# An automatically discovered chain-of-thought prompt generalizes to novel models and datasets

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# **Abstract**

Emergent chain-of-thought (CoT) reasoning capabilities promise to improve performance and explainability of large language models (LLMs). However, uncertainties remain about how prompting strategies formulated for previous model generations generalize to new model generations and different datasets. In this small-scale study we compare the performance of a range of zero-shot prompts for inducing CoT reasoning across six recently released LLMs (davinci-002, davinci-003, GPT-3.5-turbo, GPT-4, Flan-T5-xxl and Cohere command-xlarge) on a mixture of six questionanswering datasets, including datasets from scientific and medical domains. We find that a CoT prompt that was previously discovered through automated prompt discovery shows robust performance across experimental conditions and produces best results when applied to the state-of-the-art model GPT-4.

# 1 Motivation

Emergent chain-of-thought (CoT) reasoning capabilities in large language models (LLMs) promise to improve both predictive performance and explainability of models when applied to complex tasks (Wei et al., 2021). While good performance can be reached by few-shot in-context prompting with exemplars that are suitable to a specific task at hand, zero-shot prompting setups have the benefit of not requiring such task-dependent selection of exemplars (Kojima et al., 2022). The recent success of models optimized for dialog such as GPT-3.5 further increases the expectation that models reach robust performance with ad-hoc instruction prompts and are less influenced by minor prompt variations.

In this study we empirically investigate how well previously discovered zero-shot CoT prompting styles generalize to new model generations and datasets, and how they compare to ad-hoc instruction prompting. We conduct our evaluations on six question-answering datasets of varying levels of complexity, including scientific and medical domains.

### 2 Methods

#### 2.1 Datasets

For our study we used the ThoughtSource framework (Ott et al., 2023), which provides a comprehensive meta-dataset and software library designed for streamlined generation, evaluation, and annotation of chain-of-thought (CoT) reasoning. We covered a sizable range of topics and complexity levels by selecting subsamples of six datasets spanning common-sense, scientific, and medical domains. All of these question-answering datasets were multiple-choice, consisting of two to five answer options with a single correct response (Table 1).

# 2.2 Prompts

We assembled a set of ten zero-shot reasoning prompts (Table 5 and Appendix A) consisting of one baseline, two pre-existing, and seven novel designs:

- 1. Direct prompting: No specific trigger, serving as a baseline for comparison.
- Kojima: A well-established CoT prompt, "Let's think step by step." (Kojima et al., 2022)
- 3. Zhou: An enhanced version created through automated prompt engineering, "Let's work this out in a step by step way to be sure we have the right answer." (Zhou et al., 2023)
- 4. Seven original prompts designed by us, inspired by various public resources (OpenAI, 2023a; Schulhoff, 2022), and refined through iterative adaptation based on analyzing outputs. One of these prompts employed a self-

Dataset	Description
CommonsenseQA	General domain crowd-sourced questions with high semantic complexity which command the use of prior knowledge.
StrategyQA	General domain crowd-sourced questions which require implicit reasoning and multi-step answer strategies. Yes/No answers.
WorldTree v2	Elementary science questions for 3rd to 5th grade level, combining domain specific and world knowledge.
OpenBookQA	Scientific and broad common knowledge questions, which require multi-step reasoning and rich text comprehension.
MedQA	Questions from medical board exams. We used only examples from the US (USMLE subset).
MedMCQA	Real-world medical entrance exam questions.

Table 1: Descriptions of various datasets.

critique strategy, requiring the model to provide an initial answer, critique it, and then propose a revised response (Madaan et al., 2023; Saunders et al., 2022).

#### 2.3 Models

We included six instruction-tuned models based on their reported capabilities in CoT reasoning: davinci-002 (Brown et al., 2020), davinci-003 (Ouyang et al., 2022), GPT-3.5-turbo (OpenAI, 2022), and GPT-4 (OpenAI, 2023b) from OpenAI, Flan-T5-xxl from Google (Chung et al., 2022), and command-xlarge-nightly from Cohere (Cohere.ai, 2023). To access several APIs, we used the LangChain framework (Chase, 2022). Between February and April 2023, a total of 11,880 experiments were conducted, all with the model temperature set at 0 and a maximum token length of 512.

#### 2.4 Evaluation

We selected Krippendorff's alpha as our evaluation metric (Krippendorff, 2011). It allows for the combination of results from sub-datasets with different numbers of answer choices by correcting for their corresponding base probability rates. Krippendorff's alpha measures inter-rater reliability on a scale from zero (no agreement) to one (complete agreement), and was used to compare model predictions to gold standard answers (Castro, 2017).

To determine an appropriate sample size, we performed a power analysis with a significance level set at 0.05, a medium Krippendorff's alpha value of 0.8, and a base correct probability of 0.2, considering the maximum of five answer options present in our sub-datasets. The analysis yielded a required

sample size of 164 items, which we increased to 198 items, divided into six sub-datasets of 33 items each.

We used bootstrapping (r = 1000) to compute means and confidence intervals for the generated results. To guarantee accurate Krippendorff scores, which depend on the number of options, we bootstrapped each sub-dataset individually when needed and calculated confidence intervals by pooling standard deviations.

### 3 Results

A comparison of average performance across all datasets and models reveals a top result for the automatically discovered prompt by Zhou et al. (2023).

Prompt	Model avg. $\alpha$ (CI)	GPT-4 $\alpha$ (CI)
	n per prompt = 1188	n per prompt = 198
Rephrase	.54 (.51, .58)	.78 (.71, .85)
Zhou	.53 (.50, .57)	.83 (.77, .90)
Articulate	.52 (.48, .56)	.79 (.71, .86)
Kojima	.51 (.47, .55)	.80 (.73, .87)
Elaborate	.51 (.47, .55)	.77 (.70, .84)
Zhou-instr.	.50 (.46, .54)	.79 (.72, .86)
Plan	.50 (.46, .54)	.77 (.71, .84)
Self-critique	.49 (.45, .53)	.76 (.69, .84)
Direct	.49 (.45, .52)	.71 (.64, .79)
Converse	.47 (.43, .51)	.74 (.66, .81)

Table 2: Performance of prompts averaged over datasets. Average taken over all six models and exclusively for GPT-4. Krippendorff's alpha ( $\alpha$ ) with 95% confidence intervals (CI), n total = 11880.

The average performance of many prompts is notably similar. A closer examination of the results obtained from the latest model, GPT-4, highlights the overall advantage of employing specific prompts and shows the retained performance of the Zhou prompt. Interestingly, the self-critique prompt yielded relatively low scores. It also resulted in the generation of multiple answers in various observed instances, which were excluded from the scoring process. Creating an instruction prompt by placing Zhou's reasoning prompt before instead of after the question did not yield better outcomes.

FLAN-T5 shows good performance for its size, but its results are possibly affected by data contamination: It was instruction-fine tuned on the subdatasets CommonsenseQA and StrategyQA. GPT-3.5-turbo and GPT-4 were the only models that displayed decent performance on medical datasets.

	$\alpha$ (CI)
Dataset	n per dataset = 1980
WorldTree v2	.83 (.81, .85)
CommonsenseQA	.71 (.68, .73)
OpenBookQA	.65 (.63, .68)
StrategyQA	.31 (.27, .36)
MedMCQA	.31 (.28, .34)
MedQA	.21 (.19, .24)

Table 3: Performance on datasets averaged over models and prompts. Krippendorff's alpha ( $\alpha$ ) with 95% confidence intervals (CI), n total = 11880.

Better models are finding WorldTree v2 and CommonsenseQA increasingly easy, while StrategyQA suffers from peculiar items. This highlights the necessity for developing more refined general-knowledge datasets or employing domain-specific datasets, such as the two medical ones.

Model	lpha (CI)
Model	n per model = 1980
GPT-4	.78 (.76, .81)
GPT-3.5-turbo	.62 (.59, .65)
Davinci-003	.47 (.45, .50)
Flan-T5-XXL	.45 (.42, .47)
Davinci-002	.41 (.38, .44)
Command-XL	.32 (.29, .35)

Table 4: Performance of models averaged over datasets and prompts. Krippendorff's alpha ( $\alpha$ ) with 95% confidence intervals (CI), n total = 11880.

Further detailed results, as well as results reported as accuracy values can be found in the appendix.

#### 4 Limitations

The presented work has several limitations. Our study aimed to test a wide variety of combinations of prompts, datasets, and models under budgetary constraints. We therefore chose to subsample datasets based on a statistical power analysis. This limits direct comparison of our results to evaluations on full benchmark test sets. Upon inspecting results for some of the academic benchmark datasets generated through crowdsourcing we found that the quality of a sizable subset of examples was not optimal. One common pattern we found was that questions and answer choices did not allow for clearly picking a best answer. More advanced models tend to correctly point out such problems in their reasoning response and refrain from selecting a single answer choice. We did not use methods such as self-consistency (Wang et al., 2022) that maximize final accuracy at the expense of practical interpretability, i.e., we targeted situations in which users expect a single, high-quality and easily interpretable reasoning chain rather than a collection of noisy reasoning chains. Results achieved when using prompts in conjunction with ensemble methods might potentially differ. Our study included state-of-the-art closed-source models which are undergoing constant change, making replication and comparisons over time difficult. We partially address this concern by making all data generated by models at the time of our experiment openly available. The lack of documentation of closed models also leads to concerns about contamination of training data with benchmark datasets. While our comparison of different prompts is not severely impacted, we caution against strongly interpreting results across different models for this reason. We noted that Flan-T5 (Longpre et al., 2023), which was instruction-finetuned on the subsets of CommonsenseQA and StrategyQA, outperformed GPT-3.5-turbo on CommonsenseQA.

#### 5 Discussion

**Related work.** Several related studies evaluated zero-shot prompting performance. As a notable example, Liévin (Liévin et al., 2022) performed a comparable zero-shot CoT evaluations focused on medical datasets. Earlier work evaluating multiple

models and datasets zero-shot includes commonsense data (Zhou et al., 2020) and the assessment of T0 performance on multiple-choice tasks (Orlanski, 2022). HELM (Liang et al., 2022) covers a wide range of model comparisons. Our study added to current knowledge by focusing on finding simple and versatile chain-of-thought prompting approaches that work across a spectrum of questionanswering datasets and models.

**Future work.** The current study can be extended by evaluating prompts and datasets with additional models, particularly the multitude of openly available LLMs like LLaMa, the Pythia suite, dialog-tuned models like Alpaca (Touvron et al., 2023; Biderman et al., 2023; Taori et al., 2023), StableLM (Stability AI, 2023), and OpenAssistant (LAION, 2023). Finally, user evaluations of the quality and explanatory utility of reasoning chains generated by different prompts and models need to be conducted.

# 6 Acknowledgements

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# A Model input templates

This Appendix provides an overview of the text templates and prompt structures used in our research. The model input is structured as follows:

```
{instruction}
{question}
{answer_choices}
{cot_trigger}
```

Placeholder descriptions:

- {question}: The multiple-choice question that the model is expected to answer.
- {answer\_choices}: The options provided for the multiple-choice question.

Two methods of prompting are employed (only one is used at a time):

- {instruction}: Placed before the question and answer choices.
- {cot\_trigger}: Placed after the question.

Each prompt is accompanied by its type in parentheses in Table 5.

# **B** Power Calculation Formula

$$T(P_c, \alpha_{\min}, p) =$$

$$=2z_{p}^{2}\left(\frac{\left(1+\alpha_{\min}\right)\left(3-\alpha_{\min}\right)}{4\left(1-\alpha_{\min}\right)P_{c}\left(1-P_{c}\right)}-\alpha_{\min}\right)$$

Where:

 $P_c$  = the probability of value c

 $\alpha_{\min} = \text{the smallest } \alpha \text{ for coding to be accepted}$ as reliable

p =level of significance

 $z_p$  = the standardized z-statistics atp.

#### **C** Tables

Some prompts work specifically well on certain datasets. The rephrasing prompt seems to help with the ambiguous questions which we found to be prevalent in the StrategyQA dataset.

ID	Prompt Name	Text
None	Direct	"Direct prompting. No specific prompt is used. Just the question and answer choices are the input to the model."
kojima-01 (cot_trigger)	Kojima	"Answer: Let's think step by step."
zhou-01 (cot_trigger)	Zhou	"Answer: Let's work this out in a step by step way to be sure we have the right answer."
zhou-01-ins (instruction)	Zhou-instruction	"Let's work this out in a step by step way to be sure we have the right answer."
qa-10 (instruction)	Plan	"First think step by step - describe your plan for how to get to the right answer, written out in great detail. Then answer the question."
qa-12 (instruction)	Articulate	"Carefully read the question & work this out in a step by step way to be sure you have the right answer. Be certain to spell out your thoughts & reasoning so anyone can verify them. Spell out everything in painstaking detail & don't skip any steps!"
qa-13 (instruction)	Rephrase	"Instruction: First let's rephrase the question to be sure we understood it correctly. Second, let's work this out step by step by spelling out our thoughts & reasoning so anyone can verify them. Third, make sure we have the right answer."
qa-16 (instruction)	Elaborate	"Answer the following question through careful, concise step-by-step reasoning. First, complement the question with helpful knowledge and important additional facts. Second, generate sub-questions that are required to answer the original question, answer them until you can answer the original question."
qa-17 (instruction)	Converse	"Create a dialog between a professor and a student. The student asks sub-questions to the question. The professor works them out in a step by step way and makes sure that the student understood how they got to the right answer."
refl-01 (instruction)	Self-critique	"Answer the question, then critique the answer. Based on the critique, reconsider the other answer options and give a single final answer."

Table 5: Used prompts and their corresponding ID and text.

Prompt	Model avg. accuracy (CI) n per prompt = 1188			
Zhou	.68 (.65, .70)			
Articulate	.67 (.64, .70)			
Rephrase	.67 (.64, .69)			
Elaborate	.66 (.63, .69)			
Zhou-instruction	.65 (.63, .68)			
Plan	.65 (.62, .68)			
Kojima	.64 (.62, .67)			
Direct	.64 (.61, .67)			
Self-critique	.64 (.61, .67)			
Converse	.64 (.61, .66)			

Table 6: Performance of prompts averaged over datasets. In Table 5, text corresponding to the Prompt names can be found. Average taken over all six models. Accuracy with 95% confidence intervals (CI), n total = 11880.

Dataset	Accuracy (CI) n per dataset = 1980	Base Rate
WorldTree v2	.88 (.86, .89)	.25
CommonsenseQA	.77 (.75, .79)	.2
OpenBookQA	.74 (.72, .76)	.25
StrategyQA	.67 (.65, .69)	.5
MedMCQA	.49 (.46, .51)	.25
MedQA	.38 (.36, .40)	.2

Table 7: Performance on datasets averaged over models and prompts. Accuracy with 95% confidence intervals (CI), n total = 11880. Base rate for random chance, dependent on number of answer choices in datasets.

Model	Accuracy (CI) n per model = 1980
GPT-4	.85 (.83, .86)
GPT-3.5-turbo	.74 (.72, .76)
Davinci-003	.63 (.61, .65)
Flan-T5-XXL	.61 (.59, .63)
Davinci-002	.59 (.56, .61)
Command-XL	.52 (.50, .55)

Table 8: Performance of models averaged over datasets and prompts. Accuracy with 95% confidence intervals (CI), n total = 11880.

model dataset	Command-XL	Flan-T5-XXL	GPT-3.5-turbo	GPT-4	Davinci-002	Davinci-003
CommonsenseQA	.57 (.50, .64)	.81 (.75, .85)	.70 (.64, .76)	.82 (.76, .87)	.68 (.62, .74)	.68 (.62, .74)
MedQA	.06 (.01, .13)	.02 (.00, .07)	.40 (.32, .47)	.55 (.47, .61)	.09 (.03, .15)	.17 (.11, .24)
MedMCQA	.08 (.01, .14)	.10 (.03, .17)	.51 (.44, .58)	.73 (.67, .79)	.20 (.13, .27)	.21 (.14, .28)
OpenBookQA	.43 (.36, .50)	.69 (.63, .76)	.77 (.71, .83)	.91 (.87, .95)	.45 (.37, .52)	.66 (.59, .72)
StrategyQA	.10 (.00, .21)	.23 (.12, .34)	.44 (.33, .55)	.69 (.61, .76)	.20 (.09, .32)	.22 (.12, .31)
WorldTree v2	.67 (.61, .73)	.77 (.72, .83)	.89 (.85, .93)	.97 (.95, .99)	.84 (.79, .89)	.84 (.80, .89)

Table 9: Krippendorff scores of models per dataset with 95% confidence intervals (CI). The low score of Flan-T5-XXL on MedQA illustrates that the Krippendorff scores corrects the accuracy in Table 10 for the base rate in Table 7.

model dataset	Command-XL	Flan-T5-XXL	GPT-3.5-turbo	GPT-4	Davinci-002	Davinci-003
CommonsenseQA	.66 (.61, .71)	.85 (.81, .89)	.76 (.71, .81)	.85 (.81, .90)	.75 (.70, .79)	.75 (.70, .80)
MedQA	.27 (.22, .32)	.22 (.17, .26)	.53 (.47, .58)	.65 (.60, .70)	.28 (.23, .33)	.35 (.30, .40)
MedMCQA	.31 (.26, .36)	.35 (.30, .40)	.63 (.58, .69)	.80 (.76, .85)	.41 (.35, .46)	.41 (.36, .47)
OpenBookQA	.58 (.52, .63)	.78 (.73, .82)	.83 (.79, .88)	.93 (.91, .96)	.59 (.54, .65)	.75 (.70, .80)
StrategyQA	.57 (.51, .62)	.62 (.57, .68)	.73 (.68, .79)	.85 (.81, .89)	.63 (.57, .68)	.63 (.58, .69)
WorldTree v2	.75 (.71, .80)	.83 (.79, .87)	.92 (.89, .95)	.98 (.96, .99)	.88 (.85, .92)	.88 (.85, .92)

Table 10: Accuracy scores of models per dataset with 95% confidence intervals (CI).

dataset prompt	CommonsenseQA	MedQA	MedMCQA	OpenBookQA	StrategyQA	WorldTree v2
Direct	.68 (.60, .76)	.21 (.12, .30)	.28 (.18, .37)	.65 (.56, .73)	.24 (.10, .38)	.84 (.77, .90)
Kojima	.69 (.61, .77)	.22 (.14, .31)	.25 (.16, .35)	.61 (.52, .70)	.46 (.32, .59)	.79 (.72, .86)
Zhou	.72 (.64, .79)	.23 (.14, .32)	.37 (.27, .46)	.74 (.66, .81)	.32 (.19, .44)	.83 (.77, .89)
Plan	.73 (.65, .80)	.19 (.11, .28)	.30 (.21, .40)	.65 (.56, .73)	.27 (.12, .42)	.82 (.75, .88)
Articulate	.72 (.64, .80)	.22 (.14, .31)	.35 (.25, .45)	.67 (.59, .75)	.27 (.13, .40)	.88 (.83, .93)
Rephrase	.75 (.68, .82)	.21 (.13, .29)	.31 (.22, .41)	.61 (.51, .70)	.42 (.30, .55)	.87 (.82, .92)
Elaborate	.68 (.60, .76)	.25 (.17, .34)	.36 (.25, .45)	.64 (.56, .72)	.33 (.20, .47)	.82 (.75, .88)
Converse	.63 (.55, .72)	.20 (.12, .29)	.32 (.23, .41)	.63 (.55, .72)	.30 (.16, .43)	.78 (.71, .85)
Self-critique	.73 (.65, .80)	.19 (.11, .27)	.25 (.16, .34)	.66 (.56, .74)	.23 (.09, .37)	.82 (.75, .88)
Zhou-instruction	.73 (.66, .81)	.19 (.11, .28)	.26 (.17, .36)	.65 (.57, .74)	.28 (.14, .42)	.86 (.80, .92)

Table 11: Krippendorff scores of prompts per dataset with 95% confidence intervals (CI).

dataset prompt	CommonsenseQA	MedQA	MedMCQA	OpenBookQA	StrategyQA	WorldTree v2
Direct	.74 (.68, .81)	.38 (.31, .45)	.46 (.39, .53)	.74 (.68, .80)	.64 (.57, .71)	.88 (.84, .93)
Kojima	.75 (.69, .81)	.39 (.32, .46)	.44 (.37, .51)	.71 (.65, .78)	.73 (.67, .80)	.85 (.79, .90)
Zhou	.78 (.72, .84)	.40 (.33, .47)	.54 (.47, .61)	.81 (.75, .87)	.67 (.60, .74)	.87 (.83, .92)
Plan	.78 (.73, .84)	.36 (.30, .43)	.48 (.41, .56)	.74 (.68, .80)	.66 (.59, .73)	.87 (.82, .91)
Articulate	.78 (.72, .84)	.39 (.32, .46)	.52 (.44, .59)	.76 (.70, .82)	.66 (.59, .73)	.91 (.87, .95)
Rephrase	.80 (.75, .86)	.38 (.31, .45)	.49 (.42, .56)	.71 (.64, .77)	.72 (.65, .78)	.91 (.87, .95)
Elaborate	.75 (.68, .81)	.41 (.34, .48)	.53 (.46, .60)	.74 (.67, .80)	.68 (.61, .75)	.87 (.82, .92)
Converse	.71 (.64, .78)	.37 (.30, .44)	.51 (.43, .58)	.73 (.67, .79)	.66 (.59, .73)	.84 (.79, .89)
Self-critique	.79 (.73, .84)	.37 (.30, .43)	.44 (.37, .51)	.75 (.69, .81)	.62 (.55, .69)	.87 (.82, .92)
Zhou-instruction	.79 (.73, .85)	.37 (.30, .44)	.45 (.38, .52)	.74 (.68, .81)	.66 (.59, .73)	.90 (.86, .94)

Table 12: Accuracy scores of prompts per dataset with 95% confidence intervals (CI).

model prompt	Command-XL	Flan-T5-XXL	GPT-3.5-turbo	GPT-4	Davinci-002	Davinci-003
Direct	.26 (.18, .33)	.49 (.41, .58)	.61 (.53, .69)	.71 (.64, .79)	.41 (.31, .50)	.44 (.35, .53)
Kojima	.25 (.16, .34)	.46 (.38, .55)	.66 (.57, .75)	.80 (.73, .87)	.42 (.33, .51)	.45 (.36, .54)
Zhou	.35 (.27, .43)	.44 (.37, .51)	.62 (.53, .71)	.83 (.77, .90)	.53 (.45, .62)	.50 (.41, .59)
Plan	.34 (.25, .42)	.45 (.37, .53)	.61 (.52, .70)	.77 (.71, .84)	.37 (.30, .45)	.46 (.37, .55)
Articulate	.33 (.26, .40)	.50 (.42, .58)	.59 (.49, .68)	.79 (.71, .86)	.44 (.35, .53)	.52 (.43, .60)
Rephrase	.42 (.33, .51)	.46 (.38, .54)	.61 (.52, .70)	.78 (.71, .85)	.44 (.35, .53)	.46 (.37, .55)
Elaborate	.34 (.26, .42)	.42 (.33, .51)	.61 (.51, .70)	.77 (.70, .84)	.51 (.42, .60)	.43 (.35, .51)
Converse	.31 (.22, .40)	.44 (.35, .52)	.58 (.49, .67)	.74 (.66, .81)	.35 (.26, .43)	.46 (.38, .54)
Self-critique	.32 (.26, .39)	.41 (.35, .47)	.58 (.49, .68)	.76 (.69, .84)	.38 (.30, .47)	.48 (.39, .57)
Zhou-instruction	.38 (.30, .46)	.43 (.35, .51)	.64 (.54, .73)	.79 (.72, .86)	.33 (.26, .40)	.49 (.41, .58)

Table 13: Krippenforff scores of prompts per model with 95% confidence intervals (CI).

model prompt	Command-XL	Flan-T5-XXL	GPT-3.5-turbo	GPT-4	Davinci-002	Davinci-003
Direct	.47 (.40, .54)	.62 (.55, .69)	.75 (.69, .81)	.81 (.76, .87)	.59 (.52, .66)	.61 (.54, .68)
Kojima	.45 (.38, .52)	.62 (.55, .69)	.76 (.70, .82)	.86 (.81, .91)	.56 (.49, .63)	.61 (.54, .68)
Zhou	.55 (.48, .62)	.58 (.51, .65)	.75 (.69, .81)	.89 (.84, .93)	.65 (.58, .71)	.66 (.59, .73)
Plan	.53 (.46, .60)	.62 (.55, .69)	.73 (.66, .79)	.84 (.79, .89)	.55 (.48, .62)	.63 (.56, .70)
Articulate	.53 (.46, .60)	.65 (.58, .71)	.74 (.67, .80)	.86 (.81, .91)	.61 (.54, .69)	.65 (.58, .72)
Rephrase	.58 (.51, .65)	.62 (.55, .69)	.73 (.66, .79)	.84 (.79, .89)	.61 (.54, .68)	.63 (.56, .70)
Elaborate	.55 (.48, .62)	.59 (.52, .66)	.73 (.66, .79)	.84 (.79, .89)	.65 (.58, .72)	.60 (.53, .67)
Converse	.52 (.45, .59)	.61 (.55, .68)	.71 (.65, .78)	.81 (.76, .87)	.53 (.46, .61)	.62 (.55, .69)
Self-critique	.51 (.43, .58)	.58 (.51, .65)	.72 (.65, .78)	.84 (.79, .89)	.57 (.50, .64)	.64 (.57, .71)
Zhou-instruction	.56 (.49, .63)	.59 (.52, .66)	.75 (.69, .82)	.85 (.80, .90)	.54 (.47, .61)	.65 (.58, .71)

Table 14: Accuracy scores of prompts per model with 95% confidence intervals (CI).