

ESCoT: Towards Interpretable Emotional Support Dialogue Systems

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Abstract

Understanding the reason for emotional support response is crucial for establishing connections between users and emotional support dialogue systems. Previous works mostly focus on generating better responses but ignore interpretability, which is extremely important for constructing reliable dialogue systems. To empower the system with better interpretability, we propose an emotional support response generation scheme, named **Emotion-Focused and Strategy-Driven Chain-of-Thought (ESCoT)**, mimicking the process of *identifying*, *understanding*, and *regulating* emotions. Specially, we construct a new dataset with ESCoT in two steps: (1) *Dialogue Generation* where we first generate diverse conversation situations, then enhance dialogue generation using richer emotional support strategies based on these situations; (2) *Chain Supplement* where we focus on supplementing selected dialogues with elements such as emotion, stimulus, appraisal, and strategy reason, forming the manually verified chains. Additionally, we further develop a model to generate dialogue responses with better interpretability. We also conduct extensive experiments and human evaluations to validate the effectiveness of the proposed ESCoT and generated dialogue responses. Our data and code are available at <https://github.com/TeigenZhang/ESCoT>.

1 Introduction

Emotional support is conceptualized as expressing care, concern, affection, and interests, especially for the individuals feeling stressed or upset (Burlison, 2003; Albrecht and Adelman, 1987; Cutrona and Russell, 1987). Incorporating emotional support can yield positive effects in many scenarios, such as therapeutic sessions (Kennelly, 2001), customer service counters (Barnes and Halloy, 2005), and palliative cares (Skilbeck and

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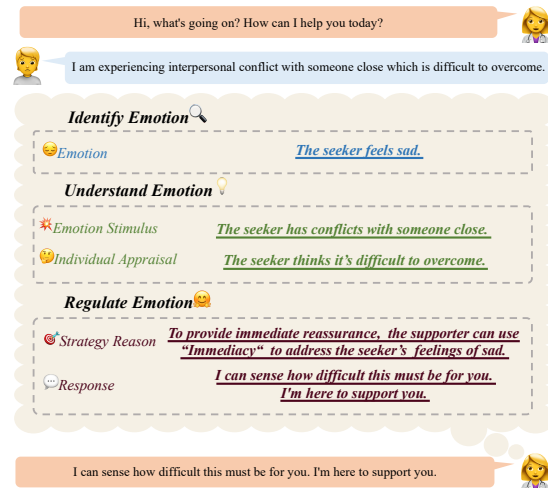


Figure 1: Illustration of the ESCoT scheme. The supporter first *identifies emotion*, then *understands emotion* from perspectives of emotional stimulus and individual appraisal, and finally chooses the appropriate strategy and responds to the seeker to *regulate emotion*.

Payne, 2003). Realizing reliable emotional support dialogue systems capable of automating these interactions is expected to expand the scope and efficacy of such services. Moreover, a reliable emotional support dialogue system should not work like a black box, providing conversational responses but unable to explain how those responses were generated (Gohel et al., 2021). As shown in Figure 1, let's imagine how a helpful supporter would work by considering the feelings of a seeker who asks for help: the supporter would first *identify* the situation and the emotion of the seeker, then *understand* and acknowledge the emotion, and finally choose appropriate strategies to respond in order to *regulate* the emotion (Vincent J. D'Andrea, 1996). Therefore, it is extremely desired to build a reliable and trustworthy emotional support dialogue system that can not only generate emotional support responses but also provide the reasoning or chain-of-thought (CoT) behind the generated responses.

Some previous endeavors have attempted to improve the interpretability of emotional support dialogue systems, such as controlling the response by emotion (Fu et al., 2023; Gao et al., 2021) or strategy (Cheng et al., 2022; Welivita and Pu, 2023), or using commonsense to augment the emotional support response (Wang et al., 2023c; Cai et al., 2023a). However, to the best of our knowledge, there is currently no such emotional support dialogue system that can provide comprehensive reasoning explanations. Therefore, in this work, we aim to build an interpretable emotional support dialogue system.

Due to the high expertise requirements for supporter roles in emotional support conversations, building a human-annotated emotional support dialogue dataset is very costly. Recently, the powerful language generation and reasoning capabilities of large language models (LLMs) have demonstrated a viable pathway to generate high-quality data. Efforts such as AUGESC (Zheng et al., 2023) and SMILECHAT (Qiu et al., 2023) have attempted to expand emotional support dialogue datasets via LLMs. However, the reasoning or chain-of-thought behind the dialogue responses has been overlooked.

In this paper, we propose an emotional support response generation scheme, named **Emotion-focused and Strategy-driven Chain-of-Thought (ESCoT)**, to generate dialogue data, inspired by the human emotional support generation process of *identifying*, *understanding*, and *regulating* emotions. Specifically, to emphasize the critical role of conversation strategies and dialogue situations, we first create diverse dialogue situations, and then enhance dialogue generation using richer emotional support strategies based on these situations. Furthermore, we complement selected dialogues with the chain-of-thought (CoT), which is represented as a quintuple (EM, ES, IA, SR, RE), reflecting the process as illustrated in Figure 1. After careful manual checking, we build the first dataset for **Emotional Support Dialogue with CoT (ESD-CoT)**, containing 1.7k+ dialogues. Moreover, we build our emotional support dialogue system with better interpretability via supervised fine-tuning a pre-trained language model on ESD-CoT, providing a strong baseline for future investigation.

Our main contributions in this work include: (1) We develop an effective emotion-focused strategy-driven chain-of-thought automatic data generation scheme called ESCoT to increase the interpretability of emotional support response generation. (2) We build the first chain-of-thought emotional sup-

port dataset ESD-CoT, containing 1.7k+ dialogues through automatic generation and manual correction. (3) We conduct human evaluations to validate from different aspects the effectiveness of our data generation scheme and the quality of our constructed dialogue dataset. (4) We build an interpretable emotional support response generation model on ESD-CoT and conduct a comprehensive assessment of the performance, providing a strong baseline for future research.

2 Related Work

Datasets Associated with Emotional Support

Lack of sufficient datasets is one of the challenges faced by emotional support dialogue systems. Due to strict personal privacy protection requirements and high expertise demands, constructing high quality and diverse empathetic and emotional support dialogue datasets is extremely challenging for humans. Sharma et al. (2020) construct a dataset for supporting the EPITOME model based on TalkLife and Mental Health Subreddits. Sun et al. (2021) scrape Q&A from the Yixinli platform and annotate responses based on psychological counseling theories to create the PsyQA Chinese dataset.

These datasets are non-dialogue datasets, but applications like psychological counseling need multi-turn dialogues. Rashkin et al. (2019) propose a new emotional dialogue generation benchmark and create a new dataset called EMPATHETICDIALOGUES, which contains 25k dialogues in emotional contexts. Liu et al. (2021) propose the ESC framework and construct a dataset named ESCoV based on this theoretical framework.

In order to obtain such datasets at a lower cost, some works leverage the power of LLMs to augment data for emotional support dialogues. Zheng et al. (2023) introduce AUGESC, an augmented dataset for the ESC (Liu et al., 2021) task by leveraging fine-tuned large language models to complete dialogues. Qiu et al. (2023) develop the SMILE approach by using ChatGPT (OpenAI, 2022) to transform single-turn dialogues into multi-turn conversations.

However, these works merely treat data augmentation as dialogue continuation or rewriting tasks, without making specific adjustments to accommodate the features of emotional support dialogues. For instance, dialogue situations and conversation strategies have not been taken into consideration.

Interpretable Dialogue Systems Deep learning models for dialogue systems are often seen as black boxes due to the complexity and opacity of their internal mechanisms. Lack of interpretability can lead to safety concerns, as it’s challenging to predict or understand the models’ decisions in critical scenarios. To address these concerns, researchers have been exploring different methods to improve the interpretability of language models.

One research direction involves integrating knowledge-based reasoning to improve the moral and ethical judgment capabilities of dialogue systems. Mehrabi et al. (2022) and Kim et al. (2022) try to incorporate external knowledge sources and structured reasoning pathways to enhance the decision-making quality of these models, particularly in scenarios requiring moral or ethical considerations. Li et al. (2023) introduce an interpretable dialogue system that employs a two-stage response generation process, enhancing response diversity and system transparency. Moreover, Izumi et al. (2024) create dialogue modules based on CBT (Beck, 1979) dialogue scenarios centered on Socratic questioning and consider the questions about ABC (Ellis, 1991). An emerging direction is to explain language models using LLMs. Bills et al. (2023) explore using GPT-4 (Achiam et al., 2023) to interpret and understand the behavior of neurons in language models such as GPT-2 XL (Radford et al., 2018). However, there is currently no emotional support dialogue system that can provide comprehensive reasoning explanations to improve the interpretability.

Chain-of-Thought Prompting Wei et al. (2022) initially introduce Chain-of-Thought (CoT) Prompting to mimic the reasoning process. Following this, various works that utilize CoT to prompt LLM for intricate reasoning tasks spring up across different domains, such as Auto-CoT (Zhang et al., 2022), SP-CoT (Wang et al., 2023b), and PsyCoT (Yang et al., 2023). To address challenges when applying CoT prompting in dialogues, Dialogue CoT (Chae et al., 2023) propose decomposing commonsense reasoning into steps and generating rationale as a sequence of inferred commonsense knowledge required for response generation to facilitate Dialogue CoT reasoning. The Cue-CoT (Wang et al., 2023a) prompts the system to infer the user status first and then generate a response based on dialogue context and user status. However, CoT for emotional

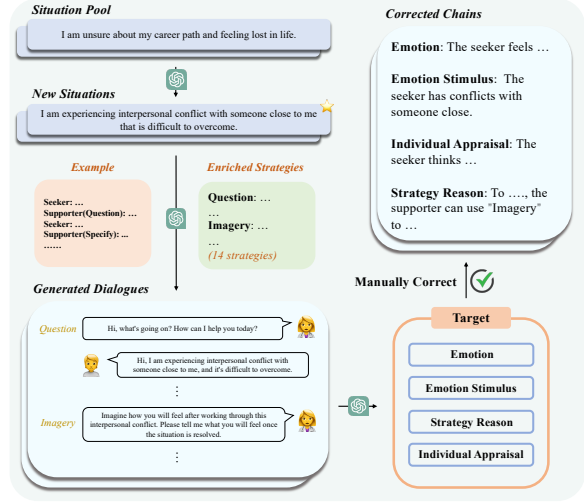


Figure 2: Illustration of our data generation scheme. We construct the ESD dataset according to the left-side process, and subsequently build the ESD-CoT dataset following the quintuple of (EM, ES, IA, SR, RE) in the right-side process.

support dialogue systems has not been well explored yet.

3 ESD-CoT Dataset Construction

Due to the high expertise requirement in the supporter role, manually constructing an emotional support dialogue dataset is very costly. Mimicking the human thought process of comforting others, we propose an Emotion-focused and Strategy-driven Chain-of-Thought (ESCoT) scheme to generate emotional support responses in an interpretable manner, and build the first Emotional Support Dialogue with CoT dataset (ESD-CoT).

The construction process of ESD-CoT dataset can be divided into two steps: (1) *ESD Construction* where we first create diverse situations, and then generate dialogues with enriched strategies based on generated situations by leveraging LLMs; (2) *ESD-CoT Construction* where we first generate reasoning chains of the selected dialogues via LLMs, and then conduct manual verification and modification to ensure the accuracy of the chains.

3.1 ESD Construction

Considering the critical role of situation and strategy in emotional support dialogues, we propose a situation- and strategy-guided dialogue generation scheme based on large language models to build a situation-diverse, strategy-rich Emotional Support Dialogue dataset (ESD). Specifically, we

first generate a more diverse range of psychological counseling situations and enrich the existing strategies used in (Liu et al., 2021). Then, we generate emotional support dialogues with the guidance of different situations and enriched emotional support strategies. Furthermore, we conduct extensive data analysis to demonstrate the quality of the generated data, and also conduct human evaluation to validate the necessity of strategy enrichment.

3.1.1 Situation Generation

The situations reflect the issues for which seekers are asking for help. In order to produce high-quality emotional support dialogues, various realistic psychological counseling situations are crucial. Inspired by (Wang et al., 2023d), we leverage the in-context learning ability of ChatGPT for extensive and diverse situation generation.

We initialize the original situation pool with 1,300 manually annotated situations in ESConv (Liu et al., 2021), forming a seed pool. We use the in-context learning method and design a situation generation prompt for ChatGPT. For each generation iteration, we randomly select eight situations from the seed pool as in-context examples and generate eight new situations adding to the seed pool. More details of the situation generation prompt are presented in Appendix A.1.

To ensure high-quality and diversity of the generated situations, we remove duplicate situations and filter out inadequate situations that lack personal pronouns or have incomplete sentences etc. Finally, 2,943 new situations are retained to enrich the generation of subsequent dialogue data.

3.1.2 Strategy Enrichment

Eight strategies are employed in the ESConv dataset (Liu et al., 2021), while other important strategies which are useful for emotional support have not yet been employed. Considering the significance of strategies in practical counseling, we therefore are motivated to further enrich the existing eight strategies established by ESConv.

Based on suggestions from experienced psychological counselors, we enrich the strategies following three principles: (1) **Distinct**: make sure each strategy focuses on different aspects compared to existing strategies. (2) **Understandable**: make sure each strategy is concise and comprehensible, even if it does not come with a short description. (3) **Identifiable**: make sure the implementation of the strategy can be easily identified from a few sen-

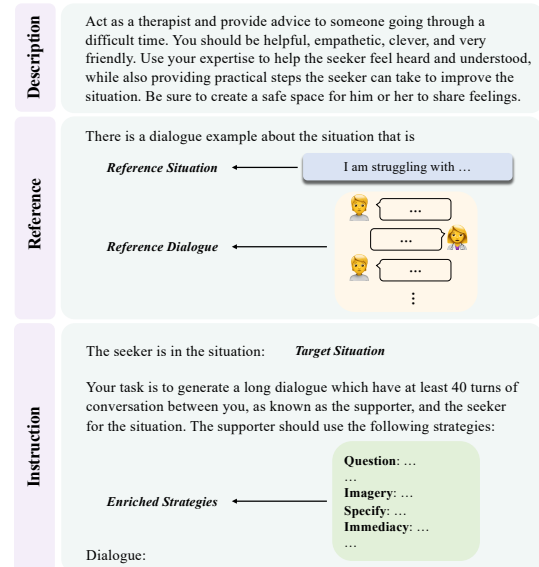


Figure 3: Prompt used for generating new dialogues.

tences. Following the above principles and under the guidance of experts, we extract six strategies from helping skills (Hill, 2009), including *Summarize*, *Imagery*, *Specify*, *Take Responsibility*, *Homework Assignment*, and *Immediacy*.

Note the focus of different strategies varies. For example, *Summarize* is a general summary of the whole conversation, while *Restatement or Paraphrasing* focuses on a simple restatement of the content just mentioned. *Homework Assignment* is a type of direct guidance, which directly tells the seeker what to do, while *Providing Suggestions* doesn't directly tell the seeker what to do. Through the expanded diverse strategies, we can generate higher quality dialogues, demonstrated by the human evaluation in 3.1.4. Detailed definitions and examples of these enriched strategies are provided in the Appendix A.2.

3.1.3 Dialogue Generation

After obtaining sufficient situations and richer emotional support strategies, we proceed to generate emotional support dialogues based on these situations and strategies.

Prompt Template The prompt format used for generating new dialogues is shown in Figure 3. We first introduce the role of a therapist and describe the task. Then, an illustrative example is provided, including *Reference Situation* and *Reference Dialogue*, serving as a template for the format and content of the dialogues we expect ChatGPT to generate. Next, the *Target Situation* is introduced, derived from the previously generated situation pool,

		ESConv	ESD (ours)
<hr/>			
Num. Dialogues		1.3K	2.9K
Avg. Turn per Dialogue		12.0	19.5
Avg. Length per Dialogue		543.6	809.0
<hr/>			
Num. Utterances		38K	113K
Avg. Length per Utterance		18.8	21.0
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Seeker	Avg. Len per Dialog	258.3	293.5
	Avg. Len per Utterance	16.8	15.2
<hr/>			
Supporter	Avg. Len per Dialog	258.4	515.6
	Avg. Len per Utterance	21.0	26.9

Table 1: Comparison between ESConv and our ESD.

to provide a specific scenario for ChatGPT to engage with. Subsequently, there is a brief restatement of the goal of the dialogue generation task to enhance ChatGPT’s comprehension of the task. In addition to the above task description and format reference, *strategy* is introduced as a crucial component, enhancing the professionalism and reliability of the generated dialogues.

Filtering and Postprocessing We find four types of undesirable dialogues from inspecting cases of the generated dialogues: (1) Inadequate Interaction Rounds; (2) Presence of Empty Utterances; (3) Insufficient Strategic Annotations; (4) Divergence from Prescribed Strategies. In order to guarantee both quantity and diversity, we regenerate filtered dialogues. We keep performing the filtering and regeneration process until finally each of the situations is paired with a high-quality dialogue. After filtering and postprocessing all the generated data, we retain dialogues with diverse and richer strategies to form our ESD dataset.

3.1.4 Statistics of ESD

The overall statistics of our generated emotional support dialogue (ESD) dataset are shown in Table 1. Compared to ESConv, our dataset is larger in scale. We also show some breakdown statistics in terms of conversation roles. Our supporter portion is significantly longer than ESConv. This aligns with our goal of enhancing the quality of responses from supporter roles in the dialogue system.

Diversity Analysis We analyze the diversity of our ESD from situation and dialogue perspectives. Situation Diversity: We assess the diversity of issues faced by seekers in the situations through word frequency analysis. The topic diversity of situations is shown in Figure 4. Our ESD dataset not only encompasses a wider range of everyday conversational themes, but also places a greater emphasis on topics related to mental well-being.

Individual discomfort issues chronic illness disability burnout infertility strain sexuality disorder chronic pain pandemic 	Career development issues job search career prospect limited resources workplace harassment career change difficult boss job loss heavy workload difficult coworker 	Economic Issues living budget bills mounting debt financial difficulties 
Mental health Issues mental illness social anxiety depression traumatic events emotional distress aftermath experiencing loneliness panic attacks ptsd 	Social Environment Issues discrimination harassment abuse prejudice bullying immigrants culture shock assault inequality 	Self-growth issues gender identity graduate body image life change life transition future prospect sexual orientation directionless feeling unfulfilled 
Marriage and family issues family conflict elderly parent caregiver childcare responsibilities divorce single parent domestic violence partner cheated newborn baby 	Interpersonal relationship issues toxic relationship friend betrayed breakup tension trouble communicating abusive relationship romantic relationship difficult roommate social isolation 	Others beliefs natural disaster 

Figure 4: The topic diversity of situations.

Dialogue Diversity: Following Zheng et al. (2023), we calculate the z-scored log odds ratio values relative to ESConv, to extract the topic features of dialogues. By analyzing the salient words of the datasets, we discover that different from ESConv which focuses solely on informal conversations and interpersonal dynamics, dialogues in our ESD are more specific, offering more professional information, and diving deeper into topics related to mental health and personal challenges. More details of the dialogue diversity can be found in Appendix A.3.

Strategy Analysis We first assess the impact of utilizing strategies in dialogue generation, and then present the statistics of application frequency of different strategies and distribution of strategies across different stages of dialogues.

Strategy Impact Assessment: To assess the impact of incorporating strategies into prompts on the quality of generated dialogues, we design and compare three different prompts: one without adding strategies, one incorporating strategies solely from ESConv, and one adding enriched strategies. Specifically, we randomly select 60 situations from ESConv and use these prompts to generate dialogues for each of these situations separately. Subsequently, we recruit 15 individuals with psychological counseling backgrounds to rank the dialogues. Following the six dimensions in AUGESC (Zheng et al., 2023), we ask the evaluators to rank the dialogues based on the given dimensions. The results are shown in Table 2. The quality of dialogues generated by ChatGPT surpasses ESConv across

	Informativeness			Understanding			Helpfulness			Consistency			Coherence			Safety		
	W	T	L	W	T	L	W	T	L	W	T	L	W	T	L	W	T	L
ESConv	237	6	297	112	5	423	153	4	383	58	22	460	72	6	462	41	63	436
Prompt w/o Strat.	273	8	259	304	10	226	284	12	244	318	42	180	311	25	204	265	141	134
Prompt w/ Original Strat.	236	10	294	305	7	228	286	10	244	278	36	226	303	24	213	253	136	151
Prompt w/ Enriched Strat.	317	10	213	343	10	187	340	8	192	355	42	143	356	21	163	282	138	120
κ	0.312			0.258			0.262			0.398			0.287			0.578		

Table 2: Evaluation of different prompts based on six dimensions: informativeness, understanding, helpfulness, consistency, coherence, and safety. Scores are presented for three evaluation measures: Win (W), Tie (T), and Lose (L). The κ (Fleiss, 1971) value in the range (0.2 < κ < 0.6) indicates fair or moderate inter-annotator agreement according to (McHugh, 2012).

	Strategy	Proportion
1	Question *	17.81%
2	Affirmation and Reassurance *	13.58%
3	Reflection of Feelings *	9.66%
4	Information *	7.59%
5	Providing Suggestions *	7.55%
6	Restatement or Paraphrasing *	6.39%
7	Self-disclosure *	3.70%
8	Homework Assignment	7.81%
9	Summarize	7.76%
10	Imagery	5.82%
11	Specify	4.31%
12	Immediacy	3.37%
13	Take Responsibility	2.85%
14	Others	1.81%

Table 3: Statistics of Strategy. * indicating the strategy also used in ESConv.

nearly all dimensions, regardless of whether strategies are applied. And incorporating our enriched strategies can generate the best dialogues in all dimensions. More details of prompts for strategy impact assessment can be found in Appendix A.4. Strategy Application Frequency: We count the usage frequency of each strategy and the proportions in Table 3. We can see that no enriched strategy shows very low frequency, indicating that our enriched strategies are well utilized in dialogue generation. Employing various strategies in emotional support dialogue generation enhances dialogue diversity and better simulates real-life interactions.

3.2 ESD-CoT Construction

Since a lack of model interpretability affects people’s trust in the model, enhancing model interpretability is a key aspect in building a reliable empathetic dialogue system for people seeking emotional support. We propose the Emotion-focused and Strategy-driven Chain-of-Thought (ESCoT) that mimics the human consultation process of identifying, understanding and regulating emotions. In this framework, understanding emotions encompasses both the emotional stimulus and the indi-

vidual’s appraisal based on the cognitive appraisal theory (Lazarus, 1991), while regulating emotions includes the strategy reason and the response generation. In general, the CoT is represented as a quintuple (EM, ES, IA, SR, RE). In this section, we supplement the chain-of-thought based on the previously generated dialogue data, and build the first dataset for Emotional Support Dialogue with CoT (ESD-CoT).

3.2.1 Chain Creation

We first automatically generate the CoT and then conduct manual correction in order to significantly reduce the annotation cost. The specific meaning of each element of the quintuple is as follows:

- 😞 **Emotion (EM)** denotes the emotion expressed by the seeker.
- ✨ **Emotion Stimulus (ES)** refers to the specific trigger that evokes the seeker’s current emotion, which can be external, such as a situation or event, or internal, such as a thought or memory.
- 😊 **Individual Appraisal (IA)** denotes the seeker’s personal interpretation, evaluation, and internal response to the emotion stimulus, based on the seeker’s past experiences, beliefs, expectations, and personal values.
- 🎯 **Strategy Reason (SR)** represents the reason why the supporter used the chosen strategy in the last utterance.
- 💬 **Response (RE)** denotes the response provided by the supporter in the ongoing dialogue.

More details about the CoT generation template are presented in Appendix B.

3.2.2 Manual Correction

After generating preliminary CoT using ChatGPT, we conduct manual correction to ensure the quality. Based on the definition of each element, we

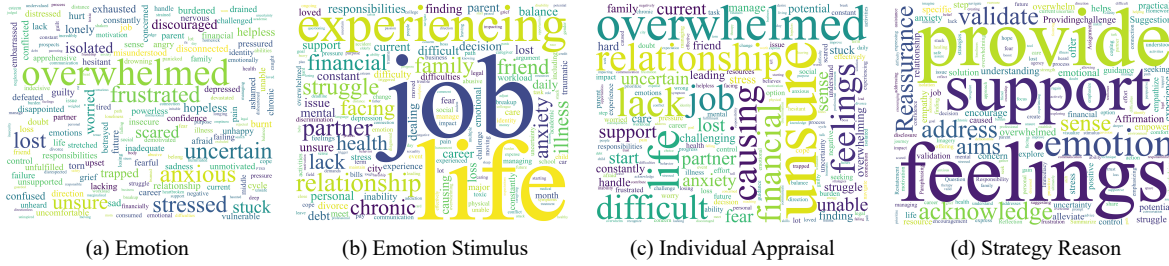


Figure 5: The word cloud of each component of ESC-CoT chain annotations.

		Num. of Dialogues	1,708
Dialogue	Num. of Turns per Dialogue		23.4
	Avg. Length per Dialogue		432.4
		Emotion (<i>EM</i>)	7.9
CoT (Avg. Length)		Emotion Stimulus (<i>ES</i>)	17.6
		Individual Appraisal (<i>IA</i>)	36.1
		Strategy Reason (<i>SR</i>)	60.5
		Response (<i>RE</i>)	26.6

Table 4: Statistics of our ESD-CoT dataset.

identify several issues in the raw CoT data: (1) Unclear Emotional Expression; (2) Lacking Specific Examples; (3) Verbose Personal Evaluations; (4) Mismatch between Strategies and Responses. Therefore, we perform manual corrections to these issues. Additionally, we filter out toxic data to enhance the security and ethics of the dataset. After processing all the generated data, we finally construct our ESD-CoT dataset with a total of 1,708 dialogues accompanied with CoT, explaining why and how emotional support responses are generated.

3.2.3 Statistics of ESD-CoT

Table 4 presents the statistics of our ESD-CoT dataset. The relatively long dialogue turns and length of ESD-CoT provide sufficient information for CoT analysis. The length of *EM* indicates that the seeker often expresses multiple emotion in the dialogue. The length of *IA* is more than twice that of *ES*, as *IA* provides a more detailed personal appraisal based on *ES*, involving more cognitive processing and emotional expression. The relatively long *SR* provides detailed explanations about the reasons for the chosen strategy, potentially enhancing interpretability. Table 5 shows the distribution of strategies in ESD-CoT dataset. We ensure that each strategy has at least 100 samples in our ESD-CoT dataset. Overall, our dataset ESD-CoT is richer in content and strategy, and provides interpretable CoT annotations, thereby enhancing the credibility of emotional support responses.

Strategy	Train	Val	Test	Total
Reflection of Feelings	68	13	19	100
Question	89	15	20	124
Providing Suggestions	123	12	41	176
Summarize	73	11	16	100
Specify	86	21	30	137
Restatement or Paraphrasing	83	9	21	113
Homework Assignments	66	11	24	101
Affirmation and Reassurance	224	31	63	318
Imagery	88	8	26	122
Information	74	11	29	114
Self-disclosure	75	11	14	100
Immediacy	76	8	19	103
Take Responsibility	70	11	19	100
Total	1195	172	341	1708

Table 5: The strategy distribution of ESD-CoT dataset.

Semantic Analysis We show the word clouds of components of the quintuple in our ESD-CoT dataset in Figure 5. The emotional words such as ‘overwhelmed’ and ‘anxious’ clearly reflect the emotional state expressed by the seeker. Additionally, the stimulus words such as ‘job’, ‘life’, and ‘partner’ help to recognize the specific issues and sources of stress that the seeker is facing, thereby providing more targeted support and understanding. In the word cloud for individual appraisal, words like ‘unsure’ and ‘lack’ frequently appear, indicating the seeker’s perception and assessment of their own situation, reflecting the seeker’s apparent awareness of uncertainty and inadequacy in aspects such as job, life, and partner relationships. The word cloud of strategy reason includes keywords such as ‘provide’, ‘support’, ‘acknowledge’, and ‘emotion’, indicating the factors that the supporter prioritizes when choosing strategies. This suggests that the supporter tends to offer support and understanding to the seeker, alleviating uneasiness and anxiety by acknowledging the seeker’s emotion.

4 Experiments

We split the dataset into train, validation, and test with the ratio of 7:1:2, as shown in Table 5. We evaluate the following pre-trained language models as backbone models for dialogue response

Row	Setting					Automatic Evaluation for Response					Human Evaluation			
	<i>EM</i>	<i>ES</i>	<i>IA</i>	<i>SR</i>	<i>RE</i>	B-1	B-2	R-L	D-1	D-2	Coh.	Inf.	Emp.	Acc.
1	✓	✓	✓	✓	✓	15.59	5.11	17.67	15.26	44.40	1.65	1.51	1.71	85%
2	✓	✗	✗	✓	✓	16.03	5.72	18.41	14.89	43.52	1.63	1.36	1.66	79%
3	✗	✗	✗	✓	✓	16.36	5.88	18.72	14.37	41.67	1.44	1.19	1.40	64%
4	✗	✗	✗	✗	✓	17.45	7.13	20.08	14.84	43.98	1.63	1.32	1.42	N/A

Table 6: Ablation study based on the LLAMA2-7B-CHAT model to explore the impact of different elements of ESCoT on the response (*RE*). All automatic evaluation results are average scores of 3 runs with random seeds. The κ values of coherence, informativeness and empathy are 0.27, 0.33 and 0.35 respectively, which indicate fair inter-annotator agreement ($0.2 < \kappa < 0.4$) as shown in (McHugh, 2012).

	B-1	B-2	B-3	B-4	R-L
BlenderBot	29.18	16.39	10.28	6.55	29.51
DialoGPT	35.10	22.15	15.50	10.22	40.50
LLAMA2-CHAT	44.87	32.37	25.85	20.66	48.16

Table 7: Comparison of chain generation performance on ESD-CoT test set with different fine-tuned backbone models. B-n: BLEU-n, R-L: ROUGE-L.

generation: (1) BlenderBot (Roller et al., 2021); (2) DialoGPT (Zhang et al., 2020); (3) LLAMA2-CHAT (Touvron et al., 2023).

Evaluation Metrics We apply three commonly used automatic evaluation metrics, BLEU-n (Papineni et al., 2002), ROUGE-L (Lin, 2004); and Distinct-n (Li et al., 2016).

As for human evaluations, following Tu et al. (2022) and Cai et al. (2023b), we recruit 3 professional annotators to evaluate randomly selected 50 responses of different settings from the *Coherence*, *Informativeness*, and *Empathy* aspects with the levels of {0,1,2}. We also conduct a human evaluation to evaluate the *Accuracy* of the consistency between the selected strategy and the corresponding response. More details of human evaluations can be found in Appendix C.

4.1 Comparison of Backbone Models

To enable chain generation with better interpretability, we fine-tune backbone models on ESD-CoT train set and report the performance of chain generation on the test set in Table 7. LLAMA2-CHAT outperforms other backbone models on all metrics, which can be attributed to larger parameters, more training data, and the utilization of reinforcement learning with human feedback in LLAMA2-CHAT. Specially, since the process of ESCoT involves reasoning, we believe the reasoning ability that emerges from increasing parameters is very important for interpretable emotional support. Due to its excellent performance, we conduct the ablation

study based on LLAMA2-CHAT in the following subsection. More implementation details of supervised fine-tuning can be found in Appendix D.1.

4.2 Ablation Study

To explore the effects of different elements of the ESCoT on the generated response, we conduct the ablation study and report the results in Table 6. Specially, we remove some nodes of the chain and train models for each setting, and calculate the metrics only based on the *RE* part of the model outputs. More implementation details of the ablation study can be found in Appendix D.2.

Generation with the entire chain, as outlined in the first row, achieves the best performance on metrics D-1 and D-2, which may be due to the fact that many steps in the entire CoT chain cause relatively greater randomness in response generation, leading to better diversity in the generated responses. We also notice that the setting of directly generating responses in the fourth row achieves the best results on B-1, B-2, and R-L, which are primarily used to assess the similarity between the prediction and ground truth. As the automatic metrics are calculated only based on the *RE* part, directly fitting the *RE* part yields the best results.

However, BLEU and ROUGE primarily focus on the similarity between the prediction and ground truth, which can not effectively measure the effects of emotional support. So, we conduct human evaluations to assess the effects of different ablation settings better. The setting of the complete chain in the first row achieves the highest performance in all human evaluation dimensions, indicating that it not only provides the most comprehensive interpretability but also delivers more coherent, informative, and empathetic responses. As for the strategy consistency assessment, the highest accuracy is also achieved by the full chain. Removing the emotion understanding component in the second row decreases strategy consistency, and further

removing the emotion identification component in the third row leads to an additional decline in strategy consistency. We demonstrate a case study for the ablation study in Appendix G.

In summary, the whole chain exhibits the best response in major aspects and offers the most comprehensive interpretability, providing a strong baseline and feasible path towards interpretable emotional support dialogue systems.

5 Conclusion

In this paper, inspired by the human consultation process of identifying, understanding, and regulating emotions, we propose a novel emotion-focused and strategy-driven chain-of-thought (ESCoT) emotional support response generation scheme and apply it in building the first dataset for emotional support dialogue with chain-of-thought named ESD-CoT. Moreover, we conduct extensive experiments and human evaluations to validate that the new benchmark based on ESD-CoT can provide effective emotional support with better interpretability. We hope our ESD-CoT dataset and baseline models can facilitate further investigation into interpretable emotional support dialogue systems in the community.

Ethics Statements

The interpretability of emotional support dialogue systems has become increasingly important in real applications. We deeply recognize the need for caution in developing datasets related to ethical issues. Our goal is to create an interpretable emotional support dialogue dataset and system. During the construction of the dataset, we strictly adhere to data source usage agreements, making diligent efforts to eliminate any biased, offensive, or inappropriate content to avoid potential unpredictable ethical harm. All human annotators and evaluators are paid according to their individual working hours. We hope that this dataset will enhance the transparency and credibility of emotional support system responses, thereby establishing a bridge of trust and understanding between users and emotional support dialogue systems.

Limitations

Although we reduce a lot of costs by utilizing ChatGPT during the generation phase, the scale of our dataset remains relatively small due to limitations in the cost of manual correction. Future

work could focus on designing more automated correction methods to reduce the manual component and lower the cost of dataset construction even more. To enhance the diversity of the generated dialogue data, we incorporate rich situations and expanded strategies into the prompt. We plan to further enhance the diversity of the emotional support dialogue dataset by introducing more personalized information, such as personality. Furthermore, the strategy annotation of current public emotional support datasets only focuses on single strategies, neglecting the compound strategies, and we annotate the major strategy when facing multiple strategies. We consider exploring compound strategies to prove more effective emotional support in the near future.

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A Details of ESD Dataset Construction

A.1 Prompt for Situation Generation

Inspired by Ouyang et al. (2022), we use the prompt in Figure 6 to generate new situations.

Come up with a series of situations:

Situation 1: {The 1st situation for reference}
 Situation 2: {The 2nd situation for reference}
 Situation 3: {The 3rd situation for reference}
 Situation 4: {The 4th situation for reference}
 Situation 5: {The 5th situation for reference}
 Situation 6: {The 6th situation for reference}
 Situation 7: {The 7th situation for reference}
 Situation 8: {The 8th situation for reference}
 Situation 9:
 Situation 10:
 Situation 11:
 Situation 12:
 Situation 13:
 Situation 14:
 Situation 15:
 Situation 16:

Figure 6: The prompt used for generating new situations.

A.2 Definitions and Examples of Enriched Strategies

Through our enriching process, we double the size of strategies based on ESConv. Table 8 presents the entire list of strategies that are employed in our emotional support dialogue generation, including both definition and example for each strategy.

A.3 Details of Dialogue Diversity Analysis

We calculate the log odds ratio values for the words of ESD relative to ESConv, which is formulated as follows:

$$\text{LogOddsRatio}(i) = \log\left(\frac{p_{i,1}/(1-p_{i,1})}{p_{i,2}/(1-p_{i,2})}\right) \quad (1)$$

where $p_{i,1}$ and $p_{i,2}$ represent the probabilities of the word i in two compared datasets. Based on the log odds ratio values, we calculate the z-score as follows:

$$z\text{-score}(i) = (\text{LogOddsRatio}(i) - \mu) / \sigma \quad (2)$$

where μ is the mean of all words’ log odds ratio, and σ is the standard deviation.

We rank all words based on their z-scores. The top 25 significant words and their z-scores for each

dataset are shown in Table 9. In the comparison between two datasets, the word with higher z-scores can represent a greater distinction within its dataset compared to the other dataset.

In the ESConv dataset, words such as ‘wow’, ‘mad’, ‘sucks’, and ‘horrible’ reflect emotional states and reactions. Additionally, word like ‘counselling’, ‘grade’, ‘zoom’ and ‘survey’ point to various types events in school. Words like ‘covid’, ‘vaccine’, ‘virus’, and ‘holiday’ suggest discussions about time and significant events. Expressions like ‘lol’, ‘bye’, and ‘ya’ indicate informal and colloquial conversations.

In contrast, our dataset contains words like ‘resilience’, ‘visualizing’, ‘caregiving’, and ‘vision’, which relate to coping strategies and empowerment. Words like ‘gender’, ‘sexuality’, and ‘accommodations’ indicate a theme related to identity and inclusivity. The presence of words like ‘substance’, ‘cognitive’, and ‘culture’ suggest that there are discussions focusing on psychological and cultural aspects in ESD dataset.

The analysis of these significant words shows that ESConv dataset are more general, focusing on everyday life, emotions, and informal interactions. In contrast, our dataset is more specific and related to more professional guidance, diving into subjects related to mental health and personal challenges deeper.

A.4 Prompts for Strategy Impact Assessment

To assess the impact of incorporating strategies into prompts on the quality of generated dialogues, we design three different prompts: (a) without adding strategies, (b) incorporating strategies solely from ESConv, and (c) adding our enriched strategies. Only the instruction parts of these prompts are different, which are outlined in Figure 7 with the differences highlighted.

B Chain Creation Prompt of ESD-CoT Dataset

The prompt template used for generating chains is shown in Figure 8. We first introduce the task and give the definition of each element. Then, we provide an *example*, which will be replaced with the chain example in the example pool. Furthermore, we provide the *dialogue*, which needs to be supplemented with the chain. Finally, we standardize the format of the output. Note the *target strategy* will be replaced with the strategy used in the formerly

	Strategy	Definition & Example
1	Question*	Asking for information related to the problem to help the seeker articulate the issues they face and open-ended questions are best. <i>E.g.: How do you define success in your life?</i>
2	Restatement or Paraphrasing*	A simple, more concise rephrasing of the seeker’s statements that could help them see their situation more clearly. <i>E.g.: It seems like you’re experiencing a crisis of faith and that it’s causing you a lot of inner turmoil and confusion.</i>
3	Reflection of Feelings*	Articulate and describe the seeker’s feelings. <i>E.g.: It seems like you’re feeling quite anxious about this decision.</i>
4	Self-disclosure*	Divulge similar experiences the supporter has had or emotions the supporter shares with the seeker to express empathy. <i>E.g.: I’ve felt similar when I was in a tough spot at work; it’s really challenging.</i>
5	Affirmation and Reassurance*	Affirm the seeker’s strengths, motivation, and capabilities and provide reassurance and encouragement. <i>E.g.: You’ve been really resourceful in handling challenges before; I’m confident you can get through this.</i>
6	Providing Suggestions*	Provide suggestions about how to change, but be careful not to overstep and tell them what to do. <i>E.g.: Perhaps trying a new approach to this problem might yield different results. Have you considered brainstorming with a team?</i>
7	Information*	Provide useful information to the seeker, e.g., data, facts, opinions, resources, or by answering questions. <i>E.g.: There are several techniques for stress management, like mindfulness and exercise, that may be helpful.</i>
8	Summarize	Brief recaps that highlight key themes from both the seeker’s and the supporter’s interactions, and make connections within the seeker’s story. <i>E.g.: So it sounds like you’re struggling to manage your debts and you feel overwhelmed by the situation. We talked about some practical steps you can take, such as reaching out to your lenders and setting up a budget. You also mentioned feeling alone and helpless, but I want to remind you that you’re not alone and there are resources and support available to you.</i>
9	Imagery	Encourage the seeker to visualize different situations or outcomes to gain insights or relieve stress. <i>E.g.: Imagine a scenario where you’ve successfully overcome your current challenges. How does that look and feel?</i>
10	Specify	Invite the seeker to provide more detail on the general statements they have previously made, for example, by using concrete instances. <i>E.g.: You mentioned feeling overwhelmed. Can you give a specific example of what triggers this feeling?</i>
11	Take Responsibility	Encourage the seeker to take suitable responsibility for their actions. <i>E.g.: Ultimately, the decision is yours to make. You have to take responsibility for the choice you make and how it impacts your future.</i>
12	Homework Assignment	Given tasks or activities to help the seeker practice what they learned in the conversation. <i>E.g.: For the next week, try to jot down your thoughts in a journal whenever you feel stressed. It might help you understand your emotions better.</i>
13	Immediacy	Involve the supporter in sharing their immediate feelings about the seeker or their relationship. <i>E.g.: I want you to know that I’m here for you if you need anything else.</i>
14	Others	Exchange pleasantries and use other support strategies that do not fall into the above categories.

Table 8: Definitions of enriched strategies. * represents the strategy also used in ESConv.

ESConv
lol (5.1), covid (5.1), bye (4.9), vaccine (4.5), wow (4.3), mad (4.2), guy (4.2), virus (4.2), holiday (4.2), yea (4.2), press (4.1), girl (4.0), sucks (4.0), horrible (4.0), pray (3.9), fine (3.8), super (3.8), bet (3.8), alot (3.8), counselling (3.8), grade (3.7), lockdown (3.7), boyfriend (3.7), zoom (3.7), survey (3.7), ya (3.6), awhile (3.6), gonna (3.6), closed (3.6), 19 (3.5)
ESD
visualizing (5.7), discrimination (5.4), resilience (5.2), visualize (5.1), visualization (5.0), caregiving (4.9), exploring (4.7), summary (4.6), specializes (4.5), infertility (4.5), incorporating (4.4), vision (4.4), bravery (4.3), unfulfilled (4.3), caregivers (4.3), gender (4.2), navigating (4.2), sexuality (4.2), accommodations (4.2), drowning (4.1), prioritize (4.0), empowered (4.0), behavioral (4.0), effectively (4.0), substance (4.0), cognitive (4.0), culture (3.9), covers (3.9), align (3.9), setbacks (3.9)

Table 9: Top 30 salient topic features. The values in parentheses are the z-scored log odds ratios for the corresponding word.

generated dialogue.

C Details of Human Evaluation

As for the response evaluation, to fairly evaluate different responses, we randomly shuffle the responses when evaluated by annotators. We pay for these 3 annotators, and all the results are proof-checked by an expert.

As for the strategy consistency evaluation, we randomly choose 100 chains for the settings containing *SR* and recruit 2 professional annotators to evaluate the consistency and another professional annotator to deal with the situation where two annotators’s assessments are inconsistent.

D Implementation Details

D.1 Supervised Fine-Tuning

BlenderBot is an open-domain conversational agent equipped with a range of communication

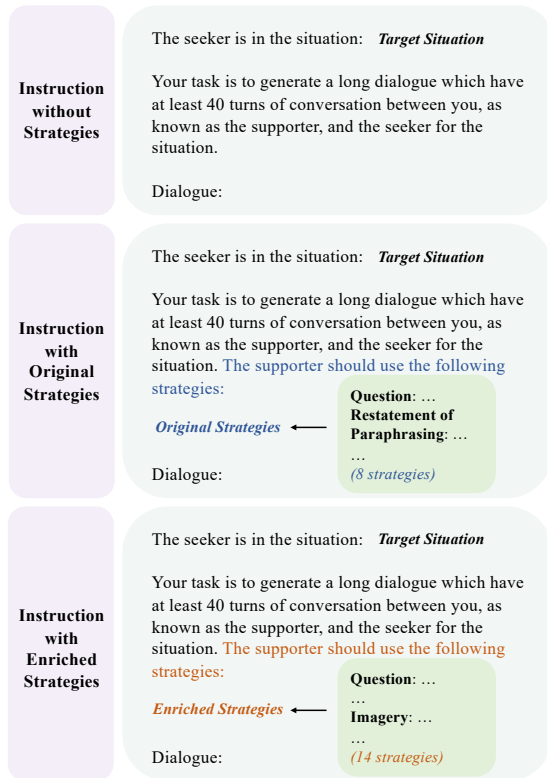


Figure 7: The instruction part of prompts used for the strategy impact assessment. The differences between the instruction parts are highlighted.

skills, including empathetic response capabilities. For our experiments, we use the small[†] version of BlenderBot. We train the BlenderBot model based on the code of ESConv[†] (Liu et al., 2021). We train the model using one A6000 GPU, with a batch size of 64, a learning rate of 3e-5, and a max sequence length of 500.

DialoGPT is a model built upon the foundation of the dialogue generative pre-trained transformer, specially, GPT-2 (Radford et al., 2018). For our experiments, we use the small[†] version of DialoGPT. We train the DialoGPT model based on the code of ESConv (Liu et al., 2021). We train the model using one A6000 GPU, with a batch size of 32, a learning rate of 5e-5, and a max sequence length of 500.

LLAMA2-CHAT is a pre-trained model optimized for dialogue use cases, which has been specifically designed to adapt to a wide range of conversational scenarios. For our experiments, we

[†]https://huggingface.co/facebook/BlenderBotbot_small-90M

[†]<https://github.com/thu-coai/Emotional-Support-Conversation>

[†]<https://huggingface.co/microsoft/DialoGPT-small>

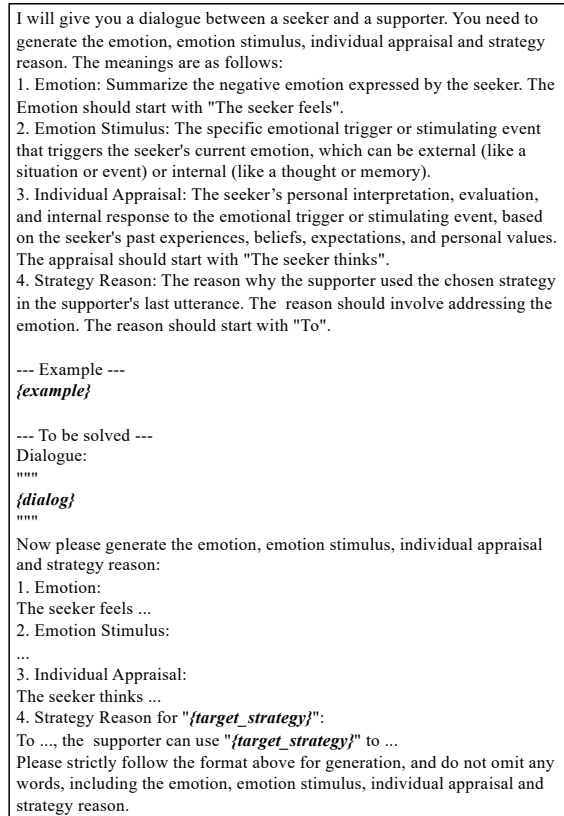


Figure 8: The prompt template used for chain creation of the ESC-CoT dataset.

use the 7B version of LLAMA2-CHAT on Hugging Face. The training of LLAMA2-CHAT model is based on the SFT trainer of Transformer Reinforcement Learning[†] (von Werra et al., 2020). We train the model using 4*A6000 GPUs, with batch size of 8 per GPU, learning rate of 5e-5, and max sequence length of 2048.

D.2 Ablation Study

We conduct the ablation study based on LLAMA2-CHAT. The model size and parameters are the same as those in Appendix D.1. The only difference between different settings is the composition of the data. For example, in the setting of {EM, SR, RE}, the instruction is "Generate the response as the supporter using the pipeline of Emotion, Strategy Reason, Response." and the corresponding ground truth consists of the manually checked Emotion, Strategy Reason, and Response. For each setting, we train the model for 10 epochs using 4*A6000 GPUs for approximately 3 hours, with batch size of 8 per GPU, learning rate of 5e-5, and max sequence length of 2048 on the training dataset, and select the best-performing checkpoint

[†]<https://github.com/huggingface/trl>

based on the validation dataset to obtain its performance metrics on the test dataset.

E Examples of ESD Dataset

We present examples of the ESD dataset in Figure 9 and Figure 10, including situations and the generated dialogues. The strategies originally present in ESConv are labeled in green, while the strategies we enriched are marked in red.

F Examples of ESD-CoT Dataset

We present examples of the ESD-CoT dataset in Figure 11 and Figure 12. The upper part is the context of the dialogue, and the lower part is the chain to generate the supporter's response. The chain and the corresponding part of the dialogue are highlighted in the same color.

G Case Study

In Table 10, we demonstrate a case of the ablation study. In this case, the seeker feels trapped and isolated in a toxic relationship and unsure about what the right thing to do is. The model's responses from different incomplete chain settings are focused only on one aspect. In the full chain setting, the model's response considers empathy and emphasizes the importance of personal responsibility. It encourages the seeker to make decisions that align with their values and goals and to clarify the next steps. Besides, the reason for the generated response can be clearly seen in the setting of the entire chain.

Situation: I'm battling chronic procrastination and experiencing difficulty sticking to schedules and deadlines, which are hampering both my personal and professional productivity.

Dialogue:

1. seeker: I'm battling chronic procrastination and experiencing difficulty sticking to schedules and deadlines, which are hampering both my personal and professional productivity.
2. supporter(*Reflection of Feelings*): It sounds like you're going through a tough time with balancing your personal and professional life, which is affecting your productivity.
3. seeker: Yes, that's right. I feel like I never have enough time to get everything done, and I end up putting things off until the last minute.
4. supporter(*Restatement or Paraphrasing*): So, you're feeling overwhelmed with your workload and struggling with time management?
5. seeker: Exactly. It's so frustrating because I know I need to be more productive, but I just can't seem to get myself to do anything.
6. supporter(*Question*): Can you tell me more about what specifically is causing you to procrastinate?
7. seeker: I think it's a combination of things. I get easily distracted by social media and other things on my phone, and sometimes I feel like I'm not good enough to complete the tasks I've been assigned.
8. supporter(*Restatement or Paraphrasing*): It sounds like you may be struggling with self-doubt and self-criticism. Does that sound accurate?
9. seeker: Yes, absolutely.
10. supporter(*Self-disclosure*): I've struggled with procrastination and self-doubt as well. It's not an easy thing to overcome, but it's definitely possible with the right tools and mindset.
11. seeker: That's good to know. I'm just feeling really down on myself lately.
12. supporter(*Affirmation and Reassurance*): I can understand why you're feeling that way, but it's important to remember that you're capable and competent. Everyone has moments of self-doubt, and it's okay to make mistakes.
13. seeker: Thank you, that helps.
14. supporter(*Information*): Have you tried using any productivity tools or techniques?
15. seeker: Not really. I've heard of things like the Pomodoro technique, but I don't know much about it.
16. supporter(*Providing Suggestions*): The Pomodoro technique is a great way to break down your work into smaller, more manageable chunks. You work for 25 minutes, then take a break for 5 minutes. It can really help with focus and productivity.
17. seeker: That sounds interesting. I'll have to try it out.
18. supporter(*Homework Assignment*): That's great. As homework, I challenge you to try using the Pomodoro technique for one task this week. See how it goes, and let me know how you feel after.
19. seeker: Okay, I can do that.
20. supporter(*Imagery*): **Imagine what it would feel like to finish a task ahead of schedule. How would it feel to have more free time because you're able to get more done during the day?**
21. seeker: It would feel amazing. I'd love to feel more in control of my time and less stressed out.
22. supporter(*Question*): What do you think is the biggest obstacle preventing you from being more productive and managing your time effectively?
23. seeker: I think it's myself. I get in my own head and tell myself I'll never be able to do it, so I don't even try.
24. supporter(*Take Responsibility*): It's good that you recognize that. It's important to take responsibility for our own thoughts and actions. How can you start to change that negative self-talk and replace it with more positive, empowering thoughts?
25. seeker: I don't know, maybe I can start by writing down some positive affirmations and repeating them to myself every day.
26. supporter(*Specify*): **That's a great idea. Can you give me an example of a positive affirmation you might use?**
27. seeker: I could say something like "I am capable and productive. I can achieve anything I set my mind to."
28. supporter(*Information*): Did you know that exercise can also be a great way to boost productivity and mood?
29. seeker: No, I didn't know that. How does that work?
30. supporter(*Information*): Exercise releases endorphins, which can help elevate mood and reduce stress. Plus, it can help increase energy levels and focus.
31. seeker: That makes sense. I definitely need to make time for exercise.
32. supporter(*Summarize*): **It sounds like you're struggling with procrastination and time management, which is causing stress and self-doubt. We talked about using tools like the Pomodoro technique, positive affirmations, and exercise to help improve productivity and mood.**
33. seeker: Yes, thank you for listening and helping me come up with some solutions. I feel better about tackling this now.

Figure 9: An example of the ESD dataset. The sentences corresponding to the **enriched strategies** are **notably distinct** from the **original strategies**. For instance, the sentence in line 20 makes the seeker see the hope and create new experiences by *Imagery* strategy. Then, the sentence in line 26 makes the seeker's methods more clearly and easier to implement by *Specify* strategy. Furthermore, the sentence in line 32 provides a comprehensive overview of the current challenges and solutions by *Summarize* strategy. These aspects were relatively uncommon in previous emotional support dialogue datasets.

Situation: I am facing legal trouble and am unsure of how to proceed with navigating the legal system and protecting my rights.

Dialogue:

1. seeker: I'm really scared. I've been charged with a crime and I don't know what to do next.
2. supporter(*Affirmation and Reassurance*): **I can imagine how scary this must be for you. It's important to remember that you are not alone. We can work through this together.**
3. seeker: Thank you. I just feel like I'm in over my head. I never thought I would be in this situation.
4. supporter(*Specify*): **Can you tell me more about the specifics of what happened and how you ended up in this situation?**
5. seeker: Well, I got into a fight with someone and it got physical. I didn't mean for it to escalate like that.
6. supporter(*Reflection of Feelings*): It sounds like you're feeling regretful about what happened and worried about the consequences.
7. seeker: Yes, exactly.
8. supporter(*Take Responsibility*): It's important to take responsibility for our actions, even if they were unintended. Have you considered reaching out to a lawyer for guidance?
9. seeker: I have, but I'm not sure if I can afford one.
10. supporter(*Information*): **There are resources available if you need help finding affordable legal representation. I can provide you with some options and we can work through this together.**
11. seeker: That would be really helpful. Thank you.
12. supporter(*Information*): There are also support groups and counseling services available for people going through similar legal troubles. Would you be interested in looking into those options?
13. seeker: Yes, definitely. I could use all the support I can get right now.
14. supporter(*Imagery*): Let's take a deep breath together and visualize a positive outcome to this situation. What would it look like if everything worked out in your favor?
15. seeker: I would be able to move on with my life without this hanging over my head and feeling like I'm a criminal.
16. supporter(*Affirmation and Reassurance*): **It's understandable to feel overwhelmed and uncertain about your future.**
17. seeker: That's comforting to hear. Thank you.
18. supporter(*Summarize*): So, it sounds like you're feeling scared and overwhelmed about the legal process, but you're also open to getting support and finding a positive outcome.
19. seeker: Yes, that's correct.
20. supporter(*Question*): What steps have you taken so far to address the legal charges against you?
21. seeker: I've spoken to a few friends and family members, but I haven't reached out to any legal resources yet.
22. supporter(*Providing Suggestions*): It might be helpful to make a plan for the next steps, such as reaching out to lawyers or counseling services. Would you be willing to create a list of action items that we can work on together?
23. seeker: Yes, that's a good idea. I would appreciate the help.
24. supporter(*Summarize*): **It sounds like you're in a difficult legal situation and feeling scared and uncertain about the future. However, you're open to seeking support and finding a positive outcome, and we can work together to create an action plan to move forward.**
25. seeker: That's a great summary. Thank you for your help and support.

Figure 10: Another example of the ESD dataset. The sentences corresponding to the **original strategies** and **enriched strategies** **both contribute** to the progression of the dialogue. For instance, the sentence in line 2 timely responds to and reassures the scare exposed by the seeker is seen by the supporter in line 1. The sentence in line 4 asks the seeker to reveal crucial specific information so that the current situation will be more clear, and gives the seeker an opportunity to express. The sentence in line 10 responds to the difficulty of the seeker in line 9 and clarifies that the supporter can offer useful resources, which gives the direction for the subsequent content. The sentence in line 16 affirms and stabilizes the seeker's emotions. Finally, the sentence in line 24 summarizes the entire dialogue and proposes further arrangements, enabling the seeker not to fall into the current situation.

Dialogue:
 seeker: I was passed over for a promotion at work and am feeling **frustrated and unsure** how to navigate my career moving forward.
 supporter: I can imagine how disappointed and frustrated you must feel after being passed over for a promotion. Can you tell me more about what happened at work?
 seeker: Well, **I worked really hard and was hoping to get promoted. But someone else got the job.**
 supporter: What kind of feedback did you get from your managers about why you didn't get the promotion?
 seeker: They said that I need to work on my leadership and communication skills.
 supporter: It sounds like your bosses think that you have some room to grow in terms of leadership and communication. How do you feel about their feedback?
 seeker: I guess it makes sense, but I'm not sure where to begin to improve those skills.
 supporter: Would you be willing to take a leadership or communication course? Or even find a mentor who can help you develop those skills?
 seeker: That's a good idea. I'll look into that.

😊 **Emotion:**
 The seeker feels **frustrated and unsure** about their career prospects.

✳️ **Emotion Stimulus:**
 The seeker was **passed over for a promotion at work.**

😊 **Individual Appraisal:**
 The seeker thinks that **their hard work wasn't recognized** and they are unsure about their future career growth.

🎯 **Strategy Reason:**
 To provide support and encouragement, the supporter can use "*Affirmation and Reassurance*" to **acknowledge the seeker's responses** and offer assistance in finding solutions.

💬 **Response:**
It's great that you're willing to take steps to improve your skills. I'm here to help if you need anything.

Figure 11: An example of the ESD-CoT dataset. The emotion and stimulus correspond to what the seeker said. The individual appraisals of “they don’t know” and “feel the need” reflect the seeker’s appraisal of the situation. The description of the strategy reason is reasonable, and the strategy and the response are also consistent.

Dialogue:
 seeker: I am feeling **isolated and lonely**, and need advice on how to make meaningful connections and build a support system.
 supporter: I hear you. It can be tough to feel alone and disconnected. Can you tell me more about what's been going on for you lately?
 seeker: Yes, I **moved to a new city a few months ago and haven't been able to meet people outside of work.** I don't know where to start.
 supporter: What are some activities that you enjoy doing outside of work? Maybe you could find some groups or clubs related to those interests.
 seeker: I like hiking and reading, but I don't know of any groups like that around here.
 supporter: I'm feeling curious about what resources are available in the area. Would you be interested in doing some research together?
 seeker: Yes, that would be helpful.
 supporter: There are several hiking groups on Meetup.com that meet regularly in the area. Have you heard of that website?
 seeker: No, I haven't. Thank you for telling me about it.
 supporter: I can tell that making connections is important to you. What are some qualities you look for in a friend or support system?
 seeker: I value honesty, loyalty, and someone who is a good listener.
 supporter: It sounds like you value meaningful connections with people who are there for you when you need them. That's a great quality to have in a friend.
 seeker: Yes, that's exactly what I'm looking for.
 supporter: Have you considered volunteering? That's a great way to meet new people who share similar values and interests.
 seeker: I haven't thought about that. What kind of volunteer opportunities are there in the area?
 supporter: Well, there are several organizations that help local communities, such as food banks, homeless shelters, and animal rescues. What do you think appeals to you the most?
 seeker: I love animals, so maybe that would be a good idea.
 supporter: Why don't you look into volunteering at the local animal shelter? It's a great way to meet people who share similar interests and give back to the community at the same time.
 seeker: That sounds like a good idea. I'll check it out.

😊 **Emotion:**
 The seeker feels **isolated and lonely**.

✳️ **Emotion Stimulus:**
 The seeker **moved to a new city a few months ago and hasn't been able to meet people outside of work.**

😊 **Individual Appraisal:**
 The seeker thinks they **lack social connections** and **feel disconnected from others.**

🎯 **Strategy Reason:**
 To provide the seeker with a **sense of validation and global understanding of their emotions and experiences**, the supporter can use "*Summarize*" to acknowledge their feelings of isolation and loneliness and their desire to build meaningful connections.

💬 **Response:**
It sounds like you're feeling isolated and lonely and are looking for ways to build meaningful connections with others. So far, we've talked about finding groups related to your interests, volunteering, and what qualities you value in friends. Does that sound accurate?

Figure 12: Another example of the ESD-CoT dataset, which uses the strategy of “*Summarize*”.

Situation	I am in a toxic or abusive relationship and am unsure of how to leave safely or how to seek help
Context	<p>Supporter: Hi there, how are you feeling today?</p> <p>Seeker: Not so great. I'm feeling really trapped in my relationship.</p> <p>Supporter: Can you tell me more about that? What's happening?</p> <p>Seeker: My partner is really controlling, and I feel like I can't do anything without their approval. I'm starting to feel really isolated from my family and friends.</p> <p>Supporter: It sounds like you're feeling trapped and controlled in your relationship, and that's leading to feelings of isolation.</p> <p>seeker: Yes, exactly. I don't know what to do.</p> <p>Supporter: If you're feeling like you're in a dangerous situation, you can call the National Domestic Violence Hotline at 1-800-799-7233 for immediate support and next steps.</p> <p>seeker: Thank you, I'll keep that in mind.</p> <p>Supporter: Based on what you're saying, it sounds like you're feeling trapped and isolated because of your partner's controlling behavior. You're not sure what to do next.</p> <p>seeker: Yes, that's right. It's hard to know what the right thing to do is.</p>
RE SR_RE EM_SR_RE	<p>Have you talked to your partner about how you're feeling?</p> <p>It sounds like you're feeling really stuck in this situation, and it's hard to see a way out.</p> <p>Imagine a future where you're no longer trapped and isolated. What does that look like to you?</p>
ESCoT	<p>Emotion: The seeker feels trapped and isolated.</p> <p>Emotion Stimulus: The seeker's partner is controlling and the seeker feels like they can't do any -thing without their approval.</p> <p>Individual Appraisal: The seeker thinks that their partner's controlling behavior is making them feel trapped and isolated, and they are unsure of what to do next.</p> <p>Strategy Reason: To provide the seeker with a sense of empowerment and support, the supporter can use "Take Responsibility" to encourage the seeker to take control of their own life and make decisions that align with their values and goals. This strategy aims to address the seeker's feelings of being trapped and isolated by emphasizing the importance of taking responsibility for their own actions and well-being.</p> <p>Response: It sounds like you're feeling really stuck in this situation, but I want you to know that you have the power to take control of your own life. You can make decisions that align with your values and goals, and that will help you feel more empowered and in control.</p>
Ground-Truth	It's important to remember that you're not alone, and that you deserve to feel supported and safe in your relationships.

Table 10: A case of the generated supportive responses by the ablation study. We show the model's responses in different experimental settings, "RE", "SR_RE", and "EM_SR_RE". In the case of "ESCoT", the entire chain setting, we display the output of all elements.