Translating Step-by-Step: Decomposing the Translation Process for Improved Translation Quality of Long-Form Texts

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Abstract

In this paper we present a step-by-step approach to long-form text translation, drawing on established processes in translation studies. Instead of viewing machine translation as a single, monolithic task, we propose a framework that engages language models in a multi-turn interaction, encompassing pre-translation research, drafting, refining, and proofreading, resulting in progressively improved translations. Extensive automatic evaluations using Gemini 1.5 Pro across ten language pairs show that translating step-by-step yields large translation quality improvements over conventional zero-shot prompting approaches and earlier human-like baseline strategies, resulting in state-of-the-art results on WMT 2024.

1 Introduction

Machine Translation (MT) has been traditionally seen as a sequence transduction task that maps a source text from one language to an equivalent translation in another language. While this simplified definition of the task served the modeling capabilities of statistical and neural machine translation systems for many years, recent advancements in large language modeling offer promise for redefining MT to align more closely with human translation processes. This shift prompts us back to a fundamental question: *what does a good translation process look like*?

Thankfully, this question has been a long-debated topic in the field of translation studies. Despite the lack of consensus around the nature of cognitive steps involved when humans translate, a common thread is apparent, i.e., translation is a multi-faceted *process* encompassing several sub-tasks that navigate a bilingual landscape. This view of translation finds a parallel in the rise of the "chain-of-thought" paradigm popularized by large language models (LLM) (Wei et al., 2022). That is, instead of attempting to generate the response to a
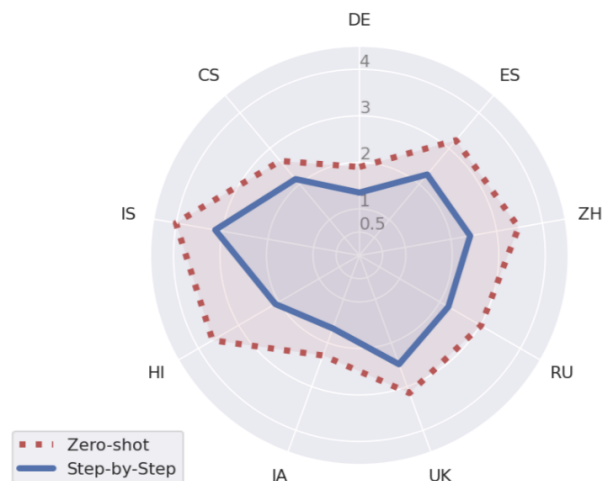

Figure 1: MetricX-23 quality improvements (where lower scores indicate better translation quality) on document-level translation on the WMT24 test set. Translate step-by-step with Gemini 1.5 Pro consistently outperforms zero-shot translation.

complex task directly, LLMs are prompted to derive their final answer by decomposing the original task into several simpler sub-tasks.

But, what form would chain-of-thought take in the context of MT? While initial attempts to model the entire translation process using complex multi-stage processes has shown mixed results (Wu et al., 2024), explicitly modeling certain pre-translation or post-translation processes has led to more consistent gains in translation quality. On the pre-translation side, He et al. (2023) proposes to generate multiple translation candidates conditioned on self-generated translation-related knowledge. On the post-translation side, recent research threads prompt LLMs for refinement with (Feng et al., 2024; Xu et al., 2023b; Ki and Carpuat, 2024) or without (Chen et al., 2023) external quality estimation feedback.

Despite the promising results reported by prior work on decomposing and re-ranking MT with LLMs, it still remains unclear whether LLMs can

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benefit from modeling the *entire spectrum of translation processes*. In this work, drawing on literature from translation studies, we view MT as a complex and iterative task adhering to distinct steps, i.e., pre-translation research, drafting, refining, and proof-reading. Based on this framework, we ask: *How well can LLMs translate in a step-by-step manner that draws from translation processes*?

Taking Gemini 1.5 Pro (Reid et al., 2024) as a case study, we start by designing instruction prompts for various translation subtasks. Concretely, our framework implements a ***multi-turn*** interaction with Gemini that breaks down the translation process into four distinct stages. It begins by prompting the model to conduct background research that identifies potential challenges in translating the source text (***research*** phase). The next interaction focuses on drafting an initial translation prioritizing faithfulness to the source text (***drafting*** phase). This draft is then revised in subsequent turns, ensuring a polished final translation (***refinement*** and ***proofreading*** phases).

To align better with human translation processes, we test the *translate step-by-step* framework on long-form documents derived from the general MT shared tasks for WMT 2023 (Kocmi et al., 2023) and WMT 2024. We evaluate out-of-English translation for ten languages, namely Chinese (ZH), Ukrainian (UK), Russian (RU), Japanese (JA), Hebrew (HE), Czech (CS), German (DE), Hindi (HI), Icelandic (IS), and Spanish (ES). Extensive automatic evaluation according to both reference-based and QE-based versions of MetricX-23 (Juraska et al., 2023) show that translating step-by-step yields strong translation quality improvements across all languages and test sets studied (see Figure 1).

2 Background

With the recent rise of LLMs, machine translation is going through a gradual but significant paradigm shift. While much research is focusing on how LLMs' training data are improving their MT capabilities (Xu et al., 2023a; Alves et al., 2024), there are also many opportunities to improve how existing LLMs can be best used for translation. This becomes evident in recent research that explores ways to augment and refine MT to align better with human translation processes. To navigate the diverse landscape of LLM-driven research, we summarize key studies in Table 1 along their four most distinct dimensions:

PAPER	PRE-TR.	POST-TR.	DEV.	PARAM.	STEPS
He et al. (2023)	✔	✗	✗	✗	3-4
Xu et al. (2023b)	✗	✔	✔	✗	Iterative
Feng et al. (2024)	✗	✔	✔	✗	3
Huang et al. (2024)	✗	✔	✔	✗	3
Li et al. (2024)	✔	✗	✗	✗	1
Chen et al. (2023)	✗	✔	✗	✔	Iterative
Ki and Carpuat (2024)	✗	✔	✗	✗	1
Wu et al. (2024)	✔	✔	✗	✔	Iterative
Step-by-Step (ours)	✔	✔	✔	✔	4

Table 1: List of prior work leveraging LLMs to improve translation quality by modeling either pre- or post-translation processes (PRE-TR. or POST-TR.). For each study we also note key aspects of their methodology: whether prompting strategies are developed on a separate development set (DEV.), whether the approach relies solely on the LLM's parametric knowledge (PARAM.), and the number of steps in the pipeline.

- **Temporal Focus**: This differentiating factor is based on whether an LLM is engaged in the translation process before (pre-translation) or after (post-translation) an initial translation is produced (whether by the same LLM or a different system).

- **Parametric vs. External Knowledge**: This dimension focuses on whether LLMs rely solely on their internal, learned knowledge (encoded in their parameters) or whether they use external resources, i.e., dictionaries, knowledge bases, retrieval engines or QE-based metrics (Mallen et al., 2023).

- **Reported Prompt Development**: This dimension considers whether the prompting strategies are clearly developed on separate development sets, as reported in papers.[1]

- **Number of Steps**: This dimension counts the number of distinct steps that are used in multi-turn interactions with the LLM.

Table 1 shows a clear trend: most studies focus on post-translation refinement. These approaches predominantly rely on external feedback to identify and correct errors, using either automatic met-

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[1]We include this column not to cast aspersions on previous work, but to encourage a culture moving forward where prompt-based research uses and reports a development set. From personal communication, some of the works receiving an "✗" here underwent little to no prompt optimization.

Pre-drafting Research

You will be asked to translate a piece of text from English into Chinese following the five stages of the translation process. Here is the context in which the text appears:

Context: However, he said the most "responsible way" to cut spending would be to pass all 12 bills. With many Republicans reticent to see a shutdown and a 1 percent cut to defense spending, the urgency to pass the bills could see enough Republicans ally with Democrats to extend the deadline on the four spending bills and reach an agreement to fund the government, even if doing so puts Johnson in hot water with some of those on the hard right.

To start, let's do some pre-drafting research on the above context:

Research:

During this phase, thorough research is essential to address components of the context text that pose translation challenges. The goal is to establish a comprehensive translation plan that covers the following category:
- Idiomatic Expressions:
  - Identify idiomatic expressions that cannot be directly translated word-for-word into Chinese.

Idiomatic Expressions in the Context:

Here are some idiomatic expressions in the context that require careful consideration for translation into Chinese:
- **"in hot water":** This idiom means to be in trouble or facing criticism. A direct translation wouldn't convey the meaning.
- **"hard right":** This refers to the most conservative faction within a political party. A literal translation wouldn't be accurate.
- **"reticent to see":** This implies reluctance or unwillingness. A more nuanced translation is needed.

Drafting

Now, let's move on to the drafting stage.

Draft Translation:

In this phase, your primary objective is to create a draft translation that accurately conveys the meaning of the source text presented below. At this stage, it is crucial to focus on adequacy, ensuring that your translation closely adheres to the source text. Your response should conclude with the draft translation. If context is missing, generate a general translation that is adaptable to various contexts. Avoid adding any additional information not present in the source text. All elements of the source text should be present in the translation.

Give your best one translation for the following piece of text based on the pre-drafting analysis without providing alternatives:

English: However, he said the most "responsible way" to cut spending would be to pass all 12 bills. With many Republicans reticent to see a shutdown and a 1 percent cut to defense spending, the urgency to pass the bills could see enough Republicans ally with Democrats to extend the deadline on the four...

然而，他表示，削减开支最"负责任的方式"是通过所有 12 项法案。由于许多共和党人不愿看到政府停摆和国防开支削减 1%，因此通过这些法案的紧迫性可能会促使足够多的共和党人与民主党人结盟，延长四项支出法案的截止日期，并达成一项为政府提供资金的协议，即使这样做会让约翰逊与一些极右翼人士产生摩擦。

Refinement

Now let's move to the next stage.

Post-editing with local refinement

In this stage, the primary aim is to refine the draft translation by making micro-level improvements that improve the draft's fluency.

Provide only one refined translation and do not output anything else after that.

然而，他表示，削减开支最"负责任的方式"是通过全部 12 项法案。鉴于许多共和党人不愿看到政府停摆和国防开支削减 1%，通过这些法案的紧迫性可能会促使足够多的共和党人与民主党人合作，延长四项支出法案的截止日期，并达成一项为政府提供资金的协议，即使这样做会让约翰逊与一些强硬的右翼人士产生矛盾。

Proofreading

You are tasked with proofreading a translation that has been revised for improved fluency. The refined translation has been generated by editing the draft translation.

Proofreading and Final Editing

The goal is to provide a polished final translation of the source text. For you reference, below are the source text, the draft, and refined translations.

Source Text
However, he said t....

Draft Translation
然而，他表示....

Refined Translation
然而，他表示....

Please proofread the refined text for grammar, spelling, punctuation, terminology, and overall fluency. Ensure the translation accurately reflects the original meaning and style. Provide only the final, polished translation.

然而，他表示，削减开支最"负责任的方式"是通过全部12项法案。鉴于许多共和党人不愿看到政府停摆和国防开支削减1%，通过法案的紧迫性可能会促使足够多的共和党人与民主党人合作，延长四项支出法案的截止日期，并达成一项为政府提供资金的协议，即使这样做会让约翰逊与一些强硬的右翼人士产生摩擦。

Figure 2: Translate Step-by-Step prompting framework. User prompts (top) and Gemini's responses (bottom) for the translation of an English document into Chinese. The full prompts for each step also appear in §A.3.

rics (Feng et al., 2024; Xu et al., 2023b; Huang et al., 2024) or human annotations of translation errors (Ki and Carpuat, 2024). A notable exception is the study of Chen et al. (2023), which shows that LLMs can iteratively refine their own outputs using only their parametric knowledge.

Comparatively fewer studies explore the pre-translation stage, investigating how LLMs can utilize background information to enhance their translation quality. He et al. (2023) explores this by prompting LLMs for different types of background information (similar examples, topics and keywords) related to the source text. However, they find that this knowledge alone is insufficient to improve the model's translation quality, and ultimately rely on external QE feedback for selection. In contrast, Li et al. (2024) operationalizes background research by incorporating idiom definitions retrieved from an external knowledge base.

A notable exception to the above is the recent work of Wu et al. (2024) which, similar to our approach, explores modeling the entire spectrum of translation processes. While conceptually aligned with our step-by-step approach, their framework is significantly more complex, with 30 distinct LLM roles interacting iteratively. Their use of non-standard metrics makes it difficult to gauge the method's success: the human evaluation does not give annotators source or reference texts, while the

bilingual automatic evaluation collects only preference decisions using the same model family as the method being tested.

Overall, in contrast to prior work, which often relies on complex multi-stage processes and external resources, our goal is to streamline the translation process, *unifying pre- and post-translation stages within one framework, by accessing only the LLM's parametric knowledge throughout*. We emphasize the methodological soundness of our pipeline by developing it on a separate development set, a practice not yet standardized in this area.

3 Translate Step-by-Step

Drawing on existing literature on translation studies (Borg, 2018), we design a series of staged prompts that attempt to map the translation process to instructions. This approach views translation as a multi-turn interaction with an LLM where each prompt guides the model's next action. Below, we describe those stages, along with what their function in the translation process is and how they are operationalized as instruction-following tasks. These stages are further illustrated in Figure 2.

Pre-translation Research Mirroring the human translation processes, our framework incorporates a pre-translation research stage. This stage primarily

focuses on using the source text (Mossop, 2000) to identify potential translation challenges drawing on real-world knowledge and knowledge of the target language (Dimitrova, 2005). We model this stage by prompting the LLM to identify and explain phrases of the source text that cannot be translated word-for-word into the target language.

Drafting Following the pre-translation research, the next stage aims at producing a draft translation, i.e., "the first stab at the rewriting" (Bassnett and Bush., 2016). This stage represents an initial attempt at rendering the source text into the target language. To that end, we initiate a subsequent interaction and prompt the model to focus on adequacy at this stage, ensuring the draft faithfully captures the meaning of the source.

Refinement The *post-drafting* stages are defined as editing tasks, with the goal of improving the overall quality of the draft translation. We define the first post-drafting stage as a subsequent interaction where the LLM is prompted to improve the draft's fluency such that the text works on its own (Borg, 2018).

Proofreading At the final, post-drafting stage, we task the LLM with the role of proofreading the refined translation to ensure it delivers a polished translation. We model this stage as a new conversation with the LLM, rather than a subsequent interaction, drawing inspiration from human studies suggesting that proofreading requires a new perspective after a break from revising (Shih, 2013).

3.1 Lessons During Development

While developing the above method, we found two factors to be important for the success of this approach: working at the document level and representing multi-step interactions as conversations.

Working at the Document Level Our multi-step process became more effective as we moved from the segments provided by WMT to working on multi-segment documents (see §4 for details on the setup). This had a large effect on the pre-translation research step, changing it in two ways. First, some phrases that appeared idiomatic or difficult at the segment level disappeared, as their translations became clear with context. Second, the LLM began identifying larger phrases. The refinement step also improved according to automatic metrics. We verified that our shift to the document level was either neutral or an improvement for our baselines (§5.3).

Domain	Literary	News	Social	Speech
# Docs.	40	43	48	111
Avg. Length	192	184	164	73

Table 2: Per-domain statistics for WMT 2024.

Multi-step Interactions as Conversations Modern LLMs use special markers to indicate human versus assistant turns in multi-turn interactions. When building an automated process like translate step-by-step, for each step, one has the option to either use previous outputs to build a completely new query that summarizes all previous interactions, or to continue the conversation, allowing the LLM to see all previous steps with its own outputs clearly marked. With the exception of the proofreading step, we found that continuing the conversation improved performance. Also, breaking the conversation into smaller turns helps with modularity for ablations.

4 Experimental Setting

We start by evaluating the translate step-by-step approach on the task of document-level translation. The experimental setting is described below.

Model Settings Throughout our experiments we use Gemini 1.5 Pro. All model outputs are generated with greedy decoding. All model prompts are provided in Appendix A.3. In zero-shot mode, the model is instructed to translate the source text directly, without providing any explanations.

To effectively isolate the artifacts from pre-translation research, we employ a secondary model call. This call restructures the natural language output into a JSON object, simplifying the parsing process for extracting artifacts.

Evaluation Sets We use WMT 2023 as our ***development*** set. Any prompt development and stage ablation experiments are conducted on this dataset. For our final ***test*** set, we use the WMT 2024 datasets. Each of these datasets was built by translating a set of English documents into multiple languages.

Both datasets are segmented for sentence- or paragraph-level evaluation, but our approach focuses on translating with as much context as possible. Therefore, we use meta-data to merge the original segments into larger ones. Ideally, this would result in complete documents, but current neural metrics have token-count limits beyond which they truncate their inputs. To accommodate neural evaluation, we set a maximum length of 250 (English

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Research	Draft	Refinement	Proofreading	ZH	UK	RU	JA	HE	CS	DE	AVERAGE
Ref-based											
1. ○	○	○	○	3.64	4.18	3.32	2.59	4.36	2.82	1.82	3.25
2. ○	●	○	○	3.48 ↓0.16	4.16 ↓0.02	3.32 ↓0.00	2.47 ↓0.12	4.54 ↑0.18	2.67 ↓0.15	1.92 ↑0.10	3.22
3. ○	○	●	○	2.92 ↓0.72	3.32 ↓0.86	2.43 ↓0.89	2.19 ↓0.40	3.24 ↓1.12	2.35 ↓0.47	1.31 ↓0.51	2.54
4. ○	●	●	○	2.85 ↓0.79	3.06 ↓1.12	2.54 ↓0.78	2.09 ↓0.50	3.18 ↓1.18	2.22 ↓0.60	1.37 ↓0.45	2.47
5. ●	●	○	○	3.00 ↓0.64	3.46 ↓0.72	2.56 ↓0.76	2.05 ↓0.53	3.89 ↓0.47	1.97 ↓0.85	1.56 ↓0.26	2.64
6. ●	●	●	○	2.63 ↓1.01	2.70 ↓1.47	2.13 ↓1.19	1.73 ↓0.86	2.88 ↓1.48	1.85 ↓0.96	1.17 ↓0.65	2.16
7. ●	●	●	●	2.67 ↓0.97	2.38 ↓1.80	2.16 ↓1.16	1.70 ↓0.89	2.75 ↓1.61	1.71 ↓1.10	1.07 ↓0.75	2.06
QE-based											
8. ○	○	○	○	2.64	4.87	4.16	1.73	5.55	5.39	3.96	4.04
9. ○	●	○	○	2.71 ↑0.07	4.78 ↓0.09	4.05 ↓0.11	1.65 ↓0.07	5.22 ↓0.33	5.14 ↓0.25	4.03 ↑0.08	3.94
10. ○	○	●	○	2.11 ↓0.52	4.33 ↓0.54	2.82 ↓1.34	1.30 ↓0.43	4.49 ↓1.06	4.31 ↓1.08	2.89 ↓1.07	3.18
11. ○	●	●	○	2.04 ↓0.59	4.12 ↓0.75	3.31 ↓0.85	1.19 ↓0.54	4.30 ↓1.25	4.40 ↓0.99	3.36 ↓0.60	3.25
12. ●	●	○	○	2.26 ↓0.38	4.18 ↓0.69	3.50 ↓0.66	1.54 ↓0.19	4.60 ↓0.95	4.62 ↓0.77	3.73 ↓0.23	3.49
13. ●	●	●	○	1.90 ↓0.73	3.39 ↓1.48	2.76 ↓1.40	1.23 ↓0.49	4.17 ↓1.38	4.12 ↓1.28	2.97 ↓0.99	2.93
14. ●	●	●	●	1.82 ↓0.81	3.43 ↓1.44	3.11 ↓1.05	1.25 ↓0.48	4.01 ↓1.54	3.56 ↓1.83	2.63 ↓1.33	2.83

Table 3: MetricX-23 evaluation results of translate step-by-step and its ablation variants on the WMT 2023 development datasets. We report both the reference-based and QE-based metric variants. Filled dots indicate active steps in the pipeline, while unfilled dots represent ablated steps. When all steps are ablated, the system defaults to zero-shot translation. Colored boxes highlight performance differences compared to zero-shot: blue shades indicate significant improvements at $p < 0.001$, green shades indicate significant improvements at $p < 0.05$, yellow shades indicate non-significant improvements ($p \geq 0.05$), while red shades indicate non-significant regressions ($p \geq 0.05$) against zero-shot. *Translate step-by-step surpasses zero-shot across the board, with each step incrementally improving translation quality.*

white-space separated) tokens each.[2] The resulting datasets consist of 192 documents of average token length 178 for WMT 2023 and, 243 documents of average token length 130 for WMT 2024, respectively. For WMT 2024 we also report per-domain results. Per-domain document counts and average lengths, as measured in English white-space separated tokens, are presented in Table 2.

Evaluation Metrics We evaluate our approach using MetricX-XXL-23 (Juraska et al., 2023), the metric adopted in the most recent WMT 2024 automatic evaluations. We report results on both the reference-based and the QE-based metric variants. Despite being trained at the sentence level, Deutsch et al. (2023) show that MetricX can effectively evaluate multi-sentence sequences, capped at its maximum window length. We note that MetricX is powered by mT5 (Xue et al., 2021), which minimizes the potential bias in favor of Gemini-generated translations.[3] We employ paired permutation tests to determine if the observed improvements across system pairs are statistically significant.[4]

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[2] We also present results for a shorter set of documents, with a maximum length of 150 tokens in Appendix A.1.

[3] We also report ChrF (Popović, 2015) in Appendix A.2.

[4] https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.permutation_test.html

5 Quantitative Results

We start by analyzing the importance of each step in the translate step-by-step pipeline. Ablation results on the WMT 2023 development sets are presented in §5.1. Next, the generalizability of our final step-by-step recipe is evaluated on the WMT 2024 test sets in §5.2, with comparison to prior work in §5.3.

5.1 Analyzing Step Importance

Automatic evaluation results on our development sets are presented in Table 3. Overall, translation artifacts extracted through the step-by-step process yield consistently better document translations compared to the zero-shot mode according to both reference- (lines 3–7 vs. 1) and QE-based (lines 10–14 vs. 8) versions of MetricX. Ablating the various steps from the pipeline gives insights into how each step contributes to the overall quality improvements. We describe those below.

Importance of Pre-translation Research Modelling pre-translation processes is crucial for achieving higher quality translations compared to the zero-shot. Simply prompting for a draft translation without asking for pre-translation research yields only small and non-significant improvements or even regressions over the zero-shot (lines 2 vs. 1

and 9 vs. 8). This result rules out the possibility that any observed improvements are solely due to a better prompt for the draft translation, which was modified to emphasize faithfulness to the source (§3). However, combining the research and draft steps achieves consistently higher quality translations compared to zero-shot (lines 5 vs. 1 and 12 vs. 8). Importantly, those improvements are consistently statistical significant ($p < 0.0001$) across languages (measured by reference-based metrics), except for Hebrew, which shows non-significant improvements compared to zero-shot ($p \geq 0.05$).

Importance of Refinement Moving to the evaluation of the *refined* document translations, we notice an interesting trend. The refinement step consistently improves the translation quality, regardless of the initial translation it processes, i.e., the zero-shot (lines 3 vs. 1 and 10 vs. 8), the single-turn draft (lines 4 vs. 2 and 11 vs. 9), and the research-informed draft (lines 6 vs. 5 and 13 vs. 12). This demonstrates that the effectiveness of the refinement stage is not conditioned on the initial translation. However, the strongest quality improvements—reaching consistently high levels of statistical significance ($p < 0.001$) over the zero-shot translations—are observed when the refinement stage is combined with the pre-translation research (lines 6 vs. 1 and 13 vs. 8), highlighting that those stages bring complimentary benefits.

Importance of Proofreading Finally, the evaluation of the *proofreading* document translations, indicate that this stage contributes modest average improvements (lines 7 vs. 6 and 14 vs. 13). Unlike previous stages, the impact of proofreading appears to be more language dependent. Ukrainian stands out as the only language that clearly benefits from a proofreading stage, while others show only minor differences in quality compared to their refined translations.

5.2 Generalizability of Step-by-Step

Table 4 presents results on the WMT 2024 test set. Across the board, translating step-by-step exhibits the same trends noticed on our development set (as discussed in §5.1). This confirms the generalizability of our proposed approach, crucially, on a wider range of languages. Concretely, the draft translations outperform the zero-shot translations. The refined stages bring additional quality improvements across the board, with the proofreading stage contributing small improvements for most languages.
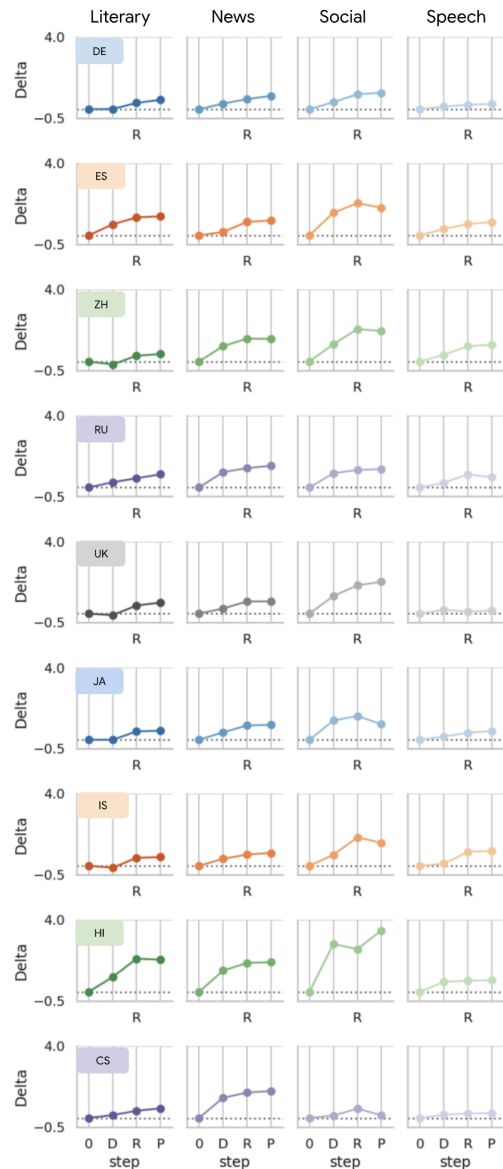
Figure 3: Domain-level comparison between zero-shot and step-by-step translations on WMT 2024 using reference-based MetricX-23. Each data point represents the delta from zero-shot (dotted horizontal line). The steps are denoted as follows: 0 (zero-shot), D (draft after research), R (refinement), and P (proofreading).

To better understand the robustness of our approach we present a per-domain analysis in Figure 3. As shown, translation quality improvements of step-by-step translations over zero-shot are observed across all domains, with speech showing the least and social the most significant gains.

5.3 Contextualizing Step-by-Step Gains

Having demonstrated how translate step-by-step improves long-form translation with LLMs over zero-shot translation, we now contextualize these gains by comparing our approach to two repre-

	DE	ES	ZH	RU	UK	JA	HI	IS	CS	AVERAGE
										Ref-based
Zero-shot	1.90	3.23	3.48	3.02	3.15	2.29	3.65	4.01	2.65	3.04
SBYS: *Research & Drafting*	1.68 ↓0.22	2.69 ↓0.54	2.99 ↓0.49	2.53 ↓0.49	2.81 ↓0.35	1.92 ↓0.37	2.52 ↓1.13	3.77 ↓0.24	2.30 ↓0.35	2.58
SBYS: *Refinement*	1.45 ↓0.45	2.29 ↓0.94	2.45 ↓1.03	2.21 ↓0.81	2.58 ↓0.57	1.64 ↓0.66	2.31 ↓1.35	3.14 ↓0.87	2.10 ↓0.55	2.24
SBYS: *Proofreading*	1.35 ↓0.54	2.27 ↓0.96	2.42 ↓1.06	2.21 ↓0.81	2.49 ↓0.66	1.67 ↓0.62	2.09 ↓1.56	3.15 ↓0.86	2.14 ↓0.51	2.20
										QE-based
Zero-shot	1.97	2.59	2.23	1.87	2.23	1.32	4.81	3.47	2.08	2.51
SBYS: *Research & Drafting*	1.72 ↓0.25	2.23 ↓0.36	2.08 ↓0.15	1.54 ↓0.33	1.81 ↓0.41	1.19 ↓0.13	4.12 ↓0.69	3.43 ↓0.04	1.97 ↓0.11	2.23
SBYS: *Refinement*	1.38 ↓0.59	1.78 ↓0.81	1.71 ↓0.52	1.21 ↓0.66	1.34 ↓0.89	0.95 ↓0.37	3.47 ↓1.34	2.79 ↓0.68	1.51 ↓0.56	1.79
SBYS: *Proofreading*	1.25 ↓0.72	1.74 ↓0.84	1.63 ↓0.60	1.14 ↓0.73	1.32 ↓0.91	0.93 ↓0.40	3.35 ↓1.46	2.65 ↓0.82	1.45 ↓0.63	1.72

Table 4: MetricX-23 results comparing step-by-step (SBYS) with zero-shot on the WMT 2024 test datasets. When all steps are ablated, the system defaults to zero-shot translation. Colored boxes highlight performance differences compared to zero-shot: blue shades indicate significant improvements at $p < 0.001$, green shades indicate significant improvements at $p < 0.05$, while yellow shades indicate non-significant improvements ($p \geq 0.05$). *Translate step-by-step surpasses zero-shot, with each step incrementally improving translation quality.*

sentative baselines: a) methods that leverage non-parametric knowledge for best translation selection, and b) segment-level baselines that translate documents using the pre-defined segmentation provided in WMT 2024 test sets.

Conditions As a representative of the first class, we compare against MAPS (He et al., 2023). This baseline employs an LLM to analyze the source text for topic, keywords, and similar examples, generating three candidate translations conditioned on each knowledge type. Then, a QE metric selects the best candidate. To create a fair comparison, we re-implement their method using Gemini 1.5 Pro, using the prompts provided in their released code. To create an even stronger baseline, we perform candidate selection with the QE variant of MetricX-23, which we know correlates well with the final reference-based MetricX-23, creating an advantage for MAPS.

For the second class of baselines, we consider two approaches: a) zero-shot translation applied to each segment individually using Gemini 1.5 Pro, both with (ZERO-SHOT IN CONTEXT) and without (ZERO-SHOT) access to the full document in the input prompt, and b) a comparison with the segment-level translations from Unbabel-Tower70B, the top-performing system of WMT 2024 based on early automatic evaluations (Kocmi et al., 2024). To get comparable document-level metrics, before evaluation, we concatenate the segment-level translation back into the mini-documents, as described in §4.

We focus our comparisons on EN-DE, EN-JA, EN-ZH, as MAPS requires in-context demonstrations that were made available only for those languages by the original authors. For a fair comparison with Unbabel-Tower70B, we exclude the speech domain from our comparison, as WMT 2024

METHOD	DOC.	EN-DE		EN-ZH		EN-JA	
UNBABEL-TOWER70B	✗	[1]	1.42	[1]	2.77	[2]	2.16
ZERO-SHOT	✗	[2]	1.98	[3]	3.65	[3]	2.60
ZERO-SHOT IN CONTEXT	✗	[2]	1.86	[2]	3.33	[2]	2.19
ZERO-SHOT	✔	[3]	2.02	[3]	3.91	[3]	2.47
MAPS	✔	[2]	1.91	[2]	3.25	[2]	2.19
SBYS: *Research & Drafting*	✔	[2]	1.75	[2]	3.32	[2]	1.94
SBYS: *Refinement*	✔	[1]	1.41	[1]	2.73	[1]	1.58
SBYS: *Proofreading*	✔	[1]	1.27	[1]	2.75	[1]	1.73

Table 5: Comparison of step-by-step (SBYS) with representative baselines (lower scores are better) on WMT 2024 according to Metric-X (reference-based). The second column indicates whether translation is performed on the entire document or by merging segment-level translations. Numbered squares represent significance clusters (Freitag et al., 2023) at $p = 0.05$. *Translate step-by-step matches or exceeds all compared baselines, crucially, without accessing external resources.*

submissions were given ASR transcripts instead of human-sourced transcripts in this domain.

Results Table 5 compares step-by-step against various baselines. Notably, even the initial stage, where the draft translation is conditioned on cross-lingual research (SBYS: *Research & Drafting*) demonstrates competitive performance against MAPS, falling within the same statistical significance cluster. This highlights the effectiveness of our pre-translation strategy compared to the background information used by MAPS. Comparing the final, proofreading stage of step-by-step (SBYS: *Proofreading*) with MAPS reveals significant translation quality gains: 0.64 improvement for DE, 0.50 for ZH, and 0.46 for JA. Notably, these improvements are achieved even though MAPS uses the same QE model family as MetricX for final candidate selection, giving it an inherent advantage. In contrast, SBYS relies solely on the model's internal, parametric knowledge throughout the entire translation process.

Comparing the final, proofreading stage of step-

by-step with the segment-level baselines helps put the improvements in perspective. Concretely, the segment-level zero-shot baselines (second and third lines in Table 5) fall significantly behind the step-by-step final translations (SBYS: *Proofreading*) across all languages by more than 0.7 and 0.4 MetricX points when compared to the out-of- and in-context variants, respectively. This demonstrates that simply translating documents at a finer granularity is not sufficient for boosting the LLM's translation quality.

Finally, comparing the final, proofreading stage of our approach with the merged translations from Unbabel-Tower70B, reveals that our approach achieves statistically comparable performance for Chinese and German (0.02 and 0.15 improvements respectively) and significantly better performance for Japanese (0.43 improvement). These improvements over the top-performing WMT 2024 system demonstrate the competitiveness of the step-by-step approach, especially given that the competing system relies on external QE metrics and computationally expensive decoding strategies to improve translation quality.

6 Qualitative Analysis

We conduct a qualitative analysis on a small subset of model outputs from all stages to understand the strengths and weaknesses of our step-by-step approach. To this end, we first compute the score difference between the final translation and the zero-shot output on WMT 2024 English to Chinese, and then randomly sample up to 5 examples from either end (i.e., examples for which the final translation quality either substantially improves or degrades over the zero-shot baseline).[5] One of the authors (native speaker of Chinese) manually inspected the sampled outputs and took notes on the salient properties of the pre-translation artifacts and the incremental changes from the different stages of the step-by-step process.

Pre-drafting For pre-drafting research, we observe that the LLM is highly capable of understanding the source in a wide variety of contexts. As showcased in Table 6, the LLM is able to correctly interpret slang (example 1: *cheeked up* in the context of making miniatures), recognize figurative

usage (example 2: *the weather didn't cooperate* in the context of flying a plane), and detect humorous expressions (example 3). This strength is especially pronounced when even the references show clear signs of human translators misinterpreting the source (see the next subsection for full examples).

On the other hand, the LLM is also prone to over-generate and seems too eager to confirm with the given instruction to find instances of indirect translation. This resulted in false positives where a direct and literal translation is already adequate (example 4: *a bit dazed* can be directly translated into Chinese), and in some cases bizarre cultural commentaries (example 5 for asking to contextualize the texture of bubble gum).

Translations The observed understanding of the source texts seems to directly contribute to more fluent and context-appropriate translations. Table 13 in §A.4 shows several interesting examples. There are quite a few instances where the step-by-step approach produces the correct translation even when the reference fails to recognize the context the phrase appears in. For example, our method correctly interprets the meaning of *cheeked up* in the first example to be "having a full cheek" when the zero-shot translates it to *blushing* and the reference translates it to *talking nonsense*. Similarly for the second example, the term *threading* is correctly understood as a thread of posts on a social media platform by all step-by-step translations, whereas the zero-shot interpretes it as a computing terminology (as in *multithreading*) and the reference interprets it as *study*.

It is also evident that the refinement improves the fluency significantly. The third example shows that both the zero-shot and the draft translates the source literally. This entails preserving the original source structure and translating the source word *ridiculous* directly. The result is somewhat awkward and sounds like translationese, which is particularly jarring considering the social media domain of the source text. This issue is rectified by both the refined translation and the reference. On the other hand, the refinement process is not perfect and does regress to less fluent outputs at times (example 4). Another prominent failure mode typical of all LLM outputs is hallucinations. In the fifth example, the refinement adds "touching the bruise", which is not present in the source.

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[5]The exact sample ranges of the score difference are [-6, -2] and [1, 6]. Examples from beyond these ranges typically demonstrate clear signs of model degeneration and are therefore excluded from this analysis.

	SOURCE SNIPPET	PRE-TRANSLATION RESEARCH	NOTES
1. ✔	trying my hand at miniatures redid the head! *[content omitted]* @user26 cheeked up. I love HER*	**"cheeked up"**: This slang term likely refers to making the miniature's cheeks fuller or more prominent. A direct translation wouldn't be accurate.	*Understanding source correctly in the context of making miniatures.*
2. ✔	#TeaganAir #pilot #flying #pa28 #PilotTraining *[content omitted]* Last week the weather didn't cooperate so we're back at it today.	**"The weather didn't cooperate"**: This is a figurative way of saying the weather was not suitable for flying.	*Good example of indirect translation.*
3. ✔	It is nice to have art and entertainment to help us make sense of our life. @user32 I could perform a liver transplant thanks to Hospital Playlist.	**"I could perform a liver transplant thanks to Hospital Playlist"**: This is a humorous exaggeration, implying that the show provided a lot of information about liver transplants.	*Good humor detection.*
4. ✗	He was covered in cuts and scratches and seemed a bit dazed, but he didn't seem too badly injured.	**"a bit dazed"**: This describes a state of confusion or disorientation. A literal translation might not convey the same meaning.	*Literal translation would do just fine.*
5. ✗	been really enjoying kneadatite (green stuff), it's like sculpting with bubble gum but you get used to that and it's tough and flexible when it cures	**"like sculpting with bubble gum"**: : This is a simile comparing the texture of Kneadatite to bubble gum. It needs to be translated in a way that makes sense to a Chinese audience who might not be familiar with the specific texture of bubble gum.	*Strange commentary on contextualizing the texture of bubble gum to a Chinese audience.*

Table 6: Samples of pre-translation research outputs along with notes from the author-annotator.

7 Conclusion

We introduce a step-by-step approach to long-form text translation using LLMs. Inspired by literature on translation studies, we decompose the translation process into distinct stages, modeling pre-translation research, drafting, refinement, and proofreading though a multi-turn interaction with Gemini 1.5 Pro. Extensive automatic evaluations on WMT 2023 and WMT 2024 tasks in ten languages demonstrate that our approach improves translation quality over directly translating the entire document with a single prompt.

Furthermore, comparison with competitive baselines, including similar human-like LLM-driven approaches and top-performing systems that employ segment-by-segment translation of a document, reveals the strong performance of our approach. Our findings highlight the potential of LLMs to progressively improve their translations, moving beyond the traditional view of machine translation as a monolithic sequence mapping task.

Limitations

While our study reveals promising step-by-step improvements across various languages and domains, we acknowledge the limitations of solely relying on automatic metrics for evaluation. While metric improvements give us a consistent signal, human evaluation is needed to further validate the effec-

tiveness of the approach and reveal a more nuanced understanding of the translation properties introduced at each step. We also acknowledge that our analysis is based solely on one family of metrics, due to context window limitations of other neural metrics in evaluating longer texts.

Finally, our pipeline is developed and tested solely on Gemini. Since different LLMs might exhibit different instruction-following capabilities across languages, the generalizability of this approach to other LLMs requires further investigation.

Ethics Statement

This paper explores the use of LLMs to improve translation quality. In doing so, our approach starts from an initial translation that prioritizes faithfulness to the source text. Subsequent stages focus on improving fluency which, as they deviate more from the source, increase the risk of hallucinations (Guerreiro et al., 2023)—a critical issue in machine translation, potentially leading to misleading translations.

Moreover, the increasing fluency of machine translations presents new challenges when prioritized over adequacy (Martindale and Carpuat, 2018), as users might trust their outputs blindly, even when incorrect. This highlights the need for careful adoption of those translation systems and the developing of strategies that help users calibrate their trust appropriately.

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A Appendices

A.1 Results on Shorter Documents

Table 9 presents automatic evaluation results of step-by-step on shorter documents, where segments are grouped together such that they do not exceed a token limit of 150 white-space separated tokens. The dataset statistics are presented in Table 10. We observe the same trends with the ones reported with larger documents in §5.

A.2 Results on ChrF

Tables 7 and 8 report ChrF scores on WMT 2023 and WMT 2024, respectively. As anticipated with string-based metrics, LLM translations which prioritize fluency receive lower scores compared to those that are by construction instructed to be closer to the source text. This behavior is in line with observations of prior work that employ similar human-like translation strategies with LLMs (Wu et al., 2024).

A.3 Prompts

Tables 11 and 12 present the complete prompts we used for our translate step-by-step framework and baselines. It has come to our attention that the prompts used in the experiments contain a few typographical errors. Preliminary results using revised prompts show comparable, if not slightly improved results (in the range of $0.1 - 0.2$ MetricX-23 score points), across all steps.

A.4 More example outputs

Table 13 gives more example outputs to support the discussion in §6.

	Research	Draft	Refinement	Proofreading	ZH	UK	RU	JA	HE	CS	DE	AVERAGE
1.	○	○	○	○	48.04	61.85	63.55	38.75	64.03	67.62	71.81	59.38
2.	○	●	○	○	48.69 ↑0.65	61.81 ↓0.04	63.93 ↑0.38	39.00 ↑0.25	64.68 ↑0.65	67.63 ↑0.01	71.79 ↓0.02	59.65
3.	○	○	●	○	41.48 ↓6.56	59.44 ↓2.41	59.33 ↓4.22	36.19 ↓2.56	60.26 ↓3.77	63.44 ↓4.18	66.89 ↓4.92	55.29
4.	○	●	●	○	43.14 ↓4.90	59.58 ↓2.27	60.37 ↓3.18	37.45 ↓1.30	60.92 ↓3.11	63.04 ↓4.58	68.71 ↓3.10	56.17
5.	●	●	○	○	45.98 ↓2.06	61.51 ↓0.34	63.04 ↓0.51	39.30 ↑0.55	62.89 ↓1.14	67.17 ↓0.45	71.07 ↓0.74	58.71
6.	●	●	●	○	41.03 ↓7.01	58.72 ↓3.13	59.44 ↓4.11	37.65 ↓1.10	59.91 ↓4.12	63.02 ↓4.60	67.61 ↓4.20	55.34
7.	●	●	●	●	40.71 ↓7.33	58.78 ↓3.07	59.23 ↓4.32	37.51 ↓1.24	59.65 ↓4.38	63.11 ↓4.51	67.49 ↓4.32	55.21

Table 7: ChrF evaluation results of translate step-by-step and its ablation variants on the WMT 2023 development datasets. Filled dots indicate active steps in the pipeline, while unfilled dots represent ablated steps. When all steps are ablated, the system defaults to zero-shot translation

	DE	ES	ZH	RU	UK	JA	HI	IS	CS	AVERAGE
Zero-shot	65.48	72.96	44.21	55.51	59.90	39.75	55.94	53.23	60.81	56.42
Research & Drafting	64.67 ↓0.81	72.30 ↓0.66	42.73 ↓1.48	57.30 ↑1.79	60.06 ↑0.16	41.19 ↑1.44	56.16 ↑0.22	53.09 ↓0.14	60.31 ↓0.50	56.42
Refinement	61.72 ↓3.76	69.22 ↓3.74	38.26 ↓5.95	55.09 ↓0.42	57.25 ↓2.65	39.15 ↓0.60	52.60 ↓3.34	52.62 ↓0.61	57.29 ↓3.52	53.69
Proofreading	61.62 ↓3.86	69.04 ↓3.92	38.41 ↓5.80	54.96 ↓0.55	57.14 ↓2.76	38.87 ↓0.88	53.47 ↓2.47	52.32 ↓0.91	56.98 ↓3.83	53.65

Table 8: ChrF results comparing step-by-step with zero-shot performance on the WMT 2024 test datasets.

	DE	ES	ZH	RU	UK	JA	HI	IS	CS	AVERAGE
										Ref-based
Zero-shot	1.89	3.10	3.25	2.90	2.99	2.31	3.03	3.79	2.37	2.85
Research & Drafting	1.67 ↓0.23	2.61 ↓0.49	2.80 ↓0.45	2.53 ↓0.37	2.67 ↓0.32	1.91 ↓0.40	2.00 ↓1.03	3.45 ↓0.34	2.16 ↓0.21	2.42
Refinement	1.44 ↓0.45	2.20 ↓0.90	2.33 ↓0.92	2.17 ↓0.73	2.34 ↓0.65	1.61 ↓0.70	1.62 ↓1.41	3.02 ↓0.76	2.00 ↓0.37	2.08
Proofreading	1.36 ↓0.53	2.11 ↓0.99	2.28 ↓0.97	2.20 ↓0.69	2.27 ↓0.72	1.65 ↓0.66	1.60 ↓1.43	3.04 ↓0.75	1.98 ↓0.39	2.05
										QE-based
Zero-shot	1.81	2.34	2.13	1.67	1.96	1.26	1.98	3.15	1.85	2.02
Research & Drafting	1.62 ↓0.18	2.03 ↓0.31	1.85 ↓0.28	1.40 ↓0.26	1.60 ↓0.36	1.10 ↓0.15	1.40 ↓0.58	2.93 ↓0.21	1.73 ↓0.12	1.74
Refinement	1.24 ↓0.57	1.61 ↓0.73	1.51 ↓0.62	1.05 ↓0.62	1.17 ↓0.79	0.91 ↓0.35	0.96 ↓1.01	2.37 ↓0.78	1.31 ↓0.53	1.35
Proofreading	1.12 ↓0.68	1.54 ↓0.80	1.44 ↓0.69	0.99 ↓0.67	1.10 ↓0.86	0.88 ↓0.38	0.92 ↓1.06	2.24 ↓0.90	1.22 ↓0.62	1.27

Table 9: MetricX-23 evaluation results comparing step-by-step with zero-shot performance on the WMT 2024 test datasets, where each document has a maximum length of 150 tokens. *Translate step-by-step surpasses zero-shot, with each step incrementally improving translation quality.*

Domain	Literary	News	Social	Speech
# Docs.	66	73	75	112
Avg. Length	120	110	105	72

Table 10: Per-domain statistics for WMT 2024, when blobbing with 150 max for total of 327 docs.

You will be asked to translate a piece of text form English into Chinese following the five stages of the translation process. Here is the context in which the text appears:

Context: *placeholder source text*

To start, let's do some pre-drafting research on the above context:

Research:
During this phase, thorough research is essential to address components of the context text that pose translation challenges. The goal is to establish a comprehensive translation plan that covers the following category:

* **Idiomatic Expressions:**
    * Identify idiomatic expressions that cannot be directly translated word-for-word into Chinese.

DRAFTING

Now, let's move on to the drafting stage.

Draft Translation:
In this phase, your primary objective is to create a draft translation that accurately conveys the meaning of the source text presented below. At this stage, it is crucial to focus on adequacy, ensuring that your translation closely adheres to the source text. Your response should conclude with the draft translation. If context is missing, generate a general translation that is adaptable to various contexts. Avoid adding any additional information not present in the source text. All elements of the source text should be present in the translation.

Give your best one translation for the following piece of text based on the pre-drafting analysis without providing alternatives:

English: *placeholder source text*

REFINEMENT

Now let's move to the next stage.

Post-editing with local refinement
In this stage, the primary aim is to refine the draft translation by making micro-level improvements that improve the draft's fluency.

Provide only one refined translation and do not output anything else after that.

PROOFREADING

You are tasked with proofreading a translation that has been revised for improved fluency. The refined translation has been generated by editing the draft translation.

Proofreading and Final Editing
The goal is to provide a polished final translation of the source text. For you reference, below are the source text, the draft, and refined translations.

Source Text
placeholder source text

Draft Translation
placeholder draft translation

Refined Translation
placeholder draft refined translation

Please proofread the refined text for grammar, spelling, punctuation, terminology, and overall fluency. Ensure the translation accurately reflects the original meaning and style. Provide only the final, polished translation.

Table 11: Complete prompts used by the translate step-by-step pipeline.

Table 12: Prompts used for baseline comparisons (zero-shot and zero-shot in context) and structuring the pre-translation research translation artifacts.

1. ✔ *Good example*		
SOURCE	@user26 cheeked up. I love HER*	
REFERENCE	@user26 口出狂言。我喜欢她*	
	*Talking nonsense. I like her***	
ZERO-SHOT	@user26 脸红了。我爱她*	
	*Blushing. I love her***	
RESEARCH AND DRAFT	@user26 脸颊做得很饱满。我喜欢她*	
	*The cheeks are very plump. I like her***	
REFINEMENT	@user26 脸颊做得鼓鼓的，超可爱！我喜欢她*	
	*The cheeks are very chubby, super cute! I like her***	
NOTES	*Both the reference and the zero-shot misinterpreted the phrase "cheeked up" in the context of making miniatures. Both the draft and the refined version understood it correctly, with the latter being a bit more colloquial.*	
2. ✔ *Good example*		
SOURCE	I donked up my threading	
REFERENCE	我完成了这部分学习	
	I finished this part of study.	
ZERO-SHOT	我把我的线程搞砸了	
	I messed up my threads [note: a terminology in computing].	
RESEARCH AND DRAFT	我搞砸了我的帖子顺序	
	I messed up the order of my posts.	
REFINEMENT	我搞砸了帖子顺序	
	I messed up the post order.	
NOTES	*The reference misinterpreted both "donked up" and "threading" in this context, and the zero-shot translation mistook the latter for the computing terminology.*	
2. ✔ *Good example*		
SOURCE	It is a ridiculous level.	
REFERENCE	这关太难了。	
	This level is too hard.	
ZERO-SHOT	这是一个荒谬的关卡。	
	This is a ridiculous level.	
RESEARCH AND DRAFT	这是一个荒谬的关卡。	
	This is a ridiculous level.	
REFINEMENT	这个关卡真是太难了。	
	This level is really too hard.	
NOTES	*Zero-shot and draft translations are direct, literal, and stylistically awkward in Chinese, especially in the social media domain.*	
4. ✗ *Bad example*		
SOURCE	Ivory chuckled from the memory.	
REFERENCE	艾弗里回忆到这里，笑了起来。	
	Ivory thought of this and laughed	
ZERO-SHOT	艾弗里想起这件事，不禁轻笑起来。	
	Ivory thought of this and couldn't help starting to chuckle.	
RESEARCH AND DRAFT	艾弗里回想起当时的情景，不禁轻笑出声	
	Ivory thought of the situation at that time and couldn't help letting out a chuckle.	
REFINEMENT	艾弗里摸了摸肩膀上上次留下的瘀伤，不禁轻笑出声。	
	Ivory touched the bruise on the shoulder left from the last time and couldn't help letting out a chuckle.	
NOTES	*All translations did a good job translating the phrase "chuckled from the memory" fluently into Chinese, but the refinement hallucinated by adding "touched the bruise."*	
5. ✗ *Bad example*		
SOURCE	one of them ran for something and grabbed it	
REFERENCE	其中一个人跑过去抓起了什么东西	
	One of them ran over and grabbed something.	
ZERO-SHOT	其中一个人跑去拿了什么东西	
	One of them ran and grabbed something	
RESEARCH AND DRAFT	其中一个人跑到某个东西那里，抓起它	
	One of them ran to something and grabbed it.	
REFINEMENT	其中一个人跑到某个东西那里，抓起它	
	One of them ran to something and grabbed it.	
NOTES	*Although all translations are adequate and capture the semantic meaning of the source correctly, the draft and the refinement keep the original source structure and the resulting translation sounds like translationese.*	

Table 13: Sample of step-by-step and zero-shot outputs along with notes.