TOOL-ED: Enhancing Empathetic Response Generation with the Tool Calling Capability of LLM

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Abstract

Empathetic conversation is a crucial characteristic in daily conversations between individuals. Nowadays, Large Language models (LLMs) have shown outstanding performance in generating empathetic responses. Knowledge bases like COMET can assist LLMs in mitigating illusions and enhancing the understanding of users' intentions and emotions. However, models remain heavily reliant on fixed knowledge bases and unrestricted incorporation of external knowledge can introduce noise. Tool learning is a flexible end-to-end approach that assists LLMs in handling complex problems. In this paper, we propose Emotional Knowledge Tool Calling (EKTC) framework, which encapsulates the commonsense knowledge bases as empathetic tools, enabling LLMs to integrate external knowledge flexibly through tool calling. In order to adapt the models to the new task, we construct a novel dataset TOOL-ED based on the EMPATHETICMPATHETICDIALOGUE (ED) dataset. We validate EKTC on the ED dataset, and the experimental results demonstrate that our framework can enhance the ability of LLMs to generate empathetic responses effectively. Our code is available at https: //github.com/caohy123/EKTC

1 Introduction

As a hot topic in building humanlike chatbots, empathetic dialogue aims to enhance the ability to fully understand the users' emotions and make appropriate responses, which plays an essential role in establishing and maintaining harmonious social connections (Keskin, 2014; Wang et al., 2023c). There are several works focused on enhancing the empathetic ability of models by understanding dialogue context from the perspective of emotions and sentiment cognition (Lin et al., 2019; Majumder et al., 2020; Li et al., 2020; Yang et al., 2024b). Due



Figure 1: Architecture for the application of a specified tool in an example of empathetic dialogue. The model owns the ability to determine the timing of empathetic tools calling actively.

to the complexity of conversations, dialogues often contain implicit knowledge (Zhou et al., 2023; Zhao et al., 2023), including psychological states, potential causality and so on. Many researchers have infused external knowledge to assist models in understanding more detailed information and generating more comprehensive responses (Sabour et al., 2022; Li et al., 2022). Nowadays, Large Language Models (LLMs) have shown excellent comprehension and powerful generation abilities by intermediate thinking or commonsense reasoning without fine-tuning (Wang et al., 2023a; Brown et al., 2020; Liu et al., 2024a; Chae et al., 2023; Wei et al., 2022). The adoption of knowledge base allows LLMs to retrieve specific information such as users' intent and emotions, thereby enhancing their empathetic capabilities and effectively mitigating hallucination phenomena during the response generation process

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(Yang et al., 2024c; Qian et al., 2023). However, some utterances such as the daily greeting statement "Hi" do not require external knowledge base assistance for analysis. Accordingly, the overly strong reliance on a specific knowledge base substantially reduces the flexibility of the models, and the continuous influx of external knowledge introduces additional noise into the model.

We prospect to enable LLMs to autonomously access external knowledge base in the empathetic conversation, rather than employing it in each round of dialogue. Tool learning is a promising approach that enables LLMs to dynamically acquire external knowledge, thereby enhancing their ability to independently solve complex problems (Qu et al., 2024; Zhao et al., 2024; Ji et al., 2023; Zhang et al., 2023). Tools can be swapped out independently of LLMs as plugins if the model owns the ability to utilize the tool. So we define the commonsense knowledge bases as tools, allowing LLMs to flexibly introduce external knowledge based on the dialogue context. However, in contrast with previous work on tool-use instances, the task on empathetic response generation does not involve direct inquiries or explicit requests from users for addressing specific issues (Qin et al., 2023; Gao et al., 2024; Tang et al., 2023). Instead, models require to decide whether to employ the empathetic tool based on a comprehensive assessment of the user's emotional intensity and contextual factors actively.

Therefore, we propose Emotional Knowledge Tool Calling (EKTC) framework, which is designed to automatically generate multi-turn tooluse instance for empathetic responses generation, enabling LLMs to perform dynamic commonsense reasoning in an end-to-end manner with minimal human and material resources, as demonstrated in the Figure 1. Although different commonsense knowledge bases have little relevance, they can be easily switched once defined as tools. So we opt COMET (Bosselut et al., 2019) as a representative tool and insert tool-use trajectory into the EMPATHETICMPATHETICDIALOGUE (ED) dataset to construct an innovative dataset, TOOL-ED. We aim to enable the model to acquire the ability to use empathetic tools, by fine-tuning them on TOOL-ED. Extensive testing experiments on the ED dataset (Rashkin et al., 2018) illustrate that our paradigm is able to take advantage of external tool, efficiently improving the quality of empathic response generation. Our contributions can be summarized as

follows:

(i) We propose a novel framework EKTC for empathetic dialogue. To our best knowledge, we are the first to use the tool learning paradigm to enhance empathetic abilities of LLMs.

(ii) We reconstruct a new dataset called TOOL-ED based on the ED dataset with the assistance of LLMs, which can be served as a benchmark for simulating the use of empathetic tools.

(iii) We define two distinct knowledge bases as tools and validate the generalization of EKTC through a plug-and-play manner. We conduct extensive experiments and analysis on the ED dataset and results demonstrate the effectiveness of our approach.

2 Related Work

2.1 Empathetic Response Generation

Empathetic response generation refers to the process of generating effective responses that resonate emotionally with them in a conversation by thoroughly understanding the user's viewpoints and emotional state. Some previous works have constructed empathetic dialogue systems by categorizing emotions, applying emotional cues (Huang et al., 2024; Song et al., 2019), and incorporating external information (Li et al., 2020; Sabour et al., 2022; Cai et al., 2023, 2024). However, limited parameters of the models restrict their ability to capture and convey complex emotions. Sabour et al. and Li et al. implement pre-trained language models and graph neural network structures to introduce common sense reasoning into the core of the empathy task. Nowadays, LLMs like ChatGPT (Achiam et al., 2023) and LLaMA3 (Touvron et al., 2023) are pretrained on vast amounts of data, covering extensive knowledge (Chen et al., 2023; Wang et al., 2023b; Sun et al., 2023). Through techniques like instruction fine-tuning, the models excel in various tasks (He et al., 2021; Liu et al., 2024b). Some researchers enhance the models' empathetic abilities by leveraging context learning, building prompt templates, combining LLMs with small models and augmenting commonsense knowledge (Lee et al., 2022; Liu et al., 2024c; Yang et al., 2024c; Qian et al., 2023). Nevertheless, the continuous introduction of external knowledge may also lead to noise effects.



Figure 2: The architecture of the EKTC framework consists of two stages: Dataset Reconstruction & Training and Inference stage. In the Dataset Reconstruction stage, the commonsense knowledge base is defined as the *Emotionknowledgebase* tool. Annotator determines the tool calls based on the context and sends the corresponding content to the tool. Reflector judges the relevance between the execution results and the golden response in the dataset, inserting the highly relevant result into the constructed dataset. In the Training and Inference stage, the LLMs are trained on the constructed dataset for active invocation during inference.

2.2 LLM Tool Learning

Nowadays, effectively leveraging tools in conjunction with LLMs to solve complex problems has become an effective paradigm. Tool learning can be classified into two categories (Tang et al., 2023): The first approach involves LLMs with strong tool-use capabilities interacting directly with external tools (Qin et al., 2023; Hsieh et al., 2023; Li et al., 2023; Shi et al., 2024), and the second approach involves fine-tuning models to use specific tools through supervised learning on a specialized dataset (Parisi et al., 2022; Schick et al., 2024; Qin et al.; Qiao et al., 2024; Yang et al., 2024a). Lu et al. combine LLMs with various tools, such as pre-trained visual models, web search engines, python functions and heristic-based modules. The combination of LLMs with such tools extends their ability to handle tasks involving both textual and visual data, as well as real-time information retrieval through web searches and external APIs. Tang et al. fine-tune the 7B and 13B parameter alpaca derivatives on a corpus composed of generated OpenAPI specifications and descriptions, allowing for multiple rounds of interaction. Gou et al. enables LLM to solve complex mathematical problems by reasoning and interacting with external computing tools. This paper defines a new framework for empathetic dialogue processes based on tuning-based theory

of tool learning and constructs scenarios for the use of the empathetic tools.

3 Method

3.1 EKTC

Continuously injecting external commonsense knowledge may lead to extra noise, so the timing of calling empathetic tools is crucial for the quality of responses. However, existing work lacks attention to the appropriate invocation of knowledge bases. Our goal is to innovatively apply the principles of tool learning, enabling models to flexibly utilize knowledge bases in a plug-and-play manner and efficiently integrate external knowledge during the generation of empathetic responses.

The overview of EKTC framework is shown in Figure 2. We firstly define the commonsense knowledge base as an empathetic tool and regard the utterances from assistant in the ED dataset as the golden responses. To equip the model with the ability to autonomously invoke tools with minimal human and material resources, LLaMA3 (AI@Meta, 2024) functions as Annotator to determine the timing of tool invocation based on the comprehensive instructions we provide, while also serving as Reflector to select the tool invocation processes with high relevance to the golden responses. Finally, the high-quality tool-use instance are inserted into the constructed dataset. After being fine-tuned on the constructed dataset, the LLM can effectively implement tool call and empathetic responses.

The inference process of the fine-tuned model is illustrated in Figure 3. Following ReAct (Yao et al., 2022), we employ an (action, observation) format template to guide LLM in accomplishing the task. Based on the dialogue history, the target output of the model can be divided into two main categories:

(i) Tool Call Responses (function call) When the model identifies to apply the empathetic tool, it will output "ASSISTANT Action" with the tool name and the corresponding prompt "AS-SISTANT Action Input" with the arguments input into the tool. For example, the output (Action: EmotionKnowledgebase Action Input: "prompt": "I was surprised when my mom bought me a car") indicates that the model will input the user's utterance as the parameter to the *EmotionKnowledgebase* tool. Then the tool execution results will be incorporated to the dialogue history via data flow, served as observation. After obtaining the dialogue history with observations, the fine-tuned model will proactively generate text responses. In this way, the commonsense knowledge can be seamlessly integrated with the model.

(ii) Original text Responses (assistant) If the model does not execute a tool call, it will generate the final textual empathetic response based on the dialogue history.



Figure 3: Inference details of empathetic response generation task based on tool learning.

3.2 Tool Definition

In this paper, we define the commonsense knowledge base as the empathetic tool, called *EmotionKnowledgebase*, enabling the model to flexibly access external information in a plug and

play manner. In this way, the model automatically treat the dialogue context as arguments that are required to input into the empathetic tool. Based on the given conversation context C, the execution process of the empathetic tool is as follows:

observation = EmotionKnowledgebase(C) (1)

where *observation* is the result of the tool. The following is the definition details of *Emotion-Knowledgebase*.

Referring to (Qian et al., 2023), we utilize the COMET BART version (Hwang et al., 2021) trained on $ATOMIC_{20}^{20}$ as the empathetic tool (*EmotionKnowledgebase*), defining it as the API for generating commonsense inferences of five types of relations ($x_{\text{Content}}, x_{\text{Need}}, x_{\text{Want}}, x_{\text{Effect}}, x_{\text{React}}$) based on the dialogue context. Given the dialogue context C, the execution result of the tool is:

$$result_r = COMET_{BART}(C, r)$$

observation = $\bigoplus_{R} result_r$ (2)

where $R = \{x_{\text{Content}}, x_{\text{Need}}, x_{\text{Want}}, x_{\text{Effect}}, x_{\text{React}}\},\$ and $r \in R$.

In terms of knowledge generation models, CI-CERO (Shen et al., 2022) has demonstrated outstanding abilities, especially in generating knowledge related to emotions. By utilizing the emotional response relationships, potential subsequent event, motivations, and causal relationships provided by CICERO, emotional recognition and conversational reasoning abilities of the model can be largely enhanced, improving the quality and effectiveness of interactions with users. Therefore, we also define CICERO as an empathetic tool, in which the process of generating knowledge by the tool is as follows:

$$result_r = CICERO(C, r)$$

$$observation = \underset{R}{\oplus} result_r$$
(3)

where $R = \{Cause, SubEv, Motiv, React\}$, and $r \in R$.

3.3 Dataset Construction

In order to enable the vanilla model to independently determine the optimal timing for tool calls and effectively integrate external knowledge, we need to create a dataset, TOOL-ED, specifically tailored for the tool learning based empathetic response generation task.

Therefore, we insert tool-use traces into the dialogue to simulate the process of the active tool call, used for training the models. Although the output of various knowledge bases may not be related, they can achieve a plug-and-play functionality through the interchange of API ports once encapsulated as tools. When constructing the dataset, we designate COMET as the representative knowledge base tool and default to setting the output of COMET as the execution result of the tool. In practice, we treat COMET merely as a plugin, so the process can be randomly substituted with other knowledge bases.

Therefore, determining whether to make a tool call is crucial, which requires deep understanding of comprehensive information, including the user's emotional intensity, dialogue context, and so on. This necessitates the assistance of a LLM with strong capabilities for accurate judgment. LLaMA3-70B (AI@Meta, 2024) excels in text generation, understanding, and complex problem-solving, so we utilize it to assist in transforming the ED dataset. The responses of the assistant in the ED dataset are served as the golden responses in this paper. The prompt templates are listed in Appendix A.1 and the example of tool usage in-stance is listed in Appendix B. The LLM performs two main tasks:

Annotator aims to determine the appropriateness of invoking the tool based on the context of the conversation, the definition of the empathetic tool, the definition of the annotation task, and the emotion intensity of the users' response.

Reflector is designed to judge the relevance between the result of tool and golden response. If Annotator determines that the tool needs to be invoked, the Reflector must evaluate the correlation between the results generated by COMET and the responses of the assistant in the ED dataset based on the tool's definition, causal consistency, intent consistency, and emotional consistency. Only if there is a high relevance will the tool usage process be inserted into the **TOOL-ED** dataset. In this way, the final dataset will be a chatbot-style dataset that includes tool-use traces.

Based on the above, as for the training dataset, we incorporate tool calls at a rate of 26.46% and select 10% of the training set randomly as a validation set. In order to investigate whether our constructed TOOL-ED enables LLMs to generate

higher quality empathetic responses by utilizing the empathetic tools, we conduct a comprehensive evaluation on the test set of the ED dataset.

3.4 Training Strategy

Given a dialogue text $U = [u_1, u_2, ..., u_n]$ of length n, including roles of user, assistant, function_call, and observation. The context of the dialogue consists of utterances from user and assistant, formally represented as $C = [u_1, u_2, ..., u_{n-1}]$. For the dialogue response generation, we use the symbol θ to represent the dialogue model. Our objective is to train the model to automatically determine whether it needs to utilize a knowledge base as an auxiliary tool and to better integrate the content returned by the tool with the generation of the model. We apply LoRA-Tuning (Hu et al., 2021) with models on the TOOL-ED dataset. The objective is to predict the response u_t that will follow the t - 1 round of dialogue context C.

$$u_t \sim P_\theta\left(\cdot \mid C\right) \tag{4}$$

where u_t has been set with specific formats, including the generation format for tool calls and ordinary text. And the loss calculation for the tool-based empathetic dialogue task is as follows:

$$L_p = \sum_{t}^{N} -logP(u_t \mid C, \theta)$$
 (5)

4 **Experiment**

4.1 Dataset

The ED dataset includes 32 emotion labels and corresponding contexts for each dialogue, which contains 33,090 dialogues. Based on the ED dataset, we have added tool usage traces to reconstruct the TOOL-ED dataset.

4.2 Baselines

To verify the effectiveness of our EKTC framework, we choose the following state-of-the-art (SOTA) models, and conduct a comparative evaluation based on their test results on the ED dataset:

CEM (Sabour et al., 2022) uses commonsense knowledge to enhance the understanding of the conversational context and the feelings of the interlocutor. **EmpDG** (Li et al., 2020) combines dialogue-level and word-level sentiment analysis with an interactive adversarial learning framework

Model	BLEU-1/2/3/4	B-S	ROU-1/2/L.	Dist-1/2
CEM*	0.1332/0.0630/0.0351/0.0209	0.8603	0.1625/0.0418/0.1508	0.0066/0.0299
EmpDG	0.1857/0.0873/0.051/0.0316	0.8611	0.1697/0.0453/0.155	0.0181/0.0694
HEF	0.1164/0.0365/0.0171/0.0084	0.8539	0.1471/0.0186/0.1196	0.0336/ 0.2096
KEMP*	0.1902/0.0767/0.0362/0.0195	0.8531	0.1618/000296/0.1418	0.0041/0.0204
IAMM	0.1505/0.0651/0.0360/0.0215	0.8633	0.1580/0.0347/0.1446	0.0098/0.0302
MOEL	0.1726/0.0773/0.0433/0.0264	0.8582	0.1653/0.0367/0.1502	0.0038/0.0160
MIME	0.2182/0.096/0.0492/0.02796	0.8613	0.1882/0.0387/0.1642	0.0032/0.0124
vicuna_base	0.1106/0.0412/0.0209/0.0111	0.8522	0.1525/0.0271/0.1254	0.0274/0.1833
vicuna_oneshot	0.1204/0.0449/0.0227/0.012	0.8544	0.1550/0.0259/0.1273	0.0283/0.1793
vicuna_lora	0.1935 /0.0879/0.0514/0.0316	0.8723	0.1740/0.0403/0.1561	0.0296/0.1424
vicuna_tool_comet*	0.1859/0.0903/0.0544/0.0339	0.8755	0.1888/0.0543/0.1735	0.0299/0.1453
vicuna_tool_cicero*	0.1877/ 0.0904/0.0545/0.0341	0.8751	0.1889 /0.0534/0.1732	0.0300 /0.1447
qwen_base	0.1046/0.0349/0.016/0.0077	0.8456	0.1356/0.0186/0.1072	0.2322/0.1720
qwen_oneshot	0.1158/0.0253/0.1780/0.0078	0.8497	0.1431/0.0211/0.1158	0.0281/0.1904
qwen_lora	0.1861/0.0883/0.0517/0.0317	0.8760	0.1846/0.0483/0.1696	0.0249/0.1172
qwen_tool_comet*	0.1936/0.0961/0.0579/0.036	0.8765	0.1941/0.0579/0.1793	0.0283/0.1358
qwen_tool_cicero*	0.1907/0.0943/0.0569/0.0352	0.8766	0.1913/0.0563/0.1768	0.0289/0.1395

Table 1: Results of automic evaluation between EKTC models and baselines. (i) "*" denotes the models that integrate external knowledge. (ii) vicuna_base and qwen_base separately represent the base models of Vicuna-7B and Qwen1.5-14B. (iii) vicuna_lora and qwen_lora respectively refer to the base models fine-tuned on the original ED dataset. (iv) vicuna_tool_comet and qwen_tool_comet denote the results of the COMET as tool after the base models fine-tuned on the TOOL-ED dataset. (v) vicuna_tool_cicero and qwen_tool_cicero signify the result of utilizing CICERO as tool after the corresponding base models fine-tuned on the TOOL-ED dataset.

to more precisely capture user emotions and generate high-quality responses. HEF (Yang et al., 2024c) combines LLMs with small models, using a two-stage emotion prediction strategy to help the LLM focus on the primary emotions emphasized by the smaller model. **KEMP** (Li et al., 2022) utilizes external knowledge graphs to extract emotional signals, learning emotional dependencies through an emotional cross-attention mechanism. IAMM (Yang et al., 2024b) employs a secondorder interactive attention mechanism to enhance the understanding capability of dialogue systems by capturing important associative words in conversations. MOEL (Lin et al., 2019) is an innovative end-to-end empathy modeling approach that captures user emotions and outputs an emotional distribution. MIME (Majumder et al., 2020) groups emotions based on their positivity or negativity, with responses mimicking the user's emotions to varying degrees, enhancing empathy and contextual relevance in the responses. We replicate them based on the open-source code of the project and conduct testing experiments on the ED dataset.

As for LLM baselines, we benchmark against Vicuna-7B (Chiang et al., 2023) and Qwen1.5-14B (Bai et al., 2023) to fine-tune them on the TOOL- ED dataset and the ED dataset for comparision.

4.3 Implementation Details

We fine-tune Vicuna-7B (Chiang et al., 2023) and Qwen1.5-14B (Bai et al., 2023) as baselines on the TOOL-ED corpus. To demonstrate the effectiveness of the EKTC framework, we also finetuned the model on the ED dataset formatted in dialogue format for comparison. The training procedure is on NVIDIA A6000 48G GPUs using the LLaMA-Factory framework¹. Moreover, we conduct oneshot tests on Vicuna-7B and Qwen1.5-14B on the ED dataset separately. We divide the Tool-ED dataset and the ED dataset into training, validation, testing with 8:1:1 ratio referring to (Rashkin et al., 2018). The parameter settings of all SOTA baseline models are consistent with those recommended in their initial paper or code. As for EKTC framework, we employ the COMET of BART version (Hwang et al., 2021) and CICERO (Shen et al., 2022) as the empathetic tools to evaluate the results on the ED dataset.

¹https://github.com/hiyouga/ LLaMA-Factory

Comparisons	Aspects	Win	Tie	Lose
. 1	Emp.	64.0%	24.0%	12.0%
qwen_tool_com	et Inf.	51.3%	40.7%	8.0%
VS.	Flu.	17.0%	71.3%	11.7%
qwen_base	Con.	67.7%	24.3%	8.0%
. 1	Emp.	61.3%	32.7%	6.0%
qwen_tool_com	et Inf.	52.0%	35.3%	12.7%
VS.	Flu.	60.0%	32.3%	7.7%
qwen_lora	Con.	63.7%	24.0%	12.3%
	Emp.	57.7%	28.0%	14.33%
vicuna_tool_coi	^{net} Inf.	15.7%	45.0%	39.3%
vs.	Flu.	34.7%	42.3%	23.0%
vicuna_base	Con.	61.0%	26.0%	13.0%
	Emp.	72.3%	22.3%	5.3%
vicuna_tool_coi	net Inf.	53.3%	33.3%	13.3%
vs.	Flu.	67.0%	29.7%	3.3%
vicuna_lora	Con.	67.7%	27.0%	5.33%

Table 2: Results of human evaluation on aspects.

Comparisons	Aspects	Win	Lose
awan tool compt	Emp.	71%	29%
qwen_tool_comet	Con.	86%	14%
vs. qwen_lora	Flu.	87%	13%
vicuna_tool_come	Emp.	77%	23%
	Con.	83%	17%
vs. vicuna_lora	Flu.	90%	10%

Table 3: Results of LLM-based evaluation on aspects.

4.4 Evaluation Metrics

Automatic Evaluation We utilize Distinct-n (Dist-1/2) (Li et al., 2016), BERTScore (B-S) (Zhang et al., 2019), ROUGE (ROU-1/2/L.) (Fang et al., 2023) and BLEU-n (BLEU-1/2/3/4) (Papineni et al., 2002) as the primary automatic metrics for evaluating response empathetic generation performance. Distinct-1 and Distinct-2 assess response diversity at the unigram and bigram levels respectively. B-S leverages the pre-trained embeddings of BERT and matches words in candidate sentences with those in reference sentences on cosine similarity. ROUGE and BLEU-n measures the similarity and relevance between generated responses and reference responses.

Human Evaluation Human evaluation remains essential for a thorough and nuanced understanding of content quality and effectiveness. Following previous methods (Sabour et al., 2022), we use A/B testing to compare the baseline models with our model. We randomly select 100 conversation samples and compare the performance of the baseline model with the qwen_tool model in pairs. We recruited three researchers specializing in emotional

dialogue systems as annotators, excluding the authors of this paper. We evaluate from four aspects: **Empathy** (Emp.) measures whether the emotional response sufficiently understands the users' emotions and intentions and generates an appropriate reply. **Informativity** (Inf.) meatures whether the response contains valuable information. **Fluency** (Flu.) measures whether the response is similar to human expression, natural, and smooth. **Consistency** (Con.) measures whether the response is concise, clear, and relevant to the topic. For the same dialogue, if our model performs better, it is annotated as Win. If it performs worse, it is annotated as Lose. If there is little difference between the two, it is annotated as Tie.

LLM-based Evaluation GPT-4 achieves a high degree of similarity to human evaluations, so we opt it to simulate human assessors for evaluating the performance of other models. We continue to assess three aspects including **Empathy**, **Fluency**, and **Consistency** by conducting an A/B test between the models fine-tuned with LoRA-Tuning on the original ED dataset and the models fine-tuned on our TOOL-ED dataset with the COMET knowledge base as the tool.

4.5 Results and Analysis

4.5.1 Main Results

Automatic Evaluation Table 1 shows the automatic evaluation results. The EKTC-based models invoking the empathetic tools outperform most compared models in terms of the evaluation metrics, demonstrating the superior comprehension and expression capabilities of the EKTC-based models. When utilizing the two different empathetic tools (COMET and CICERO), we simply replacing the API ports of the tools, observing that the performance of the model remains extremely stable. This indicates that tool learning in this end-to-end mode allows the model to operate independently of any specific knowledge base, demonstrating the robustness and generalizability of our framework. In terms of Dist-n, the performances of the EKTC-based models are slightly lower than some of the LLMs. This could be attributed to the fact that the results returned by the the knowledge base are also incorporated into the dialogue history, which limits the length of conversation history input into the model. However, a slight reduction in the diversity of empathetic responses may not necessarily be a negative outcome.

Model	BLEU-1/2/3/4	B-S	ROU-1/2/L	Dist-1/2
qwen_kno	0.1105/0.0377/0.0178/0.0086	0.8473	0.1413/0.021/0.1143	0.0294/ 0.2114
qwen_noref_comet	0.1971 /0.0919/0.0527/0.3130	0.8722	0.1797/0.0471/0.1654	0.0298/0.1409
qwen_tool_comet	0.1936/ 0.0961/0.0579/0.0360	0.8765	0.1941/0.0579/0.1793	0.0283/0.1358
qwen_noref_cicero	0.1927/0.0910/0.0528/0.3190	0.8740	0.1828/0.0499/0.1683	0.0316 /0.1464
qwen_tool_cicero	0.1907/0.0943/0.0569/0.0352	0.8766	0.1913/0.0563/0.1768	0.0289/0.1395
vicuna_kno	0.0905/0.0299/0.0139/0.0069	0.8455	0.1156/0.0155/0.0974	0.0358/0.2188
vicuna_noref_comet	0.1943/0.0925/0.055/0.0341	0.8730	0.1859/0.0527/0.1701	0.0290/0.1418
vicuna_tool_comet	0.1859/0.0903/0.0544/0.0339	0.8755	0.1888/ 0.0543/0.1735	0.0299/0.1453
vicuna_noref_cicero	0.1586/0.0731/0.0419/0.0248	0.8638	0.1845/0.0501/0.1656	0.0283/0.1427
vicuna_tool_cicero	0.1877/0.0904/0.0545/0.0341	0.8751	0.1889 /0.0534/0.1731	0.0299/0.1453

Table 4: Results of evaluation for ablation study.

Human Evaluation Table 2 shows the results of human evaluations. Compared with the baseline fine-tuned directly on the ED dataset, the EKTCbased models demonstrates superior empathy capabilities, which is primarily due to the reasonable utilization of knowledge base tools, assisting the models better understand the speaker's emotions. The advantage in relevance and fluency is attributed to the EKTC paradigm facilitating the model's ability to navigate emotional expression and phrasing. LLM-based Evaluation Table 3 shows the results of LLM-based evaluations. The EKTC-based models exhibit better empathy than the baseline finetuned on the ED dataset, mainly due to the appropriate use of knowledge base tools that assist the model in getting better understanding of the emotions of users. The advantage in relevance and fluency primarily stems from the reasonable allocation of the knowledge base tools improves the models' cognition of the users' intentions.



Figure 4: Tool-calling ratio of the fine-tuned models. (i) qwen_noref and vicuna_noref refer to Qwen1.5-14B and Vicuna-7B models after fine-tuned without reflection processes for ablation experiments. (ii) qwen and vicuna refer to the results of fine-tuned Qwen1.5-14B and Vicuna-7B on the TOOL-ED dataset.

4.5.2 Ablation Studies

We constructed the following ablation models for comparison:

(i) models using COMET in each round of dialogue with appropriate prompt for relevant knowledge reasoning, represented as qwen_kno and vicuna_kno.

(ii) models fine-tuned on the dataset where judge the tool calling process without adding a reflection process, represented as qwen_noref_comet, vicuna_noref_comet, qwen_noref_cicero and vicuna_noref_cicero.

(iii) The EKTC-based models, fine-tuned on the TOOL-ED, represented as qwen_tool_comet, vicuna_tool_comet, qwen_tool_cicero, vicuna_tool_cicero.

Table 4 and Figure 4 respectively present the results of the ablation experiments and the tool invocation ratios of the models. Although the EKTCbased models has a relatively lower tool calling ratio, the performance in generating empathic dialogue is actually better. This suggests that the timing of tool invocation designed under the EKTC framework effectively improves the quality of the responses of the models. By comparing the response generation effects of models that utilize the knowledgebase in each round with the EKTCbased models, we can prove that our framework effectively mitigates the impact of noise.

5 Conclusion

In this paper, we propose EKTC, which is a toolbased empathetic dialogue paradigm. To enable more models to be adapted to the task, we reconstruct the TOOL-ED dataset based on the ED dataset. Then we define the knowledge bases as tools, which efficiently stimulates relevant knowledge encoded by LLM and avoid noise from external knowledge in an end-to-end way. We fine-tune the models on the reconstructed dataset and validate the effectiveness of our approach through both automatic and human evaluations. Furthermore, by replacing various knowledge bases tools in a plugand-play manner to test the ability of the models to generate empathetic responses, we demonstrate the generalizability of EKTC. In the future, our proposed framework can integrate more tools and be applied to a wider range of downstream tasks.

Limitation

We has certain limitations in its definition of tools, as it does not cover the process of using multiple tools. Defining a broader range of tools and incorporating external knowledge through a hybrid approach could potentially further enhance the richness of empathetic dialogue generation.

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A Prompt

In this section, we will present detailed information about the prompt templates in our work.

A.1 Prompt for Anotator and Reflector

Figure 6 show the prompt for **Annotator** during data construction. First, we provide a comprehensive definition of the empathy dialogue task and the annotation task. Next, we offer a detailed explanation of the defination and the result of the *Emotionknowledgebase* tool. Finally, we supply annotator with contextual information and the gold responses from the ED dataset, we instruct them to evaluate whether the current conversation state represents the optimal moment for tool invocation.

Figure 7 show the prompt for **Reflector** during data construction. Similar to the prompts provided for annotators, we specify detailed definitions for the empathy dialogue task, relevance judgment task, and tool definitions. We instruct Reflector to assess the relevance between the output of the tool and the gold responses from the ED dataset, based on causal consistency, intent consistency, and emotional consistency.

A.2 Prompt Template for Tool Learning.

Based on (Zhang et al., 2024) prompt about tool learning, we have modified the format according to the characteristics of empathy dialogue tasks. The specific details of the prompt are shown in the Figure 9. Figure 8 presents the discription of the empathetic tool.

A.3 Prompt Template for Tool LLM-based evaluation.

We take advantage of gpt4 to implement LLM evaluation The prompt of specific empathy, consistency, and fluency evaluation metric are shown in the Figure 10, Figure 11, Figure 12.

B Case Study

To illustrate the tool usage process within the TOOL-ED dataset more clearly, Figure 13 provides an example of tool-use trajectory in the dataset. After the user initiates a conversation, the model can take one of two different response approaches: (1) Directly generate a reply, such as the example shown in the figure, "I'm fine. How about you?"; (2) Employ the tool, generating content in JSON format corresponding to function_call, which includes the name of the tool and the relevant input



Figure 5: Examples of conversations by the user interacting with the EKTC-based model.

parameters. After inputting these parameters into the knowledge base tool, the tool will output relevant commonsense knowledge as the observation through a data flow approach. The model then generates a response that is more contextually appropriate and aligned with the conversational tone based on the external knowledge introduced.

As shown in Figure 5, this case demonstrates the EKTC-based model's ability to actively call the *EmotionKnowledgebase* tool. By autonomously generating Action names and corresponding Action Inputs, the system can identify the need for tool invocation and then transmits external knowledge through the knowledge base, integrating it into the conversation history. The model subsequently generates a response based on the updated conversation history.

Annotator prompt

There are two roles in the conversation, including user and assistant. Assuming you are the role of assistant and you have an emotion Knowledge Base as a tool, which can provide the following additional knowledge to help you provide a better reply.

The tool can give you following information based on the dialogue context: xIntent represents their intent before the event. xNeed represents what they need in order for the event to happen. xWant represents what they would want after the event. xEffect represents the effect of the event on the person. xReact represents their reaction to the event.

The dialogue context, user utterance and assistant response are as following: dialogue context: {dialogue_context} user utterance: {user_utterance} your response: {assistant_response}

Please follow these guidelines:

Please judge the emotional intensity of the user based on user utterance
 Based on what you say in the conversation and emotional intensity of the user, please check if you have untilized this tool to answer the user's conversation, and tell me the reason. Your output should adhere to the format:
 ##Result

one of [Yes, No]

Figure 6: Prompt for Anotator

Reflector prompt
There are two roles in the conversation, including user and assistant. Assuming you are the role of assistant and you have an emotion Knowledge Base as a tool, which can provide the following additional knowledge to help you provide a better reply. Assuming you have already completed the conversation, your response, user utterance, dialogue context are as follows:
dialogue context: {dialogue_context} user utterance: {user_utterance} your response: {assistant_response}
The tool can give you following information based on the dialogue context: xIntent represents their intent before the event. xNeed represents what they need in order for the event to happen. xWant represents what they would want after the event. xEffect represents the effect of the event on the person. xReact represents their reaction to the even The execution result of this tool is as follows: execution result:{observation}
Please follow these guidelines: 1.Please judge the causal consistency of the dialogue, intent consistency between the execution result and , emotional consistency of the dialogue context. 2.Based on the consistency reflection mentioned above, please assess the correlation between the generated knowledge and the your response. ##Result one of [Yes, No]

Figure 7: Prompt for Reflector

ToolDescription

\"name\": \"EmotionKnowledgeBase\",

\"description\": \"generate additional knowledge to help provide a better reply with prompt about five commonsense relations, followed by the content of the five relations extracted from the existing conversation.\",

\"parameters\": {\"type\": \"object\", \"properties\": {\"prompt\": {\"description\": \"the context of the conversation to assist in analyzing and understanding user to generate better responses.\"}}, \"required\": [\"prompt\"]}

Figure 8: Discription of the empathetic tool

Tool learning prompt

This is an empathetic dialogue task: The first worker (Speaker) is given an emotion label and writes his own description of a situation when he has felt that way. Then, Speaker tells his story in a conversation with a second worker (Listener). The emotion label and situation of Speaker are invisible to Listener. Listener should recognize and acknowledge others' feelings in a conversation as much as possible. You are an empathetic conversational AI chatbot that can empathize with users and use emotion knowledge base tool to assist in empathy when appropriate. You only need to provide the next round of response of Listener.

You have access to the following tool: {tool description} USER: {user instruction} ASSISTANT Action: {tool name} ASSISTANT Action Input: {tool input} ASSISTANT Observation: {tool output} ASSISTANT Response: {assistant response}

Figure 9: Prompt for Tool learning

LLM-based evaluation prompt (Empathy) You are an expert in empathy assessment. Here are two statements, please evaluate their level of empathy. Dialogue history context: {history} Statement 1: {statement1} Statement 2: {statement2} Please evaluate the level of empathy between two statements based on the following criteria: 1. Understand the depth of the other person's emotions 2. Whether the response to the other person's emotions is sincere and warm If the empathy level of statement 1 is higher than that of statement 2, output 1; If the empathy level of statement2, output 0. You don't need to output the analysis process, just output 1 or 0 ##Result one of [1, 0]

Figure 10: Prompt Template for Empathy Scorer

LLM-based evaluation prompt (Consistency)

You are a relevance assessment expert. Here are two statements, please evaluate their correlation. Dialogue history context: {history} Statement 1: {statement1} Statement 2: {statement2}

Please evaluate the correlation between two statements according to the following criteria: 1. The relevance of sentence content to the theme of dialogue history

2. The correlation between sentences, including key points of the dialogue, and accurate expression

If the relevance of statement 1 is higher than that of statement 2, output 1; If the correlation of statement 1 is weaker than that of statement 2, output 0. You don't need to output the analysis process, just output 1 or 0

##Result one of [1, 0]

Figure 11: Prompt Template for Consistency Scorer

LLM-based evaluation prompt (Fluency)
You are an expert in language fluency assessment. Here are two statements, please evaluate their fluency. Statement 1: {statement1} Statement 2: {statement2}
Please evaluate the fluency of two statements based on the following criteria: 1. Grammar correctness 2. Coherence of language 3. Whether the expression is natural or not
If the fluency of statement 1 is higher than that of statement 2, please output 1; If the fluency of statement 1 is lower than that of statement 2, output 0. You don't need to output the analysis process, just output 1 or 0.
##Result

one of [1, 0]

Figure 12: Prompt Template for Fluency Scorer

user: "Hi! How are you doing today?"
assistant: "I'm fine. How about you?"
user: "Job interviews always make me sweat bullets, which makes me
uncomfortable in general to be looked at under a microscope like that."
function_call: "{\"name\": \"EmotionKnowledgeBase\", \"arguments\":
{\"prompt\": \" user:Hi! How are you doing today? assistant:I'm fine. How
about you? user:Job interviews always make me sweat bullets, which makes
me uncomfortable in general to be looked at under a microscope like that.
\"}",
observation: "{\"status_code\": 200, \"relation\": [[\"to get a job\"],
[\"nervous\"]]}"
assistant: "Don't be nervous. Just be prepared."

Figure 13: Example from the TOOL-ED dataset