topic modelling [10, 2] to extract common themes in quotes from both groups, using Verbs, nouns, and adjectives as input. Each input word was tagged with its source (from a post by P_{HS} or P_{LS}). The best performing model yielded 15 topics.

Most of the topics in the lyrics reflect hurt and grief in romantic love. Among the five most prevalent topics in lyrics, nearly all of them mainly comprise of words from P_{HS}. Table 4 (Appendix) shows the 10 most frequent keywords and themes of the seven most prevalent topics. Three of the most common topics of lyrics deal with empowerment, in particular self-empowerment. Topic 0, with

Table 3: Logistic Regression Models. NL-quote: non-lyrics quotes, B: Beta coefficient, SE: standard error of the coefficient, *: $p < 0.05$

	Model 1		Model 2	
Variables	B	SE	B	SE
ratio of positive lyrics to quote	0.52	1.02	0.40	0.79
ratio of negative lyrics to quote	-0.59	0.85	-0.14	0.69
ratio of neutral or mixed lyrics to quote	1.82	0.85*	1.89	0.84*
ratio of lyrics to total post count	-8.75	4.15*	-6.92	3.76*
ratio of positive NL-quote to quote	-0.26	0.61	-0.23	0.40
ratio of negative NL-quote to quote	0.56	0.77	1.15	0.58*
ratio of neutral or mixed NL-quote to quote	-0.22	0.41	-0.10	0.41
averaged sentiment magnitude of positive lyrics	-0.06	0.19		
averaged sentiment magnitude of negative lyrics	-0.18	0.18		
averaged sentiment magnitude of positive NL-quote	-0.02	0.19		
averaged sentiment magnitude of negative NL-quote	-0.17	0.18		
ratio of mixed/neutral posts to total post count	0.95	0.70		
ratio of negative posts to total post count	0.90	0.73		

keywords such as love, want, feel, need, think, is highly emotionally charged, and mainly comprised of words from P_{HS}, while Topic 7 comprises of lyrics that indicate introspection (e.g. feel, know). Topics from non-lyrics quotes are less varied. Most of the non-lyrics posts are dominated by two topics, which centre around life, love, and feelings towards various entities. The dominant words from topic 13 are mainly from high symptom individuals, whereas those in topic 9 are from low symptom individuals.

5 Discussion and Conclusion

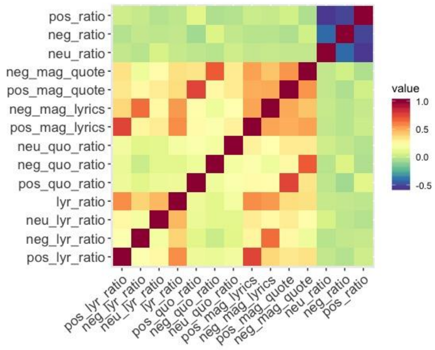
In this study, we showed that people with high levels of depressive symptoms are more likely to post quotes and lyrics on Facebook. However, there is no strong association between negative sentiment of lyrics and quotes and depressive symptom levels. Instead, people with more depressive symptoms are more likely to post lyrics, and the sentiment of those lyrics tends to be mixed or neutral.

Most of the lyrics centered around hurt, pain, and grief in a romantic relationship, which may indicate a mood regulation process [6]. Some of the lyrics reflect introspection and the desire of self-empowerment, which is part of the coping process. Therefore, we argue that lyrics and quotes should not be excluded from studies of the ways in which people with depression use social media—they may hold important clues to coping strategies.

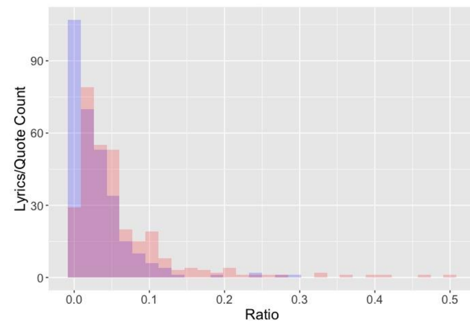
A limitation of our study is that this sample is predominantly White American female and was collected in the early 2010's. Future work should focus on digital footprints in other platforms and seek to replicate these findings on today's Facebook, where usage patterns may have evolved in the past decade.

References

1. Bachrach, Y., Kosinski, M., Graepel, T., Kohli, P., Stillwell, D.: Personality and patterns of facebook usage. In: Proceedings of the 4th annual ACM web science conference. pp. 24–32. ACM (2012)
2. Blei, D.M., Ng, A.Y., Jordan, M.I.: Latent dirichlet allocation. Journal of machine Learning research **3**(Jan), 993–1022 (2003)
3. Chen, L.L., Magdy, W., Wolters, M.K.: The effect of user psychology on the content of social media posts: Originality and transitions matter. Frontiers in Psychology **11**, 526 (2020)
4. Chen, L.L., Magdy, W., Whalley, H., Wolters, M.a.: Examining the role of mood patterns in predicting self-reported depressive symptoms. In: WebSci2020. vol. 2020, pp. 1–8 (2020)
5. De Choudhury, M., Gamon, M., Counts, S., Horvitz, E.: Predicting depression via social media. In: Seventh international AAAI conference on weblogs and social media (2013)
6. Gladding, S.T., Newsome, D., Binkley, E., Henderson, D.A.: The lyrics of hurting and healing: Finding words that are revealing. Journal of Creativity in Mental Health **3**(3), 212–219 (2008)
7. Hill, C.A.: Seeking emotional support: The influence of affiliative need and partner warmth. Journal of Personality and Social Psychology **60**(1), 112 (1991)
8. Honnibal, M., Johnson, M.: An improved non-monotonic transition system for dependency parsing. In: Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. pp. 1373–1378. Association for Computational Linguistics, Lisbon, Portugal (September 2015), https://aclweb.org/anthology/D/D15/D15-1162
9. Hunter, P.G., Schellenberg, E.G., Griffith, A.T.: Misery loves company: Mood-congruent emotional responding to music. Emotion **11**(5), 1068 (2011)
10. Newman, D., Chemudugunta, C., Smyth, P.: Statistical entity-topic models. In: Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining. pp. 680–686 (2006)
11. Orme, J.G., Reis, J., Herz, E.J.: Factorial and discriminant validity of the center for epidemiological studies depression (ces-d) scale. Journal of clinical psychology **42**(1), 28–33 (1986)
12. Radloff, L.S.: The ces-d scale: A self-report depression scale for research in the general population. Applied psychological measurement **1**(3), 385–401 (1977)
13. Routledge, C., Wildschut, T., Sedikides, C., Juhl, J., Arndt, J.: The power of the past: Nostalgia as a meaning-making resource. Memory **20**(5), 452–460 (2012)
14. Sachs, M.E., Damasio, A., Habibi, A.: The pleasures of sad music: a systematic review. Frontiers in human neuroscience **9**, 404 (2015)
15. Seabrook, E.M., Kern, M.L., Fulcher, B.D., Rickard, N.S.: Predicting depression from language-based emotion dynamics: longitudinal analysis of facebook and twitter status updates. Journal of medical Internet research **20**(5), e168 (2018)
16. Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., Kappas, A.: Sentiment strength detection in short informal text. Journal of the American society for information science and technology **61**(12), 2544–2558 (2010)
17. Tsugawa, S., Kikuchi, Y., Kishino, F., Nakajima, K., Itoh, Y., Ohsaki, H.: Recognizing depression from twitter activity. In: Proceedings of the 33rd annual ACM conference on human factors in computing systems. pp. 3187–3196. ACM (2015)
18. Wang, B., Zhuang, J.: Crisis information distribution on twitter: a content analysis of tweets during hurricane sandy. Natural hazards **89**(1), 161–181 (2017)



A. Variable correlations



B. Quotations and Lyrics Ratio

Fig. 1: Variable statistics. graph A: $p < 0.001$ for all correlations, graph B: blue:NL-quotes; red:lyrics; ratio: lyrics or quotation ratio to all post count.

Table 4: Quotes Topics, $_H$, $_L$: high or low symptom users

#	theme	docs	top 10 keywords	example
		Lyrics		
0	overwhelming	245	$love_H$, got_H, $want_H$, $thing_H$, $feel_H$, $need_H$, $make_H$, $come_H$, $think_H$, say_H	example 1: You traded in your wings for everything freedom brings. You never left me.
3	self-empowerment	305	$love_L$, see_L, $know_L$, $make_L$, $feel_L$, let_L, $time_L$, go_L, got_L, $life_L$	example 1: If you're trying to turn me into someone else. Its easy to see I'm not down with that. I'm not nobody's fool.
5	self-empowerment	129	$know_H$, $hold_H$, $wait_H$, $want_H$, $tell_H$, day_H, $love_H$, $heart_H$, $dark_H$, $live_H$	example 1: So, so you think you can tell heaven from Hell blue skies from pain, can you tell a green field
7	introspection	130	$take_H$, say_H, $good_H$, $feel_H$, got_H, $time_H$, $sleep_H$, see_H, $know_H$, $change_H$	example 1: I feel angry. I feel helpless. Want to change the world. I feel violent. I feel alone. Don't try to change my mind
12	self-empowerment	264	go_H, $know_H$, let_H, $love_H$, $time_H$, day_H, $come_H$, $fall_H$, $make_H$, gon_H	example 1: we all got holes to fill, them holes are all that's real some fall on you like a storm, sometimes you dig your own,the choice is yours to make, time is yours to take
		non-lyrics quotes		
13		1432	$love_H$, $life_H$, go_H, $know_H$, day_H, $make_H$, $thing_H$, $time_H$, $feel_H$, $people_H$	example 1: Gratitude unlocks the fullness of life. It turns what we have into enough, and more. example 2: As a girl you see the world as a giant candy store filled with sweet candy and such. But one day you look around and you see a prison and you're on death row.
9		343	$life_L$, $love_L$, $thing_L$, day_L, go_L, $time_L$, $come_L$, see_L, $think_L$, $want_L$	example 1: If you can't make it good, at least make it look good. example 2: Would you dare? Would you dare to believe that you still have a reason to sing? Cause the pain that you've been feeling can't compare to the joy that's coming. So hold on.

Table 5: Demographics

Ethnicity	No.	%
White	511	65.3
Asian	110	14.1
Black	38	4.3
Native American	13	1.6
Middle Eastern	13	1.7
Not Specified	96	12.2
Marital Status	**No.**	**%**
Single	574	73.8
Divorced	28	3.5
Married	27	3.4
Married with Children	38	4
Not specified	36	4.5