UNIVERSITY OF CALIFORNIA,

IRVINE

Exploring the Collective Wisdom of Support Interactions on Mental Health Subreddits

THESIS

submitted in partial satisfaction of the requirements

for the degree of

MASTER OF ARTS

in Social Ecology

by

Benjamin Kaveladze

Thesis Committee:
Associate Professor Stephen Schueller, Chair
Professor Roxane Cohen Silver
Professor Candice Odgers

2021

TABLE OF CONTENTS

LIST OF FIGURES

Acknowledgements

For their guidance and effort on this project, I extend my heartfelt gratitude to George Kaveladze, Elad Yom Tov, Stephen Schueller, Kathie Chang, Betty Feng, Sophia Yung Ma, Candice Odgers, Roxane Cohen Silver, and Irina Addes

I would like to thank the Summer Institute for Computational Social Science for providing funding to crowdsource response ratings.

I would also like to thank the members of r/Anxiety and r/socialanxiety for generously sharing their struggles and insights for the benefit of strangers on the internet.

ABSTRACT OF THE THESIS

Exploring the Collective Wisdom of Support Interactions on Mental Health Subreddits by

Benjamin Kaveladze

Master of Arts in Social Ecology

University of California, Irvine, 2021

Associate Professor Stephen Schueller, Chair

Introduction: Online mental health communities offer people experiencing mental health struggles a valuable source of social support. This project uses computational methods to explore the collective wisdom of thousands of archived support interactions from these spaces. **Methods**: Using a corpus of 12,325 responses to 7,646 questions from the online support forums r/Anxiety and r/socialanxiety and crowdsourced response quality ratings for 790 of the responses, we successfully trained a random forest classifier (AUC= 0.82) to label responses to anxiety-related questions as high- or low-quality. We applied this classifier to the full dataset to conduct several quantitative and exploratory analyses. **Results:** Response length was the strongest predictor of response quality among 31 metadata and linguistic features of responses. Both emotional support ($\rho = 0.47$, $p < 0.001$) and informational support ($\rho = 0.62$, $p < 0.001$) were positively correlated with response quality. Sentiment differed slightly across questions and responses as well as across subreddits. Common bigrams in high-quality responses seemed to be more positive than common bigrams in low-quality responses. **Conclusions:** This work provides insight into the content and form of supportive interactions in online mental health communities, potentially informing how these spaces are designed and moderated. Our findings can also support the development of artificial intelligence question-answering systems for mental health.

Introduction

Mental health struggles are extremely common globally, but many people lack reliable access to professional mental healthcare or sensitive social networks from which they can draw support (Kohn et al., 2004). Online mental health support communities offer accessible opportunities for people to safely exchange advice and validation with others who understand their struggles. These spaces take advantage of anonymity and ease of access to bypass common barriers to receiving mental health support, such as stigma, shyness, and physical isolation (Bargh, 2002). As such, they can be especially crucial resources for young people or members of marginalized groups who might be concerned about facing social retribution for seeking help from their in-person social networks (O'Leary et al., 2017, Rains & Tsetsi, 2017). Despite these benefits, negativity and misinformation are commonly-noted issues on these spaces (Kaveladze & Schueller, 2020).

Subreddits are free, user-led online discussion forums hosted by Reddit.com. There are many subreddits related to mental health, such as r/depression, r/aspergers, and r/OCDmemes, each offering its own subculture and unique forms of support (Sharma & De Choudhury, 2018). While the norm of using Reddit anonymously precludes researchers' ability to obtain representative demographic information on subreddit users, most of the respondents ($n>300$) to our survey of mental health subreddit users stated that they were young (50% under 24), white (79%), female (56%), and American (59%, although respondents came from 44 countries in total); in addition, most rated their mental health as terrible or poor (82%) and had received professional mental healthcare in the past (87%) (Kaveladze & Schueller, 2020).

Mental health subreddit users submit a wide variety of posts, including uplifting messages, venting, and sharing general tips. However, many common interactions across online mental health communities involve a community member posting to ask for help with a personal problem (Kaveladze & Schueller, 2020). After a question is submitted, other members comment on that submission to offer their advice or support, typically within a few minutes to a few days after the initial submission (De Choudhury & De, 2014). We found that over 15,000 such public question-response interactions occur annually on r/Anxiety alone. Because each of these interactions is archived, mental health subreddits provide a corpus of collective wisdom on responding to mental health struggles that is unprecedented in its size and the diversity of its contributors.

Subreddits are particularly amenable to computational analyses because all posts are publicly available (unless deleted by users or moderators) and because the Reddit API and interconnected data download tools like Pushshift enable large scale downloads of post data (Baumgartner et al., 2020). Several studies have used computational approaches to study patterns in support interactions in online mental health communities. The majority of these studies have focused on the features of help-seeking posts on these spaces, as opposed to support-providing responses. De Choudhury and De (2014) described various content and stylistic features of support-seeking posts, providing a broad sense of the informational and social needs that online mental health communities help to fulfil. Also, Sharma and De Choudhury (2018) found that posts in mental health subreddits that displayed “linguistic accommodation,” in that they matched linguistic style of other posts in that community, consistently received responses expressing slightly more emotional support and informational support than those that did not show linguistic accommodation. Further, Gkotsis et al. (2016) identified substantial mean-level differences across mental health subreddits in the sentiment expressed in posts, as measured by the normalized count of positively-valenced (e.g., happy, smile) and negatively-valenced (e.g., angry, cry) words in each post.

Some research has explored the characteristics of helpful and unhelpful responses to posts on online mental health communities. Peng et al. (2021) found that mental health subreddit posters preferred responses to their help-seeking posts that matched the kind of support they requested (informational vs. emotional) to responses that did not match. Also, Kavuluru et al. (2016) developed a computational model to predict responses' helpfulness from a suicide prevention perspective on the r/suicidewatch subreddit. Their model showed promising results, but only included a few predictors from the response text and left out post metadata such as time of posting. Building on this previous research, the present study includes a wider range of linguistic and metadata predictors to build a more comprehensive model of response quality.

In this project, we used computational social science methods to broadly characterize the collective wisdom of support interactions on mental health support forums (Lazer et al., 2009). Specifically, our goals were to describe the topical and linguistic elements of question-response interactions and to compare the features of high- and low-quality responses to mental health questions. Knowledge regarding these questions could inform efforts to make online mental health support forums more helpful for users or to design computational tools to support people experiencing mental health struggles.

Methods

Dataset

We chose to examine the subreddits r/Anxiety and r/socialanxiety because both had been popular for several years (at the time of data collection, we observed that r/Anxiety often had over 1,000 subscribers logged into Reddit at any given time and r/socialanxiety often had over 250) and they were relatively similar in their subject matter. To identify submissions asking questions, we took advantage of the fact that r/Anxiety and r/socialanxiety required posters to tag their submissions with one of several flairs (subreddit-specific descriptive tags) describing their submission. We gathered submissions from r/SocialAnxiety with the "Help" flair and from r/Anxiety with the "Advice needed" flair. We also gathered comments associated with each of those posts. Next, we limited our dataset to comments responding to the submission (rather than those responding to other comments) and to posts (submissions and comments) with fewer than 250 words and more than 5 words (to facilitate rating response quality because excessively short responses may have been too vague to interpret and long responses may have taken too long for human raters to read). With these inclusion criteria, we used Python to query the Pushshift API and the Reddit API, yielding a dataset of 12,325 question-response pairs and their associated metadata posted between July of 2017 and February of 2021 in r/Anxiety or r/socialanxiety.

In addition to question and response text, we obtained post-level metadata on date/time of posting and post score. A post's score is the sum of upvotes [+1] and downvotes [-1] that it receives – users with Reddit accounts can one upvote or downvote to each post. The dataset also contained user-level metadata on user karma (the sum of upvotes minus downvotes received across all of a user's Reddit posts) and account formation date/time. Finally, we created several textual variables for each post, including sentiment, readability, and the proportion of words matching several Linguistic Inquiry and Word Count (LIWC) dictionaries (negative, positive, feeling, anxiety, health, affiliative drive, body, anger, and sadness-related words) (Tausczik &

Pennebaker, 2010). We calculated average sentiment at the post level using the AFINN sentiment measure (Nielsen, 2011), which provides values from -5 (negative sentiment) to 5 (positive sentiment) for emotionally-valenced words.

Data privacy

All post data we analyzed in this work was publicly accessible and thus exempt from IRB review at the University of California, Irvine. However, most subreddit users likely do not expect that their posts will be used for research, making data privacy especially important. To protect user privacy, we refrain from mentioning any potentially identifiable information.

Rating response quality

We selected a random sample of 790 question-response interactions from our dataset and recruited 365 crowdsourced workers from Amazon Mechanical Turk (Turkers) who self-identified as fluent English-speakers to rate responses to 10 randomly-chosen questions. Turkers were presented the question and response and asked to rate how well each response answered the question (not at all well [0] – very well [3]), whether the response provided emotional support (yes/no), and whether the response provided instrumental support (yes/no). For each interaction, Turkers were instructed to imagine that they asked the question and received the response anonymously (Mazuz & Yom-Tov, 2020).

To monitor the quality of the Turker ratings, we dropped rating data from Turkers who did at least one of the following: failed the attention check that was added in place of one of the question-response interactions to check for reading, responded to the question at the end of the task indicating that they just skipped through the task, or gave the same rating to all 10 of the interactions they rated. Based on these exclusion criteria, we dropped ratings from 270/365

Turkers, leaving plausibly legitimate ratings from only 95 Turkers. To supplement the Turker ratings, we trained three research assistants to rate all 790 question-response interactions in the same way that the Turkers did. The research assistants provided reasonably consistent ratings (Krippendorff's alphas: subjective response quality=0.68, emotional support=0.69, informational support=0.75). However, the consistency between research assistants' ratings and Turkers' ratings was lower (Krippendorff's alphas: subjective response quality=0.54, emotional support=0.36, informational support=0.43). We transformed these ratings into a binary response quality variable, defining high-quality responses as those with ratings (averaged across all raters) above the scale midpoints (1.5 for the subjective response quality scale, and 0.5 for the emotional support and informational support scales). Using this binary response quality variable, 399 responses were labeled as high-quality and 391 as low-quality.

Classification model

Using the scikit-learn library (Pedregosa et al., 2011) in Python (Van Rossum & Drake, 2009), we trained a random forest feature-based classification model on the human-rated dataset to identify which lexical and metadata features were most predictive of response quality. We cross-validated the model using 10 training sets, each composed of 90% of the cases in the human-rated dataset.

Results:

All analyses were performed in the R statistical computing language using the "stats" package (R Core Team, 2013). Data manipulation and figure creation used the "Tidyverse" family of packages in R (Wickham, 2019). In analyses, we used ordinary least squares regressions to detect linear relationships, Welch's t-tests to compare group means while accounting for unequal variance across groups, and Spearman's rank-order correlations (ρ) to track associations between non-normally distributed variables.

Emotional support, informational support, and response quality

We explored the associations between subjective response quality (continuous), emotional support, and informational support (each averaged across all raters) among the 790 human-rated responses (Figure 1 shows these variables' distributions). Subjective response quality was more strongly associated with informational support ($\rho = 0.62$, $p < 0.001$) than with emotional support ($\rho = 0.47$, $p < 0.001$), and emotional support and informational support were not correlated ($\rho = -0.01$, $p = 0.71$). When including emotional support and informational support as predictors in a multiple regression model with subjective response quality as the outcome, both emotional support ($b = 1.02$, $t = 22.9$, $p < 0.001$) and informational support ($b = 1.30$, $t = 30.2$, $p < 0.001$) were predictive of subjective response quality ($R^2 = 0.65$, $F(2, 787) = 730.7$). Both emotional support ($b = 0.72$, $t = 16.8$, $p < 0.001$) and informational support ($b = 1.01$, $t = 24.3$, $p < 0.001$) were also predictive of subjective response quality when including the number of syllables (log-adjusted and mean-centered) as a covariate ($b = 1.44$, $t = 16.19$, $p < 0.001$).

Classification model

Our cross-validated response quality classification model achieved an AUC of 0.82 and accuracy of 0.72. We included 31 features in the model, broadly examining question and response length, readability, sentiment, use of various LIWC linguistic dictionaries, score, post timing, and poster karma. Each feature's importance in the model is shown in Figure 2, and a comparison of syllable length across responses rated as high and low quality is shown in Figure 3. We applied this model to classify the 11,535 responses that had not been rated by humans.

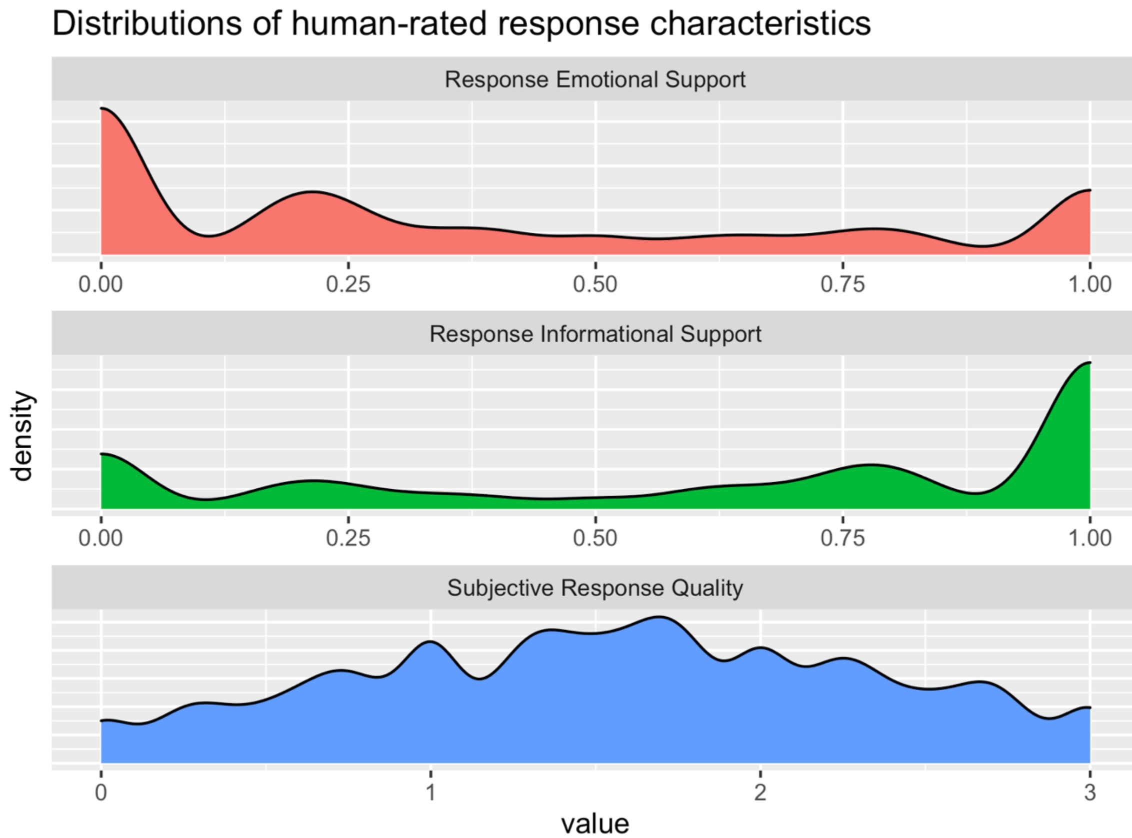

Figure 1: Distributions of the human-rated emotional support (0/1), informational support (0/1), and response quality (0-3) variables for all 790 responses. Each value was averaged across all raters' ratings for that response.

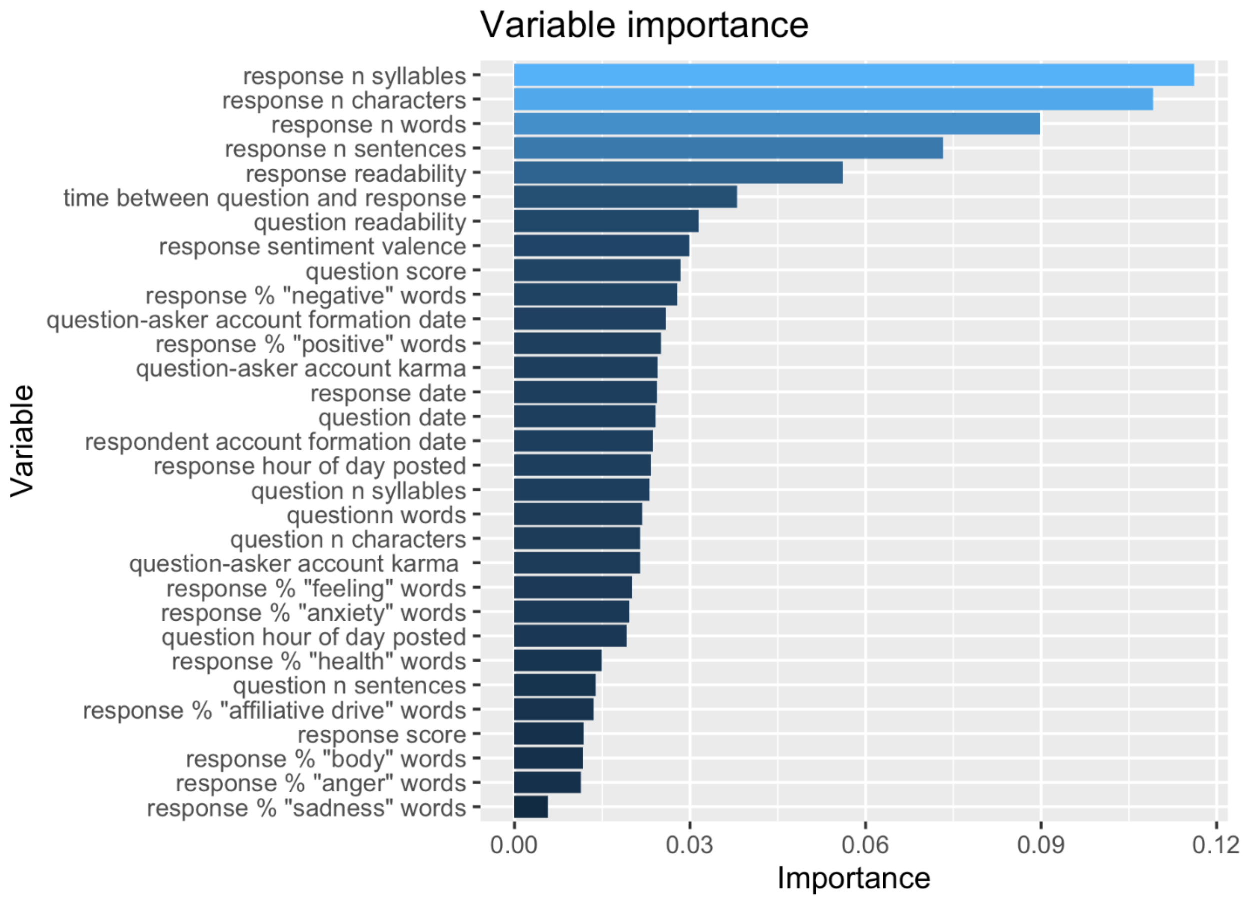

Figure 2: Each feature's importance in the random forest model predicting response quality. Lighter blue signifies higher importance.

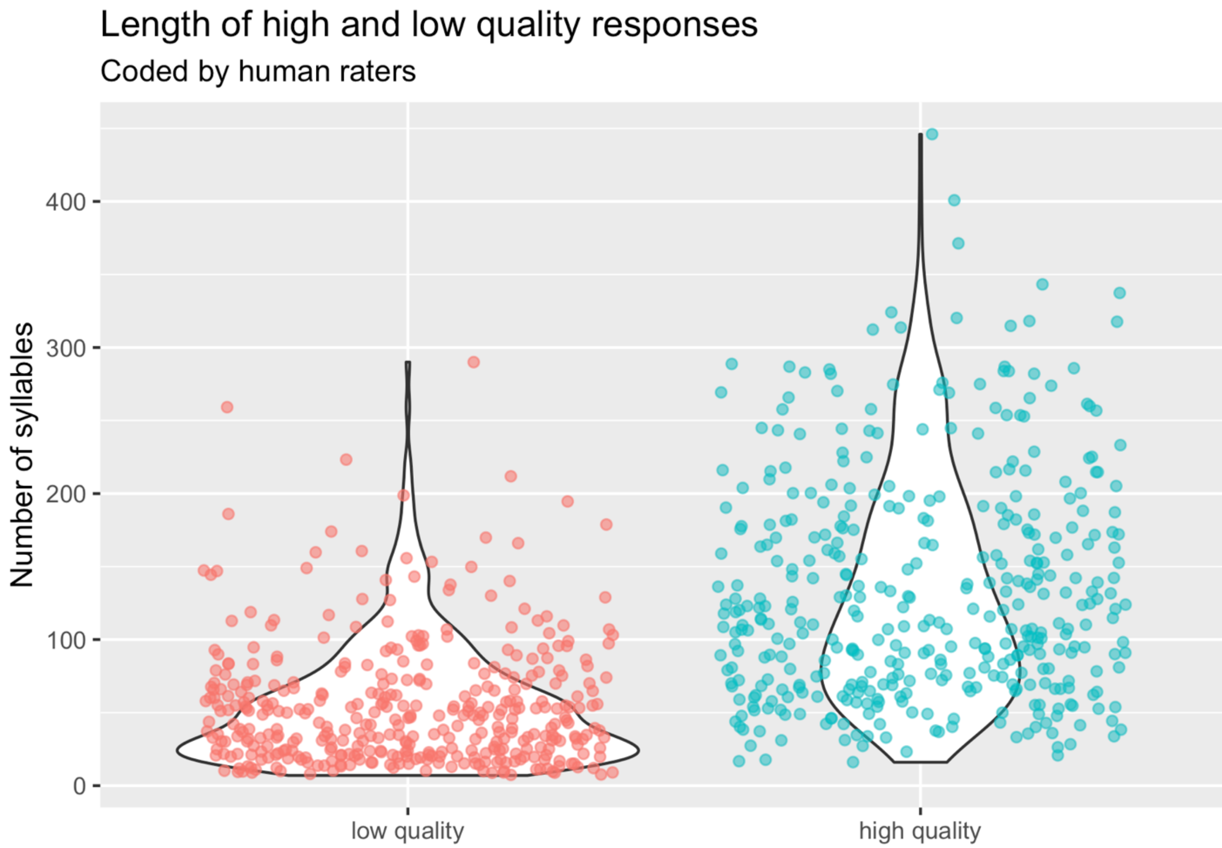

Figure 3: The number of syllables in 790 responses, across human-rated response quality

Sentiment across subreddits and response quality

We compared sentiment across subreddits and across response quality using our full dataset of 12,325 responses to 7,646 questions. The average sentiment of questions asked in r/Anxiety was lower (M=-0.56, SD=0.77, n=5,061) than in r/socialanxiety (M=-0.33, SD=0.87, n=2,585), t(4,669)= 11.31, *p*< 0.001, d= 0.28. However, the average sentiment expressed in responses did not differ between r/Anxiety (M=0.12, SD=1.22, n=8,048) and r/socialanxiety (M= 0.14, SD=1.24, n=4,277), t(8,553)= 0.92, *p*= 0.360, d= 0.02. Across both subreddits, questions (M=-0.48, SD=0.81, n=7,646) expressed, on average, slightly lower sentiment than did responses (M=0.13, SD=1.23, n=12325), t(19,896)=-42.08, *p*< 0.001, d=0.09. These differences in sentiment across subreddits and across questions vs. responses are illustrated in Figure 4. We also compared sentiment across levels of the binary response quality variable among all 12,325 responses, regardless of whether they were labeled by human raters or by the random forest model. We found that high-quality responses ($M= 0.27$, $SD= 0.97$) tended to have higher sentiment than did low-quality responses ($M= -0.05$, $SD= 1.47$); $t(9{,}153)= 14.05$, $p< 0.001$, $d= 0.26$.

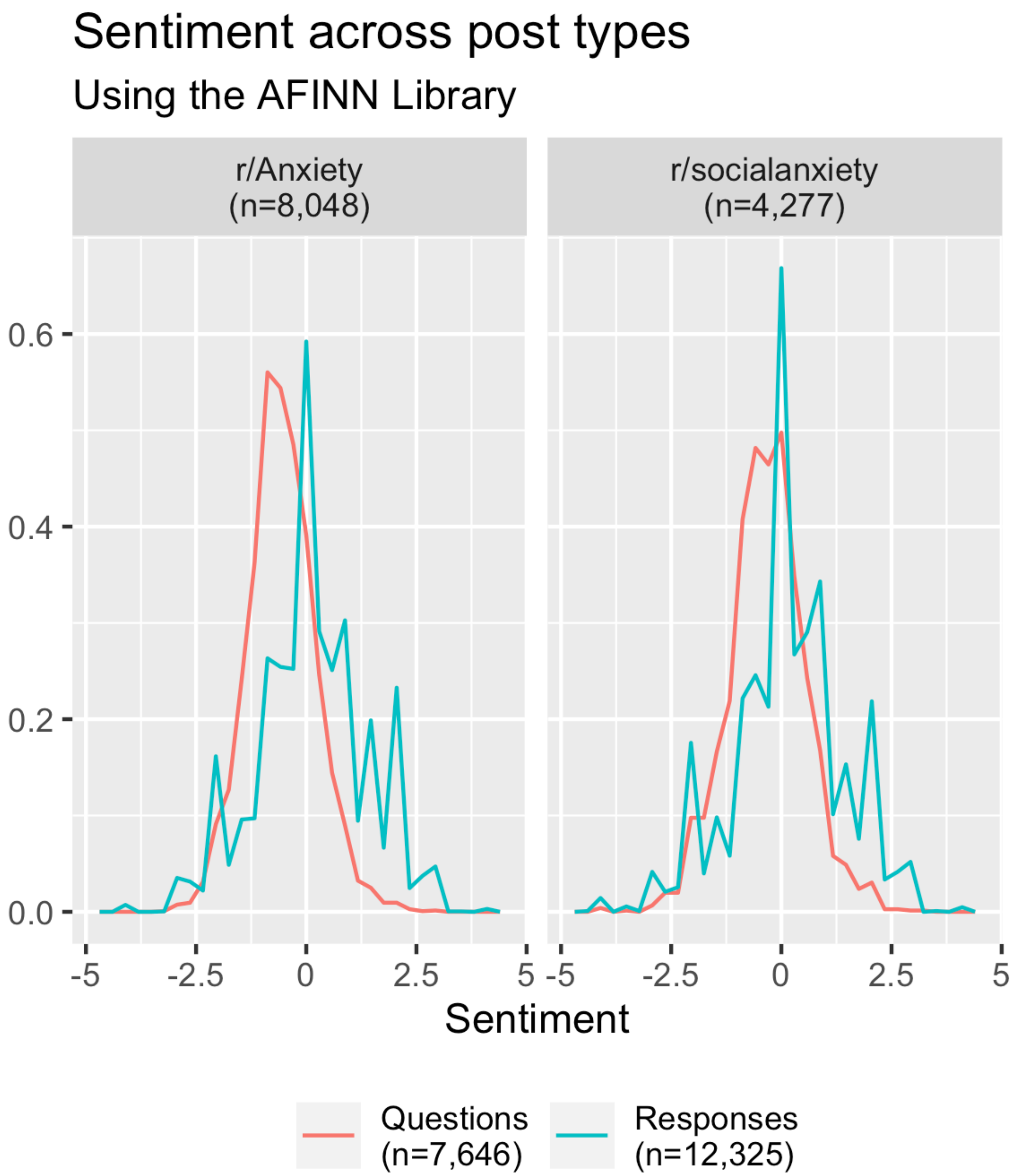

Figure 4: The distribution of post sentiment (calculated using the AFINN dictionary) across r/Anxiety vs. r/socialanxiety and questions vs. responses. On average, questions expressed lower sentiment than responses and r/socialanxiety expressed higher sentiment than r/Anxiety.

Topic Models

Next, we explored the topics expressed in questions and responses. We first examined the most common bigrams (two consecutive words) used in questions. As shown in Figure 5, the bigrams “social anxiety” and “panic attack” appeared much more frequently than other bigrams. Second, we compared the most relevant bigrams in high-quality responses to the most relevant bigrams in low-quality responses. Our measure of bigram relevance was term frequency–inverse document frequency (TF-IDF), which provides a term’s relevance to a given document in a collection of documents. Figure 6 shows the bigrams with the highest TF-IDFs separated by response quality.

Finally, we conducted an exploratory LDA topic model to identify the topics discussed in the questions, setting the model to identify 5 topics and using Gibbs sampling. The LDA appeared to reveal several possible topics, although each was fairly noisy: topic 1 seemed to involve general expressions of personal anxiety, topic 2 was primarily related to work or school, topic 3 had to do with social relationships, topic 4 involved asking for advice with an anxiety-related problem, and topic 5 was primarily related to panic attacks or other negative anxiety-related experiences, as shown in Figure 7.

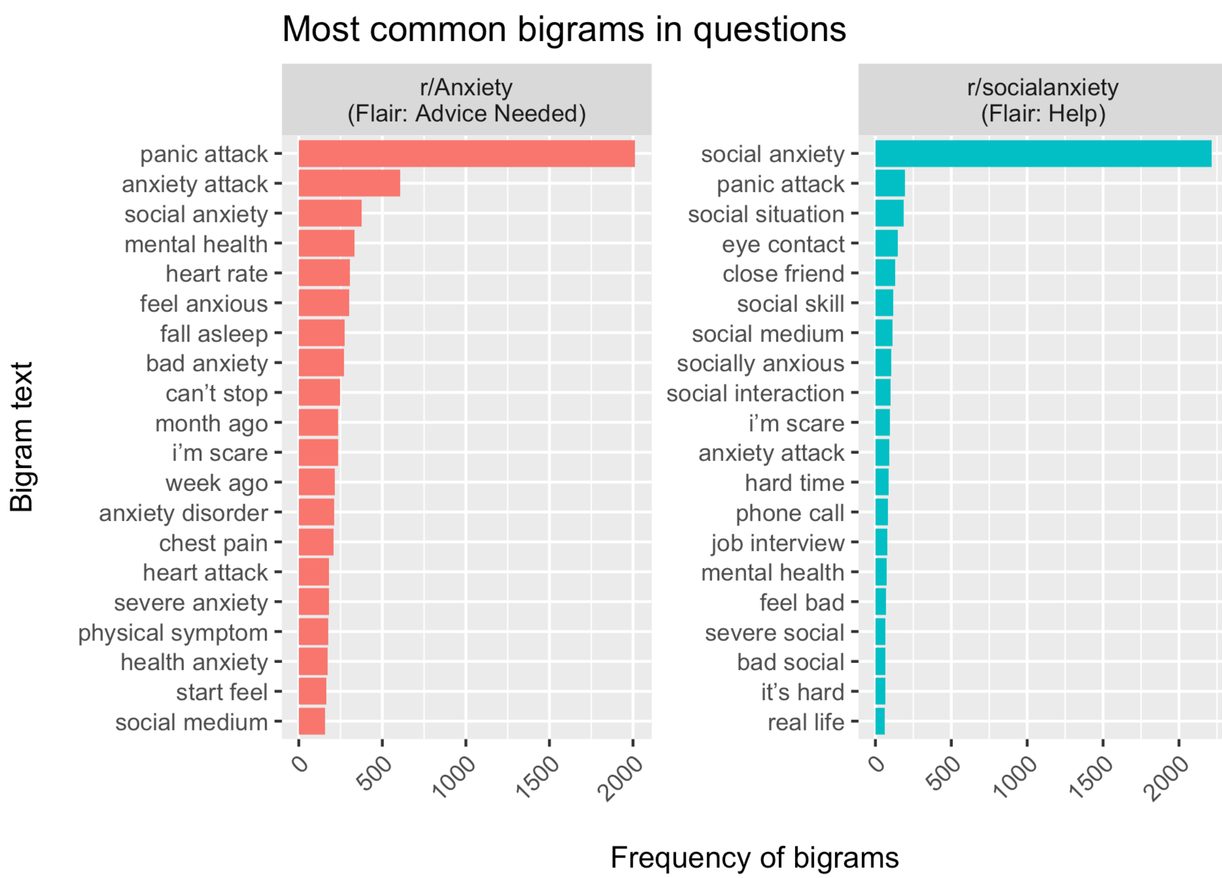

Figure 5: The 20 most common bigrams in all 7,646 questions (combining question title and body text) across r/Anxiety and r/socialanxiety

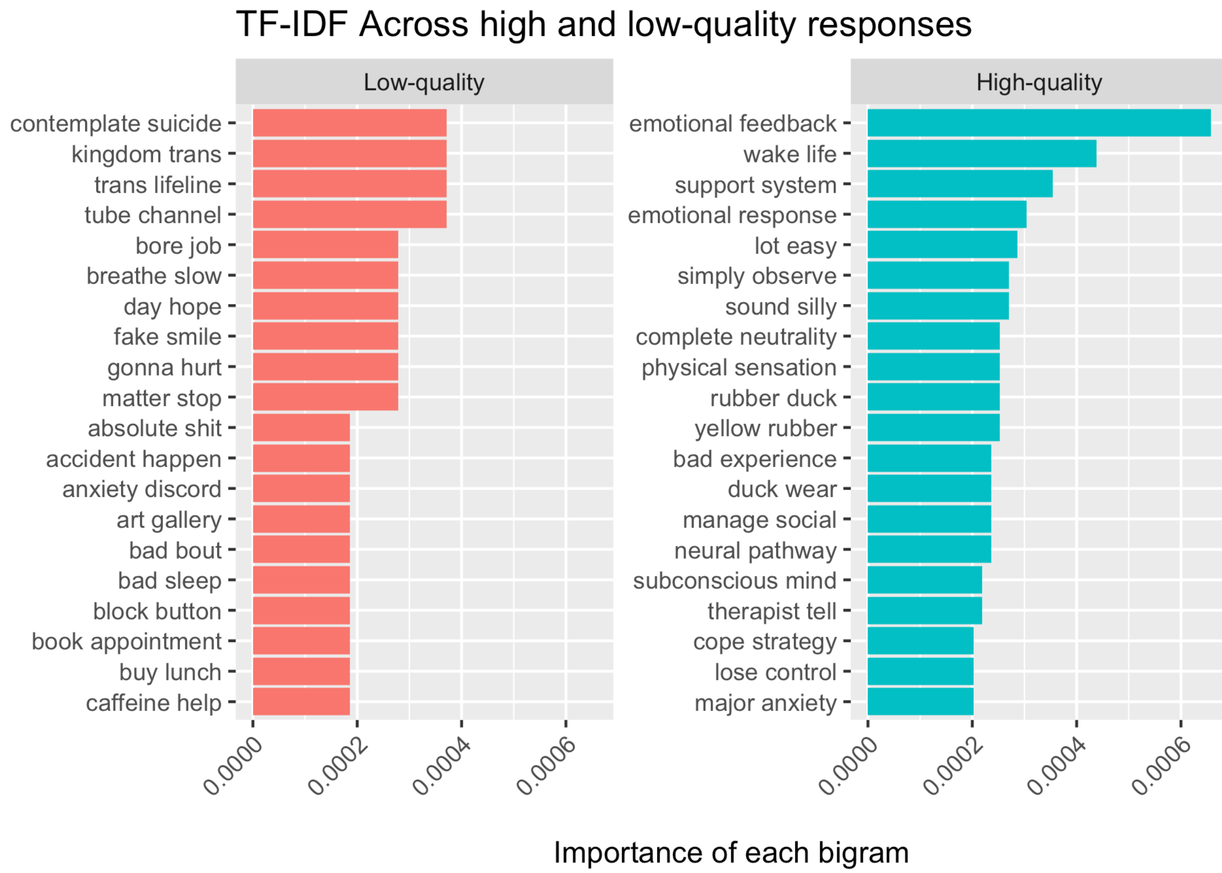

Figure 6: Term frequency–inverse document frequency (TF-IDF) for high- and low-quality responses, among all 12,325 responses. One document included all responses labelled as high quality, while the other document included responses coded as low-quality.

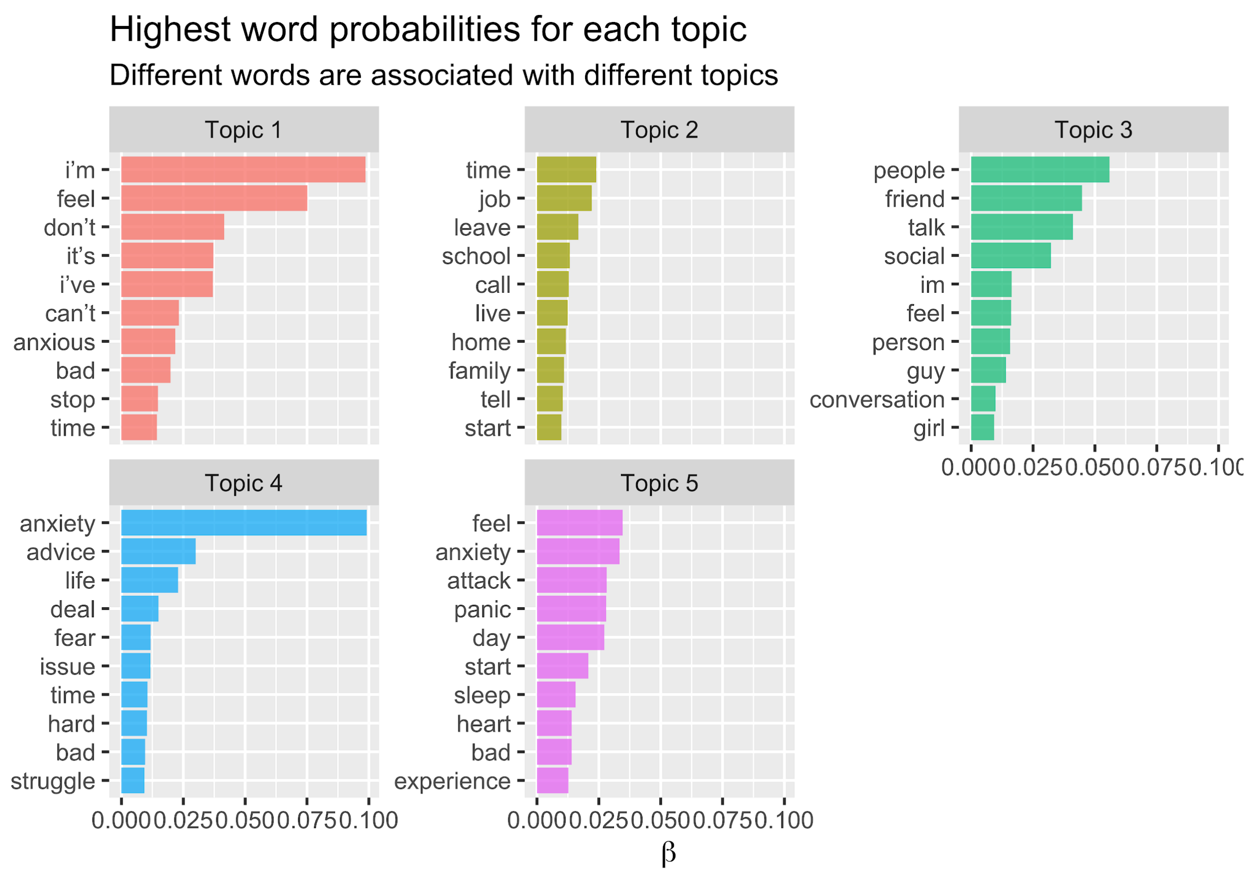

Figure 7: Latent Dirichlet Assignment (LDA) performed on all 7,646 questions. Each document consisted of the combined posts of each author.

Discussion

The present study took a computational social science approach to broadly describe the topical, linguistic, and metadata features of low- and high-quality responses to anxiety-related questions in online mental health peer support communities. To summarize, we found that 1) response quality was mostly strongly predicted by the number of syllables in the response but also somewhat predicted by many other variables such as response readability and time between question and response posting, 2) instrumental support was more predictive of response quality than was emotional support, 3) sentiment differed slightly across questions and responses and across subreddits, and 4) common bigrams in high-quality responses seemed to be more positive than were common bigrams in low-quality responses. Here, we discuss our findings' relevance to current challenges in online support communities.

Notably, the strongest predictors of response quality were simply measures of response length (e.g number of syllables), while measures of more nuanced aspects of response content (e.g. sentiment and the proportion of words from various emotion-related LIWC dictionaries), measures of a response's popularity and approval from the subreddit community (e.g. response score), and measures of a respondent's reputation and experience in the community (e.g. respondent karma and the date one's account was created) all made relatively small contributions to response quality in our model. This may suggest that writing a helpful response to a help-seeker does not necessarily require a deep knowledge of an online support community's conversational norms or a particular writing style (Sharma & De Choudhury, 2018). Finally, responses' popularity among the community (as measured by responses' scores), surprisingly, did not strongly predict response quality as rated by our team.

Among the 790 human-rated question-response interactions, we observed that response quality was more strongly associated with informational support than emotional support. This finding is relevant to mental health support forum design choices as some support forums recommend that users provide emotional support rather than advice. For example, the most popular mental health support subreddit, r/Depression, provides a guideline in their rules that states, "Empathy, support, and feedback are usually more helpful than advice". Responding to mental health questions empathically is certainly important, but our results suggest that informational support is also an important aspect of effective online support provision.

We found that questions tended to express more negative sentiment than responses did, and that posts in r/Anxiety expressed lower sentiment than those in r/socialanxiety; however, these sentiment differences were small (Cohen's d's < 0.30). Still, these patterns are consistent with previous computational work on sentiment across subreddits (Gkotsis et al., 2016) and surveys of mental health subreddit users showing that subreddits differ in their attitudes, conversational norms, and topics of discussion (Kaveladze & Schueller, 2020).

In our exploratory analysis of term frequency in questions and responses, we found that "Panic attack" ranked as one of the top bigrams in questions in both r/Anxiety and r/Socialanxiety (Figure 5), suggesting that panic attacks are a particularly salient issue for help-seekers in these communities. Also, the most relevant terms in high-quality responses seemed to relate to coping strategies, such as "simply observe" and "support system", while the most relevant terms among low-quality responses expressed more negativity or pessimism, such as "fake smile" and "gonna hurt". The LDA model was not very informative, but it did identify distinct topics related to work/school life, social relationships, and panic attacks.

Limitations

This work has a few limitations. First, our findings were observational and exploratory, so they are not independently sufficient to recommend any interventions or forum design changes. Second, although we were able to achieve reasonable consistency in response quality ratings across raters, our measure of response quality was not a precise estimate of our variable of interest: how much help seekers felt that a given response to their question was useful, informational, and empathic. An alternative strategy would have been to follow Peng et al. (2021) in evaluating help seekers' expressed satisfaction with responses (measured via linguistic analysis of their responses to other users' responses to their posts), although such an approach is also not ideal. Third, our metrics of linguistic features such as sentiment and health-related words were imprecise because they were derived from a simple word-counting computational method and did not account for conversation norms on r/Anxiety and r/socialanxiety. These metrics would have been more valid with human coding, although such a strategy would have been too labor-intensive to perform on the full dataset.

Next Steps and Future Directions

A long-term goal for this line of research is to support the developers, moderators, and members of online mental health communities by providing actionable design and community-level policy recommendations. While the present study's exploratory and observational nature prevented us from making causal claims, future research might investigate causal relationships between our variables of interest. For example, although we identified a strong connection between response quality and response length, it is unclear how much response length itself signals quality or empathy to readers, compared to how much high-quality responses take more words to express. Experimental designs that measure quality ratings after manipulating response features of interest could clarify these relationships, as could interviews and surveys of help-seekers and support-providers that use online mental health communities. Also, future work can show whether our findings replicate in non-anxiety support forums.

Another future direction is to apply our findings, as well as our classification model and dataset, to developing an artificial intelligence question-answering system. The system would use natural language processing to draw from a corpus of questions and responses and associated response quality labels to formulate responses to novel anxiety-related questions. Such a system could provide rapid anxiety-related support and resources and it might offer a unique perspective. It could also be integrated into anxiety subreddits as a bot that comments with a response as soon as a help-seeking post is posted (i.e. "Hi, I'm just a bot, but if you asked me, I'd say …"); alternatively, it could be made into a simple web/smartphone app or integrated into existing chatbots as extra support for anxiety questions. If implemented, careful attention would be necessary to ensure that its advice was never dangerous and users knew its limitations.

Finally, future work could seek to address some of the issues we faced in obtaining high-quality ratings from crowdsourced workers. Our attention checks failed to catch most Turkers who likely did not make a real effort at the task and may have been bots, so more reliable attention checks and bot-detectors would be helpful for crowdsourcing ratings in the future.

Conclusions

This work contributes several findings regarding effective responses to anxiety-related questions in online peer support communities. We hope this study will inform future research and the development of technologies to support people struggling with mental health.

References

1. Bargh, J. A., McKenna, K. Y. A., & Fitzsimons, G. M. (2002). Can you see the real me? Activation and expression of the "True Self" on the Internet. *Journal of Social Issues*, *58*(1), 33–48. https://doi.org/10.1111/1540-4560.00247
2. Baumgartner, J., Zannettou, S., Keegan, B., Squire, M., & Blackburn, J. (2020, May). The pushshift reddit dataset. In *Proceedings of the International AAAI Conference on Web and Social Media* (Vol. 14, pp. 830-839).
3. De Choudhury, M., & De, S. (2014, May). Mental health discourse on reddit: Self-disclosure, social support, and anonymity. In *Proceedings of the International AAAI Conference on Web and Social Media* (Vol. 8, No. 1).
4. Gkotsis, G., Oellrich, A., Hubbard, T. J. P., Dobson, R. J. B., Liakata, M., Velupillai, S., & Dutta, R. (2016). The language of mental health problems in social media. *CLPsych@HLT-NAACL*. https://doi.org/10.18653/v1/W16-0307
5. Kaveladze, B., Schueller, S. (2020). *Mental health subreddits offer users valuable and unique support*. Poster session presented at the 2020 Association for Psychological Science Virtual Poster Showcase. https://imgur.com/a/RO1wHJd.
6. Kavuluru, R., Williams, A. G., Ramos-Morales, M., Haye, L., Holaday, T., & Cerel, J. (2016). Classification of Helpful Comments on Online Suicide Watch Forums. *ACM Conference on Bioinformatics, Computational Biology and Biomedicine*, *2016*, 32–40. https://doi.org/10.1145/2975167.2975170
7. Kohn, R., Saxena, S., Levav, I., & Saraceno, B. (2004). The treatment gap in mental health care. *Bulletin of the World health Organization*, *82*, 858-866.
8. Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., & Van Alstyne, M. (2009). Social science. Computational social science. *Science*, *323*(5915), 721–723. https://doi.org/10.1126/science.1167742
9. Nielsen, F. Å. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. arXiv preprint arXiv:1103.2903.
10. O'Leary, K., Bhattacharya, A., Munson, S. A., Wobbrock, J. O., & Pratt, W. (2017). Design opportunities for mental health peer support technologies. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1470–1484.
11. Pedregosa, F., Varoquaux, Ga"el, Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., & Vanderplas, J (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825–2830.
12. Peng, Z., Ma, X., Yang, D., Tsang, K. W., & Guo, Q. (2021, May). Effects of support-seekers' community knowledge on their expressed satisfaction with the received comments in mental health communities. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-12).
13. R Core Team (2019). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. URL. https://www.R-project.org/.
14. Rains, S. A., & Tsetsi, E. (2017). Social support and digital inequality: Does Internet use magnify or mitigate traditional inequities in support availability? *Communication Monographs*, 84(1), 54–74.
15. Sharma, E., & De Choudhury, M. (2018). Mental health support and its relationship to

linguistic accommodation in online communities. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 641:1–641:13. https://doi.org/10.1145/3173574.3174215

16. Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1), 24-54.
17. Van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace.
18. Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L.D.A., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., & Kuhn, M., (2019). Welcome to the tidyverse. *Journal of Open Source Software*, *4(43)*, 1686, https://doi.org/10.21105/joss.01686