Chain-of-Thought Reasoning Improves Context-Aware Translation with Large Language Models

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Abstract

This paper assesses the capacity of large language models (LLMs) to translate texts that include inter-sentential dependencies. We use the English-French DiscEvalMT benchmark (Bawden et al., 2018) with pairs of sentences containing translation challenges either for pronominal anaphora or for lexical cohesion. We evaluate 12 LLMs from the DeepSeek-R1, GPT, Llama, Mistral and Phi families on two tasks: (1) distinguishing a correct translation from a wrong but plausible one; (2) generating a correct translation. We compare prompts that encourage chain-of-thought reasoning with those that do not. The best models take advantage of reasoning and reach about 90% accuracy on the first task, and COMET scores of about 92% on the second task, with GPT-4, GPT-40 and Phi standing out. Moreover, we observe a "wise get wiser" effect: the improvements through reasoning are positively correlated with the scores of the models without reasoning.

Keywords: Context-aware MT, Translation with LLMs, Chain-of-thought reasoning in LLMs.

1. Introduction

Large language models (LLMs) have shown impressive capacities for translation, among many other tasks, but their translations are still not perfect (Kocmi et al., 2024; Cui et al., 2025). To increase quality, we examine whether chain-of-thought (CoT) reasoning may help to improve referential and lexical cohesion across sentences. Indeed, when prompted to generate a step-by-step explanation of their answers, LLMs improve substantially on many tasks (Wei et al., 2022).

We hypothesize that CoT can improve the translation of elements that maintain coherence across sentences by making translation decisions explicit. To test our hypothesis, we use the DiscEvalMT English-French test suites for pronominal anaphora and lexical consistency designed by Bawden et al. (2018), in two settings. First, we ask the LLM to select the correct translation among the two contrastive alternatives present in the data. Second, we ask the LLM to translate each test sentence and score the result against its reference translation. In both settings, we demonstrate the advantages of CoT prompting, though only for the largest LLMs, which improve their performance when encouraged to reason before translating.

The paper is organized as follows. We review related work in Section 2, and present the benchmark data and the evaluation metrics in Section 3. The tested LLMs are listed in Section 4: they include 4 GPT proprietary models from OpenAl and 8 open-weight models. The prompts and the results for the contrastive evaluation task (i.e., selecting the correct translation) are presented in Section 5,

while those for the translation task are in Section 6. The main contributions are:

- We assess the capacity of 12 LLMs to translate coherently, showing that they reach a new state of the art on the DiscEvalMT benchmark for pronominal anaphora and lexical cohesion.
- We show that the translation task is reliably scored, as BLEU, chrF, BERTscore, and COMET scores vary in the same directions.
- We demonstrate that CoT prompting improves coherence, but only for the best models. The improvement is positively correlated with the initial score of each LLM, showing that powerful models have a better capacity to leverage reasoning, i.e. a "wise get wiser" effect.

2. Related Work

The translation capabilities of multilingual large language models (LLMs) have attracted growing attention since 2023, and conversational LLMs are now often used for translation tasks – around 4.5% of non-professional interactions with ChatGPT (Chatterji et al., 2025). Therefore, studies evaluating the translation capability of LLMs are of high importance, all the more that this is not tested by common benchmarks for LLMs. LLMs have been included since 2023 in the evaluations carried out at the Workshop on Machine Translation (Kocmi et al., 2023, 2024), and in 2025, the majority of submissions to the general task were LLM-based (Kocmi et al., 2025). At the same time, the first studies of LLMs for MT also include quantitative

evaluations (Vilar et al., 2023; Zhang et al., 2023; Hendy et al., 2023). Other studies are focused on evaluation only: for instance, Bawden and Yvon (2023) demonstrate the strong MT performance of the BLOOM LLM, particularly in few-shot settings and for high-resource language pairs. Fine-tuning of LLMs for document-level MT was found to be moderately beneficial (Wu et al., 2024).

Word-sense disambiguation (WSD) for translation is one of the challenges on which LLMs have been evaluated. Test suites related to WSD include DiscEvalMT (Bawden et al., 2018) which we use in this paper and describe below, as well as ContraWSD (Rios Gonzales et al., 2017), with about 7,000 sentences with reference translations (for De-En and De-Fr) and a smaller test suite to score word translations (Rios et al., 2018). The DiBiMT benchmark with about 600 examples, for translation from English to five other languages, was proposed by Campolungo et al. (2022) but remains private and systems must be submitted to its owners. DiBiMT was used by Iyer et al. (2023) to score the capacity of LLMs for WSD, either out-of-the-box, or after fine-tuning, or with in-context learning.

Similarly, the capacity to translate potentially ambiguous pronouns can be tested using test suites such as DiscEvalMT (Bawden et al., 2018), ContraPRO (Müller et al., 2018; Lopes et al., 2020), or PROTEST (Guillou and Hardmeier, 2016), which was used at WMT 2018 (Guillou et al., 2018). A test suite for En-Ru verb generation in case of ellipses was designed by Voita et al. (2019). A review of scores reached on the DiscEvalMT data by various context-aware MT systems appears below in Section 5.3.

The correct translation of pronouns or ambiguous words is often related to the more general capacity of leveraging inter-sentential dependencies and generating a contextually-correct translation, reviewed in several studies (Popescu-Belis, 2019; Maruf et al., 2021; Jin et al., 2023; Castilho and Knowles, 2025). Document-level translation and its evaluation are important because MT outputs may appear competitive with human translations at the sentence level, but not at the document level (Läubli et al., 2018). An evaluation of GPT-3.5 and GPT-4 on document-level translation (Wang et al., 2023) found that they surpassed non-LLM systems in human ratings. Karpinska and lyyer (2023) found that LLMs translate better entire paragraphs than individual sentences, in the case of literary translation. Beyond direct translation, interaction was a key element in the WSD process proposed by Pilault et al. (2023), using questions and answers as a chain-of-thought input to an LLM.

Recent work has explored how reasoning can improve LLM-based translation, based on the seminal work by Wei et al. (2022), who introduced chain-of-

thought (CoT) prompting and showed that guiding models through intermediate steps improves performance on complex tasks. Liu et al. (2025) argue that reasoning enhances translation by improving coherence, cultural alignment, and self-reflection. He et al. (2025) present R1-T1, which uses expert CoT templates and reinforcement learning to encourage inference-time reasoning for translation. Ye et al. (2025) find that reasoning models outperform standard LLMs on semantically complex and domain-specific MT, especially for longer texts.

Traditional metrics such as BLEU and chrF (Papineni et al., 2002; Popović, 2015), based on surface-level overlap, offer only limited insight into discourse-level quality. Embedding-based metrics such as BERTScore (Zhang et al., 2020), and trained metrics such as COMET (Rei et al., 2020), improve upon this by modeling semantic similarity and are frequently used, as we do here. LLMs have been put to use for MT evaluation: Kocmi and Federmann (2023) showed that GPT-based metrics reach state-of-the-art correlations with human judgments on WMT benchmarks. The benefits of LLM reasoning for this task are still under investigation: Larionov et al. (2025) found that reasoning-enabled LLMs such as DeepSeek-R1 and OpenAl's o3-mini do not always outperform their non-reasoning counterparts in terms of alignment with human judgments of quality.

3. Evaluation Data and Metrics

3.1. Benchmark Data

This study uses the DiscEvalMT benchmark (Bawden, 2018; Bawden et al., 2018), designed to evaluate challenges in English-to-French MT that arise from two types of inter-sentential dependencies: pronominal anaphora and lexical cohesion.¹ The test cases are manually constructed, and aim to test whether MT systems can make contextually-appropriate translation decisions.

Each test item consists of two English sentences ('context' and 'current'), a French translation of the first, and two alternative French translations of the second: one is contextually appropriate, preserving coherence across the two sentences, while the other introduces a discourse-level error; together, they form a contrastive pair among which a system should distinguish the correct translation.

An item for testing the translation of pronominal anaphora is shown in Table 1. The first candidate has correct gender agreement between the pronoun 'ils' (masculine plural) and the antecedent 'les bâtiments' (the translation of 'buildings'), while the second one has wrong agreement (pronoun 'elles', feminine plural).

¹https://github.com/rbawden

EN context:	The buildings will be finished next week.
EN current:	Soon they will be full of new residents.
FR translation of context (given):	Les bâtiments seront terminés la semaine prochaine.
FR translation #1 of current (correct):	Ils seront bientôt pleins de nouveaux résidents.
FR translation #2 of current (incorrect):	Elles seront bientôt pleines de nouveaux résidents.

Table 1: A contrastive test item for pronominal anaphora from DiscEvalMT (Bawden et al., 2018).

To control for chance, test items come in couples, which have a slight difference in the translation of context sentences, but have the two same alternative translations of the second source sentence. However, in one item the first alternative is correct, while in the second item, it is the second one. For instance, the item shown in Table 1 is accompanied in the dataset by another one, where the translation of 'buildings' is by the feminine noun 'résidences', which now makes the second translation correct.

For lexical choice, each item contains a word in the context sentence which can be translated in several ways, either because it is polysemous, or because the translations are synonymous. The correct translation of the current sentence is the one which translates this word with the one used in the reference translation of the first sentence.

The anaphora test set includes 200 items (100 couples), each with two candidates. Similarly, the lexical choice test set includes 200 items with two candidates each. We selected the first half of the data for development of the prompts, and keep the second half for final testing.

3.2. Metrics

In the first part of our study (Section 5), the task of the LLM is to distinguish the correct from the wrong translation (contrastive task), while in the second part (Section 6) the task of the LLM is to translate the English current sentence into French.

We score the first task using the number of times the correct translation was identified. The LLMs are prompted to execute the task by outputting their response either as 'Choice: (1)' or as 'Choice: (2)'. This can be preceded by reasoning in case of CoT prompting. Our evaluation script is tolerant to minor formatting differences in the LLM's output, and responses are accepted as correct as long as they clearly indicate the right option (1 or 2); if they cannot be parsed, they are counted as incorrect. The mean **accuracy score** (ACC) is the average over all the answers.

To avoid systematic bias in favor of either the first or the second (last) sentence, we present each item twice, once with the correct option being first, and once second. Accordingly, we also measure consistency, i.e. the sensitivity of the model to the position of the correct translation among the two options. Ideally, the model's response should not depend

on the position, therefore we define **inconsistency** (**INC**) as the normalized difference between the accuracy score when the correct option is presented first (ACC_{correct=1}) and the accuracy scores when it is presented second (ACC_{correct=2}). A lower inconsistency indicates a more reliable LLM.

$$INC = \frac{|ACC_{correct=1} - ACC_{correct=2}|}{ACC_{correct=1} + ACC_{correct=2}}$$

For the translation task, we provide the LLM with the two EN source sentences, as well as the FR translation of the context sentence, and ask it to translate the second EN sentence (again, possibly outputting reasoning before it). We parse the output to isolate the translation, and score it by comparing it to the correct translation using four metrics: BLEU, chrF, BERTscore and COMET. The first two capture surface-level overlap, while BERTScore and COMET assess semantic adequacy and fluency using embeddings. All metrics are computed using their official Python implementations available via the sacrebleu², bertscore³, and unbabel-comet⁴ packages. BLEU and chrF are calculated with the default configurations of sacrebleu. BERTScore is computed using the default multilingual model bert-basemultilingual-cased, with the language parameter set to French (lang='fr'). COMET uses the Unbabel/wmt22-comet-da model trained on human-annotated translations, which was shown to correlate strongly with human judgments in previous MT evaluation studies.

4. Evaluated LLMs

We evaluated 12 LLMs across different model families and scales. We evaluated GPT models from OpenAI – GPT-3.5-turbo, GPT-4, GPT-4-turbo, and GPT-4o – accessed through API requests.⁵ We evaluated the following open-weight models: Mistral (7.25B), Phi-4 (14.7B), three LLaMA versions (3.1 with 8B, 3.2 with 3.2B, and 3.3 with 70B parameters), and three DeepSeek-R1 models (8B, 14B, and 32B). These

²https://github.com/mjpost/sacrebleu

³https://github.com/Tiiiger/bert_score

⁴https://github.com/Unbabel/COMET

⁵https://platform.openai.com

were run locally using the <code>Ollama</code> framework, ⁶ on a Linux server with four NVIDIA RTX 2080 Ti GPUs (11 GB VRAM each), using parallel querying to maximize throughput. For each model, we used its default quantized versions provided by Ollama (Q4_0 or Q4_K_M). We do not report results with the Tower LLM (Alves et al., 2024), although it is fine-tuned specifically for translation, because it was not instructed for CoT prompting, and it obtained low scores in our pilot experiments on the contrastive task.

5. Contrastive Task

5.1. Prompts: Reasoning or Not

Prompts to LLMs are typically made of a *system prompt*, which indicates the role, persona, or style expected for the answer, and a *user prompt*, which specifies the task, ending with data for the task. Here, we instruct the LLMs to solve the contrastive task, i.e. select the correct translation, with several options for the system and user prompts.

The system prompt can be either empty, simple, or detailed. The simple version is shown in Table 2, while the detailed version is twice longer and contains more constraints, but no instruction on how to solve the task. These prompts are the same for the two benchmarks, anaphora or lexical cohesion.

The user prompt can be either a simple definition of the task, which includes the data as variables that are instantiated for each test item, or instructions on how to reason step-by-step to solve it. From lack of space, we only show in Table 3 the prompt with the step-by-step reasoning instructions for the anaphora task. The reasoning prompt for the lexical cohesion task differs from the anaphora one at the third step: "Step 3 - Find the text in English line 1 which is identical to the text found at Step 2".7

You are a language evaluation assistant. Your task is to compare two French translations of an English text and decide which is more correct.

When providing the answer, strictly follow this format: "Choice: (1 or 2)"

Do not include any explanation or additional text. Only output the specified format.

Table 2: System prompt: simple version.

Let's reason step by step to find the correct French translation of line 2.

Step 1 - Find the difference between the two translations of line 2.

Step 2 - Find the text in English line 2 which is the cause of the translation difference at Step 1.

Step 3 - Find the text in English line 1 to which the text found at Step 2 refers.

Step 4 - Find how the text from Step 3 is translated in French translation of English line 1.

Step 5 - Find the correct word in French to refer to this text.

Step 6 - Find which French translation includes this word.

Select '1' if French translation number 1 is more correct, or answer '2' if French translation number 2 is more correct.

Table 3: User prompt for the anaphora task: step-by-step reasoning instructions.

5.2. Results

We designed the prompts through a series of experiments on half of the benchmark data (development set) with 12 LLMs. We settled on four combinations of system and user prompts: (none, simple), (simple, simple), (detailed, simple) and (simple, step-by-step). The accuracy and inconsistency scores of these combinations are shown in Figure 1 on the anaphora task for all 12 LLMs. The numbers are given in Table 4 for the 5 most interesting LLMs, on the development and test sets. The systems are ranked by decreasing accuracy of the best overall prompt, which is the (simple, step-by-step) one, i.e. when models are encouraged to reason explicitly before answering. The findings from experiments with the validation sets are confirmed on the test sets. From lack of space, we do not provide the graph for the lexical task, but only show scores for 5 LLMs on both parts of the benchmark data in Table 5.

5.3. Findings of the Contrastive Task

To the best of our knowledge, the performance of previous systems on this task is as follows. The creators of DiscEvalMT designed a system which encodes and decodes jointly the pairs of sentences, reaching accuracies of 0.72 and 0.57 respectively on anaphora and lexical cohesion (Bawden et al., 2018, Table 2). In a comparative evaluation study, Lopes et al. (2020, Table 7) found that the best performing approach was the concatenation of both sentences on both sides, as proposed by Tiedemann and Scherrer (2017), reaching 0.82 and 0.55 accuracies. The encoder-decoder model proposed by Pal et al. (2024, Table 4), which used a separate encoder for the context, reached 0.54 and 0.52 accuracy, while Zhang et al. (2022, Table 5)

⁶https://ollama.com

⁷These instructions are oriented towards solving the anaphora or lexical cohesion problem, and are therefore more focused than the document-level step-by-step translation considered by Briakou et al. (2024).

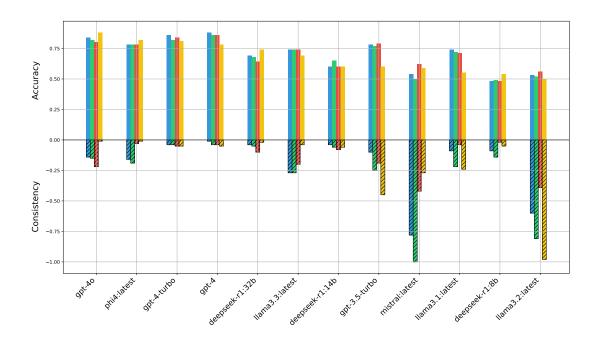


Figure 1: Mean accuracy (top bars) and inconsistency (bottom bars, smaller are better) on the contrastive anaphora task. For each LLM, the four bars are those of the prompts: (none, simple), (simple, simple), (detailed, simple) and (simple, step-by-step). LLMs are ranked by decreasing scores with the last prompt (yellow), which reaches highest overall performance.

	Develo	pment	Те	st
Model	Acc.↑	Inc.↓	Acc.↑	Inc.↓
gpt-4o	0.84	0.14	0.90	0.07
	0.82	0.15	0.92	0.06
	0.80	0.22	0.88	0.12
	0.88	0.01	0.97	0.01
gpt-4	0.88	0.01	0.94	0.04
	0.86	0.04	0.95	0.01
	0.86	0.04	0.90	0.01
	0.78	0.05	0.88	0.00
gpt-4-	0.86	0.04	0.91	0.00
turbo	0.82	0.04	0.88	0.07
	0.84	0.05	0.88	0.09
	0.81	0.05	0.84	0.03
Phi-4	0.78	0.16	0.90	0.01
(14B)	0.78	0.19	0.92	0.01
	0.79	0.04	0.89	0.04
	0.82	0.01	0.87	0.03
DeepSeek-R1	0.69	0.04	0.81	0.02
(32B)	0.68	0.05	0.80	0.02
	0.64	0.10	0.68	0.02
	0.74	0.02	0.81	0.00

Table 4: Comparison of accuracy and inconsistency on development and test sets for the anaphora task. For each model, the four lines of scores are those of the prompts: (none, simple), (simple, simple), (detailed, simple) and (simple, step-by-step).

	Develo	pment	Те	st
Model	Acc.↑	Inc.↓	Acc.↑	Inc.↓
gpt-4o	0.86	0.04	0.94	0.03
	0.88	0.04	0.94	0.04
	0.87	0.03	0.94	0.02
	0.96	0.02	0.96	0.01
gpt-4-	0.87	0.01	0.92	0.03
turbo	0.84	0.02	0.92	0.03
	0.84	0.03	0.92	0.04
	0.88	0.00	0.94	0.02
Phi-4	0.83	0.00	0.89	0.01
(14B)	0.83	0.01	0.91	0.02
	0.84	0.07	0.90	0.03
	0.80	0.05	0.92	0.02
gpt-4	0.89	0.03	0.94	0.01
	0.90	0.04	0.92	0.02
	0.89	0.04	0.92	0.03
	0.92	0.02	0.91	0.02
DeepSeek-R1	0.76	0.05	0.86	0.04
(14B)	0.76	0.01	0.88	0.03
	0.78	0.03	0.84	0.07
	0.79	0.03	0.78	0.01

Table 5: Comparison of accuracy and inconsistency on validation and test sets for the *lexical choice* task. For each model, the four lines of scores are those of the prompts: (none, simple), (simple, simple), (detailed, simple) and (simple, step-by-step).

announced 0.64 accuracy on the anaphora task. A quality estimation approach, proposing a contextual version of the COMET-QE metric (Vernikos

et al., 2022), reached respectively 0.83 and 0.68 accuracy.

On the anaphora task (Table 4), the best results

on the validation set came from GPT-40 with the reasoning prompt and from GPT-4 with the simplest prompt (no reasoning), both reaching 0.88 accuracy. However, GPT-40 with reasoning outperformed GPT-4 on the test set, reaching a nearly perfect accuracy of 0.97. For both systems, the presentation order of the alternatives had almost no influence on the answer, with an inconsistency of only 0.1. GPT-4 also did well with the other prompts, except the reasoning one, scoring up to 0.86 with a consistency of 0.04, and GPT-4-turbo followed closely. GPT-3.5-turbo showed a larger variability, with inconsistency scores up to 0.45 on the validation set.

Among LLMs run locally, Phi-4 stood out with 0.82 accuracy with the reasoning prompt and very stable outputs (inconsistency of 0.01), making it the most reliable open-source model. DeepSeek-R1 32B peaked at 0.74 accuracy also with a low inconsistency of 0.02, but smaller DeepSeek variants like the 14B and 8B models dropped to around 0.60 and were less consistent.

At the lower end, models like LLaMA 3.2 and Mistral struggled on the validation set, and were not tested any further. LLaMA 3.2 was totally unable to understand the reasoning prompt, reaching only 0.50 accuracy (random level) and an inconsistency of 0.98. Mistral scored between 0.54 and 0.59, with inconsistencies over 0.75 in several cases.

Overall, higher accuracy goes hand-in-hand with better consistency. The reasoning prompt was helpful for models that could handle it. For smaller or less instructed models, more complex prompts often led to worse outcomes or to output formatting issues.

On the lexical choice task (Table 5) the trends are similar. The scores are even higher than for anaphora, with excellent consistency. The best performance came from GPT-40 with the reasoning-style prompt, reaching an accuracy of 0.96 and a very low inconsistency of 0.02. GPT-4 also performed strongly, with up to 0.92 accuracy, although its results varied slightly more across prompts. Again, models with strong reasoning capabilities, such as GPT-40 and GPT-4, consistently outperformed others, especially when the prompt encouraged CoT reasoning, and among open-source options, Phi-4 offers the best combination of performance and efficiency.

In terms of the **length of response** (a correlate of cost for OpenAl models), DeepSeek-R1 models consistently generated long responses (over 600 tokens), regardless of the prompt, as they are trained to perform CoT reasoning. In contrast, most other models had output lengths that were more clearly shaped by the prompt. LLaMA 3.3 and Phi-4 produced some of the longest reasoning responses apart from DeepSeek-R1, with 279 and 227 tokens

on average under the reasoning prompt. On the contrary, GPT-3.5-turbo, Mistral, and LLaMA 3.2 generated very short outputs, even under reasoning prompts, rarely exceeding 10 tokens. Therefore, given the higher cost of CoT responses, reasoning prompts are only worth using when they improve performance, as in the case of GPT-40 and Phi-4.

6. Translation Task

In this section, we test the ability of LLMs to correctly translate a sentence when inter-sentential constraints, i.e., pronominal anaphora and lexical cohesion, are involved. Indeed, as observed by Post and Junczys-Dowmunt (2024) for encoder-decoder MT systems, scores on the contrastive task are not necessarily correlated to translation quality.

Using the same dataset, we give to each LLM the two source sentences (EN) and the reference translation of the first sentence (FR). Using several possible prompts, we obtain the translation of the second sentence from the LLM and score it against the reference translation present in the dataset using the four evaluation metrics presented in Section 3.2 above: BLEU, chrF, BERTScore, and COMET. As prompt engineering relied less on the development set as than for the first task, and we report below the results on the full set of 200 examples for each task.

6.1. Prompts: Reasoning or Not

Our goals are again to determine the best performance of LLMs on the two benchmarks, and to find if CoT reasoning improves performance over translation with no reasoning. The no-reasoning prompt is the same for both benchmarks: the system part is shown in Table 6, while the user part simply provides the two EN sentences and the FR translation of the first one.

You are a professional translator. Your task is to translate short English texts into French. ### Instructions:

- You will receive two English sentences: a context sentence and a sentence to translate.
- You will also be given the French translation of the context sentence.
- Translate only the second English sentence into French.
- Return only the French translation of the second sentence.
- Do not include any explanation or additional text.

Table 6: System prompt without reasoning for the translation task.

For the reasoning prompt, we state in the system prompt several steps that guide the reasoning for

each task, shown for both benchmarks in Table 7. An additional instruction at the end (not shown here) requires the LLM to enclose the reasoning between XML-like tags. We found that this instruction led to similar or better performance and an easier to parse output in comparison to an unstructured one.

[Same as Table 6 except its last two lines.]

To achieve this, think step by step to resolve pronouns and references correctly using the context:

- 1. Identify pronouns/references in the second sentence.
- 2. Find their referent in the first sentence.
- 3. Check how that referent is translated in the French context.
- 4. Choose the correct French pronoun/reference.

[Same as Table 6 except its last two lines.] To ensure lexical consistency:

- 1. Identify any key word or expression in the second sentence in English that could be translated in more than one way into French.
- 2. Check if the translation of the first sentence into French already provides a preferred translation for that key word or expression.

Use the same choice if appropriate for your translation of the second sentence into French.

Table 7: System prompts with reasoning instructions for the translation task on the anaphora benchmark (top) and the lexical cohesion one (bottom).

6.2. Results

The translation scores on the anaphora benchmark, with or without reasoning, and their difference (Δ) , are shown in Table 9. For the lexical choice benchmark, the ranking of the LLMs is similar; from lack of space, we only show the scores of the two best systems in Table 10. These numbers are discussed in the next section.

On both the anaphora and lexical choice experiments, we observe a surprising effect. Unlike many techniques which tend to improve weaker models but do not benefit the top-scoring ones, here reasoning is more beneficial to the LLMs which already score highest without it. Table 8 shows the Pearson correlations and the Spearman rank correlations between baseline scores without reasoning and the improvements obtained with reasoning (Δ) , for both

		BLEU	chrF	BERT	COMET
				Score	
Anaphora	r_P	0.81	0.76	0.60	0.59
	r_S	0.68	0.72	0.64	0.74
Lexical	r_P	0.40	0.21	0.31	0.30
choice	r_S	0.52	0.27	0.30	0.25

Table 8: Pearson (r_P) and Spearman (r_S) correlations between baseline scores (without reasoning) and improvements due to reasoning (Δ) .

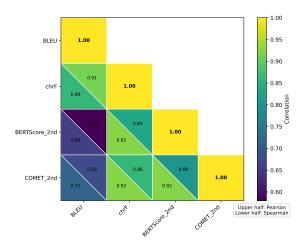


Figure 2: Correlations between Δ values (reasoning minus no_reasoning) obtained with various MT metrics for 12 LLMs, on anaphora translation. Each cell shows Pearson (upper part) and Spearman (lower part) correlations.

tasks. For anaphora, high coefficients for all metrics (0.59–0.81) confirm a consistent "wise-get-wiser" pattern: models that start from higher baselines tend to benefit more from reasoning. The effect is weaker for lexical choice, although correlations remain positive (0.21–0.52).

Moreover, we confirm that the variations of translation scores between the prompts without reasoning and those with reasoning are consistent across all metrics. This is important because the scoring of LLM translations relies on MT metrics which correlate imperfectly with human preferences, unlike the accuracy metric of the first part. Figure 2 shows correlations among the Δ values of all systems, between all pairs of metrics. The large coefficients (Pearson: 0.58–0.91, Spearman: 0.66–0.92) indicate that when a model improves (or degrades) on one metric, it usually improves (or degrades) on others as well. Similar values are observed for the lexical choice task.

6.3. Findings

The results in Table 9 reveal a clear pattern in how models perform on the anaphora benchmark. The GPT family delivers the strongest performance, and the largest increase when reasoning is encouraged. The smaller "turbo" versions benefit most from reasoning in terms of BERTScore and COMET. Phi-4 exhibits the highest improvement on all metrics when reasoning is used. Together with Llama 3.3, they are the highest scoring open-weight models, though Llama 3.3 draws only modest benefits from reasoning. The DeepSeek models present a mixed picture: only the largest model improves its BLEU score, though not the other scores. Models with

		BLE	U		chrl	F		BERTS	Score		CON	IET
Model	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ
gpt-4	49	53	+3.78	70	71	+1.77	.92	.93	+0.0033	.92	.92	+0.0006
gpt-4o	49	54	+5.35	70	71	+1.96	.92	.92	+0.0016	.91	.91	+0.0017
gpt-4-turbo	45	49	+4.17	67	67	+0.90	.92	.90	-0.0173	.91	.90	-0.0084
gpt-3.5-turbo	44	49	+5.22	66	68	+2.15	.91	.91	+0.0017	.91	.90	-0.0080
LLaMA 3.3	44	47	+2.68	66	67	+1.08	.92	.91	-0.0046	.90	.90	-0.0043
Phi-4	43	49	+5.58	64	68	+4.39	.91	.92	+0.0096	.88	.91	+0.0270
DS-R1 32B	35	39	+4.34	59	59	-0.04	.89	.84	-0.0551	.87	.84	-0.0286
LLaMA 3.1	34	30	-3.78	58	54	-3.35	.89	.87	-0.0213	.86	.85	-0.0130
DS-R1 14B	34	33	-1.06	58	53	-4.91	.89	.79	-0.0927	.86	.79	-0.0647
Mistral	27	27	-0.03	51	50	-0.80	.86	.85	-0.0084	.82	.80	-0.0182
LLaMA 3.2	27	23	-3.48	51	47	-3.83	.87	.83	-0.0390	.82	.76	-0.0579
DS-R1 8B	24	21	-2.48	50	45	-4.75	.86	.77	-0.0908	.80	.77	-0.0298

Table 9: Translation quality scores on the *anaphora benchmark*: without reasoning (w/o), with reasoning (w/), and difference (Δ) between the latter and the former. Values for w/o and w/ are rounded to 2 digits, and Δ values to 4. Positive values of Δ indicate progress due to reasoning. 'DS' stands for DeepSeek.

		BLE	U		chrl	=	E	BERTS	Score		CON	IET
Model	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ
gpt-4o	54	54	+0.31	70	69	-0.26	.92	.92	-0.0015	.89	.88	-0.0054
gpt-4	51	54	+2.58	67	69	+2.16	.91	.92	+0.0051	.86	.87	+0.0070

Table 10: Translation quality scores (rounded) on the lexical choice benchmark for the two best LLMs.

weaker baselines i.e., DeepSeek-R1 8B and 14B, LLaMA 3.1 and 3.2, and Mistral decline across all metrics when prompted to reason.

For lexical choice, the results in Table 10 reveal a very similar picture. Within the GPT family, reasoning improves GPT-4, GPT-4o, and GPT-3.5-turbo across most metrics. While GPT-4-turbo shows an unexpected small decline, GPT-4 seems to make a slightly more effective use of the reasoning instructions, despite GPT-4o's stronger baseline score. Among open-weight models, Phi-4 again improves on all metrics with the CoT prompt, while LLaMA 3.3 and DeepSeek-R1 32B improve only in BLEU and chrF, Mistral gains slightly, and the other models degrade. Lexical choice may pose a more difficult challenge compared to pronominal anaphora, as possible translations of ambiguous words are more numerous. This may explain why improvements through reasoning are slightly less consistent for the lexical choice task.

7. Conclusion

This paper evaluated the capacity of several LLMs to pass two benchmarks for contextual MT, one targeting pronoun translation and the other one lexical disambiguation and coherence. We compared several types of prompts, and showed that CoT prompting elicits reasoning that leads to the best results. We found that the best models improve considerably the state of the art on the contrastive task, with accuracies slightly above 0.95 for both targeted phenomena. They also score highly on

the four translation quality metrics, with COMET scores of 0.92 and 0.89. Moreover, we observed a "wise get wiser" effect, as the improvement brought by reasoning is positively correlated to the scores of the same LLMs without reasoning. In other words, the strongest models are also those that benefit the most from reasoning.

These results point to a possible future solution for improving translation with LLMs thanks to reasoning. The solution would need first to identify locations in documents where reasoning is likely to be beneficial, then generate the reasoning that makes translation choices explicit, separating it with markup from the actual translation. Either a generic CoT prompt could be used, or a specific one could be applied depending on the identified difficulties – as we did here with slightly different prompts for anaphora and lexical choice. Such a self-reflecting behavior could lend itself naturally to an agentic Al approach, in which a first-pass translation generated without reasoning could be improved by explicitly solving inter-sentential dependencies.

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Appendix

A. Contrastive Task

A.1. Prompt Variants

This section presents the full text of the prompts used in our *contrastive* evaluation. Each configuration has a *system prompt* (except when 'none' is indicated) and a *user prompt*. The various prompts differ in their structures and instruction levels, while maintaining a consistent task format. Placeholders appear in curly braces in the prompt templates: {context_en}, {source_sentence}, {context_fr}, {option1}, {option2}. In the contrastive setting, two candidate translations are presented, and the model must output a constrained choice, either as "Choice: 1" or as "Choice: 2".

(none, simple)

System prompt

(none)

User prompt

```
Here is a short text with two sentences in English:
{context_en}
{source_sentence}
Here are two different translations into French:
1. {context_fr}
{option1}
2. {context_fr}
{option2}
Which one is more correct?
Please answer 1 if the first one is more correct or answer 2 if the second one is more correct. Do not add explanations.
MAKE SURE you only answer in the following manner: Choice: (1 or 2)
```

(simple, simple)

System prompt

You are a language evaluation assistant. Your task is to compare two French translations of an English text and decide which is more correct.

When providing your answer, strictly follow this format: Choice: (1 or 2)

Do NOT include any explanation or additional text. Only output the specified format.

User prompt

```
Here is a short text with two sentences in English:
{context_en}
{source_sentence}
Here are two different translations into French:
1. {context_fr}
{option1}
2. {context_fr}
{option2}
Which one is more correct?
Please answer 1 if the first one is more correct or answer 2 if the second one is more correct.
```

(detailed, simple)

System prompt

```
You are a strict translation evaluation assistant. Your ONLY task is to determine which of two French translations of an English text is more correct. ### Instructions:
```

- You will receive an English text containing two sentences.

- You will be provided with two different translations in French.
- Your task is to determine which translation is more accurate.
- You must respond in EXACTLY this format: Choice: (1 or 2)
- You MUST NOT provide any explanations, thoughts, or additional text.
- Any deviation from the required format is strictly prohibited.
- If you understand the instructions, respond ONLY in the required format.

User prompt

```
Here is a short text with two sentences in English:
{context_en}
{source_sentence}
Here are two different translations into French:
1. {context_fr}
{option1}
2. {context_fr}
{option2}
Which one is more correct?
```

(simple, step-by-step) - Anaphora

System prompt

You are a helpful assistant. You have to find which translation from English to French is correct. Always keep your answers short.

User prompt

```
Which one is more correct? Please answer 1 if the first one is more correct or an-
swer 2 if the second one is more correct.
Short text with two lines in English.
English line 1: {context_en}
English line 2: {source_sentence}
French translation of English line 1: {context_fr}
French translation number 1 of line 2: {option1}
French translation number 2 of line 2: {option2}
Let's reason step by step to find the correct French translation of line 2.
1. Find the difference between the two translations of line 2.
2. Find the text in English line 2 which is the cause of the translation difference
at Step 1.
3. Find the text in English line 1 to which the text found at Step 2 refers.
4. Find how the text from Step 3 is translated in French translation of English line
1.
5. Find the correct word in French to refer to this text.
6. Find which French translation includes this word.
Select 1 if French translation number 1 is more correct, or 2 if French translation
number 2 is more correct.
When providing your answer, strictly follow this format: Choice: (1 or 2)
```

(simple, step-by-step) - Lexical Choice

System prompt

You are a helpful assistant. You have to find which translation from English to French is correct. Always keep your answers short.

User prompt

```
Which one is more correct? Please answer 1 if the first one is more correct or answer 2 if the second one is more correct.

Short text with two lines in English.

English line 1: {context_en}

English line 2: {source_sentence}

French translation of English line 1: {context_fr}

French translation number 1 of line 2: {option1}

French translation number 2 of line 2: {option2}
```

Let's reason step by step to find the correct French translation of line 2.

- 1. Find the difference between the two translations of line 2.
- 2. Find the text in English line 2 which is the cause of the difference at Step 1.
- 3. Find the text in English line 1 which is identical to the text found at Step 2.
- 4. Find how the text from Step 3 is translated in French translation of English line 1.
- 5. Find the correct word in French to refer to this text.
- 6. Find which French translation includes this word.

Select 1 if French translation number 1 is more correct, or 2 if French translation number 2 is more correct.

When providing your answer, strictly follow this format: Choice: (1 or 2)

A.2. Results: Anaphora

A.2.1. Accuracy and Inconsistency Scores, Elapsed Time and Cost

This section reports results on the **contrastive anaphora benchmark**, for each LLM and prompt configuration.

Model	(none, simple)	(simple, simple)	(detailed, simple)	(simple, step-by-step)
gpt-4o	0.84 / 0.14	0.82 / 0.15	0.80 / 0.22	0.88 / 0.01
Phi-4 (14B)	0.78 / 0.16	0.78 / 0.19	0.79 / 0.04	0.82 / 0.01
gpt-4-turbo	0.86 / 0.04	0.82 / 0.04	0.84 / 0.05	0.81 / 0.05
gpt-4	0.88 / 0.01	0.86 / 0.04	0.86 / 0.04	0.78 / 0.05
DeepSeek-R1 (32B)	0.69 / 0.04	0.68 / 0.05	0.64 / 0.10	0.74 / 0.02
LLaMA 3.3 (70B)	0.74 / 0.27	0.74 / 0.27	0.74 / 0.20	0.69 / 0.04
DeepSeek-R1 (14B)	0.60 / 0.04	0.65 / 0.06	0.60 / 0.08	0.60 / 0.06
gpt-3.5-turbo	0.78 / 0.10	0.77 / 0.25	0.79 / 0.19	0.60 / 0.45
Mistral (7B)	0.54 / 0.78	0.50 / 1.00	0.62 / 0.42	0.59 / 0.27
LLaMA 3.1 (8B)	0.74 / 0.09	0.72 / 0.22	0.71 / 0.04	0.55 / 0.24
DeepSeek-R1 (8B)	0.48 / 0.09	0.49 / 0.14	0.48 / 0.02	0.54 / 0.05
LLaMA 3.2 (3B)	0.53 / 0.60	0.52 / 0.81	0.56 / 0.39	0.50 / 0.98

Table 1: Accuracy (acc \uparrow) and inconsistency (inc \downarrow) across models and prompts on the **anaphora** validation set (separated by '/' in each cell). The systems are ranked by decreasing accuracy of the best overall prompt, which is the (simple, step-by-step) prompt.

Model	(none, simple)	(simple, simple)	(detailed, simple)	(simple, step-by-step)
Phi-4 (14B)	0.36	0.39	0.36	2.13
DeepSeek-R1 (32B)	10.02	10.26	9.15	8.49
LLaMA 3.3 (70B)	3.03	2.64	2.46	62.43
DeepSeek-R1 (14B)	6.93	5.01	4.50	6.84
Mistral (7B)	0.30	0.27	0.27	0.39
LLaMA 3.1 (8B)	0.30	0.33	0.30	1.35
DeepSeek-R1 (8B)	4.11	4.41	4.62	3.42
LLaMA 3.2 (3B)	0.27	0.27	0.33	0.42
gpt-4o	0.228	0.258	0.234	0.768
gpt-4-turbo	0.294	0.276	0.252	0.894
gpt-4	0.798	0.960	1.308	3.060
gpt-3.5-turbo	0.192	0.240	0.198	0.204

Table 2: Mean elapsed time per prompt (seconds) across prompt configurations on the **anaphora** validation set. Open-source (Ollama) models listed first, followed by OpenAI models.

Model	(none, simple)	(simple, simple)	(detailed, simple)	(simple, step-by-step)
gpt-4o	0.090086	0.109572	0.137068	0.499464
gpt-4-turbo	0.364640	0.431000	0.550140	1.417670
gpt-4	1.036560	1.268280	1.604280	4.095720
gpt-3.5-turbo	0.017634	0.022219	0.027188	0.037896

Table 3: Total API cost (USD) by prompt configuration for OpenAI models on the **anaphora** validation set. Experiments were run in spring 2025; reported costs reflect that period's pricing and our token usage.

Model	System	User	Val. Acc.	Val. Inc.	Test Acc.	Test Inc.
gpt-4o	none	simple	0.84	0.14	0.90	0.07
gpt-4o	simple	simple	0.82	0.15	0.92	0.06
gpt-4o	detailed	simple	0.80	0.22	0.88	0.12
gpt-4o	simple	step-by-step	0.88	0.01	0.97	0.01
Phi-4 (14B)	none	simple	0.78	0.16	0.90	0.01
Phi-4 (14B)	simple	simple	0.78	0.19	0.92	0.01
Phi-4 (14B)	detailed	simple	0.79	0.04	0.89	0.04
Phi-4 (14B)	simple	step-by-step	0.82	0.01	0.87	0.03
gpt-4-turbo	none	simple	0.86	0.04	0.91	0.00
gpt-4-turbo	simple	simple	0.82	0.04	0.88	0.07
gpt-4-turbo	detailed	simple	0.84	0.05	0.88	0.09
gpt-4-turbo	simple	step-by-step	0.81	0.05	0.84	0.03
gpt-4	none	simple	0.88	0.01	0.94	0.04
gpt-4	simple	simple	0.86	0.04	0.95	0.01
gpt-4	detailed	simple	0.86	0.04	0.90	0.01
gpt-4	simple	step-by-step	0.78	0.05	0.88	0.00
DeepSeek-R1 (32B)	none	simple	0.69	0.04	0.81	0.02
DeepSeek-R1 (32B)	simple	simple	0.68	0.05	0.80	0.02
DeepSeek-R1 (32B)	detailed	simple	0.64	0.10	0.68	0.02
DeepSeek-R1 (32B)	simple	step-by-step	0.74	0.02	0.81	0.00

Table 4: Comparison of accuracy (Acc \uparrow) and inconsistency (Inc \downarrow) on validation and test sets for the **anaphora** task, across prompt configurations. Validation uses the first 100 couples and reproduces the scores from Table 1 above; test uses the held-out 100 couples. Each couple is presented in both option orders (correct option first/second), and scores are averaged across the two presentations.

A.2.2. Graphical Representation of Scores

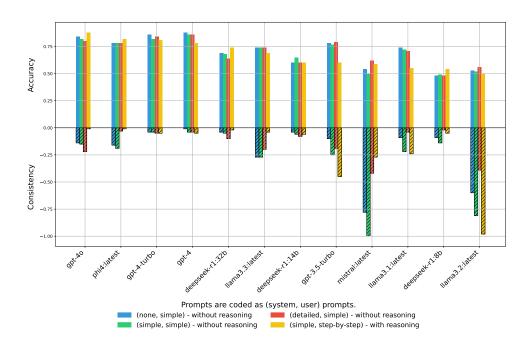


Figure 1: Mean accuracy (top) and inconsistency (bottom; lower is better) across prompt configurations for each model on the **anaphora** validation set. Reproduced here from the main text to keep the appendix self-contained.

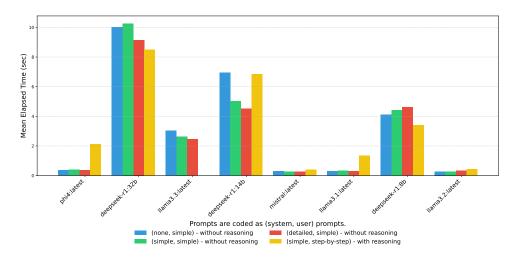


Figure 2: Average response time per prompt for open-source models on **anaphora**. Larger models tend to be slower; complex prompts increase latency.

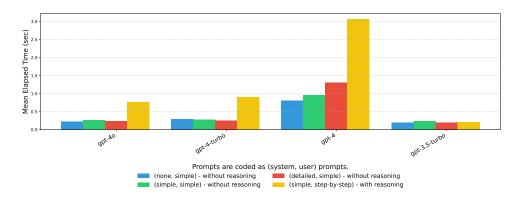


Figure 3: Average response time per prompt for OpenAI models on **anaphora**. GPT-4 is slowest overall, especially with the reasoning prompt.

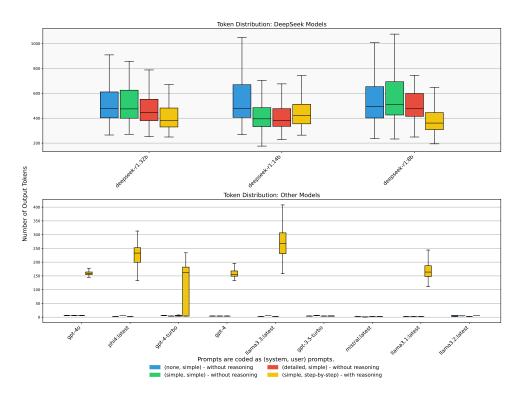


Figure 4: Distribution of output token lengths by model and prompt on **anaphora**. Top: DeepSeek models (consistently longer outputs). Bottom: all other models. Reasoning prompts generally increase length, though the effect varies by model.

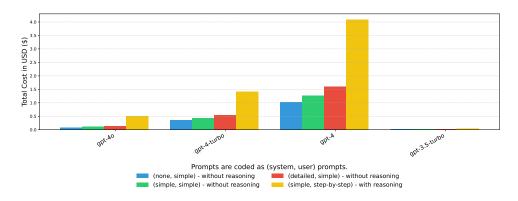


Figure 5: Total API cost by prompt configuration for OpenAI models on **anaphora**; reasoning prompts consume more tokens and cost more. Experiments were run in spring 2025, so costs reflect that period's pricing and our token usage.

A.3. Results: Lexical Choice

A.3.1. Accuracy and Inconsistency Scores, Elapsed Time and Cost

This section reports results on the **contrastive lexical choice benchmark**, for each LLM and prompt configuration.

Model	(none, simple)	(simple, simple)	(detailed, simple)	(simple, step-by-step)
gpt-4o	0.86 / 0.04	0.88 / 0.04	0.87 / 0.03	0.96 / 0.02
gpt-4	0.89 / 0.03	0.90 / 0.04	0.89 / 0.04	0.92 / 0.02
gpt-4-turbo	0.87 / 0.01	0.84 / 0.02	0.84 / 0.03	0.88 / 0.00
LLaMA 3.3 (70B)	0.86 / 0.04	0.86 / 0.02	0.86 / 0.00	0.82 / 0.03
Phi-4 (14B)	0.83 / 0.00	0.83 / 0.01	0.84 / 0.07	0.80 / 0.05
gpt-3.5-turbo	0.80 / 0.05	0.83 / 0.05	0.84 / 0.04	0.80 / 0.08
DeepSeek-R1 (14B)	0.76 / 0.05	0.76 / 0.01	0.78 / 0.03	0.79 / 0.03
Mistral (7B)	0.58 / 0.69	0.50 / 1.00	0.64 / 0.46	0.76 / 0.19
DeepSeek-R1 (32B)	0.75 / 0.04	0.75 / 0.00	0.76 / 0.08	0.74 / 0.02
DeepSeek-R1 (8B)	0.67 / 0.07	0.60 / 0.11	0.62 / 0.12	0.66 / 0.02
LLaMA 3.1 (8B)	0.76 / 0.13	0.78 / 0.01	0.77 / 0.05	0.64 / 0.12
LLaMA 3.2 (3B)	0.66 / 0.32	0.58 / 0.57	0.68 / 0.24	0.52 / 0.90

Table 5: Accuracy (acc \uparrow) and inconsistency (inc \downarrow) across models and prompts on the **contrastive lexical choice** validation set (separated by '/' in each cell). The systems are ranked by decreasing accuracy of the best overall prompt, which is the (simple, step-by-step) prompt.

Model	(none, simple)	(simple, simple)	(detailed, simple)	(simple, step-by-step)
LLaMA 3.3 (70B)	2.49	2.79	2.16	52.53
Phi-4 (14B)	0.33	0.36	0.30	1.95
DeepSeek-R1 (14B)	4.53	3.51	3.21	4.47
Mistral (7B)	0.27	0.24	0.27	0.33
DeepSeek-R1 (32B)	8.55	7.92	6.27	7.29
DeepSeek-R1 (8B)	2.97	3.09	2.82	2.61
LLaMA 3.1 (8B)	0.30	0.27	0.30	1.35
LLaMA 3.2 (3B)	0.24	0.24	0.24	0.39
gpt-4o	0.408	0.498	0.444	1.788
gpt-4	0.504	0.480	0.480	3.432
gpt-4-turbo	0.552	0.564	0.576	1.404
gpt-3.5-turbo	0.348	0.348	0.360	0.396

Table 6: Mean elapsed time per prompt (seconds) across prompt configurations on the **lexical choice** validation set. Open-source (Ollama) models listed first, followed by OpenAI models.

Model	(none, simple)	(simple, simple)	(detailed, simple)	(simple, step-by-step)
gpt-4o	0.083888	0.103422	0.131416	0.495446
gpt-4	0.952440	1.183200	1.519200	3.696600
gpt-4-turbo	0.335800	0.402520	0.524720	1.063320
gpt-3.5-turbo	0.016230	0.020799	0.025751	0.036889

Table 7: Total API cost (USD) by prompt configuration for OpenAI models on the **lexical choice** validation set. Experiments were run in spring 2025; reported costs reflect that period's pricing and our token usage.

Model	System	User	Val. Acc.	Val. Inc.	Test Acc.	Test Inc.
gpt-4o	none	simple	0.86	0.04	0.94	0.03
gpt-4o	simple	simple	0.88	0.04	0.94	0.04
gpt-4o	detailed	simple	0.87	0.03	0.94	0.02
gpt-4o	simple	step-by-step	0.96	0.02	0.96	0.01
gpt-4-turbo	none	simple	0.87	0.01	0.92	0.03
gpt-4-turbo	simple	simple	0.84	0.02	0.92	0.03
gpt-4-turbo	detailed	simple	0.84	0.03	0.92	0.04
gpt-4-turbo	simple	step-by-step	0.88	0.00	0.94	0.02
Phi-4 (14B)	none	simple	0.83	0.00	0.89	0.01
Phi-4 (14B)	simple	simple	0.83	0.01	0.91	0.02
Phi-4 (14B)	detailed	simple	0.84	0.07	0.90	0.03
Phi-4 (14B)	simple	step-by-step	0.80	0.05	0.92	0.02
gpt-4	none	simple	0.89	0.03	0.94	0.01
gpt-4	simple	simple	0.90	0.04	0.92	0.02
gpt-4	detailed	simple	0.89 0.04		0.92	0.03
gpt-4	simple	step-by-step	0.92	0.02	0.91	0.02
LLaMA 3.3 (70B)	none	simple	0.86	0.04	0.88	0.00
LLaMA 3.3 (70B)	simple	simple	0.86	0.02	0.87	0.00
LLaMA 3.3 (70B)	detailed	simple	0.86	0.00	0.86	0.04
LLaMA 3.3 (70B)	simple	step-by-step	0.82	0.03	0.90	0.04
gpt-3.5-turbo	none	simple	0.80	0.05	0.84	0.04
gpt-3.5-turbo	simple	simple	0.83	0.05	0.86	0.02
gpt-3.5-turbo	detailed	simple	0.84	0.04	0.86	0.05
gpt-3.5-turbo	simple	step-by-step	0.80	0.08	0.84	0.00
DeepSeek-R1 (14B)	none	simple	0.76	0.05	0.86	0.04
DeepSeek-R1 (14B)	simple	simple	0.76	0.01	0.88	0.03
DeepSeek-R1 (14B)	detailed	simple	0.78	0.03	0.84	0.07
DeepSeek-R1 (14B)	simple	step-by-step	0.79	0.03	0.78	0.01

Table 8: Comparison of accuracy (Acc \uparrow) and inconsistency (Inc \downarrow) on validation and test sets for the **lexical choice** task, across prompt configurations. Validation uses the first 100 couples and reproduces the scores from Table 5 above; test uses the held-out 100 couples. Each couple is presented in both option orders (correct option first/second), and scores are averaged across the two presentations.

A.3.2. Graphical Representation of Scores

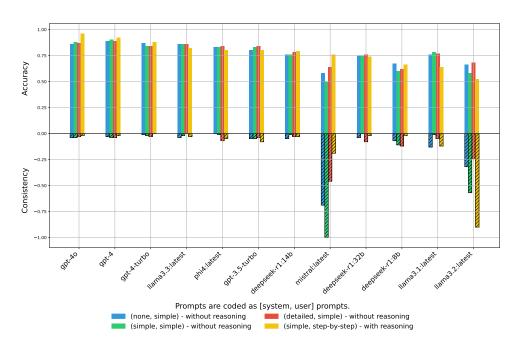


Figure 6: Mean accuracy (top) and inconsistency (bottom; lower is better) across prompt configurations for each model on the **lexical choice** validation set.

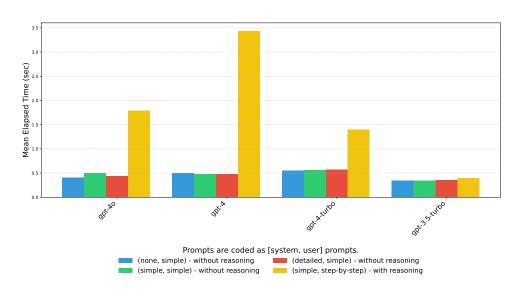


Figure 7: Average response time per prompt for OpenAI models on the **lexical choice** validation set. GPT-4 has the highest latency under reasoning prompts.

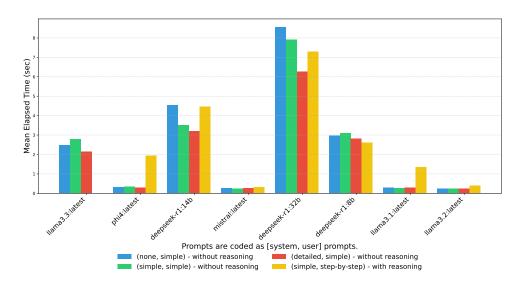


Figure 8: Average response time per prompt for open-source models on the **lexical choice** validation set. Phi-4 is fastest; DeepSeek and LLaMA 3.3 are notably slower.

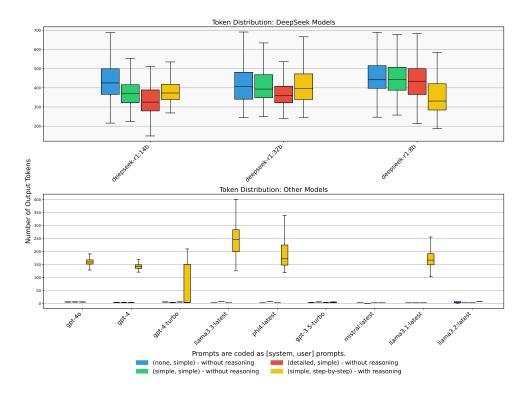


Figure 9: Distribution of output token lengths by model and prompt on the **lexical choice** validation set. DeepSeek models produce notably longer outputs; most other models remain concise under the prompts.

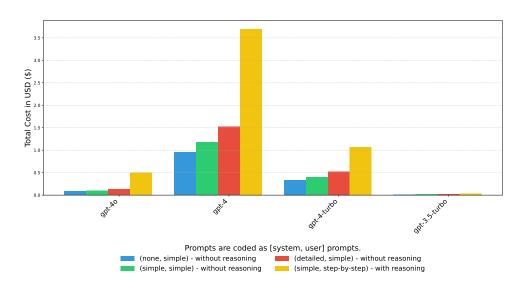


Figure 10: Total API cost by prompt configuration for OpenAI models on the **lexical choice** validation set; reasoning prompts increase token usage and cost, especially for GPT-4. Experiments were run in spring 2025, so costs reflect that period's pricing and our token usage.

B. Generative Task

B.1. Prompt Variants

This section presents the full text of the prompts used in our *generative* evaluation. Similarly to the contrastive prompts, each configuration has a *system prompt* and a *user prompt*. and the placeholders appear in curly braces: {context_en}, {source_sentence}, {context_fr}, {option1}, {option2}. In the generative setting, the model must produce the French translation of the second sentence, with output format rules depending on the reasoning prompt used.

Prompt without reasoning - identical for anaphora and lexical choice

System prompt

You are a professional translator. Your task is to translate short English texts into French.

Instructions:

- You will receive two English sentences: a context sentence and a sentence to translate.
- You will also be given the French translation of the context sentence.
- Translate ONLY the second English sentence into French.
- Return ONLY the French translation of the second sentence.
- Do NOT include any explanation or additional text.

User prompt

```
Here is a short text with two sentences in English:
{context_en}
{source_sentence}
Here is the French translation of the first sentence:
{context_fr}
Please translate the second sentence into French.
```

Structured reasoning (XML-style) - Anaphora

System prompt

You are a professional translator. Your task is to translate short English texts into French.

Instructions:

- You will receive two English sentences: a context sentence and a sentence to translate.
- You will also be given the French translation of the first sentence.
- Translate the second English sentence into French.
- To achieve this, think step by step to resolve pronouns and references correctly using the context:
- 1. Identify pronouns/references in the second sentence.
- 2. Find their referent in the first sentence.
- 3. Check how that referent is translated in the French context.
- 4. Choose the correct French pronoun/reference.
- Finally, output only this XML (valid single root):

```
<result>
```

```
<reasoning></reasoning><answer></answer>
```

</result>

User prompt

```
Here is a short English passage:
{context_en}
{source_sentence}
Here is the French translation of the first sentence:
{context_fr}
```

Please translate the second sentence into French, following the instructions. Output only the XML format specified.

(Structured reasoning (XML-style) – Lexical Choice

System prompt

You are a professional translator. Your task is to translate short English texts into French.

Instructions:

- You will receive two English sentences: a first sentence and a second sentence.
- You will also receive the French translation of the first sentence.
- Translate the second English sentence into French.

To ensure lexical consistency:

- 1. Identify any key word or expression in the second sentence that could be translated in more than one way into French.
- 2. Check whether the French translation of the first sentence already provides a preferred translation for that word or expression,

and use the same choice if appropriate for your translation of the second sentence.

```
- Finally, output only this XML (valid single root):
```

<result>

<reasoning></reasoning>

<answer></answer>

</result>

User prompt

Here is a short English text with two sentences:

{context_en}

{source_sentence}

Here is the French translation of the first sentence:

{context_fr}

Please translate the second sentence into French, following the instructions in the system prompt.

Output only the XML format specified.

B.2. Results: Anaphora

Model	BLEU↑			chrF ↑			BERTScore (2nd) ↑			COMET (2nd) ↑		
	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ
gpt-4	49.08	52.86	+3.78	69.58	71.35	+1.77	0.9242	0.9275	+0.0033	0.9161	0.9167	+0.0006
gpt-4o	49.06	54.41	+5.35	69.53	71.49	+1.96	0.9234	0.9250	+0.0016	0.9101	0.9118	+0.0017
gpt-4-turbo	45.00	49.17	+4.17	66.51	67.41	+0.90	0.9163	0.8990	-0.0173	0.9114	0.9030	-0.0084
gpt-3.5-turbo	43.97	49.19	+5.22	65.66	67.81	+2.15	0.9125	0.9142	+0.0017	0.9116	0.9036	-0.0080
LLaMA 3.3	43.90	46.58	+2.68	66.30	67.38	+1.08	0.9179	0.9133	-0.0046	0.9019	0.8976	-0.0043
Phi-4	43.43	49.01	+5.58	63.89	68.28	+4.39	0.9084	0.9180	+0.0096	0.8782	0.9052	+0.0270
DeepSeek-R1 32B	35.02	39.36	+4.34	58.85	58.81	-0.04	0.8930	0.8379	-0.0551	0.8736	0.8450	-0.0286
LLaMA 3.1	34.13	30.35	-3.78	57.76	54.41	-3.35	0.8891	0.8678	-0.0213	0.8594	0.8464	-0.0130
DeepSeek-R1 14B	34.04	32.98	-1.06	58.20	53.29	-4.91	0.8855	0.7928	-0.0927	0.8551	0.7904	-0.0647
Mistral	26.69	26.66	-0.03	50.59	49.79	-0.80	0.8553	0.8469	-0.0084	0.8229	0.8047	-0.0182
LLaMA 3.2	26.67	23.19	-3.48	51.24	47.41	-3.83	0.8667	0.8277	-0.0390	0.8163	0.7584	-0.0579
DeepSeek-R1 8B	23.74	21.26	-2.48	49.96	45.21	-4.75	0.8586	0.7678	-0.0908	0.8010	0.7712	-0.0298

Table 9: Translation task on the **anaphora benchmark** using a structured (XML-style) reasoning prompt. Scores are aggregated over 200 examples (validation+test). Columns show performance *without* reasoning (w/o), *with* reasoning (w/), and the difference $\Delta = w/-w/o$.



Figure 11: Heatmaps of gains from the structured (XML-style) reasoning prompt. Left: absolute changes for BLEU, chrF, BERTScore, and COMET; right: the same changes as percentages relative to the noreasoning baseline. Positive cells indicate improvements; negative cells indicate declines, allowing a quick scan of which models/metrics benefit from reasoning.

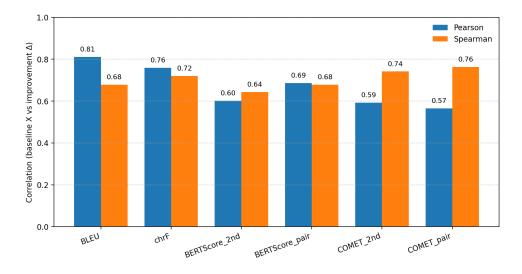


Figure 12: Correlation between baseline (no-reasoning) scores and gains Δ under the structured (XML-style) reasoning prompt. Bars show Pearson and Spearman coefficients for BLEU, chrF, BERTScore, and COMET. Positive correlations across metrics support the "wise get wiser" effect: higher-performing models tend to benefit more from reasoning.

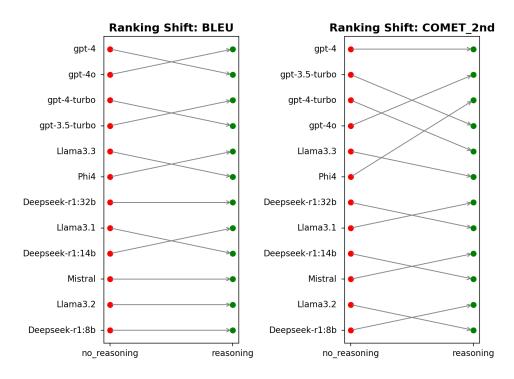


Figure 13: Ranking shifts from no reasoning (left) to structured reasoning (right) for BLEU and COMET. Each line traces a model's rank: upward moves indicate improved ranking; crossings show notable reorderings. This highlights which systems improve their rank relative to others when reasoning is enabled.

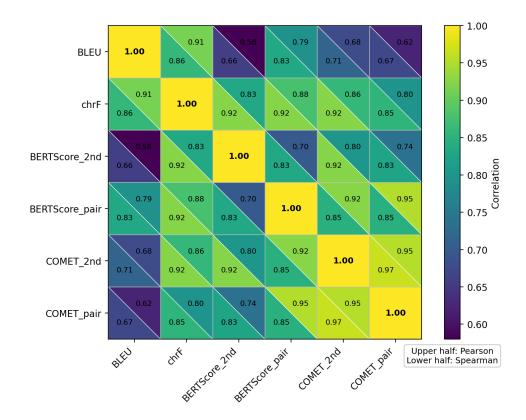


Figure 14: Correlation matrix of improvements Δ (reasoning - no_reasoning) under the structured (XML-style) prompt across twelve models. Each cell reports Pearson (upper triangle) and Spearman (lower triangle); colors are scaled to the observed min–max range for contrast. Strong positive cells indicate that models improving on one metric tend to improve on others as well.

B.3. Results: Lexical Choice

Model	BLEU ↑			chrF ↑			BERTScore (2nd) ↑			COMET (2nd) ↑		
	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ	w/o	w/	Δ
gpt-4o	53.84	54.15	+0.31	69.67	69.41	-0.26	0.9223	0.9208	-0.0015	0.8851	0.8797	-0.0054
gpt-4	51.41	53.99	+2.58	66.63	68.79	+2.16	0.9128	0.9179	+0.0051	0.8643	0.8713	+0.0070
gpt-4-turbo	49.56	49.25	-0.31	65.67	64.84	-0.83	0.9120	0.8911	-0.0209	0.8683	0.8557	-0.0126
gpt-3.5-turbo	47.31	49.42	+2.11	64.88	65.69	+0.81	0.9061	0.9102	+0.0041	0.8619	0.8560	-0.0059
Llama3.3	46.43	46.58	+0.15	62.47	63.37	+0.90	0.9023	0.9005	-0.0018	0.8479	0.8449	-0.0030
Phi-4	42.58	44.35	+1.77	59.63	61.37	+1.74	0.8936	0.9000	+0.0064	0.8334	0.8355	+0.0021
DeepSeek-R1 32B	38.87	40.94	+2.07	56.25	58.26	+2.01	0.8827	0.8816	-0.0011	0.8194	0.8140	-0.0054
DeepSeek-R1 14B	38.43	33.33	-5.10	55.13	51.14	-3.99	0.8732	0.8506	-0.0226	0.8031	0.7701	-0.0330
Llama3.1	35.08	29.37	-5.71	52.10	48.57	-3.53	0.8717	0.8573	-0.0144	0.7925	0.7664	-0.0261
DeepSeek-R1 8B	30.89	30.26	-0.63	48.33	48.05	-0.28	0.8558	0.8331	-0.0227	0.7632	0.7517	-0.0115
Mistral	26.62	27.79	+1.17	44.89	45.00	+0.11	0.8444	0.8490	+0.0046	0.7436	0.7537	+0.0101
Llama3.2	25.19	22.38	-2.81	42.47	43.10	+0.63	0.8311	0.8190	-0.0121	0.7297	0.7041	-0.0256

Table 10: Translation task on the **lexical choice benchmark** with a structured (XML-style) reasoning prompt. Scores over 200 examples (validation+test): without reasoning (w/o), with reasoning (w/), and $\Delta = w/-w/o$ (positive = gain, negative = drop). The XML tags constrain both reasoning and the final translation, reducing format errors and easing parsing.

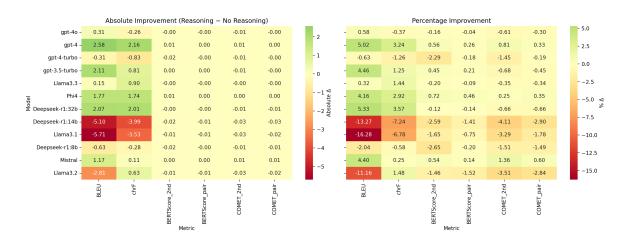


Figure 15: Heatmaps of gains from the structured (XML-style) reasoning prompt on the **lexical choice** task. Left panel shows absolute changes for BLEU, chrF, BERTScore, and COMET; right panel shows percentage changes relative to the no-reasoning baseline. Positive cells indicate improvements, negative cells declines, enabling a quick comparison across models and metrics.

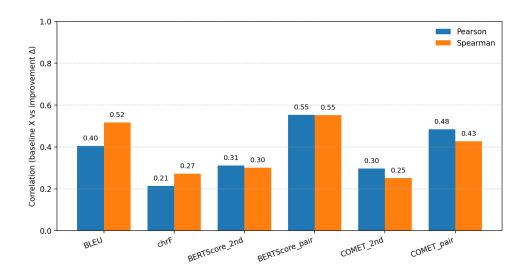


Figure 16: Correlation between baseline (no-reasoning) scores and gains Δ under the structured (XML-style) reasoning prompt on the **lexical choice** task. Bars report Pearson and Spearman coefficients for BLEU, chrF, BERTScore, and COMET. Positive values across metrics support the "wise get wiser" effect: higher-scoring models tend to benefit more from reasoning.

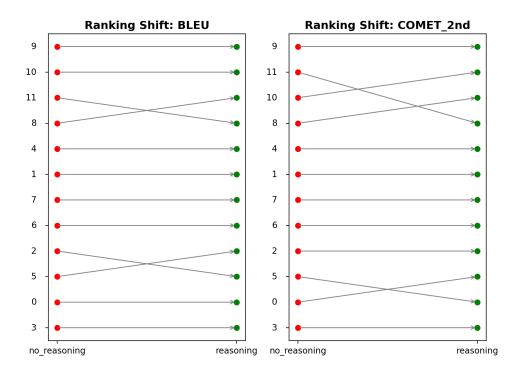


Figure 17: Ranking shifts from no_reasoning (left) to structured reasoning (right) for BLEU and COMET. Lines show how each model's relative position changes: upward trajectories signal gains; crossings indicate reorderings between models. Focus on these two metrics makes differences in lexical fidelity and semantic adequacy easy to compare.

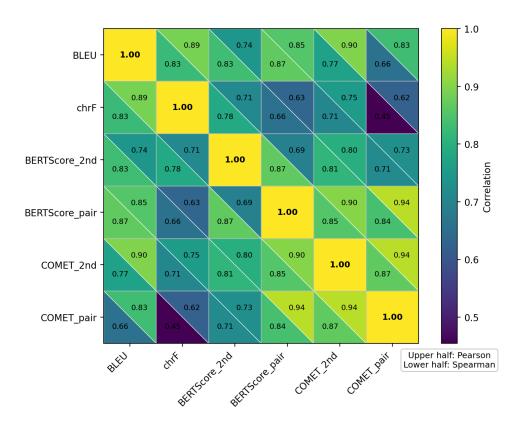


Figure 18: Correlation matrix of improvements Δ (reasoning – no_reasoning) under the structured (XML-style) prompt on the **lexical choice** task. Each cell reports Pearson (upper triangle) and Spearman (lower triangle) correlations across models. Positive cells indicate that gains tend to move together across metrics, while negative cells suggest trade-offs.