

# NeoAMT: Neologism-Aware Agentic Machine Translation with Reinforcement Learning

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## Abstract

Neologism-aware machine translation<sup>1</sup> aims to translate source sentences containing neologisms into target languages. This field remains underexplored compared with general machine translation (MT). In this paper, we propose an agentic framework, NeoAMT, for neologism-aware machine translation equipped with a Wiktionary-based search toolkit. Specifically, we first construct a dedicated dataset for neologism-aware machine translation and build a search toolkit grounded in Wiktionary. The dataset covers 16 languages and 75 translation directions in total, derived from approximately 10 million records of an English Wiktionary dump. The retrieval corpus of the search toolkit is also constructed from around 3 million cleaned records of the same dump. We then leverage the dataset and toolkit to train a translation agent via reinforcement learning (RL) and to evaluate the accuracy of neologism-aware machine translation. Furthermore, we propose an RL training framework featuring a novel reward design and an adaptive rollout generation strategy that exploits “translation difficulty” to further improve the translation quality of translation agents using our search toolkit<sup>2</sup>.

## 1 Introduction

Recently, reasoning-based language models (OpenAI, 2024; Guo et al., 2025; Yang et al., 2025a; Team et al., 2025) have gained a lot of attention because of the power of test-time scaling (Snell et al., 2025; Muennighoff et al., 2025; Li et al., 2026). Various attempts have been made to explore how to use large language models (LLMs)

<sup>1</sup>“Neologism-aware machine translation” is used here to denote translating source sentences containing neologisms, not translating neologisms individually at the word level. Regarding the use of the term “neologism”, we follow the Wiktionary definition: <https://en.wiktionary.org/wiki/Wiktionary:Neologisms>.

<sup>2</sup>The code, dataset and search toolkit will be available at <https://github.com/gpgg/neoamt>.

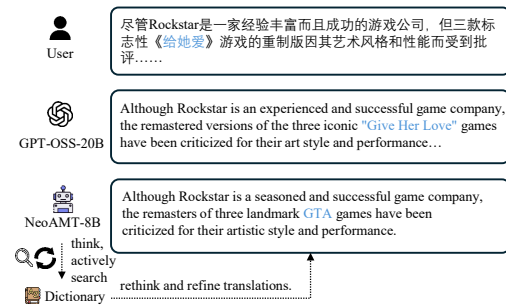



Figure 1: A Chinese-English neologism-aware machine translation example from our Neko dataset. The text in blue highlights a neologism or its translation. The source text in Chinese contains a neologism “给她爱” which in this context refers to “GTA”, an action-adventure video game series, rather than carrying its literal surface meaning of “giving her love”. The circle  denotes that the thinking and searching processes can be repeated. The detailed thinking and searching process of our model can be found in Table 20, Appendix D.

and reasoning with reinforcement learning (RL) on machine translation (MT) (Feng et al., 2025; Li et al., 2025b; Yang et al., 2025b; Wang et al., 2025a,b). These studies mainly focus on the reward design to improve the MT performance of LLMs by leveraging their reasoning ability elicited by prompts and parametric knowledge. For example, MT-R1-Zero (Feng et al., 2025) introduces a mixed reward mechanism. DeepTrans (Wang et al., 2025b) leverages DeepSeek-V3 (Liu et al., 2024) to design tailored format, thought, and translation rewards to enhance overall translation quality.

However, language is constantly evolving (Nowak and Krakauer, 1999), driven by various factors such as cultural exchange, technological advancement, migration and generational change. People coin new words while the internal parametric knowledge in LLM-based neural machine translation systems remains frozen. Thus, they cannot translate relatively new words well

only using the reasoning ability and parametric knowledge, as shown in Figure 1.

To tackle the aforementioned problem, we investigate how to enhance LLM performance on neologism-aware machine translation through a range of approaches, including supervised fine-tuning (SFT), RL with reasoning, and teaching LLMs how to consult dictionaries in an agentic way. Our contributions can be summarized as follows:

- To the best of our knowledge, our research represents the first effort in exploring the effectiveness of neologism-aware machine translation agents by leveraging the interleaved reasoning and searching process with a dictionary.
- We propose a novel RL training framework, NeoAMT, based on GRPO (Shao et al., 2024) which consists of a novel reward design and an adaptive sampling approach using the proposed translation difficulty metric.
- For training and evaluation, we construct a new dataset for neologism-aware machine translation and develop an accompanying search toolkit derived from an English Wiktionary dump.

## 2 Overcoming Data Scarcity for Neologism-Aware Machine Translation

### 2.1 Construction of Neko Dataset

The first challenging issue in neologism-aware machine translation is that there is no solid testbed which contains high-quality translation pairs and neologism definitions. Although the previous study Neo-bench (Zheng et al., 2024) has a neologism-aware machine translation subset, it is relatively small (240 in total) and contains only one language pair and not publicly available as shown in Table 1.

Wiktionary<sup>3</sup> is a free and multilingual project that hosts a large number of word entries containing annotated tags including “neologism”, word definitions and optional example sentences and their translations. Therefore, we select the English Wiktionary as our data source to build our new dataset, Neko, which is short for Neologism Example Sentences from WiKtiOmary. Note that the English Wiktionary is a multilingual dictionary in which glosses are written in English. Sixteen languages

<sup>3</sup><https://www.wiktionary.org/>

spanning across WMT20-23 are chosen as our research languages. The sixteen languages are English (en), Icelandic (is), Russian (ru), Khmer (km), Hausa (ha), German (de), Japanese (ja), Chinese (zh), Czech (cs), Ukrainian (uk), Tamil (ta), Polish (pl), French (fr), Hebrew (he), Croatian (hr) and Pashto (ps).

Dataset	# Langs	# Examples (train/val/test)
Neo-bench	2	240 ( - / - / 240 )
Neko (ours)	16	11,521 ( 10,425 / 83 / 1,013 )

Table 1: Comparison of neologism-aware machine translation datasets. The number of translation pairs in training, validation and testing splits of Neko are listed in Table 28 and 27. The test split of the Neko dataset has 743 examples for other-language-to-English directions and 270 examples for English-to-other-language directions in total.

We cleaned around 10M records from a recent English Wiktionary dump<sup>4</sup> and obtained 3,312,877 records in 16 languages in which 3,606 word entries are tagged as neologisms. We then classify the cleaned records into three types:

- **Type 1** represents the word entries that are neologisms and have example sentences and corresponding translations.
- **Type 2** denotes the word entries that are neologisms and have example sentences without translations.
- **Type 3** are the other word entries except **Type 1** and **Type 2**. Note that this type of data may contain neologisms without example sentences and corresponding translations, besides regular word entries.

The entire cleaning and processing pipeline is illustrated in Figure 2. After data cleaning and classification, we obtained 831 **Type 1**, 2,581 **Type 2** and 3,309,465 **Type 3** word entries, respectively.

**Validation and test data.** We extract the example sentences and their translations from **Type 1** word entries. After that, we split them into the validation and test sets because these translation pairs have been carefully examined by Wiktionary editors and thus they are of high-quality and human-verified. This original test split only contains other-lang-to-English translation directions since we use

<sup>4</sup>Specifically, we use the raw data from <https://kaikki.org/dictionary/rawdata.html> (JSONL) dated 2025-08-23.

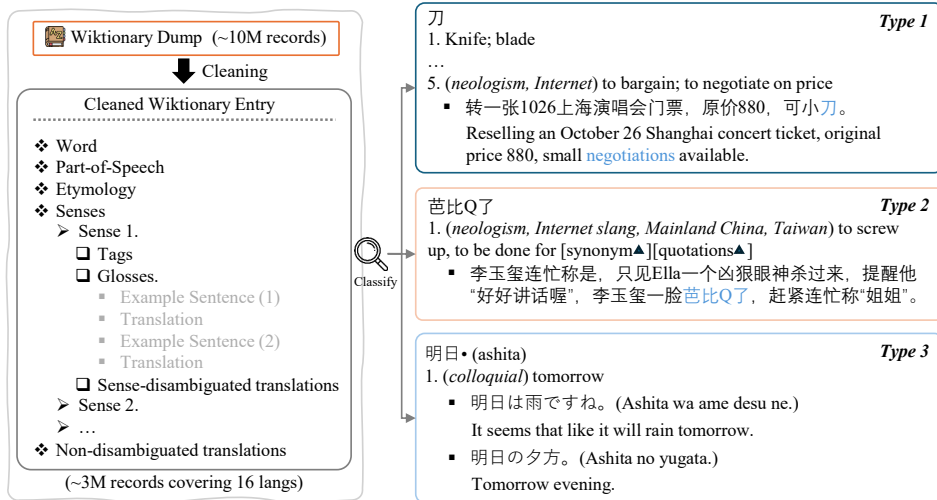


Figure 2: The construction process of our Neko benchmark. We clean about 10M records from a Wiktionary dump. In each cleaned word entry, we have word, part-of-speech, etymology, senses and non-disambiguated translations. In word senses, we have tags, such as “neologism”, “Internet”, glosses and so on. Glosses contain definitions of words. Example sentences and translations are available for some words. We obtain three types of Wiktionary word entries from the cleaned records. Blue words are neologisms or their translations.

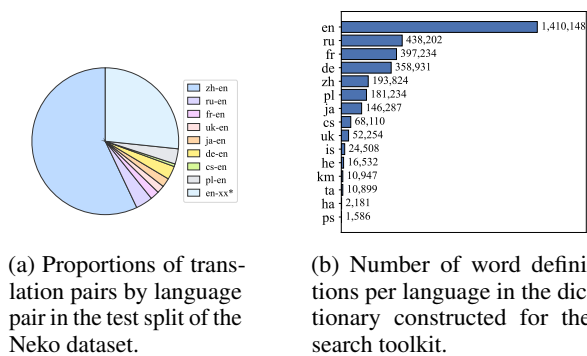


Figure 3: Statistics of the test split of Neko dataset and the constructed dictionary in the search toolkit.

the English Wiktionary. Other language versions of Wiktionary were also examined (e.g., the Japanese and Chinese Wiktionary dumps); however, only a very limited number of English-to-other-language translation pairs containing neologisms were found. Therefore, we selected 270 word entries from **Type 2** word entries containing neologism definitions and example sentences and used them for reference-free evaluation. The proportions of language pairs in the test split can be found in Figure 3a. En-xx\* in the figure indicates that this translation direction is evaluated in a reference-free way provided with the neologism definitions.

**Training data.** For training data, we extract 700 example sentences with neologism definitions from **Type 2** data except those used in the reference-free

evaluation and use gpt-5-2025-08-07 to translate the source example sentences into the other 15 languages with the neologism definitions in the prompt. In addition, we also obtain the aligned spans  $\mathcal{S}$  in the target sentences for the neologisms in the source sentences. The details of the alignment process and the human validation on the translation quality can be found in Appendix E.1 and E.2 respectively. The final step is to convert the translation pairs into the correct prompt formats for training and evaluation.

## 2.2 Search Toolkit

**Dictionary.** Unlike question answering (QA) and mathematical tasks, an MT-oriented dictionary is required for translation agents. Specifically, we collect word definitions from our cleaned 3,312,877 word entries. Each word definition includes “part-of-speech”, “etymology”, “senses”, and optional “word translations” in other languages. These word definitions are compiled into a dictionary for later retrieval by translation agents. The distribution of word definition counts for different languages in the constructed dictionary is presented in Figure 3b. To better capture word semantics, we encode the entire word definition including “part-of-speech”, “etymology”, “senses”, and optional “word translations” into a semantic vector. This is because some headwords share the same form but differ in their glosses (senses) and etymologies; encoding headwords alone would be insufficient to distinguish

these distinct lexical entries.

**Retrieval Engine.** Multilingual embedding models (Sturua et al., 2024; Zhao et al., 2024; Chen et al., 2024; Miao et al., 2024; Zhang et al., 2025) have demonstrated superior performance across a variety of retrieval tasks. We utilize the widely used multilingual embedding model bge-m3<sup>5</sup> (Chen et al., 2024) to obtain dense representations of items in the constructed dictionary. The reason why we choose bge-m3 is that it is one of SOTA embedding models for retrieval and the pretraining data of bge-m3 covering 194 languages contains a large amount of translation-related corpora, for example, NLLB (Team et al., 2022), CCMatrix (Schwenk et al., 2021), which should reduce the possible bias or domain mismatch. We use cosine similarity to measure the relevance of two items. The faiss library<sup>6</sup> (Johnson et al., 2019; Douze et al., 2024) is leveraged to retrieve relevant items given a query.

The search toolkit that we proposed based on the Wiktionary is quite flexible. You can add custom words or replace ambiguous ones at any time to further refine the dictionary knowledge base. This framework can also be used with other dictionaries in many different languages because we use a multilingual embedding model, bge-m3. The bge-m3 can also be replaced with the latest multilingual embedding models, MT-specific or dictionary-specific embedding models.

### 3 RL Algorithm

The proposed approach comprises two key components: a carefully designed reward scheme and a translation difficulty-based adaptive sampling for GRPO (Shao et al., 2024). We begin by establishing the notation adopted throughout this section. Let  $x$ ,  $\hat{y}$ , and  $y^{\text{ref}}$  denote the source text, the model-generated translation, and the reference translation, respectively.

**Prompt Template.** To train our models, we design a prompt template that guides the initial LLM through a series of predefined steps for translating the source texts. The minimal output structure comprises four main steps: an initial reasoning process, a search process, a subsequent reasoning process, and a final translation generation step. The reasoning and search processes can be iteratively repeated by the LLM as needed. The predefined steps are

<sup>5</sup><https://huggingface.co/BAAI/bge-m3>

<sup>6</sup><https://github.com/facebookresearch/faiss>

not compulsory. The prompt template can be found in Table 2.

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```

You are a professional {src_lang} to {tgt_lang} translator. Please
translate the following text from {src_lang} to {tgt_lang} .
You must conduct reasoning inside <think> and </think> first. After
reasoning, you can use the search tool by enclosing your query within
<search> and </search>. The query could be unfamiliar terms, relevant
keywords, or example sentences. The search tool will then return the
top results between <information> and </information>. You can use
the returned information to improve your translation. You can reason
and search as many times as you want. In the end, you should
directly provide the final translation inside <translation> and
</translation> with a new line, without detailed illustrations.
...
{src_lang} text: {src_text}

```

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Table 2: Training template of NeoAMT. The full prompt can be found in Table 10 in Appendix A.2.

### 3.1 Reward Design

**Outcome reward.** The outcome reward incorporates three components: a neologism-specific reward, a neural model reward, and a format reward.

We propose a neologism-specific reward  $R_{\text{neo}}$  to encourage accurate translation of neologisms. This reward is adapted from the terminology success rate metric used in the WMT Terminology Translation Track (Semenov et al., 2023). We lemmatize the generated translation  $\hat{y}$  to obtain  $\hat{y}_l$ , along with the corresponding spans of neologisms in the target language. The reward is then computed by checking whether the lemmatized neologism spans exist in  $\hat{y}_l$ . The detailed computation procedure for  $R_{\text{neo}}$  is presented in Algorithm 1. The neural model reward  $R_{\text{neural}}$  is designed to ensure semantic fidelity between  $x$  and  $\hat{y}$ . It combines scores from XCOMET-XL (Guerreiro et al., 2024) and CometKiwi-DA-XL (Rei et al., 2023) as follows:

$$R_{\text{neural}} = \delta \cdot s_{\text{XCOMET}} + (1 - \delta) \cdot s_{\text{CometKiwi-DA}}, \quad (1)$$

where  $s_{\text{XCOMET}}$ ,  $s_{\text{CometKiwi-DA}}$  represents the scores of  $\text{XCOMET-XL}(x, y^{\text{ref}}, \hat{y})$  and  $\text{CometKiwi-DA-XL}(x, \hat{y})$  respectively, and  $\delta$  is set to 0.5. We also incorporate a format indicator reward  $\mathbb{1}_{\{\text{format}\}}$  to encourage the model to produce translations in the expected format. Specifically, the total reward is set to zero if the model fails to enclose the final translation within the  $\langle \text{translation} \rangle$  and  $\langle / \text{translation} \rangle$  tags. The final reward can be denoted as follows if we use outcome-based reward for training:

$$R = \mathbb{1}_{\{\text{format}\}} \cdot (\lambda R_{\text{neo}} + (1 - \lambda) R_{\text{neural}}). \quad (2)$$

**Process reward.** We also explore a process reward to evaluate its effectiveness. This reward assigns a score  $R_q$  to the search queries based on whether the lemmatized queries generated by the model during reasoning contain the lemmatized neologism span. The final reward can be denoted as follows if we incorporate the process reward:

$$R = \mathbb{1}_{\{\text{format}\}} \cdot (\lambda R_{\text{neo}} + \sigma R_q + (1 - \lambda - \sigma) R_{\text{neural}}), \quad (3)$$

where  $\lambda$  and  $\sigma$  are set to 0.1 by default.

### 3.2 Adaptive Sampling based on Translation Difficulty

The source texts in the Neko dataset exhibit varying levels of difficulty. Difficult source texts require LLMs to engage in intensive reasoning and explore a wider range of trajectories prior to translation, resulting in a comparatively slower learning process. To effectively capture the distinction, we define a metric ‘‘translation difficulty’’ based on relative quality estimation scores (RQE) to measure how hard it is to translate source texts. The definition is as follows:

**Definition 1 (Translation Difficulty)**

$$v = \Phi(x, y^{\text{ref}}) - \Phi(x, \hat{y}), \quad (4)$$

where  $\Phi$  denotes the quality estimation model and  $\Phi(x, y) \in [0, 1]$ . The quality estimation model  $\Phi$  is CometKiwi-DA-XL. We adopt this value rather than  $1 - \text{XCOMET-XL}(x, y^{\text{ref}}, \hat{y})$  because can, in some cases, produce translations that surpass human references, a scenario that  $1 - \text{XCOMET-XL}(x, y^{\text{ref}}, \hat{y})$  fails to capture accurately. By leveraging translation difficulty, we encourage the model to generate more rollouts for challenging source texts, thereby increasing the likelihood of obtaining higher-quality translations. Conversely, we reduce the number of rollouts for easier translations to conserve computational resources.

Given the total budget of a batch  $\mathcal{N} = |\mathcal{B}| * G$  where  $\mathcal{B}$  is the input batch and  $G$  is the group size in GRPO, we sample more trajectories for the training examples whose  $v > 0$  during the rollout generation stage. We sample fewer trajectories when  $v < 0$ . The number of trajectories for one training example is  $g = g_{\text{initial}} \exp(r)$ . The computation of  $r$  can be denoted as follows:

$$r = \begin{cases} \alpha v + \psi, & v \geq 0 \\ \gamma v + \psi, & v < 0. \end{cases} \quad (5)$$

We clamp  $g$  between a minimum value  $g_{\text{min}}$  and a maximum value  $G$  to prevent extreme values. At last, if the total number of current rollouts  $\sum_{j=1}^{j=|\mathcal{B}|} g_j < \mathcal{N}$ , we assign the remaining budget  $\mathcal{N} - \sum_{j=1}^{j=|\mathcal{B}|} g_j$  to samples where  $v_j > 0$  according to the ratio:  $v_j / \sum_{j=1}^{j=|\mathcal{B}|} v_j$  where  $v_j > 0$ .

**Policy Optimization.** Our policy optimization approach is based on GRPO. In our RQE-based policy optimization, for each source text  $x_i$ , we sample multiple outputs  $\{o_1, o_2, \dots, o_g\}$  according to the adaptive group size  $g$ . The  $g$  is obtained through our RQE-based adaptive sampling method. The policy model  $\pi_\theta$  is optimized by maximizing the following objective:

$$\begin{aligned} \mathcal{J}(\theta) = & \mathbb{E}_{x \sim \mathcal{D}, \{o_i\}_{i=1}^g \sim \pi_{\text{old}}(\cdot|x;\mathcal{E})} \\ & \left[ \frac{1}{g} \sum_{i=1}^g \frac{1}{\sum_{t=1}^{|o_i|} I(o_{i,t})} \sum_{t=1: I(o_{i,t})=1}^{|o_i|} \right. \\ & \min \left( \frac{\pi_\theta(o_{i,t}|x, o_{i,<t}; \mathcal{E})}{\pi_{\text{old}}(o_{i,t}|x, o_{i,<t}; \mathcal{E})} \hat{A}_{i,t}, \right. \\ & \left. \left. \text{clip} \left( \frac{\pi_\theta(o_{i,t}|x, o_{i,<t}; \mathcal{E})}{\pi_{\text{old}}(o_{i,t}|x, o_{i,<t}; \mathcal{E})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A}_{i,t} \right) \right. \\ & \left. - \beta \mathbb{D}_{KL} [\pi_\theta || \pi_{\text{ref}}] \right], \quad (6) \end{aligned}$$

where  $\pi_\theta$  and  $\pi_{\text{ref}}$  are the current and reference policy models.  $\pi_{\text{old}}$  is the old policy model used to generate rollouts.  $\mathcal{E}$  represents the retrieval engine.  $\hat{A}_{i,t}$  is the advantage computed by using the relative rewards of outputs within the group  $\{o_1, o_2, \dots, o_g\}$ .  $\epsilon$  and  $\beta$  are hyperparameters.  $I(o_{i,t})$  denotes the loss masking function. Following previous studies, like Search-R1 (Jin et al., 2025) and ARPO (Dong et al., 2025), we exclude the retrieved information in the policy optimization step by loss masking on the retrieved results. Therefore,  $I(o_{i,t})$  is 1 when  $o_{i,t}$  is a model-generated token and  $I(o_{i,t})$  is 0 when  $o_{i,t}$  is a retrieved token.

## 4 Experiments

We address the following main research questions through experiments.

**RQ1.** How to better address neologism-aware machine translation: using SFT, RL with reasoning, or teaching the model to consult dictionaries in the reasoning process using RL?

**RQ2.** How should rewards be designed to enhance the performance of the neologism-aware machine translation agent?

#### 4.1 Setup

In this section, we illustrate our experimental settings, including datasets and evaluation. As described in § 2.1, we split the example sentences and their translations from *Type 1* of the Neko dataset into validation and test sets. We utilize 700 example sentences from *Type 2* of the Neko dataset and their translations as our train set. The statistics about the train, val and test splits of Neko dataset are presented in Table 1, 27 and 28 in Appendix F. The performance of our model on the WMT24++ (Deutsch et al., 2025) is also reported in Appendix G.1. Baselines are introduced in Appendix C.1.

#### 4.2 Evaluation

We evaluate translation quality from two perspectives: neologism-specific quality and overall quality.

**Neologism-Specific Metrics.** For neologism-specific metrics, we use four metrics, exact translation success rate  $s_{\text{exact}}$ , fuzzy translation success rate  $s_{\text{fuzzy}}$ , lemma-exact translation success rate  $s_{\text{lem-exact}}$ , and lemma-fuzzy translation success rate  $s_{\text{lem-fuzzy}}$ . These scores use different string matching approaches, such as lemmatization, exact string matching and fuzzy string matching<sup>7</sup>. The four metrics aim to check if the translations of neologisms can be found in the reference translations or not. These metrics can complement each other to ensure the stability and accuracy of the evaluation. The detailed computation procedures of neologism-specific metrics are presented in Appendix C.3.

**Overall Quality Metrics.** For overall quality, we mainly use LLM-as-a-judge evaluation. In this evaluation, we use the GEMBA-DA prompt (Kocmi and Federmann, 2023) with gpt-5-2025-08-07 to evaluate the translations. In addition to the GEMBA evaluation, we also provide additional neologism gloss information in the prompt to aid

<sup>7</sup>For lemmatization, we use stanza (1.10.1). For fuzzy string matching, we use fuzzywuzzy (0.18.0). These four metrics are adapted from the terminology success rate used in terminology translation track of WMT (Semenov et al., 2023, 2025). Our metric implementation is based on this code snippet provided by the WMT25 terminology translation track: [https://colab.research.google.com/drive/1b\\_M4tHnJxYT1JHZakjq44YJJIVsOP38h?usp=sharing](https://colab.research.google.com/drive/1b_M4tHnJxYT1JHZakjq44YJJIVsOP38h?usp=sharing).

the backbone LLM to better judge the translation quality from both neologism and overall semantic-matching perspectives. The detail of the LLM-as-a-judge prompts can be found in Table 15 and Table 16, Appendix C.

#### 4.3 Experimental Results

We present main results in Table 3. The results show that our training framework can improve the model performance and demonstrate the effectiveness of the reward design.

**The improvement of neologism translation quality using SFT is limited.** For the neologism-specific scores, SFT result shows that the fine-tuned models cannot elicit the ability of translating neologisms well even if they are finetuned on the training data. This result supports the assumption that the base model itself has little inherent knowledge about neologisms.

**RAG struggles to follow instruction/gets lost in retrieved word definitions.** We use the same queries as our model, that is, NeoAMT-4B and NeoAMT-8B in RAG for retrieval to ensure a fair comparison and investigate the effect of queries. The results about neologism-specific scores and overall quality are display in Table 31, Appendix G.6 and Table 4 respectively. RAG outperforms other baselines in the neologism-specific scores, suggesting that the retrieved word entries could benefit the neologism translation even under the RAG setting. This result also demonstrates that the queries generated by our model are beneficial for translating neologisms. However, the overall quality of RAG is not satisfying and we observe that augmented prompts with retrieved word entries cause the model not to follow the instruction and hallucinate; for example, it continually generates fake word entries.

**Performance on English-to-other-language directions.** Table 5 presents the LLM-as-a-judge results of various finetuning approaches on the English-to-Japanese and English-to-Chinese translation directions. The results demonstrate the effectiveness of our training framework on English-to-other-language directions. Note that the dictionary used here is the same one employed for the other-language-to-English directions, derived from English Wiktionary. The glosses for English neologisms are provided in the source language, i.e., English.

MODEL	NEOLOGISM-SPECIFIC				OVERALL QUALITY	
	EXACT	FUZZY	LEM-EXACT	LEM-FUZZY	GEMBA(GPT5)	LJ(GPT5)
<i>General Purpose LLMs</i>						
Llama-3.1-8B-Instruct	11.44	13.46	13.19	14.54	60.64	47.79
Aya-23-8B	12.92	15.88	15.48	17.36	63.77	50.26
Aya-expanse-8B	14.54	17.22	17.63	19.38	70.20	56.18
Qwen3-4B	13.19	16.02	17.23	18.57	65.24	51.94
Qwen3-8B	17.36	19.11	20.32	21.13	71.24	58.13
Qwen3-14B	18.30	20.05	21.53	22.34	76.91	63.56
Qwen3-32B	19.65	22.21	22.75	24.36	76.68	63.72
GPT-OSS-20B	18.84	22.07	21.67	23.42	73.96	62.62
<i>Translation-Specific LLMs</i>						
ALMA-R-7B	10.09	13.86	13.06	15.75	62.56	48.78
MT-R1-Zero-7B-Mix	16.29	18.30	18.84	19.11	67.22	53.80
X-ALMA	13.46	15.07	16.55	17.09	71.28	58.87
TowerInstruct-7B-v0.2	11.71	14.40	14.27	16.15	60.20	47.49
mExTrans-7B	13.46	18.71	16.42	19.78	70.37	57.42
Hunyuan-MT-7B	16.15	17.63	19.78	20.19	69.46	55.81
Qwen3-4B	13.19	16.02	17.23	18.57	65.24	51.94
SFT-4B	13.73	16.96	17.23	18.84	66.92	54.00
GRPO-4B	13.73	15.74	16.82	18.98	71.29	55.34
NeoAMT-4B	<u>17.63</u>	<u>19.11</u>	<u>20.05</u>	<u>21.53</u>	<u>72.93</u>	<u>58.16</u>
NeoAMT-4B + process reward	<b>19.25</b>	<b>23.55</b>	<b>23.55</b>	<b>27.19</b>	<b>74.06</b>	<b>64.43</b>
Qwen3-8B	17.36	19.11	20.32	21.13	71.24	58.13
SFT-8B	15.61	18.17	19.11	20.32	72.39	60.01
GRPO-8B	17.63	<u>21.13</u>	20.19	22.75	72.84	61.11
NeoAMT-8B	<b>22.34</b>	<b>26.24</b>	<b>25.84</b>	<b>28.67</b>	<u>78.28</u>	<u>66.40</u>
NeoAMT-8B + process reward	<u>18.57</u>	<u>21.13</u>	<u>23.82</u>	<u>26.78</u>	<b>79.50</b>	<b>67.58</b>

Table 3: Main results of various models on the test split of our Neko dataset for other-language-to-English translation directions. The ‘‘GEMBA(GPT5)’’ column reports results obtained using the original GEMBA-DA-Ref prompt (Kocmi and Federmann, 2023) with gpt-5-2025-08-07. ‘‘LJ(GPT5)’’ denotes our neologism-aware LLM-as-a-judge evaluation, in which we supply the *neologism definition* within a GEMBA-style prompt to help the backbone LLM better assess translation quality.

MODEL	GEMBA(GPT5)	LJ(GPT5)
Qwen3-4B + RAG	65.30	52.88
NeoAMT-4B	72.93	58.16
Qwen3-8B + RAG	69.57	56.14
NeoAMT-8B	78.28	66.40

Table 4: Overall quality scores about the RAG ablation study.

## 5 Analysis

In this section, we present a series of analyses and ablation studies based on the NeoAMT-8B model. The detailed analysis can be found in the Appendix G. We also present the LLM-as-a-judge results including GEMBA-DA and neologism-aware evaluation by language pairs in Figure 8 and XCOMET and MetricX24 results in Table 30.

### 5.1 Latency of Reasoning-Retrieval Loop

The reasoning-retrieval loop introduces additional latency compared to standard end-to-end MT systems. To quantitatively assess this latency overhead, we measure the inference time of both systems. Table 6 presents the inference time of a standard MT

	LJ(GPT5, en-ja)	LJ(GPT5, en-zh)
Qwen3-4B-SFT	51.22	65.74
GRPO-4B	56.82	63.24
NeoAMT-4B	55.69	65.87
NeoAMT-4B + process reward	57.93	69.53
Qwen3-8B-SFT	60.27	69.86
GRPO-8B	64.96	70.51
NeoAMT-8B	68.80	76.84
NeoAMT-8B + process reward	68.36	78.27

Table 5: LLM-as-a-judge reference-free evaluation results of English-to-Japanese and English-to-Chinese directions.

system and our agentic model, NeoAMT, using the same model size under identical conditions.

As shown in the table, the average generation time of NeoAMT-8B is approximately 0.77 seconds per example, which is sufficiently efficient for direct deployment even without further optimization. In addition, the reasoning-retrieval loop is conducted once in most cases as shown in Figure 7. When our model thinks that it has the knowledge to deal with the source sentences, it will not retrieve any words from the external knowledge base.

	Standard MT	NeoAMT-8B
Prompt template	Table 12	Table 10
Total time (s)	247.86	571.37
Avg. time / sent (s)	0.33	0.77
Number of examples	743	743

Table 6: Comparison of actual inference time. The main component of the standard MT system is a Qwen3-8B model equipped with the direct translation prompt shown in Table 12. The experiments are conducted on a computing node with dual AMD EPYC 7742 CPUs and 8 NVIDIA A100 GPUs, each with 80 GB of device memory. The detailed environment setup is shown in Table 11.

## 5.2 Impact of RQE

We investigate the impact of RQE-based adaptive sampling in this section. We train another model using the same base model and hyperparameters without RQE sampling, that is, NeoAMT w/o. RQE. The results of NeoAMT and NeoAMT w/o. RQE are presented in Table 7 and Table 8. RQE improves the model performance in almost all cases, especially for neologism-specific scores. The results demonstrate the effectiveness of RQE-based policy optimization.

MODEL	EXACT	FUZZY	LEM-EXACT	LEM-FUZZY
NeoAMT	<b>22.34</b>	<b>26.24</b>	<b>25.84</b>	<b>28.67</b>
w/o. RQE	20.19	23.15	23.01	25.17

Table 7: Neologism-specific scores about the ablation study of RQE.

MODEL	GEMBA(GPT5)	LJ(120B)	LJ(GPT5)
NeoAMT	<b>78.28</b>	<b>63.72</b>	<b>66.40</b>
w/o. RQE	77.65	61.69	64.50

Table 8: Overall quality scores about the ablation study of RQE.

## 5.3 Human Evaluation

We conduct a human evaluation to compare the translation quality of three models, Qwen3-8B, our base model, Hunyuan-MT-7B, a state-of-the-art MT model, and our model NeoAMT. For each input sentence, three anonymized translation outputs (one per model) are presented to two human volunteers, who were asked to rank them from best to worst in terms of translation quality given the source sentence, reference translation and neologisms and their definitions. We sample 100 examples from the Chinese-English translation test split

and we remove those examples in which two or more of the three translation candidates are identical. The result is shown in Table 9. This result verifies the result of LLM-as-a-judge evaluation and demonstrates the effectiveness of our training framework.

Model	% 1st	% 2nd	% 3rd	Average Rank
Qwen3-8B	3.33	25.56	71.11	2.68
Hunyuan-MT-7B	11.67	62.78	25.56	2.14
NeoAMT	85.00	11.67	3.33	1.18

Table 9: Human evaluation.

## 5.4 Sanity Check about Thinking Paths of NeoAMT

We analyze the success and failure patterns by carefully investigating the thinking paths of our model NeoAMT from three perspectives: (1) how many queries are related to neologisms? (2) do the retrieved results contain the neologism definitions? (3) does NeoAMT use the retrieved results for thinking? We randomly sample 100 model responses from the Chinese-English translation pairs. Human volunteers are asked to check the model responses from the above three points. The analysis shows that 86.90% of search queries are related to neologisms. 76.71% of retrieved results given related neologism queries contain the neologism definitions. 96.43% of the model thinking paths after receiving the retrieved results use the retrieved neologism information for reasoning. This indicates that (1) most of the model queries are related to neologisms; (2) the retrieval component still has room for improvement and is likely the dominant performance bottleneck; (3) NeoAMT actively utilizes the retrieved information in its reasoning paths.

## 5.5 Case Studies on Thinking Patterns

We observe two intriguing thinking patterns in our model NeoAMT outputs: **finding new meaning pattern** and **confirmation pattern**. **Finding new meaning pattern** denotes the cases where NeoAMT first makes an incorrect translation or has no idea about neologism after the initial reasoning, but after searching and finding the new meaning of the query word by itself, the model corrects its reasoning path and generates the translation accordingly. **Confirmation pattern** indicates the cases in which NeoAMT generates candidate translations about neologisms in its reasoning process at

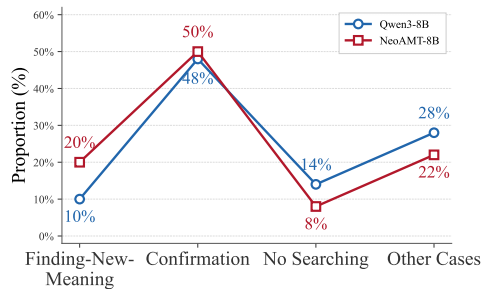


Figure 4: Thinking pattern distribution.

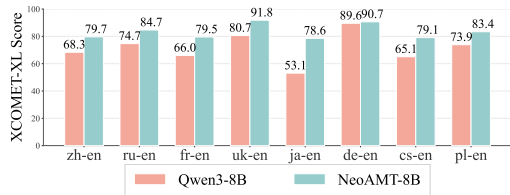


Figure 5: Comparison of XCOMET-XL scores.

first, and one of them is a correct assumption about the neologism. The model then uses the external search tool to verify the correct assumption and generates final translation. The full examples of two patterns can be found in Table 21 and Table 22, Appendix D respectively. To further investigate the shift in thinking pattern distribution, we sample 100 Chinese-English translations from the base model, Qwen3-8B, and NeoAMT-8B, all configured with the same Wiktionary search toolkit and prompt. Figure 4 illustrates the distribution of different thinking patterns. The XCOMET-XL scores of the two models on the Neko test set are presented in Figure 5. We observe that: (1) the confirmation thinking pattern dominates in both models; (2) RL training encourages more active use of the search tool, enabling the trained model to leverage the external dictionary more effectively; (3) NeoAMT-8B achieves substantially higher translation quality than Qwen3-8B, indicating implicitly that the training process enhances the model’s ability to leverage external search tools for improved translation.

## 6 Related Work

**Improving Machine Translation via Reinforcement Learning.** Recent studies on this direction mainly focus on how to design the reward empowered with test-time scaling. For example, MT-R1-Zero (Feng et al., 2025) explores the effect of mixed rule-based and neural model-based metric score as rewards. SSR-Zero (Yang et al., 2025b)

utilizes self-evaluation score as the reward for training. TAT-R1 (Li et al., 2025b) employs word alignment (Jalili Sabet et al., 2020; Nagata et al., 2020; Wu et al., 2023; Latouche et al., 2024; Miao et al., 2025) to design rewards. DeepTrans (Wang et al., 2025b) uses DeepSeek-V3 (Liu et al., 2024) to generate format, thought and translation rewards.

**Neologism Translation.** Neologism translation is a challenging task because of rapid change of languages and the insufficient data. Lerner and Yvon (2025) try to solve this issue using term definitions and in-context learning. Neo-bench (Zheng et al., 2024) provides a benchmark dataset about neologisms in which one sub-task is machine translation. However, the machine translation subset in this benchmark is relatively small and not publicly available. Other similar studies include social-media, culture-aware and poetry translations (Yao et al., 2024; Zhao et al., 2026; Chen et al., 2025)

**Agentic Search.** Recent work explores the integration of search tools into reasoning paths of LLMs to enhance accuracy and factuality on QA and math tasks (Jin et al., 2025; Dong et al., 2025; Li et al., 2025a). For example, Search-R1 (Jin et al., 2025) uses Wikipedia articles as the search source to improve the performance of models on QA tasks. ARPO (Dong et al., 2025) utilizes the entropy to control the branching sampling during reasoning with external tools. These works mainly focus on QA and math tasks. In this paper, we focus on an MT-specific domain, neologism-aware machine translation, which remains underexplored.

## 7 Conclusion

In this paper, we first construct a new multilingual neologism-aware machine translation dataset named Neko that covers 16 languages and contains solid neologism definitions. The test split of this dataset provides a testbed for neologism-aware machine translation. Furthermore, to fill in the gap that it remains unclear that whether reasoning-based RL with search tools improves neologism-aware machine translation, we conduct experiments to analyze the results of various methods and propose a new RL training framework, NeoAMT, consisting of a novel reward design and an adaptive sampling approach based on the translation difficulty to train the neologism-aware machine translation agent. The results of experiments demonstrate the effectiveness of our method.

## Limitations

We use a general-purpose embedding model, bge-m3, for retrieving word entries in this paper. This model is not specifically designed for machine-translation related retrieval tasks though its training dataset contains translation-related corpora and the human analysis in § 5.4 also shows that there is room for improvement about the retrieval performance. Another point is that NeoAMT does not follow the output format exactly specified in the user instruction prompt during the thinking process. The reason might be that our reward design only imposes a constraint on the final translation format.

## Ethical Considerations

This research aims to investigate the effect of agentic RL with search tools on the neologism-aware machine translation. Our new dataset Neko is constructed from the English Wiktionary dump. Some of the word entries may be derogatory and related to politics and subcultures. We process the data in compliance with the license of Wiktionary. The views contained in the dataset are independent of the authors. We have tried our best to remove such words. In addition, we use various LLMs in this paper adhering to the respective model licenses. We used ChatGPT and Claude Opus 4.6 to improve the writing of certain sections of this paper while preserving the original meaning.

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## A Implementation Details

### A.1 Neologism-Specific Reward

The computation procedure of the neologism reward is listed in Algorithm 1.

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**Algorithm 1** Neologism-Specific Reward Computation

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**Require:** Source text  $x$ , generated translation  $\hat{y}$ , the set of corresponding spans of neologisms in  $y^{\text{ref}}$ :  $\mathcal{S}$ , lemmatization function  $\mathcal{L}$ , exact string matching function  $\mathcal{M}$ .

**Ensure:** Neologism-specific reward  $R_{\text{neo}}$ .

- 1: Initialize count:  $c \leftarrow 0$ .
  - 2: Initialize the number of spans in  $\mathcal{S}$ :  $s = |\mathcal{S}|$ .
  - 3: Lemmatize  $\hat{y}$  to obtain  $\hat{y}_l$ :  $\hat{y}_l \leftarrow \mathcal{L}(\hat{y})$ .
  - 4: **for**  $s \in \mathcal{S}$  **do**
  - 5:   Lemmatize  $s$  to obtain  $s_l$ :  $s_l \leftarrow \mathcal{L}(s)$ .
  - 6:   **if**  $M(s_l, \hat{y}_l)$  is true **then**
  - 7:     Increment count  $c \leftarrow c + 1$ .
  - 8:   **end if**
  - 9: **end for**
  - 10: **return** final neologism reward  $R_{\text{neo}} = c/s$ .
- 

### A.2 Hyperparameters and Prompt Templates

The full training template of our model NeoAMT is shown in Table 10.

Qwen3-4B and Qwen3-8B are base models for training. The code that we use is mainly adapted based on verl (Sheng et al., 2025).

We use 8 NVIDIA A100 GPUs with 80GB memory to train our models and conduct inference. For software aspect, we use PyTorch (2.7.1) (Ansel et al., 2024) and our code is mainly adapted from the verl (0.5.0.dev0, GitHub commit id: 0e15c9b) (Sheng et al., 2025) and vllm (Kwon et al., 2023) (0.10.1.1) libraries.

NeoAMT models are trained for 1 epoch. The “train\_batch\_size” is 32. The “ppo\_mini\_batch\_size” is 16. The “ppo\_micro\_batch\_size\_per\_gpu” is 2. The maximum number of tokens for user prompts is 1024. The maximum number of tokens for model responses (including retrieved results) is set to 4096. The maximum turns of searching of our agentic MT models is 3. The number of retrieved results is 5. The maximum character length of retrieved result for a single turn is 2000. The maximum training time for a single experiment is approximately 40 hours. The  $\lambda$  for  $R_{\text{neo}}$  is 0.1. The  $\alpha$ ,  $\gamma$  and  $\psi$  for RQE are 10, -5 and 0.0 respectively.

The  $g_{\text{min}}$  and  $G$  are 4 and 8, respectively. The  $g_{\text{initial}}$  is set to 4.

For the searching tool, we cache the retrieved results to speed up the training process. The caching mechanism is based on the ARPO implementation (Dong et al., 2025).

We use the same hyperparameters as NeoAMT for the GRPO row except the prompt. The prompt we use for the GRPO row is presented in Table 19.

For SFT row in Table 3, the input and output formats that we use for training are shown in Table 17. We use the “fsdp\_sft\_trainer” of verl. “micro\_batch\_size\_per\_gpu” is set to 4 and the total batch size is 32. The number of epoch is 3. The max length is set to 4096. We use the default setting of “fsdp\_sft\_trainer” for other hyperparameters.

## B Latency Testing Environment

The environment that we use for latency testing is the same as the training environment. The details about the environment are shown as in Table 11.

---

<i>Environment</i>	
CPU	Dual AMD EPYC 7742
GPU	NVIDIA A100 80GB $\times$ 8
Software	vllm (0.10.1.1), verl (0.5.0.dev0, commit: 0e15c9b)
Batch Size	96
vLLM GPU Utilization	0.8
Max Prompt Length	1024
Max Response Length	4096
Sampling	Greedy

---

<i>Search Tool Setting</i>	
Max Retry Count	1
Timeout Limit	10s
Max Workers	64
Max Search Turns	3

---

<i>Retrieval Engine Setting</i>	
Max Search Results	5
Backend	FastAPI + FAISS
Retriever Batch Size	1
Loading & Saving Cache	Enabled

---

Table 11: Details of the latency testing environment.

## C More Evaluation Details

### C.1 Baselines

We evaluate various models including general-purpose and MT-specific models on this dataset to report their performance on neologism-aware machine translation. We also present the results of Supervised Fine-Tuning (SFT), Retrieval-Augmented Generation (RAG) (Lewis et al., 2020), RL-based fine-tuning without searching (GRPO) (Guo et al., 2025). The reward for GRPO is  $R = \mathbb{1}_{\{\text{format}\}} * R_{\text{neural}}$ . We use the same queries as our model NeoAMT for RAG to ensure a fair comparison. For general-purpose models, we include Llama-3.1-8B-Instruct (Grattafiori et al., 2024),

---

You are a professional `{src_lang}` to `{tgt_lang}` translator. Please translate the following text from `{src_lang}` to `{tgt_lang}` .

You must conduct reasoning inside `<think>` and `</think>` first. After reasoning, you can use the search tool by enclosing your query within `<search>` and `</search>`. The query could be unfamiliar terms, relevant keywords, or example sentences. The search tool will then return the top results between `<information>` and `</information>`. You can use the returned information to improve your translation. You can reason and search as many times as you want. In the end, you should directly provide the final translation inside `<translation>` and `</translation>` with a new line, without detailed illustrations. For example, `<think>` reasoning process here `<think/>` `<search>` query here `</search>``<information>` returned information `</information>``<think>` another reasoning process here `<think/>``<search>` another query here `</search>``<information>` another returned information `</information>``<think>` yet another reasoning process`</think>``<translation>` final translation here `</translation>`.

`{src_lang}` text: `{src_text}`

---

Table 10: Full training template of NeoAMT.

Aya-23-8B (Aryabumi et al., 2024), Aya-expanse-8B (Dang et al., 2024), Qwen3-8B, Qwen3-14B, Qwen3-32B (Yang et al., 2025a) and GPT-OSS-20B (Agarwal et al., 2025). We also conduct evaluation on several strong MT-specific models, including ALMA-R-7B (Xu et al., 2024b), X-ALMA (Xu et al., 2025), MT-R1-Zero-7B-Mix (Feng et al., 2025), TowerInstruct-7B-v0.2 (Alves et al., 2024), Hunyuan-MT-7B (Zheng et al., 2025), mExTrans-7B (Wang et al., 2025c). The implementation details and prompts of various baselines, including general-purpose LLMs, MT-specific LLMs, RAG, SFT and GRPO, can be found in Appendix A and Appendix C.2.

## C.2 Evaluation Configuration

We adopt the similar setting as MT-R1-Zero (Feng et al., 2025) when evaluating the performance of general purpose baseline models on the test set. For open weight models, we deploy them locally using the transformers implementation. We use the sampling decoding strategy and the temperature is set to 0.2 and top\_p is 0.95. The maximum generation length is capped at 4096 tokens. For MT-specific models, we use their corresponding prompt formats to obtain translations. The detailed prompts can be found in Table 13 and Table 14.

We mainly use the prompt format in Table 12 for general purpose models to obtain outputs because some of the general-purpose models tend to generate other content that is not directly related to translation. Therefore, we ask models to generate translations within the specific tags `<translation>` and `</translation>` to obtain the translations. We use the raw outputs as final translations when models fail to generate translations within the specific

tags. We apply their chat templates when necessary. For XCOMET and MetricX-24, we use the XL version.

---

You are a professional `{src_lang}` to `{tgt_lang}` translator. Please translate the following text from `{src_lang}` to `{tgt_lang}`. Please provide the translation directly without reasoning inside `<translation>` and `</translation>`. For example, `<translation>` translation here `</translation>`.

`{src_lang}` text: `{src_text}`

---

Table 12: Direct translation prompt.

---

Translate this from `{src_lang}` into `{tgt_lang}`:  
`{src_lang}`: `{text}`  
`{tgt_lang}`:

---

Table 13: ALMA prompt (Xu et al., 2024a,b, 2025).

---

Translate the following segment into `{tgt_lang}`, without additional explanation.

`{text}`

---

Table 14: Hunyuan-MT prompt.

For LLM-as-a-judge evaluation, the prompt with additional neologism definitions is presented in Table 15. We also present the results of using the original GEMBA prompt in Table 3. The original GEMBA prompt that we use is shown in Table 16.

For RAG row in Table 3, the prompt is shown in Table 18. The hyperparameters, such as temperature and top\_p, of the RAG baseline are the same as other baselines.

---

You are an expert in evaluating the quality of translations.

You will be given a source sentence, a reference translation, and a candidate translation.

The source sentence contains a neologism (a newly coined word or expression).

Your task is to determine how well the candidate translation captures the meaning of the source sentence, especially focusing on the neologism.

Please consider the following criteria when conducting your evaluation:

1. Neologism Quality (score: 0-50).
2. Overall Translation Quality (score: 0-50).

After evaluating the candidate translation based on the above criteria, please provide your assessment in the following format: <evaluation> score </evaluation>.

The final "score" is a numerical value between 0 and 100. A higher score indicates a better translation.

Here is the information you will need for your evaluation:

Source Sentence: {source\_sentence}

Neologism and Its Meaning: {neologism} ({neologism\_meaning})

Reference Translation: {reference\_translation}

Candidate Translation: {candidate\_translation}

---

Table 15: Neologism-aware LLM-as-a-judge prompt. We provide additional neologism information in the prompt to help LLMs judge the translation quality from both neologism and overall perspectives following the GEMBA-style prompt (Kocmi and Federmann, 2023).

### C.3 Neologism-Specific Metrics

The detailed procedure of computing neologism exact, fuzzy, lem-exact and lem-fuzzy scores are presented in Alogirhtm 2, 3, 4 and 5. These metrics complement each other to ensure stable evaluation of neologism translation and reduce evaluation bias.

## D Examples

In this section, we provide some detailed examples of outputs generated by NeoAMT. Table 20 and 21 present **finding new meaning pattern** examples. Table 22 shows an example of the **finding new meaning pattern**.

## E Construction Details of Neko Dataset

### E.1 Construction Process.

We use the raw Wiktionary data version (19.6GB) (Ylonen, 2022) dated 2025-08-23<sup>8</sup> for extracting word entries.

<sup>8</sup><https://kaikki.org/dictionary/rawdata.html>

---

Score the following translation from {source\_lang} to {target\_lang} with respect to human reference on a continuous scale 0 to 100 where score of zero means "no meaning preserved" and score of one hundred means "perfect meaning and grammar".

{source\_lang} source: "{source\_seg}"

{target\_lang} human reference: {reference\_seg}

{target\_lang} machine translation: "{target\_seg}"

Score:

---

Table 16: GEMBA prompt.

---

**Input** You are a professional {src\_lang} to {tgt\_lang} translator. Please translate the following text from {src\_lang} to {tgt\_lang}. Please provide the translation directly without reasoning inside <translation> and </translation>. For example, <translation> translation here </translation>. {src\_lang} text: {src\_text}

**Output** <translation> translation here <translation>

---

Table 17: SFT prompt.

Table 23 presents the prompt that we use to translate the example sentences in the *Type 2* word entries of Neko dataset. We sample 700 examples from the *Type 2* word entries and translate the source text into the other 15 languages, totaling 10,425 translation pairs for training. Note that we provide the definitions of neologisms to make the translation process easier for gpt-5-2025-08-07.

Table 24 shows the prompt that use for finding the corresponding spans in the target sentences for the neologisms in the source sentences. Note that we provided additional information about the neologisms, such as definitions and the part-of-speech tags to make the alignment process easier. For one neologism that might correspond to multiple words in the other language, we annotate the word that most reflects the meaning of the neologism. The reason why we use gpt-5-2025-08-07 rather than word alignment models is that these neologisms are relatively new and may not be seen in the training process of the current word alignment models and we can provide additional information about the neologisms in the prompt of gpt-5-2025-08-07 to make the alignment process more accurate, which we cannot do if we use word alignment models. After obtaining the corresponding spans of neologisms, we employ human volunteers to validate and refine the generated spans for Japanese-English and Chinese-English pairs. We find that the quality of spans generated by gpt-5-2025-08-07 is quite

---

You are a professional {src\_lang} to {tgt\_lang} translator. Please translate the following text from {src\_lang} to {tgt\_lang}. Please provide the translation directly without reasoning inside <translation> and </translation>. For example, <translation> translation here </translation>. {src\_lang} text: {text} {retrieved\_result}

---

Table 18: RAG prompt.

---

You are a professional {src\_lang} to {tgt\_lang} translator. Please translate the following text from {src\_lang} to {tgt\_lang}. You must conduct reasoning inside <think> and </think> first. In the end, you should directly provide the final translation inside <translation> and </translation> with a new line, without detailed illustrations. For example, <think> reasoning process here </think><translation> final translation here </translation>. {src\_lang} text: {src\_text}

---

Table 19: GRPO prompt.

high and there is almost no need to modify them.

## E.2 Human Validation on the Synthetic Translations of the Neologism for Type 2 data

The way of generating the synthetic translations is divided into two steps:

- The first step was that we provided the details of the neologisms in the source sentences for gpt-5-2025-08-07 to generate translations. Therefore, it is relatively easy for gpt-5-2025-08-07 to translate the source sentences containing neologisms.
- The second step was using gpt-5-2025-08-07 to find the corresponding spans in the generated translations in step 1 given the source sentences, neologisms with part-of-speech and gloss information and generated translations.

We found that the synthetic translations using the above approach were of high quality, fluent and natural.

Specifically, we randomly sampled 200 English-Japanese and English-Chinese synthetic translations from our training data and conducted a human analysis to verify if the translations are accurate and convey the meaning of source sentences and neologisms or not. We use the pass rate to check

---

### Algorithm 2 Neologism Exact Metric

---

**Require:** Source text  $x$ , generated translation  $\hat{y}$ , the set of corresponding spans of neologisms in  $y^{\text{ref}}$ :  $\mathcal{S}$ , exact string matching function  $\mathcal{M}$ .

**Ensure:** Neologism exact score: REGEX.

- 1: Initialize count:  $c \leftarrow 0$ .
  - 2: Initialize the number of spans in  $\mathcal{S}$ :  $s = |\mathcal{S}|$ .
  - 3: **for**  $s \in \mathcal{S}$  **do**
  - 4:     **if**  $\mathcal{M}(s, \hat{y})$  is true **then**
  - 5:         Increment count  $c \leftarrow c + 1$ .
  - 6:     **end if**
  - 7: **end for**
  - 8: **return** neologism exact matching score:  $c/s$ .
- 

---

### Algorithm 3 Neologism Fuzzy Metric

---

**Require:** Source text  $x$ , generated translation  $\hat{y}$ , the set of corresponding spans of neologisms in  $y^{\text{ref}}$ :  $\mathcal{S}$ , fuzzy string matching function  $\mathcal{F}$ .

**Ensure:** Neologism fuzzy score: FUZZY.

- 1: Initialize count:  $c \leftarrow 0$ .
  - 2: Initialize the number of spans in  $\mathcal{S}$ :  $s = |\mathcal{S}|$ .
  - 3: **for**  $s \in \mathcal{S}$  **do**
  - 4:     **if**  $\mathcal{F}(s, \hat{y})$  is true **then**
  - 5:         Increment count  $c \leftarrow c + 1$ .
  - 6:     **end if**
  - 7: **end for**
  - 8: **return** neologism fuzzy matching score:  $c/s$ .
- 

the quality with the result shown in Table 25. The failure reasons and the error spans in the synthetic translations that did not pass human validation are shown in Table 26.

## F Statistics of Neko Dataset

The statistics about the train, val and test splits of Neko dataset can be found in Table 1, 27 and 28.

Language pair	# (val)	# (test)
zh-en	61	578
ru-en	4	38
fr-en	1	20
uk-en	2	17
ja-en	7	20
de-en	3	30
cs-en	-	6
pl-en	5	34
en-xx (ref-free)	-	270

Table 27: Number of examples grouped by language pairs in the **val** and **test** splits of the Neko dataset.

---

**Algorithm 4** Neologism Lem-Exact Metric

---

**Require:** Source text  $x$ , generated translation  $\hat{y}$ , the set of corresponding spans of neologisms in  $y^{\text{ref}}$ :  $\mathcal{S}$ , lemmatization function  $\mathcal{L}$ , exact string matching function  $\mathcal{M}$ .

**Ensure:** Neologism lem-exact score.

- 1: Initialize count:  $c \leftarrow 0$ .
  - 2: Initialize the number of spans in  $\mathcal{S}$ :  $s = |\mathcal{S}|$ .
  - 3: Lemmatize  $\hat{y}$  to obtain  $\hat{y}_l$ :  $\hat{y}_l \leftarrow \mathcal{L}(\hat{y})$ .
  - 4: **for**  $s \in \mathcal{S}$  **do**
  - 5:   Lemmatize  $s$  to obtain  $s_l$ :  $s_l \leftarrow \mathcal{L}(s)$ .
  - 6:   **if**  $\mathcal{M}(s_l, \hat{y}_l)$  is true **then**
  - 7:     Increment count  $c \leftarrow c + 1$ .
  - 8:   **end if**
  - 9: **end for**
  - 10: **return** neologism lem-exact score:  $c/s$ .
- 

---

**Algorithm 5** Neologism Lem-Fuzzy Metric

---

**Require:** Source text  $x$ , generated translation  $\hat{y}$ , the set of corresponding spans of neologisms in  $y^{\text{ref}}$ :  $\mathcal{S}$ , lemmatization function  $\mathcal{L}$ , fuzzy matching function  $\mathcal{F}$ .

**Ensure:** Neologism lem-fuzzy score.

- 1: Initialize count:  $c \leftarrow 0$ .
  - 2: Initialize the number of spans in  $\mathcal{S}$ :  $s = |\mathcal{S}|$ .
  - 3: Lemmatize  $\hat{y}$  to obtain  $\hat{y}_l$ :  $\hat{y}_l \leftarrow \mathcal{L}(\hat{y})$ .
  - 4: **for**  $s \in \mathcal{S}$  **do**
  - 5:   Lemmatize  $s$  to obtain  $s_l$ :  $s_l \leftarrow \mathcal{L}(s)$ .
  - 6:   **if**  $\mathcal{F}(s_l, \hat{y}_l)$  is true **then**
  - 7:     Increment count  $c \leftarrow c + 1$ .
  - 8:   **end if**
  - 9: **end for**
  - 10: **return** neologism lem-fuzzy score:  $c/s$ .
- 

## G More Analysis

The following analysis is conducted using NeoAMT-8B.

### G.1 WMT24++

We also analyze the performance of our model on the general MT task using the subset of WMT24++ covered by our research language range. We remove the bad source example sentences and translations. Post-edited translations are utilized as reference translations.

This evaluation is a type of out-of-domain setting because our model is trained on the Neko dataset. Figure 6 presents the comparison results grouped by language pairs before and after the training using the Neko dataset.

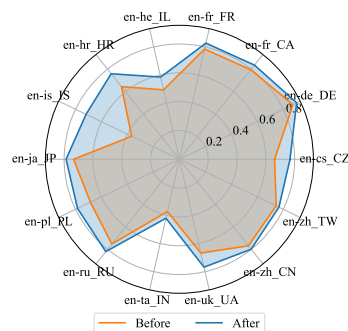


Figure 6: Comparison of XCOMET-XL scores on the WMT24pp test dataset grouped by language pairs between before and after our training using the training split of the Neko dataset.

### G.2 Training Dynamics

We analyze the training dynamics of the number of search turns, over training steps. The result of search turns of the validation set is presented in Figure 7. We find that (1) at the beginning, 30% of the responses do not use searching and over the training steps, the proportion of not using searching first get larger and declines; (2) most of responses use searching once; (3) The proportion of not using search shows an opposite trend to the output length. This aligns with our intuition that using search tends to increase the output length.

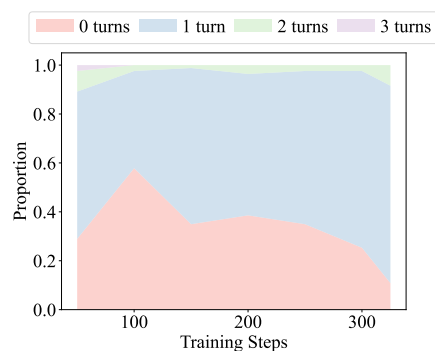


Figure 7: Change of the proportions about the search turns on the validation set over the course of training.

### G.3 Case Studies

Table 29 shows some translation examples of NeoAMT-8B.

### G.4 XCOMET and MetricX24 Scores

XCOMET-XL and MetricX-24 scores of NeoAMT-8B are presented in Table 30.

MODEL	XCOMET	METRICX-24
<i>General Purpose LLMs</i>		
Llama-3.1-8B-Instruct	78.81	6.6
Aya-23-8B	79.27	6.3
Aya-expanse-8B	81.09	5.8
Qwen3-8B	81.12	5.7
Qwen3-14B	83.36	5.6
Qwen3-32B	83.33	5.2
GPT-OSS-20B	81.39	5.8
<i>Translation-Specific LLMs</i>		
ALMA-R-7B	79.11	6.1
MT-R1-Zero-7B-Mix	79.86	6.0
X-ALMA	82.88	5.4
TowerInstruct-7B-v0.2	78.03	6.6
mExTrans-7B	80.81	5.7
Hunyuan-MT-7B	82.36	5.2
<i>Qwen3-8B</i>		
SFT	80.60	5.6
RAG	75.42	6.7
GRPO	82.30	5.5
NeoAMT	<b>83.42</b>	<b>5.1</b>

Table 30: Main results of XCOMET and MetricX-24.

### G.5 LLM-as-a-judge Evaluation by Language Pair

Table 8 shows the LLM-as-a-judge scores of NeoAMT-8B on the test split of the Neko dataset.

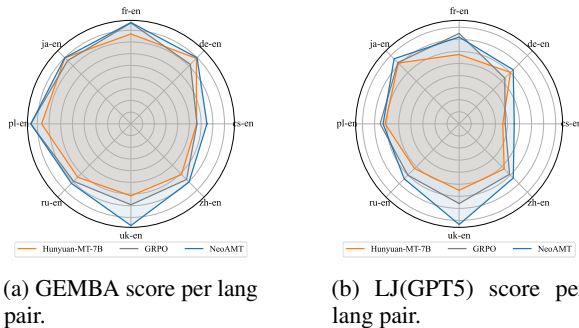


Figure 8: LLM-as-a-judge results grouped by language pairs.

### G.6 Ablation study of RAG

Neologism-specific scores of the RAG ablation study are shown in Table 31.

MODEL	EXACT	FUZZY	LEM-EXACT	LEM-FUZZY
Qwen3-4B + RAG	30.95	27.72	34.58	31.22
NeoAMT-4B	17.63	19.11	20.05	21.53
Qwen3-8B + RAG	23.68	23.14	26.64	25.43
NeoAMT-8B	22.34	26.24	25.84	28.67

Table 31: Neologism-specific scores about the RAG ablation study.

### H Screenshot of Translation Ranking Annotation Application.

Human volunteers use an in-house application to rank translations. The screenshot of the application is shown in Figure 9.

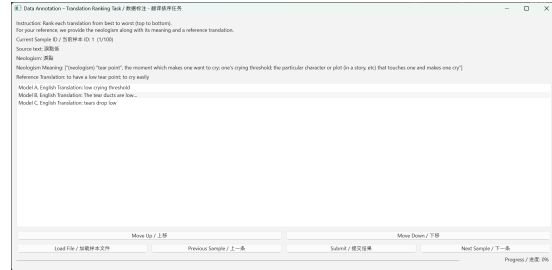


Figure 9: Screenshot of translation ranking annotation application.

**NeoAMT Instruction** You are a professional Chinese to English translator. Please translate the following text from Chinese to English. You must conduct reasoning inside <think> and </think> first.

[...]

<translation> final translation here </translation>.

**Input** Chinese text: 尽管Rockstar是一家经验丰富而且成功的游戏公司，但三款标志性《给她爱》游戏的重制版因其艺术风格和性能而受到批评.....

**Output** <think> Okay, I need to translate the given Chinese sentence into English. Let's start by understanding the original text. The sentence is: "尽管Rockstar是一家经验丰富而且成功的游戏公司，但三款标志性《给她爱》游戏的重制版因其艺术风格和性能而受到批评....." First, breaking it down. "尽管" translates to "Although" or "Despite". "Rockstar是一家经验丰富而且成功的游戏公司" – "Rockstar is a seasoned and successful game company". "但" here is "but". Then, "三款标志性《给她爱》游戏的重制版" – "the three landmark 'Give Her Love' games' remasters" or "remake versions". "因其艺术风格和性能而受到批评" – "have been criticized for their artistic style and performance". The ellipsis at the end might indicate the sentence is continuing, but maybe it's just a pause. Wait, "《给她爱》" is the title of the games. Let me check if that's the correct translation. "给她爱" could be "Give Her Love" or maybe "Love Her" – but perhaps the actual game title is different. Maybe I should verify that. Let me search for "《给她爱》游戏" to confirm the English title.

<search> 《给她爱》游戏的英文名</search>

<information>

Doc 1(Title: Word: 给她爱) 给她爱Part-of-speech: name Etymology: From English Grand Theft Auto → initialism GTA → pinyin Gěitā'ài. [...] Word senses: 1. (Mainland China, neologism, euphemistic) Grand Theft Auto (video game franchise published by Rockstar Games)

Doc 2(Title: Word: otome game) otome game (plural otome games) Part-of-speech: noun Etymology: Borrowed from Japanese 乙(おと)女(め)ゲーム (otome gēmu, literally "girl game"). Word senses: 1. A story-based video game in which the player attempts to establish a romantic relationship between the female player character and one of several male characters. \*\*Non-disambiguated translation entries\*\*: Sense: romance simulation game (usually the protagonist is a woman) - Japanese: 乙女ゲーム

[...]

</information>

Hmm, so "《给她爱》" is mentioned in the context of being a game. The first document says that "给她爱" is a neologism in China for Grand Theft Auto (GTA), specifically GTA V, since China banned GTA V. But the original sentence mentions three landmark games. Wait, Rockstar Games has several titles like GTA III, GTA IV, GTA V, etc. Maybe the user is referring to three of their flagship games. But the original text says "《给她爱》游戏", which according to the search result, is a term used in China for GTA.

[...]

But since the search shows that "给她爱" is a term for GTA, perhaps that's the case.

[...]

I think that's the right approach. So the final translation would use "GTA" instead of "Give Her Love". </think>

<translation>Although Rockstar is a seasoned and successful game company, the remasters of three landmark GTA games have been criticized for their artistic style and performance.</translation>

Table 20: Instruction, input and output of a **finding new meaning pattern** example when NeoAMT translates the Chinese text that contains a neologism. In this example, NeoAMT actively searches the neologism, finds the new meaning of the word, and reduces the ambiguous meaning of the word successfully by looking up a dictionary.

**NeoAMT Instruction** You are a professional Chinese to English translator. Please translate the following text from Chinese to English. You must conduct reasoning inside <think> and </think> first.

[...]

<translation> final translation here </translation>.

**Input** Chinese text: 奧利給, 幹了兄弟們!

**Output** <think>Okay, I need to translate the Chinese text "奧利給, 幹了兄弟們!" into English. Let's start by breaking down the sentence. First, "奧利給" – that's probably a name. "奧利" could be "Oli" or "Aoli", and "給" here might be part of a phrase.

Wait, maybe it's "奧利給" as a name, like "Ollie" or "Aolie".

Then "幹了兄弟們!" – "幹了" could be "go" or "do" something. "幹了" might be an exclamation. "兄弟們" is "brothers" or "guys".

Wait, "幹了" could be part of a slang or a phrase.

Maybe "幹了" here is "Let's go" or "Do it".

So maybe the whole phrase is "Ollie, let's go, brothers!" or "Ollie, do it, guys!" Hmm. Alternatively, "幹了" could be "干了" which is "do" or "carry out". So maybe "Ollie, let's do it, brothers!" or "Ollie, go for it, guys!" I should check if "奧利給" is a known name or if there's a common translation. Let me search for "奧利給" in Chinese to English.

<search>奧利給 英文名</search>

<information>

[...]

Doc 2(Title: Word: 奧利給) 奧利給Part-of-speech: intj Etymology: Reversal of 給力噢/给力噢 (gěilì ō, "come on!"). Popularized through a Kuaishou video uploaded by Huang Chunsheng (黃春生), known as Chaoyang Winter Swimming Strange Pigeon on the Internet (with original sentence quoted below). The meaning of feces derives from video creator Daoshilaoba (島市老八), who mimicked the former quote before livestreaming coprophagy. Word senses: 1. (neologism, slang) come on!; go for it!; go!

[...]

</information>

Okay, so "奧利給" seems to be a slang term derived from "給力噢" (gěilì ō), which means "come on!" or "go for it!". [...] Alternatively, if "奧利給" is a name, then "Oli Ji, let's go, brothers!" but the search shows that "奧利給" is a slang term. So perhaps the translation is "Come on, brothers! Let's do it!" or "Come on, guys! Let's go!" I think the best translation would be "Come on, brothers! Let's do it!" or "Come on, guys! Let's go!" Wait, "幹了" could also be "gàn le", which is "done", but in this context, it's an exclamation. So maybe "Let's go, brothers!" or "Let's do it, guys!" So combining "奧利給" (come on!) and "幹了兄弟們" (let's go, brothers!), the translation could be "Come on, brothers! Let's go!" or "Come on, guys! Let's do it!" I think the most accurate translation based on the search results is "Come on, brothers! Let's go!" or "Come on, guys! Let's go!" Alternatively, maybe "Oli Ji, come on, brothers!" but since "奧利給" is a slang term, perhaps the name is "Oli Ji" but that might not be necessary. The original sentence might be a call to action, so "Come on, brothers! Let's go!" or "Let's do it, guys!" I'll go with "Come on, brothers! Let's go!" as the translation. </think>

<translation>Come on, brothers! Let's go!</translation>

Table 21: Instruction, input and output of a **finding new meaning pattern** example when NeoAMT translates the Chinese text that contains a neologism. In this example, NeoAMT actively searches the neologism, finds the new meaning of the word, and reduces the ambiguous meaning of the word successfully by looking up a dictionary.

**NeoAMT Instruction** You are a professional Chinese to English translator. Please translate the following text from Chinese to English. You must conduct reasoning inside <think> and </think> first.

[...]

<translation> final translation here </translation>.

**Input** Chinese text: 視頻來源：優兔

**Output** <think> Okay, I need to translate "視頻來源：優兔" from Chinese to English. Let's start by breaking down the sentence. "視頻" is "video", "來源" is "source" or "from". "優兔" is probably a proper noun, maybe a platform or a name. Wait, "優兔" could be "YouTu" or maybe it's a misspelling of "YouTube". Oh, right, YouTube's Chinese name is sometimes written as "优兔" or "YouTube". So "視頻來源：優兔" would be "Video source: YouTu" or "Video source: YouTube". But I should confirm if "優兔" is indeed YouTube. Let me check that.

<search>什么是優兔</search>

<information>

Doc 1(Title: Word: 優兔) 優兔Part-of-speech: name Etymology: Borrowed from English YouTube. Word senses: 1. (neologism) YouTube

Doc 2(Title: Word: 玉兔) 玉兔Part-of-speech: noun Word senses: 1. (Chinese mythology) The Jade Rabbit; alternative name for 月兔(yuètù, "the Moon Rabbit"). 2. (literary, figuratively) the moon

Doc 3(Title: Word: 優輝) 優(ゆう)輝(き) • (Yūki) Part-of-speech: name Word senses: 1. a male given name

Doc 4(Title: Word: 優也) 優(ゆう)也(や) • (Yūya) Part-of-speech: name Word senses: 1. a male given name

[...]

</information>

Okay, so "優兔" is mentioned as a neologism for YouTube. So the translation should be "Video source: YouTube". But maybe the original text is using "優兔" as the name, so perhaps it's better to keep it as "YouTu" or "You Tube". Wait, the search result says "優兔" is a borrowed term from YouTube. So the correct translation would be "Video source: YouTube". Alternatively, if they want to keep the original name, maybe "Video source: YouTu". But since the search says it's YouTube, I should go with that. So the final translation would be "Video source: YouTube". Let me check again. The original text is "視頻來源：優兔", so "源" is "video source" or "source of the video". "优兔" is YouTube. So the translation is "Video source: YouTube" or "Video source: YouTu". But according to the search, "优兔" is YouTube. So probably "Video source: YouTube". Yeah, that makes sense. </think>

<translation>Video source: YouTube</translation>

Table 22: Instruction, input and output of a **confirmation pattern** example when NeoAMT translates the Chinese text that contains a neologism. In this example, NeoAMT makes a correct assumption about the neologism, and use the search tool to find and verify the meaning of the word by looking up dictionary items.

---

You are a professional {src\_lang} to {tgt\_lang} translator.

I will provide you with the part-of-speech and gloss information of some words. Please use this information to translate the sentence.

Word: {word}

Part-of-speech: {pos}

Glosses: {glosses}

Please conduct the reasoning process first, and subsequently present the finalized translation enclosed within the tags: <translation> final translation </translation>.

{src\_lang} text: {src\_text}.

---

Table 23: Translation prompt used to obtain translations of example sentences in the train set of Neko dataset. The model that we use for translation is gpt-5-2025-08-07.

---

You are a professional word aligner.

I will provide a translation pair along with the part-of-speech and gloss information for a specific word in {src\_lang}.

Your task is to identify the corresponding word in {tgt\_lang}.

{src\_lang} text: {src\_text}

{tgt\_lang} text: {tgt\_text}

{src\_lang} Word: {word}

Part-of-speech: {pos}

Glosses: {glosses}

Please identify the corresponding word in the {tgt\_lang} text.

Present the identified word enclosed within the tags: <aligned\_word> corresponding word </aligned\_word>

---

Table 24: The prompt that we use for finding the corresponding spans in the target sentences for the neologisms in the source sentences. The model that we use for finding alignments is gpt-5-2025-08-07.

Language-pair	Pass rate
English-Japanese	94.5%
English-Chinese	97.5%

Table 25: Pass rate of the training data by human validation.

Failure reason	English-Japanese	English-Chinese
Copy paste without explanation (affecting the meaning)	Hu, HODL, hu, Chican@s	Melfie, MGTOW
Surface meaning translation without explanation	アマトノーマティブな, シューフィー, スウィフト ボート式中傷, パルーザ, シット, レシオ	泡泡糖坏女孩核, 解融合
Unusual Human Name Translation	-	Daniel -> 但以理 (More common translation is 丹尼尔)
Language Mixing (Code-switching)	websideマナー	-

Table 26: Failure reasons and errors spans in the synthetic training set.

Language pair: Number
en-is, en-ru, en-km, en-ha, en-de, en-ja, en-cs, en-uk, en-ta, en-pl, en-fr, en-he, en-zh, en-hr, en-ps: 603
fr-en, fr-is, fr-ru, fr-km, fr-ha, fr-de, fr-ja, fr-cs, fr-uk, fr-ta, fr-pl, fr-he, fr-zh, fr-hr, fr-ps: 18
zh-en, zh-is, zh-ru, zh-km, zh-ha, zh-de, zh-ja, zh-cs, zh-uk, zh-ta, zh-pl, zh-fr, zh-he, zh-hr, zh-ps: 68
de-en, de-is, de-ru, de-km, de-ha, de-ja, de-cs, de-uk, de-ta, de-pl, de-fr, de-he, de-zh, de-hr, de-ps, is-en, is-ru, is-km, is-ha, is-de, is-ja, is-cs, is-uk, is-ta, is-pl, is-fr, is-he, is-zh, is-hr, is-ps: 3

Table 28: The number of examples grouped by language pairs in the **train** split of the Neko dataset.

Source text	Model	Translation
「我一直在长草这部美剧啊, 可惜太忙了没时间看。」	Qwen3-8B	"I've always wanted to watch the TV series 'The Office,' but I've been too busy to watch it."
	Hunyuan-MT-7B	"I've been wanting to watch that amazing TV series 'Grass' for a long time, but unfortunately I'm too busy to find the time to watch it."
	NeoAMT	I've been really looking forward to this American TV show all along, but unfortunately, I've been too busy to watch it.
lo娘	Qwen3-8B	Lo娘
	Hunyuan-MT-7B	lo娘
	NeoAMT	Lolita girl
自己都会笑称自己系一个「铁胶」	Qwen3-8B	One would even laughingly call oneself a "steel glue"
	Hunyuan-MT-7B	I even joke with myself about being a "glue stick" (a person who gets stuck to things easily).
	NeoAMT	One would jokingly call oneself a 'railfan'.
放黑枪	Qwen3-8B	Fire a shot in the dark
	Hunyuan-MT-7B	Draw the black gun.
	NeoAMT	to launch a covert attack

Table 29: Case studies.