Empathetic Response Generation for Distress Support

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Abstract

AI-driven chatbots are seen as an attractive solution to support people undergoing emotional distress. One of the main components of such a chatbot is the ability to empathize with the user. But a significant limitation in achieving this goal is the lack of a large dialogue dataset containing empathetic support for those undergoing distress. In this work, we curate a large-scale dialogue dataset that contains ≈1.3M peer support dialogues spanning across more than 4K distress-related topics. We analyze the empathetic characteristics of this dataset using statistical and visual means. To demonstrate the utility of this dataset, we train four baseline neural dialogue models that can respond empathetically to distress prompts. Two of the baselines adapt existing architecture and the other two incorporate a framework identifying levels of cognitive and emotional empathy in responses. Automatic and human evaluation of these models validate the utility of the dataset in generating empathetic responses for distress support and show that identifying levels of empathy in peer-support responses facilitates generating responses that are lengthier, richer in empathy, and closer to the ground truth.

1 Introduction

Psychological distress refers to a state of extreme sorrow, pain, or suffering, both emotional and physical. It is often associated with feelings of discomfort, anxiety, or anguish. The World Health Organization estimates that psychological distress affects 29% of people in their lifetime (Steel et al., 2014). Despite the availability of mental health services, people hesitate to reach them because of the public stigma associated with mental health. There is also a severe shortage of mental health workers (Vaidyam et al., 2019). Thus, recent work investigates how technology can be utilized to meet the needs of people suffering from distress. One such solution is the development of conversational agents or chatbots to deliver distress support (Fitzpatrick et al., 2017; Inkster et al., 2018; Mousavi et al., 2021).

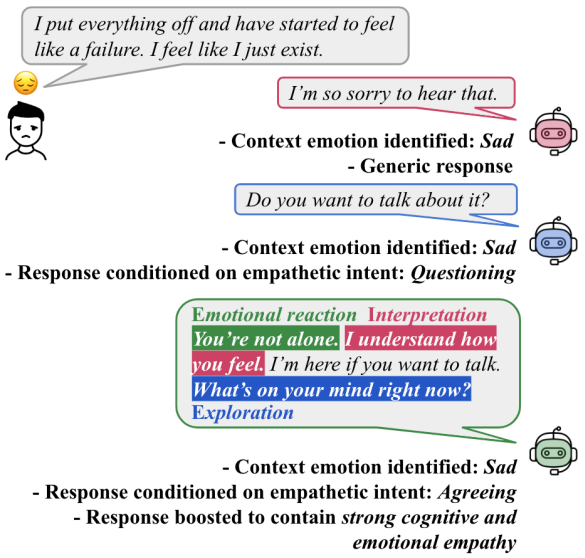

Figure 1: Distress support responses generated by our different chatbot models trained on peer support dialogues. The last response boosted with cognitive and emotional empathy communication mechanisms stands out from the rest as its lengthier and richer in empathy.

Deep neural networks work very effectively in the development of task-oriented and open-domain conversational agents (Sutskever et al., 2014; Vinyals and Le, 2015; Wen et al., 2015). Most of such dialogue agents can generate syntactically correct and contextually relevant responses. But a major challenge faced by these systems is identifying human emotion and responding in an empathetic manner (Rashkin et al., 2018; Welivita et al., 2021). This is very important when developing chatbots to support distress as one of the major components that contributes to the success of such interaction is the ability to empathize (Bohart et al., 2002; Thwaites and Bennett-Levy, 2007). Recently, researchers have curated emotion-labeled and empathetic datasets such as EmotionLines (Hsu et al.,

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2018), EmoContext (Chatterjee et al., 2019), EmpatheticDialogues (Rashkin et al., 2018), and ESConv (Liu et al., 2021) to enable training dialogue systems that can generate emotion-aware and empathetic responses. However, the above datasets include only a limited amount of dialogues dealing with distress. The dialogues in the first three datasets are more open-domain and span across topics less related to distress. The ESConv dataset that is more focussed on distress contains only 1.3K dialogues covering only 13 distress-related topics. Recent research has curated and conducted analysis on real counseling conversations (Althoff et al., 2016; Zhang and Danescu-Niculescu-Mizil, 2020). But these datasets are not publicly accessible due to privacy and ethical reasons.

To address the above limitations, we curated a large-scale dialogue dataset, named RED (Reddit Emotional Distress), containing ≈1.3M dialogues spanning across more than 4K distress-related topics. The dialogues are scraped from the popular peer support forum, Reddit. Peers are seen to actively engage in such forums to support others undergoing distress and thus they contain distress-related dialogues in abundance spanning a wide range of topics. Prior work has also found that responses from peers contain higher empathic concern for posts seeking help as many peers share similar distressful experiences (Hodges et al., 2010). But as these conversations are available as long threads, the turn-taking structure has to be explicitly extracted and the conversations have to undergo a rigorous pre-processing pipeline including the removal of profanity before they are used to train chatbots. Even then, the dataset can still possess less ideal responses to distress since peers are not trained in delivering distress support as professionals. We take steps to address this by making use of existing empathetic frameworks based on psychology that can be used to identify highly empathetic responses in such dialogues and enabling chatbot models to favor such responses over others.

Empathy is a complex multi-dimensional construct with two broad aspects related to emotion and cognition. The emotion aspect refers to the ability to share the feelings of another person and the cognition aspect refers to the ability to understand and acknowledge how a person feels. In mental health therapy, both emotional and cognitive empathy are equally important (Selman, 1981). Thus, for the development of distress support chatbots, it is vital to understand these types of empathy and the techniques by which these different types of empathy can be elicited. We apply such empathy recognition frameworks on RED to develop several distress support chatbots models. Figure 1 shows an example. In the first instance, identification of the context emotion enables the chatbot to produce a suitable generic response. In the second instance, the chatbot's response is conditioned on a specific empathetic response intent that helps to generate a diversified response. In the third instance, training the model to favour more cognitive and emotional empathy helps in generating lengthier responses containing specific cognitive and emotional empathy communication strategies.

Our contributions are three folds. 1) We curate a large-scale dialogue dataset containing ≈1.3M distress support dialogues spanning across more than 4K distress topics, from a set of carefully selected subreddits. 2) We describe the empathetic dialogue characteristics between the speakers and the listeners in this dataset using statistical and visual means. 3) Using this dataset as a benchmark, we develop four baseline chatbot models. The first two baseline models adapt existing empathetic response generation architectures. On top of them, we develop two new baselines by incorporating a framework that can identify levels of emotional and cognitive empathy in responses contained in RED. Automatic and human evaluation of the models' responses validate the utility of the RED dataset in facilitating empathetic response generation and show that identifying different levels of emotional and cognitive empathy enables generating responses that are lengthier, richer in empathy, and closer to the ground-truth. The code and the datasets are available at `https://github.com/yehchunhung/EPIMEED`

2 Related Work

Many dialogue datasets such as IEMOCAP (Busso et al., 2008), SEMAINE (McKeown et al., 2011), and MELD (Poria et al., 2019) are developed to make chatbots understand users' emotions and respond appropriately. These datasets contain visual, acoustic, and textual signals. More recent work such as EmotionLines (Hsu et al., 2018), OpenSubtitles (Lison et al., 2019), and EDOS (Welivita et al., 2021) are conversation datasets containing TV and movie transcripts translated from voice to text. Though these works intend to build dialogue

datasets by improving the sentence quality, they are still unable to fully model interactions occurring only via text. And most of the dialogues contained in these datasets represent generic day-to-day situations and not psychological distress in particular.

Rashkin et al. (2018) developed the EmpatheticDialogues dataset, inclusive of 25K dialogues grounded on 32 positive and negative emotions. Liu et al. (2021) developed the ESConv dataset, containing ≈1.3K dialogues discussing emotional distress and whose responses are grounded on the Helping Skills Theory (Hill, 2009). But the crowdsourced artificial setting used to curate them makes the dialogue prompts less authentic and the responses less genuine. Because of the cost of crowdsourcing, it also limits the size of these datasets as well as their topic coverage. Thus, a large-scale topically diverse dataset focused on textual conversations between speakers who are emotionally distressed and listeners who actively offer emotional support is lacking in the literature. This type of conversation could be available as recorded therapy sessions between psychologically distressed patients and therapists. However, such counseling datasets used to conduct recent research (Althoff et al., 2016; Zhang and Danescu-Niculescu-Mizil, 2020) are not directly accessible to the public due to ethical reasons. To address these limitations, we curate a large dataset containing peer support dialogues related to a variety of distress-related topics and validate that combined with existing empathy-identifying frameworks, it can potentially be used to develop chatbots that can offer empathetic support to distressful user prompts.

3 Reddit Emotional Distress Dataset

3.1 Data Curation and Preprocessing

Online peer support forums encourage open discussion of often stigmatized psychological concerns and personal distress (De Choudhury and De, 2014; Sharma et al., 2017). They provide alternative means for connection and support when other means of care are less accessible. The anonymity in such platforms facilitates self-disclosure and such discussions help people to feel more supported and less stressed in times of crisis (De Choudhury and De, 2014; Smith-Merry et al., 2019). Reddit is one such platform, which ranks among the most visited websites in the world (Sharma et al., 2017). Reddit users can create community forums called "subreddits" to discuss and support each other on a breadth of topics. Reddit policies also allow researchers to scrape its data and use them for research. Since many people interact in Reddit in a day-to-day basis, the distress-related topics it covers are abundant and have a wide variety. Because of these reasons we chose Reddit to curate conversations that provide support for people in distress.

For this purpose, we choose 8 subreddits: *depression*; *depressed*; *Off My Chest*; *SuicideWatch*; *Depression Help*; *sad*; *Anxiety Help*; and *Mental Health Support*, where such conversations were abundantly present. We used the Pushshift API (Baumgartner et al., 2020) to scrape English textual conversations from the above subreddits. We extracted one dyadic dialogue per conversation thread, selected randomly, thereby diversifying the conversation topics in the dataset. To preserve anonymity, we replaced the usernames with *speaker* and *listener*. The *speaker* here is the user who posted the Reddit post and the *listener* here is the person who commented on it. Dyadic conversations were extracted by selecting comment threads in which only the poster (speaker) and one other commenter (listener) were engaged. For simplicity, we call the original post by the speaker or the first turn in the conversation as the *distress prompt*. Next, we removed HTML tags and URLs from the data, and replaced numerals with a special tag <NUM>. But punctuation marks, emoticons, and emojis were preserved as they can be useful indicators to identify users' emotions.

3.2 Removal of Profanity

To remove profanity from the dataset, we applied `profanity-check` (Zhou et al., 2020), a fast and robust library to detect offensive language. Instead of using hard-coded lists of profane words, it makes use of a linear Support Vector Machine (Cortes and Vapnik, 1995) trained on 200k human-labeled samples of clean and profane text. It is simple but surprisingly effective generalized approach towards profanity checking. When it is applied to a text message, it returns the probability of predicting profanity. Thus, we could set up a threshold to classify the message as profane or not. In our case, we manually set the threshold to be as high as 0.95 because the users sometimes express their feeling aggressively but with no mean intention. This threshold was determined after a thorough inspection of the profane text returned at different thresholds. We removed profane lis-

teners' utterances above this threshold, however, retained profane speakers' utterances as they contain cues about the speakers' state of mind. All the dialogue turns following a removed utterance were also removed to maintain consistency.

3.3 Descriptive Statistics

The resultant RED dataset contains ≈1.3 million dyadic conversations. Table 1 displays the summary of descriptive statistics of conversations present in the dataset as well as in individual subreddits. We used Agglomerative clustering (Murtagh and Legendre, 2014) to cluster distress prompts and recognize clearly identifiable topic clusters. At an optimal clustering threshold of 0.85, the prompts were separated into 4,363 topic clusters. By applying TF-IDF based topic modeling on these clusters, we uncovered some clearly distinguishable distress-related topics. Some of the most common topics identified were *Suicidal ideation*, *Anxiety attacks*, *Weight gain*, *Loneliness*, *Failing college*, and *Covid19*. The topics and their associated keywords are included in the appendices.

3.4 Emotion and Intent Analysis

To analyse the emotions and intents expressed in the RED dataset, we used a BERT transformer-based classifier proposed by Welivita and Pu (2020) and classified the utterances in RED into one of 32 fine-grained emotions and 8 empathetic response intents. This classifier was trained on the EmpatheticDialogues dataset and has a classification accuracy of 65.88% on the EmpatheticDialogues test set, which is comparable with the state-of-the-art emotion classifiers. Manual validation of the labels proposed by the classifier on a random subset of 100 utterances from the RED datasets yielded an accuracy of 64%, which allows us to have reasonable judgments about the RED dataset using the predicted labels. In Figure 2, we visualize the emotion and intent distributions in speaker and listener turns in the RED dataset. It could be seen that the speakers' emotions are mostly centered around negative emotions. The most frequent speakers' emotions that can be observed are *ashamed* (9.98%), *lonely* (8.41%), *sad* (7.52%), and *apprehensive* (5.32%).

A significant proportion of the listener turns contain empathetic response intents. The listeners' intents are mostly centered around *questioning* (10.26%), *agreeing* (7.98%), *suggesting* (5.49%), and *sympathizing* (4.56%). Though empathetic response intents take prominence in the listener turns, they also contain emotional statements that mostly reflect the *sad* emotion (4.98%). This can possibly be explained by the study of affective asymmetry by Vaish et al. (2008) that states negative emotional experiences have more power in triggering negative emotions in the listener as humans are more sensitive to negative emotions.

Figure 3 shows the conversational dynamics in terms of emotion-intent flow patterns that could be observed in the first four dialogue turns. The first and the third turns represent the speaker turns, while the second and the fourth turns represent the listener turns. According to statistics, 93.71% dialogues in the dataset start with a negative emotion. Then in the next turn, the listeners tend to show empathy by means of intents such as *questioning* (35%), *agreeing* (12.43%), *suggesting* (8.11%), and *sympathizing* (7.23%). As the dialogues proceed, we can observe a 278.59% increase of positive emotions expressed in the third turn compared to the first. The speakers mostly express emotions such as *grateful* (7.50%), *trusting* (7.26%), and *hopeful* (6.56%) as a result of the support offered by the listeners. Such conversational dynamics further validate the use of RED in applications concerning empathetic chatbots that can lift up the emotions of people suffering from distress.

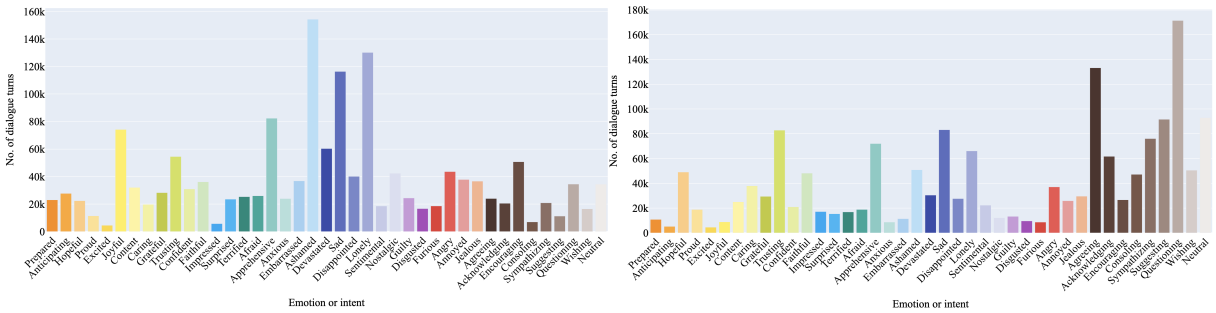
4 Conversational Baselines

Using the RED dataset as a benchmark, we trained four baseline dialogue models. The first two baselines adapted the architecture of EmoPrepend (Rashkin et al., 2018) and MEED (Xie and Pu, 2021), which are state-of-the-art empathetic chatbot models. We also examined different ways existing models can be combined to produce more empathetic responses for distress prompts. For this purpose, we developed another two experimental baselines, EPIMEED and EPIMEED+, by combining MEED with EPITOME (Sharma et al., 2020), which is a theoretically-grounded framework that can identify levels of cognitive and emotional empathy in text-based conversations and extract rationales underlying its predictions. All the models were trained on 80% of RED conversations, leaving 10% of the conversations each for validation and testing. Figure 4 show the architecture of the different models we used for evaluation.

EmoPrepend: This model proposed by Rashkin et al. (2018) is a transformer based encoder-decoder model. During training and inference, the

Subreddit	# Dialogues	# Turns	# Tokens	Avg. # turns per dialog	Avg. # tokens per dialogue	Avg. # tokens per turn
r/depression	510,035	1,396,044	106,967,833	2.74	209.73	76.62
r/depressed	10,892	23,804	1,940,000	2.19	178.11	81.50
r/offmychest	437,737	1,064,467	109,459,738	2.43	250.06	102.83
r/sad	18,827	42,293	3,088,562	2.25	164.05	73.03
r/SuicideWatch	262,469	791,737	59,267,000	3.02	225.81	74.86
r/depression_help	23,678	51,849	5,412,390	2.19	228.58	104.39
r/Anxietyhelp	8,297	18,351	1,428,287	2.21	172.14	77.83
r/MentalHealth Support	3,551	7,931	772,952	2.23	217.67	97.46
All	**1,275,486**	**3,396,476**	**88,336,762**	**2.66**	**226.06**	**84.89**

Table 1: Descriptive statistics of the conversations in the RED dataset.



(a) Speaker turns

(b) Listener turns

Figure 2: Emotion and intent distributions in speaker and listener turns in the RED dataset. The last 9 bars depict empathetic intents and the rest depict emotional statements.

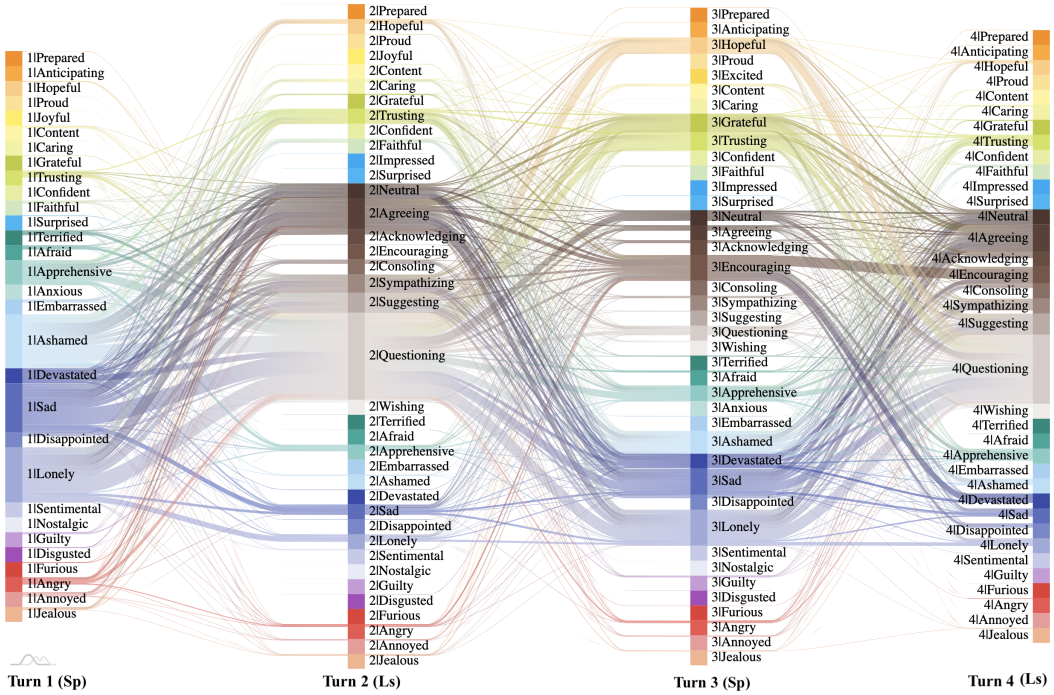


Figure 3: Frequent emotion-intent flow patterns in the RED dataset. For simplicity, only the first four dialogue turns are visualized.

top-k predicted emotion labels from a supervised classifier for the corresponding dialogue context is prepended to the beginning of the token sequence as encoder input. We initialized the encoder of this model with weights from the pre-trained language model RoBERTa (Liu et al., 2019) and trained it on RED, prepending the top-1 emotion or intent predicted by the BERT transformer-based classifier

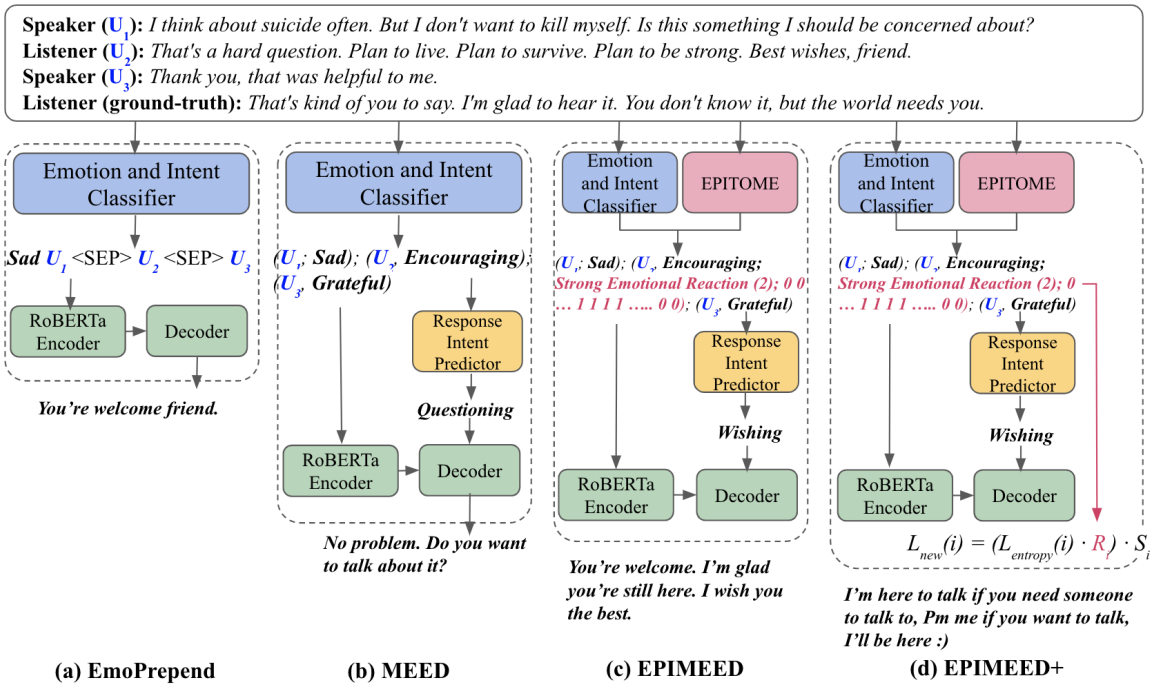


Figure 4: The four models EmoPrepend, MEED, EPIMEED, and EPIMEED+ used for evaluation.

proposed by Welivita and Pu (2020).

MEED: This model proposed by Xie and Pu (2021) consists of two modules: 1) a response emotion/intent prediction module; and 2) a response generation module. The response generation module is an encoder-decoder model that uses the transformer architecture, in which the encoder is initialized with weights from RoBERTa. The response emotion/intent prediction module takes the dialogue context as input and predicts what the emotion or intent of the response should be. This prediction is used to condition the response generated by the decoder in the first module.

EPIMEED: In therapy, interacting empathetically with clients is fundamental to success (Bohart et al., 2002; Elliott et al., 2018). Even though empathy can be interpreted as reacting with emotions of warmth and compassion (Buechel et al., 2018), a separate but key aspect of empathy is also to communicate a cognitive understanding of others, referred to as cognitive empathy. For mental health support, both emotional and cognitive empathy are equally important (Selman, 1981). Thus, it is important to identify such emotional and cognitive empathetic responses amongst other responses that appear in RED and train models in such a way that they favor such responses that reflect cognitive and emotional empathy over others. To support this, we experimented with a new model EPIMEED, by combining MEED with an existing text-based cognitive and emotional empathy identifying framework named EPITOME (Sharma et al., 2020). EPITOME recognizes three empathetic communication mechanisms 1) Emotional reactions (emotional empathy); 2) Interpretations (cognitive empathy); and 3) Explorations (cognitive empathy). For each of these mechanisms, it predicts a numerical value, 0, 1, or 2 — 0: peers not expressing them at all (no communication); 1: peers expressing them to some weak degree (weak communication); 2: peers expressing them strongly (strong communication). Table 2 shows some examples of these communication levels identified in peer support communications.

Empathy type	Communication mechanism	Examples
Emotional	Emotional reactions	- *Everything'll be fine.* (weak) - *I really hope things would improve.* (strong)
Cognitive	Interpretations	- *I realize how you feel.* (weak) - *If that happened to me, I would feel really isolated.* (strong)
Cognitive	Explorations	- *What happened?* (weak) - *I wonder if this makes you feel isolated.* (strong)

Table 2: Examples of emotional and cognitive empathy communication mechanisms identified by EPITOME.

We use this framework to assign a numerical value to each token contained in the listener re-

sponses of the RED dataset. This numerical value is the total of the values predicted by the EPITOME framework for emotional reactions, interpretations, and explorations. This is termed the rationale mask. Next, we feed this information as an additional embedding (in addition to the token embeddings, segment embeddings, position embeddings and emotion embeddings) to the encoder of the response emotion/intent prediction module and response generation module in MEED. We call this additional embedding the *communication embedding*. The rationale behind incorporating this communication embedding is to recognize and give more weight to the parts of the conversation history that expresses empathy. The accuracy, precision, and recall of the response emotion/intent predictor of MEED were increased by 22.88%, 62.65%, and 22.89%, respectively after incorporating this additional information.

EPIMEED+: To enable the model to favour responses containing stronger emotional reactions, interpretations, and explorations while decoding, we further tweaked the loss function associated with MEED such that it incorporates levels of emotional and cognitive empathy predicted by EPITOME. We modified the loss function to be the dot product between the cross entropy loss and the rationale mask predicted by EPITOME. The rationale mask predicted by EPITOME may assign 1 to each token in a text subsequence that may be considered more empathetic than the rest of the text. It acts as an amplifier to the loss so that the model will predict better the tokens with larger empathetic values as predicted by EPITOME. Compared to the original loss $L_{old\,(i)}$, the new loss $L_{new\,(i)}$ given an input sequence i can be written as:

$$L_{old\,(i)} = L_{entropy\,(i)} \cdot S_i$$
$$L_{new\,(i)} = (L_{entropy\,(i)} \cdot R_i) \cdot S_i$$

where $L_{entropy\,(i)}$, R_i, and S_i represent the cross entropy between the predicted and the ground-truth responses, the rationale mask, and the segment mask (the segment mask recognizes the speaker's tokens as 0 and the listener's tokens as 1) of the input i, respectively. By doing so, it facilitates the model to have a higher tendency to generate tokens with stronger levels of emotional and cognitive empathy as recognized by EPITOME.

5 Automatic Evaluation

Automatic evaluation of the models was conducted using a variety of automatic metrics used in evaluating chatbots. They are grouped into diversity-based, word-overlap-based, and embedding-based metrics (details in appendices). Table 3 shows results on the RED test dataset. Accordingly, MEED ranks the top in terms of distinct-unigram and distinct-bigram scores that measures the diversity of the responses. EPIMEED+ ranks the top in majority of word-overlap based metrics and also in embedding average cosine similarity, indicating that responses generated by EPIMEED+ are most likely to contain words from the ground-truth. We also computed the average no. of tokens contained in the responses and EPIMEED+ ranked at the top generating lengthier responses closer to the average length of the ground-truth.

The levels of emotional reactions, interpretations, and explorations computed by EPITOME in the responses generated by the four models are denoted in Table 4. Accordingly, EPIMEED+ generates responses that contain stronger levels of cognitive empathy (as means of interpretations and explorations) than the rest.

6 Human Evaluation

A human evaluation experiment was designed to evaluate the empathetic appropriateness of the responses generated by the four models, by recruiting workers from Amazon Mechanical Turk. We randomly selected 200 dialogue prompts from the RED test dataset and the responses generated by the four models for these prompts to be evaluated by the crowdworkers. The workers were asked to drag and drop the responses generated by the models into areas *Good*, *Okay*, and *Bad*, depending on how empathetically appropriate those responses were to the given prompt. This new way of rating makes it easy to compare many models at once instead of traditional A/B testing, which only allows the comparison of a pair of models at a time. Three workers rated the same response and the final results were computed based on the majority vote.

The human evaluation scores for each of the models is denoted in Table 5. Accordingly, it could be observed that ≈83% of the responses generated by MEED trained on the RED dataset and ≈74% of the responses generated by EPIMEED are rated *Good* with above 90% majority agreement between the workers. None of the responses

Model	Diversity metrics		Word-overlap metrics				Embedding-based metrics		Avg. length (# tokens)
	D1	D2	B1	B2	ROUGE-L	METEOR	Skip Thought	Embedding Average	
EmoPrepend	0.0317	0.1178	0.0513	0.0157	0.0662	0.0434	0.4842	0.7346	16.55
MEED	**0.0618**	**0.2889**	0.0283	0.0123	0.0690	0.0331	0.4874	0.7408	9.68
EPIMEED	0.0487	0.1912	0.0271	0.011	**0.0746**	0.0365	**0.4911**	0.7285	10.30
EPIMEED+	0.0039	0.0181	**0.0543**	**0.0191**	0.0559	**0.0637**	0.4268	**0.7650**	**40.82**

Table 3: Automatic evaluation metrics computed on the RED test dataset. D1 and D2 stands for Distinct-1 and Distinct-2 metrics and B1 and B2 stands for BLEU-1 and BLEU-2 metrics.

Model	Emotional Reactions	Interpre -tations	Explora -tions	Total
EmoPrepend	**1.148**	0.216	0.364	1.728
MEED	0.464	0.412	0.520	1.396
EPIMEED	0.480	0.168	0.732	1.380
EPIMEED+	1.036	**0.728**	**0.948**	**2.712**

Table 4: Average levels of empathy computed for the responses generated by each model, as computed by the EPITOME framework. The maximum value for each of *emotional reactions*, *interpretations*, and *explorations* is 2, making the maximum value for *total* 6.

Model	Good	Okay	Bad	2/3 agree -ment
EmoPrepend	51.82%	21.95%	26.22%	82.00%
MEED	**83.42%**	16.58%	**0.00%**	**99.50%**
EPIMEED	74.07%	**25.93%**	**0.00%**	94.50%
EPIMEED+	42.14%	25.16%	30.70%	79.50%

Table 5: Human evaluation results.

generated by the above models were rated *Bad*. This further validates the potential of the RED dataset in generating more emotionally supportive and empathetic responses for distress-related prompts. Compared to the above models, there is more disagreement between the workers on the ratings of the responses produced by EPIMEED+ (79.5% compared to 99.50% majority agreement in MEED), leading to EPIMEED+ scoring low on the percentage of *Good* ratings. We elaborate on this under the case study.

6.1 Case Study

Table 6 shows some example responses produced by the four models for two different distress prompts. It could be observed that in both cases, the four models generate responses that are emotionally supportive and empathetic to the given prompt. In the first case, the response generated by EPIMEED+ stands out from the rest since it is lengthier and contains stronger emotional reactions and explorations than the responses generated by the other three models. The same observation could be made for EPIMEED+ when responding to the second dialogue prompt, however, it could be noticed that the response is composed of repetitive statements, which was observed in a number of other responses as well. We believe that this is why workers might have more disagreement when assigning a rating to the responses produced by EPIMEED+. Future work should address such repetitive statements in the responses produced by EPIMEED+, while preserving the empathy-richness brought by emotional reactions, interpretations, and explorations.

Prompt 1: *My cat died today, and I can't get it out of my mind. I keep think of him running on a sunny hill but that only makes me cry more.*	
EmoPrepend	*I'm so sorry you're going through this.*
MEED	*I'm sorry for your loss.* **(Sympathizing)**
EPIMEED	*I'm so sorry for your loss.* **(Sympathizing)**
EPIMEED+	*I'm so sorry for what you're going through. I hope you'll be able to reach out to someone who's going through something similar. Have you looked into getting help?* **(Sympathizing)**
Prompt 2: *School is almost over. Things still haven't fixed with my best friend. I want to talk to her about it but I fear it'll just make my situation worse than it already is.*	
EmoPrepend	*I'm so sorry you're going through this. I hope things get better for you soon.*
MEED	*How long have you been together?* **(Questioning)**
EPIMEED	*Do you want to talk about it?* **(Questioning)**
EPIMEED+	*Wanna talk about it? I'm here if you want to talk about it. I'm here to listen if you need someone to talk to. You're not alone.* **(Questioning)**

Table 6: Examples of responses generated by the models for dialogue prompts from the RED test dataset. The sentences highlighted in red are repetitive statements.

7 Discussion and Conclusion

In this paper, we addressed the problem of responding empathetically to distress by curating dialogues from the peer support forum, Reddit, and develop-

ing models by adapting and hybridizing existing empathetic response generation architectures and empathy identifying frameworks. The RED dataset can be used as benchmark to develop similar and better performing chatbot models that can respond to distress. The results of the emotion and intent analysis as well as the automatic and human evaluation results of the experiments conducted on the four baseline chatbot models validate the utility of this dataset in generating emotionally supportive and empathetic responses for distress-related dialogue prompts.

But there are some limitations to this work. Since users responding to distress-related posts in Reddit are not professionals, caution must be taken if these conversations are directly used for training automatic systems that can offer emotional support. Removal of profanity is one step that we have taken towards making such systems reliable and fail-safe. The shift in the emotion of the speaker towards more positive emotions such as gratefulness is also another indicator that the responses do help the speaker lift his/her mood. But deeper analysis such as measuring the level of speaker satisfaction in subsequent dialogue turns and identifying the specific communication techniques that lead to positive outcomes are required when developing an emotionally supportive chatbot based on these conversations. We showed that incorporating existing empathetic frameworks such as EPITOME (Sharma et al., 2020) and conditioning the response on specific empathetic response intents such as in MEED (Xie and Pu, 2021) are good advances in addressing such limitations.

8 Ethics Statement

Data curation: In social sciences, analysis of posts of a website like Reddit is likely considered "fair play" as individuals are anonymous, and users can understand their responses remain archived on the site unless taken action to delete them. The Reddit privacy policy states it allows third parties to access public Reddit content through the Reddit API and other similar technologies and users should take that into consideration when posting.[*] And Reddit data is already widely available in larger dumps such as Pushshift (Baumgartner et al., 2020). We collected only publicly available data in Reddit and it did not involve any interaction with Reddit users. But a study on user perceptions on social media research ethics (Fiesler and Proferes, 2018) highlights some potential harms that can be caused due to social computing research as internet users rarely read or could fully understand website terms and conditions and are unaware that the data they share publicly could be used for research. In particular, this dataset contains sensitive information. So, as suggested by Benton et al. (2017)'s guidelines for working with social media data in health research, in this paper, we share only anonymized and paraphrased excerpts from the dataset. The shared dataset will also contain anonymized usernames and post identifiers. References to usernames and URLs are removed from dialogue content for de-identification. The dataset as well as the models are intended for research purposes only.

Distress support agents: The idea of supportive chatbots for distress is not a new concept. Chatbots such as SimSensei (DeVault et al., 2014), Dipsy (Xie, 2017), Emma (Ghandeharioun et al., 2019), Woebot (woebothealth.com), and Wysa (www.wysa.io) are some examples. As Czerwinski et al. (2021) state, *About 1 billion people globally are affected by mental disorders; a scalable solution such as an AI therapist could be a huge boon*. Thus, even though empathetic and distress support chatbots may encompass certain ethical implications as pointed out by several researchers (Lanteigne, 2019; Montemayor et al., 2021; Tatman, 2022), based on previous studies we already can acknowledge that the use of chatbots has the potential to improve mental health services notably in relation to accessibility and anonymity. It should be noted that we only address the empathetic component of such distress support agents in this paper. Delivery of therapeutic interventions for distress support should be addressed separately and does not fall under the scope of this paper. And with the significant performance achieved by recent pre-trained language models, going for a deep learning-based solution is one of the choices that can be taken when developing such an agent. But it should not be undermined that because of the unpredictability associated with generative models, they always carry a risk when delivering emotional support to those undergoing distress. Thus, caution should be taken to avoid the delivery of inappropriate responses.

[*] www.redditinc.com/policies/privacy-policy-october-15-2020

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A Topic Coverage

We used automatic clustering to identify clearly distinguishable topics present in the Reddit distress dialogues. For this purpose, we used "Agglomerative Clustering" tuned for large datasets (Murtagh and Legendre, 2014). It recursively merges pairs of clusters that minimally increase a given linkage distance. The linkage distance was computed using the cosine similarity between pairs of embeddings generated by Sentence-BERT (Reimers and Gurevych, 2019) since the resulting embeddings have shown to be of high quality and working substantially well for document-level embeddings.

We experimented with 8 similarity thresholds from 0.6 to 0.95 with 0.05 increments to cluster distress prompts. At an optimal threshold of 0.85 identified by manual inspection of a randomly selected subset of 10 clusters resulted in 4.93% of the distress prompts ($47,109$ prompts in total) getting clustered into $4,363$ clearly identifiable clusters. After applying TF-IDF-based topic modeling to these clusters, clearly distinguishable topics were uncovered. Table 7 shows some distress-related topics and their corresponding keywords.

Distress topic	Keywords
Suicidal	*commit, killing, death, painless, option*
Anxiety attacks	*anxiety, anxious, attacks, social, attack*
Weight gain	*eating, weight, eat, lose, fat*
Loneliness	*lonely, surround, connect, isolated, social*
Failing college	*study, college, class, semester, failing*
Alchoholic	*drinking, drink, alcohol, drunk, sober*
US election	*trump, president, donald, election, war*
Covid19	*covid, 19, pandemic, shambolic, brought*

Table 7: Some distress-related topics identified in the RED dataset along with corresponding keywords.

B Human Evaluation Experiment

In the human evaluation experiment, randomly selected 200 dialogues were bundled into 20 HITs (Human Intelligent Tasks) with each HIT containing 10 such dialogues. Three workers were assigned per HIT. To evaluate the workers' attentiveness to the task, we randomly inserted 3 checkpoints among the 10 dialogues by including the ground-truth response to be rated among the other chatbot-generated responses. Ideally, the ground-truth response should be rated either as *Good* or *Okay* by the workers. If a worker was able to pass at least 2 out of the 3 checkpoints, he was offered a bonus of $0.1 in addition to the compensation of $0.4 offered for completing an assignment. The bonus compensation was used as a mean to motivate workers to pay attention to the task and deliver quality work. In addition, workers who accepted more than 10 HITs were blocked automatically to avoid one worker monopolising the task. We also monitored the total time a worker takes to complete an assignment and rejected all the assignments that were completed in less than 2 minutes and added them back to the pool of available assignments. This enabled us to avoid ratings generated by inattentive workers and spammers. Figure 5 shows the task interface. An overall inter-annotator agreement score (Fleiss' kappa) of 0.2294 was observed, indicating fair agreement between the workers.

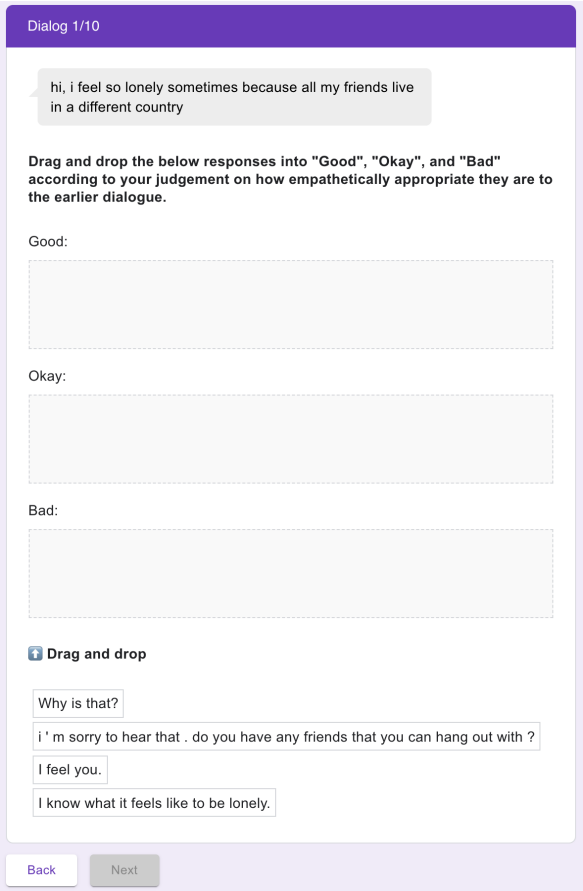

Figure 5: Dialogue response rating interface. A drag and drop mechanism was implemented for ease of rating dialogue responses by the crowdworkers.

C Example Dialogue Responses

Table 8 shows some additional example dialogue responses generated by the four models EmoPrepend, MEED, EPIMEED, and EPIMEED+ for dialogue prompts from the RED test dataset.

Speaker: *Back then I used to be all cheery, and went through my day. Now I just sit at my chair, looking down on myself, and sleeping days away. I reflect on myself no matter what, especially how I am around other people. I just lost all drive to do anything. I just want to lay down, and wish death.*	
EmoPrepend	*I'm so sorry you're going through this. You talked to anyone in your life about any of the stuff you're going through?*
MEED	*What kind of stuff is making you feel this way?* **(Questioning)**
EPIMEED	*Do you want to talk about it?* **(Questioning)**
EPIMEED+	*I've been in a similar situation. You're not alone. Did you tell anyone what you're going through or looked into getting help?* **(Questioning)**
Speaker: *I want out. I want to shoot someone, I want to be shot. I don't know what the fuck I want, I know exactly what I want. I want someone to shoot me, I don't want a new prescription doc, I want to be f**ing shot.*	
EmoPrepend	*What country do you live in?*
MEED	*Why do you want to do this?* **(Questioning)**
EPIMEED	*Why would you want to do this?* **(Questioning)**
EPIMEED+	*What's going on in your life? I'm here to talk if you want to talk. PM me if you need someone to talk to.* **(Questioning)**
Speaker: *I don't have one friend, when my family come into this house all they do is look threw me. No one talks to me unless it's something perverted online. I feel terrible.*	
EmoPrepend	*I'm sorry you're going through this.*
MEED	*How old are you?* **(Questioning)**
EPIMEED	*I'm here if you want to talk. What's going on?* **(Questioning)**
EPIMEED+	*What's making you feel this way? I'm here if you need someone to talk to.* **(Questioning)**
Speaker: *I'm dealing with severe anxiety. I feel like I'm failing my fiance. Sorry for rambling but I just feel like giving up. I just feel like I can't win.* **Listener:** *I'm going through a similar situation. I also feel like I'm failing at life.* **Speaker:** *Well, I guess we can at least go down swinging. At least I'm not alone.*	
EmoPrepend	*I'm sorry you're going through this.*
MEED	*You're not alone.* **(Agreeing)**
EPIMEED	*That's a good point.* **(Acknowledging)**
EPIMEED+	*You're not alone. I'm in the same boat. I can relate to this. I wish you'd be happy to talk to me if you want to talk about it.* **(Acknowledging)**
Speaker: *I just want to be dead, I don't want to live in this shitty world, I want to be released. I'm planning to kill myself later in life. Nobody will notice about my success.*	
EmoPrepend	*I'm so sorry you're going through this. I hope things get better for you soon.*
MEED	*Why do you want to die?* **(Questioning)**
EPIMEED	*Please don't. Why do you feel this way?* **(Questioning)**
EPIMEED+	*Why do you want to kill yourself? Why do you feel like you want to do this? Have you told anyone what you're going through or looked into getting help? If you want to talk I'm here.* **(Questioning)**
Speaker: *They say one person eventually gets attached, Funny how it's always me..* **Listener:** *How did it become that?* **Speaker:** *Cos I'm a very emotional person who gets attached very easily. I eventually become some side pet in any relationship.*	
EmoPrepend	*I'm so sorry you're going through this.*
MEED	*Are you in an open relationship?* **(Questioning)**
EPIMEED	*That's why I don't want any relationship.* **(Neutral)**
EPIMEED+	*I'm sure you're not the only one. I'm here to talk if you need to talk.* **(Neutral)**

Table 8: Examples of responses generated by the models for dialogue prompts from the RED test dataset.