Understanding the Role of Questions in Mental Health Support-Seeking Forums

Aylin Gunal, Ian Stewart, Rada Mihalcea, Verónica Pérez-Rosas

Abstract People who seek mental health help online often receive supportive comments from other users, but their intentions may not be clear, as when someone asks a question that does not require a response. In this work, we explore the role of questions asked in response to support-seeking posts during online interactions centered around mental health support. We introduce a new dataset consisting of 1,089 mental health related post-response pairs from Reddit containing response questions annotated as rhetorical, information-seeking or not applicable. Through several experiments, we find that we can effectively distinguish between rhetorical and information seeking questions using linguistic features. Our findings highlight the importance of surrounding context and functional features (e.g., auxiliary verbs) as opposed to semantic (e.g., words related to mental processes) being significant predictors of question type.

1 Introduction

Online mental health communities are growing as more people seek support or offer it to others. Several works have explored the nature of interactions within these communities, including expressions of empathy and members' motivations for participation (Zhang et al., 2017; Chen and Xu, 2021; Sharma et al., 2020).

Aylin Gunal
University of Michigan, e-mail: gunala@umich.edu

Ian Stewart
Pacific Northwest National Laboratory, e-mail: ian.stewart@pnnl.gov

Rada Mihalcea
University of Michigan, e-mail: mihalcea@umich.edu

Verónica Pérez-Rosas
University of Michigan, e-mail: vrncapr@umich.edu

However, few studies have examined the role and characteristics of *questions* posed by members of these communities (Zhang et al., 2014; Frank, 1990), which can reflect how people request information and make arguments about mental health.

In this work, we study the linguistic cues associated with different types of questions posed in mental health forums on Reddit. We focus on interactions where supporters ask questions in response to support-seekers, since understanding the nature of these questions can help counselors and non-professionals alike understand how to connect meaningfully with patients. While online help-seeking interactions might differ from their counseling counterparts they also share important characteristics such as information probing through questioning and expressing empathy. We believe that our study can contribute to understanding what types of questions are asked by support givers around mental health topics in both peer and counseling settings. Furthermore, since questions play a key role in counseling techniques such as Motivational Interviewing (Miller and Rollnick, 2012), our work presents a first step into understanding the intent and nature of questions in psychotherapy.

We introduce Mental heAlTh quEstions (MATE), a new dataset of questions from mental health subreddits that are labeled as information-seeking or rhetorical.[1] We evaluate the use of linguistic features in the task of classifying rhetorical vs. information-seeking questions. Our findings show that functional features (e.g., auxiliary verbs) are significant predictors of question type, and that question classification models benefit from the addition of context-related features. This study provides insights into differences in the way questions are asked in the mental health domain. In addition, our work contributes an important resource for question generation studies, where training with low-quality data can lead to harmful generated text (Gupta et al., 2022).

2 Related Work

Proposed taxonomies of questions often focus on sentence structure (e.g., wh-word appearance; Kearsley 1976), and on the intent of the speaker (comparison vs. explanation; Nielsen et al. 2008). Two particularly common question categories in online discussions are information-seeking, where the inquirer looks for new information, and rhetorical, where the inquirer uses the implied answer to the question as a rhetorical device (Ranganath et al., 2018). Prior work on the classification of rhetorical vs. information-seeking questions has demonstrated that a bag-of-words representation provides a strong baseline (Zhuang and Riloff, 2020; Bhattasali et al., 2015), but has done less to explore the relative importance of different linguistic features. Our work provides an analysis of different semantic, functional, and contextual features in question classification, specifically within mental health discussions where determining question intent can prove critical to a successful conversation.

[1] We will release the code and annotated dataset upon completion of screening the dataset for personal identifiable information, in line with previous similar work (Gupta et al., 2022).

3 Data Collection

We use the dataset collected by (Lahnala et al., 2021), consisting of posts and responses discussing mental health issues on Reddit. This dataset both aligns with the domain as well as the dialogue structure we are interested in observing, i.e. questions asked in response to common mental health concerns. From the full set, we focus on posts with responses that include follow-up questions. We identify the post-response pairs by filtering responses that contain question marks–a simple approach that previous works have successfully applied (Zhuang and Riloff, 2020; Bagga et al., 2021) to identify questions on social media.

We further filter the resulting set to remove posts written by known bots, questions duplicating content from the original post, and URLs that were incorrectly identified as questions due to their use of question marks. Because some comments include multiple questions, we create multiple post-comment pairs by extracting each individual question from the comment. We obtain 76,476 post-response pairs from 48,784 unique responses from which we collect their post content and corresponding author "flairtags" i.e., a label indicating the support provider expertise (e.g., "Mental Health Practitioner"). Table 1 shows an example of a post-comment pair from the resulting set along with its author flairtag.

Table 1 Example of a post and a responding comment that contains a question.

Post	Comment	Post-Author Flairtag	Comment-Author Flairtag
How should I ask my therapist for my diagnosis?	**Are you paying with insurance?** Because many therapists actually are very hesitant to formally diagnose clients. However, when using insurance it is required in order to get paid.	No Expertise	High Expertise

3.1 Annotation

To enable our experiments, we manually annotate a randomly sampled subset of 1,100 questions with three main types of questions as described below.

Information-Seeking (IS) Questions that explicitly ask for information from the author of the original post.

Rhetorical (R) Questions that address the author of the original post but do not explicitly seek information.

Not Applicable (NA) Questions that were neither IS or R due to one of the following conditions: (1) being unrelated to mental health support (e.g., seeking career advice);

Table 2 Example questions with context from the dataset.

Questions with context	Label
Would therapy help? I'd say there's a good shot.	R
Some people have difficulties with more intimate relationships. **Do you believe you could be on the spectrum?**	IS

(2) not being directed towards the author of the original post (e.g., community post); (3) including harmful content (e.g., trolling, bigotry).

Two annotators independently label each question. The annotators are undergraduate students who read the instructions carefully and practiced the guidelines before annotating. During the annotation task, they are shown the question as well as the sentences preceding and following the question, whenever available. Annotators discard 11 post-responses that do not fit into any of the IS, R, or NA categories (e.g. emojis). Disagreements are resolved by a third annotator. The overall inter-annotator agreement is 79% and Cohen's Kappa was .68.

The final dataset includes 1,089 questions, annotated as 485 IS, 296 R, and 308 NA respectively and distributed across 38 different mental health subreddits. The most popular subreddits in the final set include r/ADHD (394), r/mentalhealth (257), r/relationship_advice (166), r/askatherapist (56), and r/offmychest (27). Examples of questions in the dataset including preceding or following context are shown in Table 2, and the dataset statistics are shown in Table 3.

Table 3 Dataset statistics.

Statistics	IS	R
Avg. sentence length (tokens)	10.9	10.7
Questions with preceding context	325 (67.0%)	224 (75.6%)
Questions with following context	224 (46.1%)	261 (88.2%)

4 Features

We explore the effectiveness of different linguistic features in the classification between information-seeking and rhetorical questions, focusing on lexical, functional, semantic, and contextual features.

Lexical Features We extract unigrams using TF-IDF counts and word embeddings with Word2Vec by obtaining the mean of embeddings for individual words in the question.

Functional Features A question-asker may indicate their intention by changing how their question is framed. We therefore extract words that serve a syntactic function, rather than content, within a question.[2] (1) *Head Nouns.* We extract head nouns i.e., nouns located within the main noun phrase of a sentence, from questions using the heuristic designed by (Metzler and Croft, 2005). (2) *Auxiliary Verbs.* We extract the leftmost auxiliary verb i.e., verbs that add context to the main verb, in a target sentence. (3) *Wh-keywords.* We extract the leftmost wh-question word (e.g., "where").

Semantic Features We obtain features that capture semantic aspects of the question's content. (1) *Lexical Diversity metrics.* Lexical diversity measures the diversity of words that a speaker uses to convey an idea, which may indicate a more information-heavy sentence and therefore information-seeking. We use the following metrics: Measure of Textual Lexical Diversity, Hypergeometric Distribution, Maas (Mass, 1972), Type-Token Ratio, Mean Word Frequency, Yules K, and Yules I (Oakes, 1998). (2) *LIWC features.* Prior work in mental health conversations has found that the Linguistic Inquiry Word Count (LIWC) lexicons prove useful in identifying different mental processes (Pérez-Rosas et al., 2018), which we hypothesize may extend to expressing rhetorical intent. We derive semantic features using the LIWC lexicon (Pennebaker et al., 2001) for the 80 semantic classes in the lexicon. (3) *Concreteness.* Words that are highly concrete and refer to well-formed concepts (e.g. "hair") may correlate with the intent to seek new information. Concreteness scores are computed per-word using the dataset from (Brysbaert et al., 2014), and we use the mean over all words in the question as the feature. (4) *Polarity and NPIs.* We calculate the polarity of questions using TextBlob.[3] Following previous findings (Sadock, 1971) that consecutive sentences with opposite polarities may indicate rhetorical intent, we calculate negative-polarity indicators (NPIs) by parsing the dependencies of the question and its corresponding context sentences, and note whether the question or either context sentence includes a negative dependency.

Contextual Features We extract both linguistic and social contextual features of a question. (1) *Context.* We extract the unigrams TF-IDF embedding for the sentence immediately preceding the question and for the sentence immediately following the question within the full response. (2) *Context-Question Similarity.* Under the same intuition from the NPI index above, we compute cosine similarity and Word Mover's Distance (Kusner et al., 2015) between the word embedding of question and corresponding context sentences. (3) *User Expertise.* We embed information about the level of user expertise using their Reddit flairtags. We label users as *high expertise* if their tags indicate subject matter expertise (e.g., 'Psychiatry PhD'), *low expertise* for tags that indicate knowledge but not necessarily authority in mental health (e.g., 'depression') and *no expertise* for tags that do not reference mental health experience at all.

---

[2] For extraction of features that require a parser (e.g., auxiliary verbs), we use SpaCy (`https://spacy.io`)

[3] `https://textblob.readthedocs.io/en/dev/`

Table 4 Baseline performances for mental health question classification using SVM.

Features	# Feat.	Acc.	F1-IS	F1-R
Word2Vec	100	.611	.718	.365
Uni	1467	**.743**	**.796**	**.644**

5 Experiments and Results

We conduct a series of experiments to distinguish between rhetorical and information seeking questions using the extracted features separately and jointly. Due to the imbalanced class distribution in our dataset, we upsample using SMOTE (Chawla et al., 2002) to synthetically generate minority class labels. We use a linear SVM as our main classifier[4] and evaluate using five-fold cross-validation, with accuracy, precision, recall, and F-score as performance metrics. We use the machine learning algorithm implementations available in the Scikit-learn[5] library with their default parameters.

Baseline Models We establish a baseline performance for the classification task using lexical features only. Classification results when using word embeddings (Word2Vec) and unigrams (Uni) are shown in Table 4. We did not observe a performance gain when combining these features. Similar to prior work (.69 F1 in (Zhuang and Riloff, 2020), .76 F1 in (Oraby et al., 2017)), we show that a simple classifier using only the question text achieves reasonable F1 scores, which supports the task's validity.

Feature Groups We conduct experiments using each of the feature groups defined in Section Features separately, and in combination with question unigrams. Results are shown in Table 5. The Functional feature set does the best overall, and auxiliary verbs are often the key features in the set: IS questions typically begin with primary auxiliary verbs ("Do you have a plan to be safe?") whereas some R questions begin with modal auxiliary verbs ("Would I recommend that?"). Overall, the Contextual feature group that includes the question embedding provides the highest performance for IS prediction.

Feature Ablation We conduct a set of ablation experiments in order to find the most important predictive features to classify question type. We start with a model including all features and then we remove one feature set at the time. Results are shown in Table 6. The best performing model includes all features except for the question-context similarity metrics, with an F1-IS of .84 and F1-R of .71.

Performance falls significantly when context sentences are dropped from the feature set. Interestingly, dropping auxiliary verbs reduces model performance more than dropping either or both context sentences. Disregarding context, the most dra-

[4] We experimented with other classifiers and found the best performance using the SVM model.

[5] `https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html`

Table 5 Grouped feature results. Underlined values are highest in groups including unigrams (uni), and bold values are highest in groups excluding unigrams.

Feature Set	# Feat.	Acc.	F1-IS	F1-R
Functional	194	.695	**.759**	**.581**
Functional + uni	1702	.748	.800	<u>.657</u>
Semantic	107	.629	.692	.530
Semantic + uni	1615	.748	.801	.655
Contextual	3012	.683	.743	.576
Contextual + uni	4520	.764	<u>.821</u>	.653

Table 6 Ablation results. Bold numbers indicate greatest drop in performance within the feature group.

Feature Set	Acc.	F1-IS	F1-R
All features	.784	.832	.696
Functional features			
– Auxiliary verbs	.766	**.820**	**.663**
– Head nouns	.771	.821	.679
– Wh-keywords	.775	.826	.680
Semantic features			
– Concreteness	.772	**.823**	**.680**
– LIWC	.780	.830	.685
– Polarity	.782	.831	.694
– NPIs	.785	.833	.696
– Lexical diversity	.785	.832	.696
Contextual features			
– Expertise	.777	.827	.688
– Cosine + WMD	.793	.838	.710
– Prec.	.775	.823	.688
– Foll.	.767	.819	**.672**
– Prec. + Foll.	.764	**.814**	.677

matic drops in performance for both IS and R questions occur when functional features and concreteness are dropped as features.

Question Context Since we observe that dropping context sentences substantially reduces performance, we train and test models with context sentences and question unigrams. Results are shown in Table 7.

Following context predicts both IS questions and R questions more accurately than preceding context, and following context also predicts R questions more accurately than the combination of both preceding and following context. This performance may reflect the fact that rhetorical questions are more likely to have following context than information seeking questions (as shown in Table 3).

Table 7 Effects of adding context sentences. All sentences are represented with the same unigram features as before.

Feature Set	# Feat.	Acc.	F1-IS	F1-R
Q + Prec.	2975	.750	.807	.647
Q + Foll.	3048	.766	.823	**.667**
Q + Prec. + Foll.	4515	**.768**	**.827**	.643

Adding both preceding and following sentences to the question yields the highest performance for IS question classification. A possible explanation is that IS questions may often appear in groups, not in isolation. For example, our data includes the sequences of IS questions ”Are you really depressed? Could it possibly be a personality disorder?” A mental health counselor may therefore choose to ask questions in tandem, rather than in separate turns, to make it clear that they are actually seeking new information.

Additionally, we manually went through the questions that our model fails to predict correctly. We group the main failures into the following categories:

- **Context dependence**. For many questions, the model predicted IS when it should have predicted R given the context. For instance, the R question “Does it sound likely that it would or is happening?” is followed by the context “Not at all to me” but the model predicts IS, possibly because the question’s well-formed grammar outweighs the role of context in prediction.
- **Challenges**. Some R questions reflect a *challenge* to the original poster rather than an intention to engage them in good faith: the R question “And really, do the labels - ADHD, personality, or character flaw - really matter?” was predicted as IS by the model. This kind of R question may require more subtle lexical features than those utilized here, such as discourse markers like “really” Pavalanathan et al. (2017).
- **Non-standard question form**. The model sometimes predicted R instead of IS when the question had a non-standard form, as in “I am curious about what the flare up looks like when it starts to turn for you?” In such cases, more advanced text preprocessing may be needed to identify the structure of the underlying question, i.e. removing embedding phrases like “I am curious about.”

6 Conclusion and Future Work

In this work, we developed MATE, a dataset of mental health-focused questions annotated by type, and we evaluated the role of linguistic features in question type classification.

Through extensive feature ablation, we found that functional features–particularly auxiliary verbs–provide more predictive power than semantic features, which reinforces prior findings about the limits of content-based features in question classification (Kalouli et al., 2021). We also found that the combination of preceding and following context best predicts information-seeking questions. Overall, the study shows that subtle choices in wording and sentence order may be more important than content when it comes to predicting supporters' question-asking intentions.

Future work may include further exploration of the relationship between domain experts and the kinds of questions they produce; in the realm of mental health support, it seems logical to assume that professionals in the field are more likely to try to achieve a better understanding of a patient's state rather than make a point, which is a common function of rhetorical questions (Bagga et al., 2021). Similarly, we note that there are several repeat posters across various subreddits, and it may be interesting to study how similar users respond to different types of posts.

Additionally, future work may consider how user behavior varies between different online communities. The distribution of subreddits in MATE is highly uneven, and a significant portion of the most popular subreddits are more geared towards a general audience (e.g. r/mentalhealth). These subreddits accommodate a variety of users with different degrees of severity of mental health ailments. It may be insightful to analyze how such different users ask or answer questions, because different conditions lend themselves to different information-seeking needs.

7 Limitations

Because our dataset includes online interactions, the language used includes informal phrases, slang, or abbreviations, and the questions may be phrased in non-traditional ways ("You OK?"). The heuristics we used to extract features such as head nouns and auxiliary verbs require a correct parse of the sentence structure, and proper sentence structure is not always to be expected from social media interaction data (Eisenstein, 2013). A possible way to mitigate this issue as well as reduce bias associated with interactions from Reddit would be to expand our data sources to include formal online counseling platforms such as CrisisTextLine.

Additionally, the validity of our data labels relies on the quality of annotation. We acknowledge the difficulty in achieving high inter-annotator agreement in such a subjective task–even for annotators collaborating closely throughout the process. Future work may be centered around mitigating disagreement by adding the "Ambiguous" label in annotation.

8 Ethics

We acknowledge that mental health is a sensitive area, where the cost of incorrect model predictions can be disproportionately high compared to the general population (Chancellor et al., 2019). We do not intend for any of the models trained in this work to be deployed without more careful testing of possible biases and performance shortcomings (e.g., systematic misclassification of abusive content). The models used in this work should not be used to replace a supporter judgment of what makes a question information-seeking vs. rhetorical, but instead to augment their judgment (Thieme et al., 2020) by showing which features may contribute to different perceptions of their questions.

Acknowledgements This material is based in part upon work supported by the John Templeton Foundation (#62256) and by the University of Michigan Precision Health Initiative. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the John Templeton Foundation or the Precision Health Initiative. We thank members of the LIT Lab, including Ashkan Kazemi, Naihao Deng, and Shinka Mori as well as Ava Luna Pardo-Keegan for their help in developing and carrying out the annotation task, and for providing feedback on early results.

References

Bagga S, Piper A, Ruths D (2021) “are you kidding me?”: Detecting unpalatable questions on Reddit. In: Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, Association for Computational Linguistics, Online, pp 2083–2099, DOI 10.18653/v1/2021.eacl-main.179, URL https://aclanthology.org/2021.eacl-main.179

Bhattasali S, Cytryn J, Feldman E, Park J (2015) Automatic identification of rhetorical questions. In: Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), Association for Computational Linguistics, Beijing, China, pp 743–749, DOI 10.3115/v1/P15-2122, URL https://aclanthology.org/P15-2122

Brysbaert M, Warriner AB, Kuperman V (2014) Concreteness ratings for 40 thousand generally known english word lemmas. Behavior research methods 46(3):904–911

Chancellor S, Birnbaum ML, Caine ED, Silenzio VM, De Choudhury M (2019) A taxonomy of ethical tensions in inferring mental health states from social media. In: Proceedings of the conference on fairness, accountability, and transparency, pp 79–88

Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP (2002) SMOTE: Synthetic minority over-sampling technique. Journal of Artificial Intelligence Research 16:321–357, DOI 10.1613/jair.953, URL https://doi.org/10.1613%2Fjair.953

Chen Y, Xu Y (2021) Exploring the effect of social support and empathy on user engagement in online mental health communities. International Journal of Environmental Research and Public Health 18(13):6855

Eisenstein J (2013) What to do about bad language on the internet. In: Proceedings of the 2013 conference of the North American Chapter of the association for computational linguistics: Human language technologies, pp 359–369

Frank J (1990) You call that a rhetorical question?: Forms and functions of rhetorical questions in conversation. Journal of Pragmatics 14(5):723–738

Gupta S, Agarwal A, Gaur M, Roy K, Narayanan V, Kumaraguru P, Sheth A (2022) Learning to automate follow-up question generation using process knowledge for depression triage on Reddit posts. In: Proceedings of the Eighth Workshop on Computational Linguistics and Clinical Psychology, Association for Computational Linguistics, Seattle, USA, pp 137–147, DOI 10.18653/v1/2022.clpsych-1.12, URL `https://aclanthology.org/2022.clpsych-1.12`

Kalouli AL, Kehlbeck R, Sevastjanova R, Deussen O, Keim D, Butt M (2021) Is that really a question? going beyond factoid questions in NLP. In: Proceedings of the 14th International Conference on Computational Semantics (IWCS), Association for Computational Linguistics, Groningen, The Netherlands (online), pp 132–143, URL `https://aclanthology.org/2021.iwcs-1.13`

Kearsley GP (1976) Questions and question asking in verbal discourse: A cross-disciplinary review. Journal of psycholinguistic research 5(4):355–375

Kusner M, Sun Y, Kolkin N, Weinberger K (2015) From word embeddings to document distances. In: International conference on machine learning, PMLR, pp 957–966

Lahnala A, Zhao Y, Welch C, Kummerfeld JK, An LC, Resnicow K, Mihalcea R, Pérez-Rosas V (2021) Exploring self-identified counseling expertise in online support forums. In: Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pp 4467–4480

Mass HD (1972) Über den zusammenhang zwischen wortschatzumfang und länge eines textes. Zeitschrift für Literaturwissenschaft und Linguistik 2(8):73

Metzler D, Croft WB (2005) Analysis of statistical question classification for fact-based questions. Information Retrieval 8(3):481–504

Miller WR, Rollnick S (2012) Motivational interviewing: Helping people change. Guilford press

Nielsen RD, Buckingham J, Knoll G, Marsh B, Palen L (2008) A taxonomy of questions for question generation. In: Proceedings of the Workshop on the Question Generation Shared Task and Evaluation Challenge

Oakes MP (1998) Statistics for Corpus Linguistics. Edinburgh University Press, URL `http://www.jstor.org/stable/10.3366/j.ctvxcrdkd`

Oraby S, Harrison V, Misra A, Riloff E, Walker M (2017) Are you serious?: Rhetorical questions and sarcasm in social media dialog. In: Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, Association for Computational Linguistics, Saarbrücken, Germany, pp 310–319, DOI 10.18653/v1/W17-5537, URL `https://aclanthology.org/W17-5537`

Pavalanathan U, Fitzpatrick J, Kiesling SF, Eisenstein J (2017) A multidimensional lexicon for interpersonal stancetaking. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp 884–895

Pennebaker JW, Francis ME, Booth RJ (2001) Linguistic inquiry and word count: Liwc 2001. Mahway: Lawrence Erlbaum Associates 71(2001):2001

Pérez-Rosas V, Sun X, Li C, Wang Y, Resnicow K, Mihalcea R (2018) Analyzing the quality of counseling conversations: the tell-tale signs of high-quality counseling. In: Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)

Ranganath S, Hu X, Tang J, Wang S, Liu H (2018) Understanding and identifying rhetorical questions in social media. ACM Transactions on Intelligent Systems and Technology (TIST) 9(2):1–22

Sadock JM (1971) Queclaratives. In: seventh regional meeting of the Chicago Linguistic Society, vol 7, pp 223–232

Sharma A, Miner A, Atkins D, Althoff T (2020) A computational approach to understanding empathy expressed in text-based mental health support. In: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp 5263–5276

Thieme A, Belgrave D, Doherty G (2020) Machine learning in mental health: A systematic review of the HCI literature to support the development of effective and implementable ML systems. ACM Transactions on Computer-Human Interaction (TOCHI) 27(5):1–53

Zhang T, Cho JHD, Zhai C (2014) Understanding user intents in online health forums. In: Proceedings of the 5th ACM Conference on Bioinformatics, Computational Biology, and Health Informatics, Association for Computing Machinery, New York, NY, USA, BCB '14, p 220–229, DOI 10.1145/2649387.2649445, URL https://doi.org/10.1145/2649387.2649445

Zhang X, Liu S, Deng Z, Chen X (2017) Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users. Computers in Human Behavior 75:797–810

Zhuang Y, Riloff E (2020) Exploring the role of context to distinguish rhetorical and information-seeking questions. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop, pp 306–312