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Understanding In-Context Machine Translation for Low-Resource Languages: A Case Study on Manchu

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Abstract

In-context machine translation (MT) with large language models (LLMs) is a promising approach for low-resource MT, as it can readily take advantage of linguistic resources such as grammar books and dictionaries. Such resources are usually selectively integrated into the prompt so that LLMs can directly perform translation without any specific training, via their in-context learning capability (ICL). However, the relative importance of each type of resource, e.g., dictionary, grammar book, and retrieved parallel examples, is not entirely clear. To address this gap, this study systematically investigates how each resource and its quality affect the translation performance, with the **Manchu** language as our case study. To remove any prior knowledge of Manchu encoded in the LLM parameters and single out the effect of ICL, we also experiment with an enciphered version of Manchu texts. Our results indicate that high-quality dictionaries and good parallel examples are very helpful, while grammars hardly help. In a follow-up study, we showcase a promising application of in-context MT: parallel data augmentation as a way to bootstrap a conventional MT model. When monolingual data abound, generating synthetic parallel data through in-context MT offers a pathway to mitigate data scarcity and build effective and efficient low-resource neural MT systems.¹

1 Introduction

Neural machine translation (NMT) systems have achieved remarkable performance in high-resource language pairs for which parallel sentence-level or document-level data are abundant (Bahdanau et al., 2015; Vaswani et al., 2017; Tiedemann and Scherer, 2017; Lübbli et al., 2018). However, parallel

data is scarce or even unavailable for many low-resource or endangered languages (Haddow et al., 2022), which prevents the training of dedicated MT systems for these languages. While multilingual models partly mitigate this issue (Costa-jussà et al., 2024), they only cover a small fraction of the world’s languages and their performance remains unsatisfactory for many language pairs.

On the other hand, owing to the work of field linguists, grammatical descriptions or dictionaries are available for more than 60% of the world’s languages (Nordhoff and Hammarström, 2011; Zhang et al., 2024b).² Some low-resource languages are well-documented, with rich linguistic resources gathered over decades of meticulous fieldwork and analysis by linguists: this is for instance the case of Japhug, a minority Sino-Tibetan language, for which a comprehensive grammar, including plentiful glossed and translated examples, has been released by Jacques (2021). The situation of Manchu is even more favorable, as multiple grammar books, dictionaries, and textbooks are readily available. Yet, all these languages are still considered low-resource in the context of data-driven MT, simply due to the scarcity of parallel data. A natural question is then to explore whether such linguistic knowledge can make up for the lack of parallel data, and help develop MT systems.

The recent emergence of LLMs seems to offer new promising ways to address this question, based on their in-context learning ability (Tanzer et al., 2024; Zhang et al., 2024b; Hus and Anastasopoulos, 2024; Merx et al., 2024). In these studies, linguistic resources such as dictionaries, parallel examples, and grammar books are integrated into the prompt and encoded together with the sentence to be translated. We continue this line of work, trying to better analyze the role and impact of each

*Equal contribution.

†Equal advising.

¹We make our code and data publicly available at: <https://github.com/cisnlp/manchu-in-context-mt>.

²This includes long grammatical books (24%), short grammatical books (13%), and grammatical sketches (25%), according to <https://glottolog.org/langdoc/status>.

type of linguistic knowledge that can be put to use in LLM-based machine translation systems.

For this, we perform a systematic investigation of how each component affects the in-context MT performance, with the translation from **Manchu** into English³ as a case study. Specifically, we leverage a wide range of state-of-the-art open-source and closed-source LLMs and consider the following linguistic resources (components): dictionaries, parallel examples, grammar books, and Chain-of-Thought (CoT) prompting. For each component, we consider several variants that vary in the amount of information or the degree of relevance to the sentence to be translated. To quantify the influence of prior knowledge of Manchu in LLMs, we perform a character-level encipherment to disentangle the effect of LLMs’ prior knowledge of Manchu from their in-context learning ability. In addition, we demonstrate a use case of our in-context MT system, using it as a data-augmentation tool to turn a monolingual Manchu corpus into a parallel corpus. With these synthetic parallel data incorporated into the training set, we fine-tune the mT5 model (Xue et al., 2021), achieving a substantial performance gain compared to the baseline that only uses actual parallel data.

The main contributions of this work are as follows: **(i)** We conduct a comprehensive investigation of in-context MT for Manchu, exploring the most important knowledge sources provided in the context, highlighting the positive role of high-quality dictionaries and closely related parallel examples. **(ii)** Using an enciphered version of Manchu, we isolate the limited prior knowledge of Manchu encoded in the LLMs considered in our work and show that most of their translation performance depends on their in-context learning abilities. **(iii)** We use in-context MT to generate synthetic parallel data from monolingual data of Manchu and measure how much this form of data augmentation actually benefits low-resource NMT.

2 Related Work

Low-resource NMT The challenges posed by limited parallel data has motivated extensive research on innovative strategies for low-resource NMT (Haddow et al., 2022; Yazar et al., 2023). Various approaches have been proposed to improve translation quality in such settings. Data augmen-

tation techniques, such as back-translation (Sennrich et al., 2016; Edunov et al., 2018) and forward-translation (Bogoychev and Sennrich, 2020), have been widely used to generate synthetic parallel data and improve model performance. Data augmentation, coupled with unsupervised and semi-supervised methods for bilingual dictionary induction, has enabled translation with minimal parallel data, relying instead on monolingual resources (Lample et al., 2018; Artetxe et al., 2018). Transfer learning has also proven effective, where models pretrained on high-resource language pairs can be adapted to low-resource languages (Zoph et al., 2016; Tars et al., 2022; Her and Kruschwitz, 2024). Recent advancements in multilingual NMT also show that models trained on multiple language pairs can better deal with low-resource languages (Ko et al., 2021; Mohammadshahi et al., 2022; Costa-jussà et al., 2024). Despite these advancements, achieving high-quality translation in low-resource scenarios remains a significant challenge.

LLM-based In-context MT for Low-Resource Languages Although not explicitly trained for machine translation, LLMs can perform translation by following instructions and demonstrations in the prompt (Brown et al., 2020; Lin et al., 2022; Vilar et al., 2023). LLM-based MT, however, struggles with rare words that appear infrequently in the training data (Ghazvininejad et al., 2023). This issue is particularly pronounced for low-resource languages that are underrepresented in the LLM’s training corpora (Le Scao et al., 2023; Touvron et al., 2023). To mitigate this, some studies incorporate linguistic resources into prompts, such as **dictionary entries** and **parallel sentence examples** (Ghazvininejad et al., 2023; Zhang et al., 2024a), as well as **grammars** (Tanzer et al., 2024; Hus and Anastasopoulos, 2024). Some works also include **morphological analyzers** to decompose input sentences into morphemes (Zhang et al., 2024b). Additionally, prompting strategies such as **CoT** reasoning have been explored in the context of MT (Elsner and Needle, 2023). However, little attention has been given to how the quality of each component affects the LLM-based in-context MT. Moreover, there is a lack of clear ablation studies disentangling the effects of an LLM’s prior knowledge of the language and the linguistic information provided in context. Addressing these limitations of previous studies, our work systematically investigates the role of each of these components in

³Translation into from Manchu into Chinese is also considered in Appendix F.

LLM-based MT for low-resource languages, using Manchu as a case study.

3 Language, Data and General Setup

Manchu Language Manchu (ISO 639-3: mnc) is a critically endangered Tungusic language native to Northeast China. It is the traditional language of the Manchu people and was one of the official languages of the Qing dynasty (1644-1911) of China. Because of its significant historical importance, Manchu has been extensively studied, and there exist abundant linguistic resources, including dictionaries, grammar books, and some bilingual parallel sentences, which make Manchu well-suited for our case study. A more detailed description of the Manchu language is given in Appendix A.

Dictionary We use the comprehensive dictionary from Norman (2020),⁴ which contains rich information such as the multiple senses for polysemous words as well as frequent collocations. It serves as our main Manchu-English lexicon. Additionally, we compile a dictionary for Manchu suffixes based on (Clark, 1980), which contains brief explanations for each suffix.⁵

Parallel Corpus The main source of parallel data is a Manchu-Chinese dictionary (Hu, 1994), which contains parallel example sentences for many dictionary entries.⁶ We extract parallel sentences from the dictionary, followed by data-cleaning and filtering steps, to ensure that the Chinese sentences are in modern Standard Chinese. The result is a Manchu-Chinese parallel corpus consisting of 3,520 sentence pairs, encompassing diverse genres, including everyday conversations, historical records, and literary works. We then use the Google Cloud Translation API to translate the Chinese sentences into English, thereby creating a Manchu-English parallel corpus.⁷

Monolingual Corpus We also compile a monolingual Manchu corpus consisting of 42,240 sentences collected from websites, encompassing a diverse range of genres.⁸ During our data augmentation experiment presented in §6, this monolingual

Manchu corpus serves to build a synthetic Manchu-English parallel corpus.

Grammar We use two grammar books: a concise grammar book (Norman, 1965) and a more detailed grammar from (Gorelova, 2002).

Evaluation Set We compile a test set of 337 Manchu-English parallel sentences for evaluation. This test set consists of 70 sentences from *No-geoldae*, a book containing dialogues in Manchu, paired with English translations (Zhang et al., 2024b), and 267 sentence pairs extracted from (Di Cosmo, 2007).⁹ We have made sure that the parallel corpus and the evaluation set do not overlap.

Models We conduct our experiments with multiple LLMs: GPT-4o (Achiam et al., 2024), DeepSeek-V3 (Liu et al., 2024), and Llama3 models (Dubey et al., 2024). For the Llama3 family, we test models of varying sizes – 1B, 3B, 8B, and 70B – to evaluate how model size impacts performance.

Evaluation Metrics We use BLEU (Papineni et al., 2002) and chrF (Popović, 2015) to measure the translation quality, as implemented by SacreBLEU (Post, 2018).¹⁰ Additionally, we use SBERT (Reimers and Gurevych, 2019), an encoding based-metric, which assesses the semantic relatedness between a hypothesis and a reference using the cosine similarity of their embeddings (scores are multiplied by 100 to ensure a uniform magnitude).

4 Assessing Each Component

Following the standard pipeline for in-context MT (Tanzer et al., 2024; Hus and Anastasopoulos, 2024; Zhang et al., 2024b,a), our goal is to conduct a rigorous investigation of the importance of each type of linguistic resource (component) and its quality to the translation performance. For each input Manchu sentence, a structured prompt is constructed by integrating various components. This prompt is then fed to the LLM to generate a response, from which the translation is extracted. The translation is finally evaluated against the ground truth reference using various metrics.

Formulation of Prompts We represent the prompt formulation as $\pi(\cdot)$ which takes several ar-

⁴<https://buleku.org/home>.

⁵Manchu exclusively uses suffixation, therefore neither prefixation nor circumfixation is involved.

⁶Data is available from <https://gere1.net/>.

⁷<https://cloud.google.com/translate?hl=en>

⁸<https://manc.hu/> and <https://gere1.net/>

⁹https://github.com/ulingga/Manchu-English_babyMT.

¹⁰Signature: nrefs:1|case:lc|eff:no|tok:13a|smooth:exp|version:2.4.3.

guments as input. Let \mathbf{x} be the Manchu sentence to be translated. The simplest prompt is $\pi(\mathbf{x})$, which asks the LLM to directly translate \mathbf{x} into the target language, without providing any additional information. The prompt template can be augmented by adding optional arguments as follows – each representing one component.¹¹

- A morphological analyzer $\mu(\cdot)$, which transforms \mathbf{x} into segmented and analyzed morphemes. The result is represented as $\mu(\mathbf{x})$.
- Dictionary entries D retrieved from a bilingual dictionary \mathcal{D} .
- Parallel examples P retrieved from a parallel corpus \mathcal{P} .
- Grammar excerpts G retrieved from a grammar book \mathcal{G} .
- CoT prompting instructions C selected from a set of prompting varieties \mathcal{C} .

Sequential Integration of Components Given that many components in our pipeline have multiple implementations of varying quality, exhaustively evaluating all possible combinations would be computationally infeasible. Therefore, we add components to $\pi(\cdot)$ sequentially and compare performance between implementations for that component. The best-performing one is used as a new baseline when we evaluate the next component. Specifically, starting with the simple baseline $\pi(\mathbf{x})$, we first add the morphological analyzer, a fundamental element for subsequent retrieval components, resulting in $\pi(\mu(\mathbf{x}))$.¹² We then consider components that have multiple variants. To begin with, we consider various ways to specify D and select the best one $\pi(\mu(\mathbf{x}), D^*)$ which is the new baseline for subsequent add-ons. We then follow the order P, G, C , resulting in $\pi(\mu(\mathbf{x})^*, D^*, P)$ (assessing multiple ways to select parallel examples), $\pi(\mu(\mathbf{x})^*, D^*, P^*, G)$ (assessing a variety of grammar excerpts), and $\pi(\mu(\mathbf{x})^*, D^*, P^*, G^*, C)$ (assessing variants of CoT instruction). This order prioritizes components that are expected to be most beneficial, with less helpful components introduced at later stages, as suggested by previous works (Zhang et al., 2024b; Hus and Anastasopoulos, 2024). The pipeline is depicted in Figure 1. In

¹¹Prompt templates are illustrated in Appendix B.

¹²We only consider one version of $\mu(\mathbf{x})$, which constitutes an essential component for all other linguistic resources.

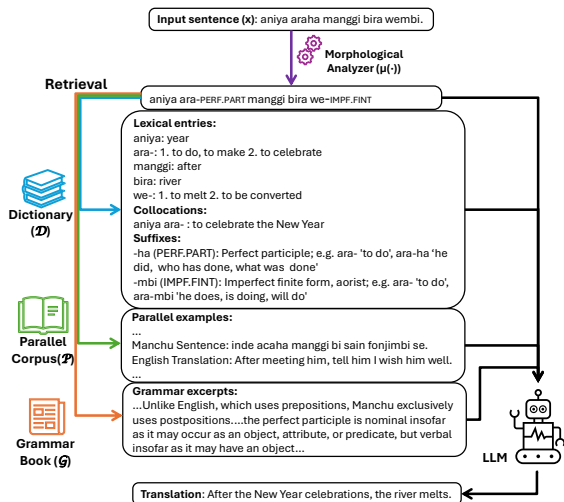


Figure 1: Illustration of the in-context MT pipeline with the components of π , i.e., $\mu(\mathbf{x})$, D , P and G .

the following sections, we study each component in detail and report experimental results obtained using the **GPT-4o model** on the evaluation set of 337 Manchu-English parallel sentences.

4.1 Morphological Analysis

Morphological analysis is usually performed in a naive way in previous studies. For instance, Zhang et al. (2024b) simply perform a dictionary look-up – searching for **inflected word forms** in a dictionary, the coverage of which is limited.¹³ As Manchu is an agglutinative language and exclusively uses suffixation, identifying word stems and suffixes is straightforward. Therefore, we implement a rule-based morphological analyzer that splits an input word into a stem and a sequence of suffixes. Both the **list of word stems** and the **set of allowed suffixes** are obtained from the dictionary. Our morphological analyzer then attempts to recursively detach a suffix from the end of a string until the remaining segment matches a known word stem. After the morphological analysis, a Manchu sentence is transformed into a list of morphemes (containing word stems and suffixes), which serves as the basis for retrieving dictionary entries, parallel examples, and grammar excerpts.

It is possible for a Manchu word to have multiple analyses. For example, *tere* could be a demonstrative pronoun meaning “that”, or it could be analyzed as *te-re*, meaning “sitting” as the present participle of the verb *te* “to sit”. In such cases, we include all possible analyses in the prompt and

¹³The dictionary is from Norman (2020). It can be accessed at <https://buleku.org/home>.

let the LLM resolve the ambiguity by selecting the most contextually appropriate interpretation, as shown in Table 11 of Appendix I.

4.2 Dictionary

The dictionary \mathcal{D} comprises lexical entries, suffixes, and their corresponding collocations. These three elements – lexical entries, suffixes, and collocations – form the foundation of our three variants:

- D^l includes only the **lexical** entries retrieved for each word in the input sentence, without explanation¹⁴ for the suffixes.
- D^{l+s} includes both the **lexical** entries and explanations for **suffixes** for all morphemes appearing in the input sentence.
- D^{l+s+c} includes the **lexical** entries, explanations of **suffixes**, and the **collocations** for all morphemes in the input sentence.

Variant	BLEU	chrF	SBERT
$\pi(\mathbf{x})$	3.44	21.86	34.21
$\pi(\mu(\mathbf{x}))$	3.10	21.68	33.49
w/ D^l	7.40	31.84	58.91
w/ D^{l+s}	7.47	32.93	59.78
w/ D^{l+s+c}	7.55	32.71	61.07

Table 1: MT scores for direct prompting $\pi(\mathbf{x})$ and prompting with morphologically analyzed sentences $\pi(\mu(\mathbf{x}))$, and with **dictionary** entries of increasing complexities. **Bold**: best result for each column.

Comprehensive dictionary entries are important. As shown in Table 1, using a morphological analyzer alone is not helpful – $\pi(\mu(\mathbf{x}))$ performs worse than $\pi(\mathbf{x})$. This is expected as simply transforming the input sentence to a segmented list of morphemes does not provide the model much knowledge about Manchu. Once the explanations for the lexical entries are included, performance improves significantly. The translation quality can be further improved with the inclusion of suffixes (D^{l+s}) and then collocations (D^{l+s+c}). Although the chrF score of D^{l+s+c} is slightly lower than D^{l+s} , both the BLEU and SBERT scores suggest that the D^{l+s+c} delivers the best overall translations. Therefore, $\pi(\mu(\mathbf{x}), D^{l+s+c})$ will be used as a new baseline when assessing the following component. We illustrate the benefits of dictionary information (lexical entries, suffixes, and collocations) for translation in Tables 11 and 12 in Appendix I.

¹⁴Explanations (in English) document the meaning and function of each suffix. See example in Appendix I.

4.3 Parallel Examples

Parallel examples are drawn from the corpus introduced in §3. Ideally, these parallel examples \mathcal{P} should closely resemble the input sentence, as higher similarity with the source text is known to improve translation quality (Zhang et al., 2024a). To explore this, we construct three variants for \mathcal{P} , each exhibiting a different degree of similarity:

- P^r includes 10 parallel sentences **randomly** selected as few-shot examples.
- P^d includes up to 10 parallel sentences retrieved based on shared terms. As the parallel sentences are extracted from the **dictionary**, they are originally meant to illustrate the meaning of a specific dictionary entry. Therefore, for a lexeme in the input sentence, the parallel examples for its dictionary entry are retrieved.
- P^{bm} includes 10 parallel sentences retrieved using the **BM25** algorithm (Robertson et al., 1995) implemented by Rank-BM25.¹⁵ The terms used by the retriever are morphemes segmented by the analyzer of §4.1.

Variant	BLEU	chrF	SBERT
$\pi(\mu(\mathbf{x}), D^*)$	7.55	32.71	61.07
w/ P^r	7.66	32.94	60.85
w/ P^d	8.10	32.95	61.04
w/ P^{bm}	8.84	33.72	61.35

Table 2: Performance comparison between the baseline (no parallel examples) and 3 ways to select **parallel examples**. **Bold**: best result for each column.

More similar parallel examples improve the translation. As shown in Table 2, randomly retrieved parallel examples provide only a slight improvement over the baseline, as they do not seem to introduce much useful information into the context. On the other hand, selecting parallel examples that are similar to the input sentence yields more noticeable improvements (see lines P^d and P^{bm} in Table 2). P^{bm} achieves the best performance across all 3 evaluation metrics, as BM25 aims to retrieve parallel examples that are globally similar to the input sentence; $\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$ will be used as a new baseline when assessing the following component. An example of how parallel examples help translation is in Table 13 in Appendix I.

¹⁵https://github.com/dorianbrown/rank_bm25

4.4 Grammar

As mentioned in §3, two grammar books – a short and a more detailed one – serve as source materials. For each book, we manually compile 26 tuples consisting of (*feature, excerpt*), in which each Manchu grammatical feature is paired with the corresponding excerpt from the short or the long grammar book. With our morphological analyzer, we extract a set of grammatical features from the source Manchu sentence and generate a tailored grammar combination accordingly, consisting of only excerpts that are relevant to that sentence. This approach is much more efficient than dumping the entire grammar book into the context. We consider 3 ways to retrieve excerpts G from grammar books:

- G^s is a combination of grammar excerpts, retrieved from the **short** book.
- G^l is a combination of grammar excerpts, retrieved from the **long** grammar book with more detailed explanations.
- G^{l+p} additionally adds **parallel** examples that illustrate the grammar excerpts, which are originally included in the **long** grammar book.

In addition to the excerpts, we include a fixed paragraph shared by all variants, which contains basic information about the word order and typological features of Manchu (see Appendix B).

Variant	BLEU	chrF	SBERT
$\pi(\mu(\mathbf{x}), D^*, P^*)$	8.84	33.72	61.35
w/ G^s	8.26	33.12	60.70
w/ G^l	8.46	33.79	61.17
w/ G^{l+p}	8.90	33.77	60.40

Table 3: Performance comparison between the baseline without **grammar** and 3 different variants of retrieving grammar excerpts. **Bold**: best result for each column.

Grammars hardly help. As shown in Table 3, G^s yields scores worse than the baseline. With more detailed explanations, G^l leads to a slight improvement in chrF score, and when further accompanied by parallel examples, G^{l+p} leads to a small improvement in BLEU score. Nevertheless, compared to the performance reported for the other components, i.e., dictionary and parallel examples (cf. Tables 1 and 2), the improvement seems marginal and is not reflected in SBERT scores. This suggests that grammars do not help

much in in-context MT, which is consistent with the findings reported by Aycock et al. (2024). Nevertheless, we have found instances where grammar explanations could aid translation, such as the example of Table 14 in Appendix I. Moreover, since the next component – CoT – involves grammatical annotation and syntactic analysis, which are closely tied to the information provided in the grammar excerpts, we will still include the grammar component in the new baseline for assessing the CoT component. The variant G^{l+p} is selected based on the BLEU score.

4.5 Chain-of-Thought

CoT prompting instructs LLMs to generate a series of intermediate results before solving the final task (Wei et al., 2022). We draw CoT prompt templates from LingoLLM (Zhang et al., 2024b), which are explicit instructions provided in the context. We consider 2 variants for CoT prompting C :

- C^a asks the LLM to **annotate** the grammatical and semantic features of each word in the sentence before computing the translation.
- C^{a+s} asks the LLM to proceed step by step, first to annotate the grammatical and semantic features of each word, then analyze the sentence’s **syntactic structure**, and finally produce the translation.

Variant	BLEU	chrF	SBERT
$\pi(\mu(\mathbf{x}), D^*, P^*, G^*)$	8.90	33.77	60.40
w/ C^a	8.01	33.13	59.81
w/ C^{a+s}	8.49	33.43	59.01

Table 4: Performance comparison between the baseline without CoT prompting and 2 variants of CoT. **Bold**: best result for each column.

CoT does not help the model generate better translations. Explicitly prompting the model to perform intermediate generation steps results in a noticeable decline in both C^a and C^{a+s} . This aligns with the findings of Elsner and Needle (2023), where CoT does not improve performance. This discrepancy seems to arise from erroneous or incomplete deductions within the intermediate steps (cf. Table 15 in Appendix I). This further indicates that, even with the CoT prompting, the model is still unable to effectively utilize the grammar. Consequently, we exclude the CoT component and the Grammar component from our final pipeline.

Model	BLEU	chrF	SBERT
Llama3-1B	0.27	9.95	16.37
Llama3-3B	1.81	21.95	38.46
Llama3-8B	3.05	26.59	49.10
Llama3-70B	6.31	31.01	56.82
GPT-4o	8.84	33.72	61.35
DeepSeek-V3	12.35	37.93	65.64

Table 5: Performance of various LLMs using the best setting, i.e., $\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$. **Bold**: best result for each column.

5 In-Depth Analysis of Performance

5.1 Performance Across Models

We have so far used the GPT-4o model to assess the importance of each component and its quality, finding that the best setting is $\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$. We now study performance variation across models for this setting. Results are in Table 5.

Model size matters. The smallest model, i.e., Llama3-1B, yields an extremely low BLEU score of 0.27. When manually checking the translation, we found that the Llama3-1B model often does not follow the instructions, generating outputs where the translation is difficult to extract or missing entirely. With the size increase in the Llama3 family, we see a consistent improvement in translation scores. Through manual inspection of the translations from varying model sizes (see Table 17 in Appendix I), we observe that larger models not only exhibit better instruction-following abilities but are also better at leveraging the information included in the context. Therefore, we hypothesize that LLM-based MT relies on both good instruction-following and in-context learning abilities, which are closely related to the model size.

The performance could be underestimated

The best performance is obtained with DeepSeek-V3, achieving BLEU scores of 12.35. The score is still low, especially when compared with LLM-based translation for high-resource languages (Alves et al., 2023; Sia et al., 2024). However, we often observe that the in-context translations are semantically close to the reference, yet exhibit significant differences in wordings, suggesting that BLEU and chrF scores actually underestimate the MT quality, as illustrated by the example in Table 6. When assessed with SBERT, the best-performing model (DeepSeek-V3) achieves a score of 65.64, indicating a strong semantic similarity between the

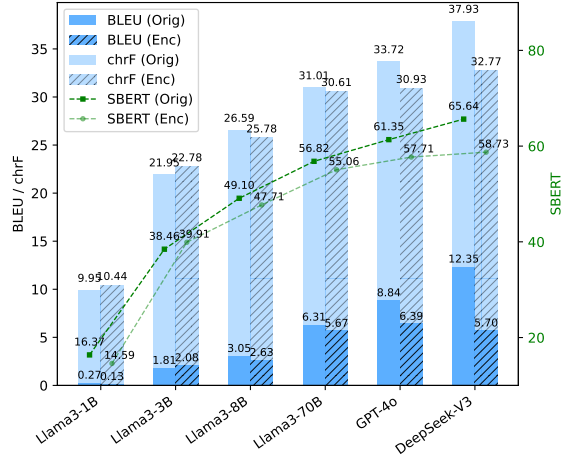


Figure 2: Performance comparison between enciphered $\pi(\mu(\mathbf{x}), D_e^{l+s+c}, P_e^{bm})$ and original $\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$ across multiple LLMs.

translation and the reference.

Input:	<i>ereci julesi gurgu elgiyen</i>
Translation:	From this point forward, wild animals are abundant.
Reference:	From there onwards beasts were plentiful.
BLEU:	4.99
chrF:	24.02
SBERT:	62.42

Table 6: An example where BLEU and chrF scores (sentence-level) underestimate the translation quality, while SBERT better reflects the translation quality.

5.2 Exposing Prior Knowledge of Manchu with Character-Substitution Cipher

We have so far assumed that the MT performance of LLMs is mostly attributed to their **in-context abilities**, rather than to some **prior knowledge of Manchu** that can possibly be acquired during its training stage. To explore this question, we create a “fake Manchu” aimed at eliminating this possible confounding factor. As Yuan et al. (2024) and Marmonier et al. (2025) have demonstrated, LLMs’ prior knowledge can be bypassed using substitution ciphers. In this work, we “encipher” all Manchu tokens by a simple character-level substitution cipher as follows: each vocalic character in Manchu (a, e, i, o, u), is substituted with the **next** character in this list, e.g., $a \rightarrow e, e \rightarrow i$, and $u \rightarrow a$. The same substitution rule applies to consonantal characters in ($b, c, d, f, g, h, j, k, l, m, n, p, q, r, s, t, v, w, x, y, z$). Using this scheme, a Manchu token *amban* is enciphered as *encep*.

The encipherment applies to all tokens in the input Manchu sentence as well as the linguistic resources involving Manchu, such as dictionary entries and parallel examples, while the English parts remain unchanged. This approach ensures that the LLM can only rely on the information provided in the prompt and its in-context learning ability. Enciphered prompts are denoted with the subscript e as in: $\pi(\mu(\mathbf{x})_e, D_e, P_e)$. We experiment with the original template $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ and its enciphered version $\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$.¹⁶ The results achieved for multiple LLMs are in Figure 2.

LLMs already know some Manchu. The performance of the enciphered version tends to be slightly lower than the original version for all LLMs. This suggests that all models have seen some Manchu in their pretraining stage, possibly due to contamination – pretraining corpora often contain significant amounts of non-English texts, including many low-resourced ones (Blevins and Zettlemyer, 2022). The performance drop is particularly noticeable for DeepSeek-V3. We hypothesize that DeepSeek-V3 has seen more Manchu data during its pretraining stage because it was trained on large Chinese corpora, which may contain more Manchu texts.

LLMs rely more on their in-context learning ability. Even though all LLMs have some prior knowledge of Manchu, as indicated by the drop in performance from the original version to the enciphered version, the enciphered versions can still achieve comparable results, and the performance gap remains relatively small (except for DeepSeek-V3). This confirms that LLMs are not fully relying on their prior knowledge, but are rather mainly depending on their in-context learning ability. This argument can be further supported by the consistent performance improvement for both the original and the enciphered Manchu texts when increasing the model size. Since the Llama3 family models are trained on the same data, the observed performance gain, such as from Llama3-1B to Llama3-70B, should be largely attributable to the enhanced in-context learning capabilities of the larger model.

5.3 Validating the Translation Quality Through Human Evaluation

In order to further validate the quality of our MT outputs beyond automatic evaluation metrics such

¹⁶We use $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ because the grammar excerpts contain a mixture of Manchu and English tokens, which makes it difficult to encipher only the Manchu tokens.

Variant	DA score	z-score
$\pi(\mathbf{x})$	29.04	-0.63
$\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$	56.12	0.19
$\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$	64.47	0.44

Table 7: Average DA scores and z-scores of the MT outputs across the 3 variants $\pi(\mathbf{x})$, $\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$, and $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$. **Bold:** best result for each column.

as BLEU, chrF, and SBERT, we have conducted a human evaluation in the form of the Direct Assessment (DA) (Graham et al., 2013). Specifically, we have recruited 3 Manchu language experts who are fluent in both Manchu and English, and have asked them to rate how adequately the English translations express the meaning of their corresponding source sentences in Manchu, on a continuous scale from 0 to 100. The complete instruction given to the human raters is in Appendix H.

For the human evaluation, we randomly select 33 sentences from the evaluation set described in §3. For each sentence, we include the MT outputs of 3 variants using the GPT-4o model: $\pi(\mathbf{x})$ (direct prompting), $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ (the best setting), and $\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$ (enciphered version of the best setting), resulting in a total of 99 evaluation items. The identities of the system variants are anonymized. In addition, the order of the items is randomized for the evaluation.

To account for potential differences in how individual raters use the scoring scale, the raw DA scores are normalized to z-scores before being aggregated across raters. The inter-rater agreement among the three raters is strong, with an average Pearson correlation coefficient $r = 0.864$.

We report the average z-scores as well as average raw DA scores in Table 7. The results show that the 2 variants enhanced with dictionary entries and parallel examples achieve substantially higher scores compared to the baseline $\pi(\mathbf{x})$. This further validates the effectiveness of our proposed pipeline. Moreover, $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ achieves higher average scores than the enciphered version $\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$.

We run the Wilcoxon rank-sum test to test the statistical significance. The results indicate that both $\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$ and $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ differ significantly from the baseline $\pi(\mathbf{x})$, both with $p < 0.001$. On the other hand, although the enciphered version has lower average scores, the difference between $\pi(\mu(\mathbf{x})_e, D_e^{1+s+c}, P_e^{bm})$ and

$\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$ is not statistically significant, with $p = 0.27$. This also aligns with our previous finding using the automatic metrics, that the performance gap between the enciphered and the original version is relatively small: LLMs rely more on their in-context learning ability.

6 NMT Data Augmentation

We present a follow-up study where we use our in-context MT system to generate more parallel data for training an NMT model. This data augmentation approach follows the *forward-translation* method (Burlot and Yvon, 2018; Bogoychev and Sennrich, 2020).

Translating Monolingual Corpus. Specifically, we use our in-context MT system to translate 42,240 sentences from the monolingual Manchu corpus (cf. §3) into English, using our best-performing method $\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$ with DeepSeek-V3. The resulting synthetic parallel corpus is combined with the real parallel corpus to train an NMT model of Manchu-to-English.

Fine-Tuning mT5. We fine-tune mT5-small (Xue et al., 2021), an encoder-decoder multilingual pre-trained model on the Manchu-to-English translation task. To systematically assess the impact of synthetic data, we use different data-mixing strategies, e.g., only real parallel data, or additionally with synthetic data that is several times larger than the real data. The performance is evaluated on the same evaluation set of 337 parallel sentences (cf. §3).

Figure 3 presents the results. The model trained exclusively on real data performs extremely badly across all metrics, suggesting that 3,520 parallel sentences are insufficient for training an effective NMT model. However, as more synthetic parallel data is introduced, performance improves consistently. The best-performing model – trained with real data and synthetic parallel data that are 12 times larger than the real data – achieves results comparable to or even surpassing Llama3-70B. The resulting fine-tuned mT5-small model only contains around 300M parameters and is significantly more efficient than a 70B-parameter in-context MT system. This study underscores the potential of leveraging in-context MT for data augmentation, enabling the development of more effective and efficient NMT models for low-resource languages.

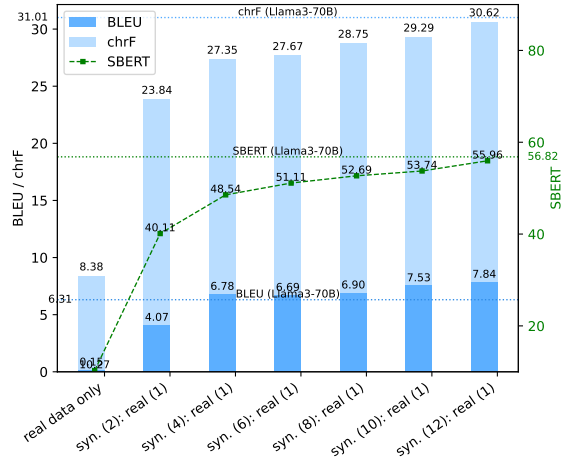


Figure 3: Performance comparison of the fine-tuned mT5 model using only real parallel data versus incorporating varying proportions of synthetic parallel data generated by our in-context MT system. We observe a steady improvement in performance as more synthetic parallel data is added, ultimately achieving scores that match the in-context MT results of Llama3-70B.

7 Conclusion

In this paper, we conduct a comprehensive investigation of in-context MT for low-resource languages, using Manchu as a case study. We examine the impact of different types of resources and the quality of each component on translation performance. Our findings highlight that high-quality dictionaries and properly retrieved parallel examples are the most influential factors, while grammar and CoT prompting appears to have no noticeable benefit. Furthermore, through the encipherment experiment, we disentangle the effects of LLMs’ prior knowledge of Manchu from their in-context learning ability. Our results show that while LLMs possess some prior knowledge of the language, they primarily rely on in-context learning for translation. Finally, our follow-up study shows a practical application of in-context MT: generating synthetic parallel data. This approach has the potential to enhance NMT systems, offering a viable strategy for improving translation in low-resource languages.

Limitations

Our current work only includes a single language, Manchu, as a case study. Although our encipherment method can be considered a generalization effort applicable to any language unfamiliar to the LLMs, the encipherment did not alter the fundamental properties of Manchu, which is an aggluti-

native language characterized by a relatively clear separation between morphemes. It is not fully clear whether our findings extend to other typologically distinct languages.

We have only focused on the translation direction from Manchu to English and have not explored the reverse direction. However, if the goal is to produce synthetic parallel data of good quality, we believe it is advantageous to translate authentic low-resource language into a high-resource language that the LLM is proficient in. This ensures fluency and authenticity of the texts in both the source and target languages.

Lastly, we have only explored a limited range of CoT strategies. Our current results indicate that the extra CoT steps often introduce new errors, resulting in a poorer final translation. Future work could investigate ways to mitigate these undesired effects, such as through better prompt engineering or by providing guiding examples for the CoT process.

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A Manchu Language

Manchu (ISO 639-3: mnc) is a critically endangered Tungusic language native to Northeast China (historically also known as Manchuria). Typologically, Manchu is a head-final agglutinative language that makes exclusive use of suffixation for denoting grammatical features, with each suffix having one single function. In this regard, Manchu is often grouped together with other typologically similar languages across Eurasia, e.g., Japanese, Korean, Mongolian, Turkish, and Hungarian.

Manchu is the traditional language of the Manchu people, who founded the Qing dynasty (1644-1911) of China. During this period, Manchu was one of the official government languages, leaving behind a rich collection of historical texts. However, from the 18th century onward, the Manchu language experienced a gradual decline, which accelerated significantly after the fall of the Qing dynasty up until 1980s, at which point the number of native speakers was down to only a few hundreds,¹⁷ out of more than 10 million ethnic Manchu population.

Starting from the 1980s, there have been increased efforts to revitalize the Manchu language, as the Manchu communities strive to restore their lost heritage. Primary schools in several Manchu Autonomous Counties, as well as some universities, began offering Manchu courses at various levels. Through the revitalization movements, despite the ultra-small number of genuine native speakers, the number of people who can now speak Manchu as a second language has been steadily growing.

Traditionally, Manchu is written in the Manchu script, an alphabetic writing system that can be easily transliterated into Latin script. All the Manchu data used within our research were already in the form of Latin transliteration.

Manchu is a low-resource language in terms of the available text data on the internet. On the other hand, because of its significant historical importance, Manchu has been extensively studied by generations of linguists and philologists. There exist abundant linguistic resources, including dictionaries, grammar books, some bilingual parallel sentences, and a decent amount of monolingual

¹⁷This number excludes the speakers of the Xibe language (ISO 639-3: sjo), which is sometimes considered as a dialect of Manchu. Xibe is in more vigorous usage and has around 30,000 native speakers. The written form of Xibe is mostly identical to Manchu, aside from several orthographical conventions.

text, which makes Manchu well-suited for our case study.

B Prompts

- **Direct Translation:**

Please help me translate the following sentence from {source language} to {target language}:
{sentence}

Please try your best to translate, it's okay if your translation is bad. Do not refuse to try it. I won't blame you.

Please enclose your translation in ###. For example, if your translation is "Hello world", the last part of your output should be ###
Hello world ###

- **Direct Translation with Morphologically Analyzed Sentence:**

Please help me translate the following sentence from {source language} to {target language}:
{morphologically analyzed sentence}

The morphemes in this sentence have been segmented: the verb stem and verbal suffixes are separated by '=' , the noun stem and nominal suffixes are separated by '~'. Note that some words can be either analyzed as a whole or as a word stem plus a suffix; the different analyses are separated by '/'. In such a case, explanations for both analyses are given below, and you need to choose which one is the most appropriate in the given context.

Please try your best to translate, it's okay if your translation is bad. Do not refuse to try it. I won't blame you.

Please enclose your translation in ###. For example, if your translation is "Hello world", the last part of your output should be ###
Hello world ###

- **General Template for Prompts with Components:**

Please help me translate the following sentence from {source language} to {target language}:
{morphologically analyzed sentence}

The morphemes in this sentence have been segmented: the verb stem and verbal suffixes

are separated by '=', the noun stem and nominal suffixes are separated by '~'. Note that some words can be either analyzed as a whole or as a word stem plus a suffix; the different analyses are separated by '/'. In such a case, explanations for both analyses are given below, and you need to choose which one is the most appropriate in the given context.

{components}

Using all the information provided above, now please translate the sentence into {target language}. Remember your source sentence is: {morphologically analyzed sentence}

Please enclose your translation in ###. For example, if your translation is "Hello world", the last part of your output should be ###
Hello world ###

- **Component Dictionary:**

For the translation task, you are given the word by word mapping from the {source language} words to the {target language} words. Some words can be polysemous and there might be multiple possible English translations. In such a case, please choose the most appropriate one. Note that for some words, they might be derived from a more basic form, we call this the parent word. The parents are also given in the word-by-word translation. Here are the dictionary entries for each individual word in the source sentence:

{dictionary entries}

Note that sometimes two or more words can form a collocation and express a specific meaning. You should refer to the collocations listed under the dictionary entries. For example, 'mama' means 'grandmother', 'erxe=' means 'to attend', but 'mama erxe=' as a collocation means 'to get smallpox'. In such a case, explain which collocation meaning you think is most appropriate in the context.

- **Component Parallel Examples:**

To help with the translation, here are some {source language}- {target language} parallel sentences that may be helpful for your translation:

{parallel examples}

- **Component Grammar:**

You are also given this grammar book below.

Feel free to rely on this grammar book in your translation task:

- Manchu Grammar Book

The Manchu language is typologically similar to the Mongolic and Turkic languages. All Manchu phrases are head-final; the head-word of a phrase (e.g., the noun of a noun phrase, or the verb of a verb phrase) always falls at the end of the phrase. Thus, adjectives and adjectival phrases always precede the noun they modify, and the arguments to the verb always precede the verb. As a result, Manchu sentence structure is subject–object–verb (SOV). Manchu also makes extensive use of converb structures and has an inventory of converbial suffixes to indicate the relationship between the subordinate verb and the finite verb that follows it.

Unlike English, which uses prepositions, Manchu exclusively uses postpositions.

The Manchu language is agglutinative in word structure, meaning that words are formed by adding suffixes to the root, and each morpheme in a word has one distinct meaning or grammatical function.

{grammar excerpts}""

• **Component Chain-of-Thought Prompting (Annotation):**

Given the previous information, please first annotate the meaning and grammatical features of each word in the sentence.

For each word, based on their English translation and whether it ends with '=' (marker of verb stems), first decide whether the word is nominal (noun/adjective), or a verbal (verb, converb) or else (other part of speech such as adverb, postposition ect.).

Then for each noun, please annotate its number (singular/plural) and case (Nominative/Genitive /Dative-Locative/Accusative/Ablative), based on the particles/suffixes that follow the noun. And for each verb, please annotate its tense (perfect/imperfect) and form (Affirmative/Negative/Interrogative/Imperative/Optative/Desiderative), based on the suffixes attached to the verb.

Then based on the annotations, translate the sentence from {source language} into {target language} based on the annotations and the analyzed sentence structure.

• **Component Chain-of-Thought Prompting (Annotation + Syntactic Analysis):**

Given the previous information, please proceed with the following steps:

Step 1:

Please first annotate the meaning and grammatical features of each word in the sentence. For each word, based on their English translation and whether it ends with '=' (marker of verb stems), first decide whether the word is nominal (noun/adjective), or a verbal (verb, converb) or else (other part of speech such as adverb, postposition etc.).

Then for each noun, please annotate its number (singular/plural) and case (Nominative/Genitive /Dative-Locative/Accusative/Ablative), based on the particles/suffixes that follow the noun. And for each verb, please annotate its tense (perfect/imperfect) and form (Affirmative/Negative/Interrogative/Imperative/Optative/Desiderative), based on the suffixes attached to the verb.

Step 2:

Then based on the annotations, please analyze the sentence structure by figuring out what the subject and object of each verb is. Keep in mind that {source language}'s basic word order is subject–object–verb (SOV) and it is a head-final language, so that the adjectives and participles always precede the noun they modifies, and the arguments to the verb always precede the verb.

Note that clauses can be combined into a single sentence by using converbs, which relate the first action to the second.

The final step:

Translate the sentence into {target language} based on the annotations and the analyzed sentence structure.

C Implementation Details

Hyperparameters of LLM Generations For the Llama3 models, we performed our translation experiments using vLLM.¹⁸ The model was configured to use half-precision (dtype='float16') with a maximum context length of 20,000 tokens. For generations, we used a temperature of 0.9, top-*p* sampling with *p* = 0.9, and a maximum output length of 5,000 tokens.

¹⁸<https://github.com/vllm-project/vllm>

For translation with GPT-4o and DeepSeek-v3, we used OpenAI and DeepSeek’s APIs, respectively, with their default settings (i.e., a temperature of 1.0 and top- p sampling with $p = 1.0$).

Hyperparameters of Fine-Tuning For fine-tuning mT5-small, we set the learning rate to $5e-4$ and a batch size of 16. We evaluated the model per epoch and employed the early stopping: the training is terminated if no improvement (drop in loss on validation set) is observed over 2 consecutive evaluation steps. The best-performing checkpoint (with the minimum loss on the validation set) is selected as the final model.

D Relative Order of the Parallel Examples and Grammar

As explained in §4, the order of adding components is based on which components are expected to be most beneficial, as suggested by previous works. There has been a concern about this order, that the benefit of the parallel sentences from the grammar books might be overshadowed by the retrieved parallel sentences.

To address this concern, we have conducted an additional experiment of comparing $\pi(\mu(\mathbf{x}), D^*, G^*)$ with the baseline $\pi(\mu(\mathbf{x}), D^*)$ to test the benefit of adding Grammar component alone. Still, the results showed minimal improvement (BLEU: 7.55 \rightarrow 7.58, chrF: 32.71 \rightarrow 33.08, SBERT: 61.07 \rightarrow 59.89), confirming our previous claim in §4.4 that “Grammars hardly help”.

E Vocabulary Mismatch Between the Test Set and the ICL Data

The vocabulary mismatch between the data used during ICL (dictionary + parallel sentences) and the test set could be a reason for the underestimated BLEU and chrF scores, as mentioned in 5.1. In order to measure the similarity between the test set and the data used during ICL, we tokenized all the Manchu and English text involved in the prompts versus the test set, and calculated the number of subword-type overlaps as shown in Table 8:

As shown in Table 8, the vocabulary mismatch on the Manchu side is minimal (only 3%), while the English side exhibits a substantially higher mismatch (25%). This vocabulary mismatch on the English side could lead to lower BLEU and chrF scores, even when the translation is correct, as is evident in the case of Table 6.

	English	Manchu
Subwords in D and P	6,378	2,270
Subwords in test set	1,353	814
Overlapping subwords	1,017	790
% of non-overlapping subwords in test set	25%	3%

Table 8: Subword overlap between the test set and the ICL data.

F Manchu-Chinese Translation

In addition to the Manchu-to-English translation, we have also explored the translation direction of Manchu-to-Chinese. Taking the best setting $\pi(\mu(\mathbf{x}), D^{l+s+c}, P^{bm})$ from our Manchu-to-English experiments, we use Hu (1994) as the dictionary and the parallel example sentences from Hu (1994) as the parallel corpus. We have experimented with GPT-4o and DeepSeek-V3 and the translation is again evaluated using BLEU, chrF, and SBERT. For Chinese word segmentation, we have used Jieba.¹⁹ The results are shown in Table 9:

Model	BLEU	chrF	SBERT
GPT-4o	5.21	14.72	75.62
DeepSeek-V3	9.28	19.39	79.44

Table 9: Manchu-to-Chinese translation performance with GPT-4o and DeepSeek-V3.

Similar to the trend observed in our Manchu-to-English experiments, DeepSeek-V3 has achieved superior performance compared to GPT-4o, across all three metrics. Interestingly, the SBERT score is noticeably higher for Manchu-to-Chinese translation compared to Manchu-to-English, suggesting that Manchu may be more easily translated into Chinese, likely due to their closer linguistic and cultural affinity. On the other hand, the BLEU and chrF scores are lower for Manchu-to-Chinese. We hypothesize that this is primarily because Chinese MT outputs seem to exhibit lower n-gram overlap with references even when semantically correct, which could be attributed to some inherent characteristics of Chinese, such as more flexible lexical choices and a much larger character inventory. Moreover, recent findings suggest that BLEU and chrF tend to assign disproportionately lower scores to shorter sentences, which may further penalize valid Chinese translations (Song et al., 2024).

¹⁹<https://github.com/fxsjy/jieba>

G Statistical Significance Test

To test the statistical significance of our results, we have conducted bootstrap resampling with 1000 samples. For each component, the best variant is compared to its baseline to see whether its performance as measured by the BLEU, chrF, and SBERT scores, is statistically significantly higher than the baseline.

Hypothesis tested (variant > baseline)	Metric	Variant	Baseline	p-value
$\pi(\mu(x), D_{\text{lsc}}) > \pi(x)$	BLEU	7.55***	3.44	0.0009
	chrF	32.71***	21.86	0.0009
	SBERT	61.07***	34.21	0.0009
$\pi(\mu(x), D_{\text{lsc}}, P_{\text{bm}}) > \pi(\mu(x), D_{\text{lsc}})$	BLEU	8.84*	7.55	0.04
	chrF	33.72*	32.71	0.03
	SBERT	61.35	61.07	0.3
$\pi(\mu(x), D_{\text{lsc}}, P_{\text{bm}}, G_{\text{lp}}) > \pi(\mu(x), D_{\text{lsc}}, P_{\text{bm}})$	BLEU	8.90	8.84	0.4
	chrF	33.77	33.72	0.4
	SBERT	60.40	61.35	0.9
$\pi(\mu(x), D_{\text{lsc}}, P_{\text{bm}}, G_{\text{lp}}, C_{\text{as}}) > \pi(\mu(x), D_{\text{lsc}}, P_{\text{bm}}, G_{\text{lp}})$	BLEU	8.49	8.90	0.4
	chrF	33.43	33.77	0.7
	SBERT	59.01	60.40	0.9

Table 10: Statistical significance (p-values) of BLEU, chrF and SBERT scores for each added component over its immediate baseline. Asterisks denote statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As shown in Table 10, the performance gains of adding the best variant of Dictionary and Parallel Examples are statistically significant (with the only exception of SBERT for Parallel Examples), while for Grammar and CoT the performance is not statistically significantly better than the baseline, which aligns with our claims. In the case of Parallel Examples, although the p-value for SBERT is not statistically significant, both BLEU and chrF show significant improvements. Therefore, considering all three metrics together, we still find it valid to claim that Parallel Examples is beneficial.

H Instructions Given to Human Raters

In this evaluation task, you will evaluate 99 English translations of Manchu sentences. For each evaluation item, you will be shown:

- The original Manchu sentence
- An English reference sentence
- A system-generated English translation

Your evaluation should be based on how well the translation captures the meaning of the original Manchu sentence. The English reference translation is included only to help resolve ambiguities — do not score based on how closely the system-generated translation matches the reference. If the system-generated translation uses different words or phrasing but adequately conveys the meaning, it should not be penalized.

The focus of this evaluation is on how well the system-generated English translation conveys the meaning of the original Manchu sentence. Do not penalize translations for awkward or unnatural English phrasing as long as the meaning is adequately preserved.

You will use a slider (0%–100%) to score each translation. Below are example cases to help guide your judgments:

- 0% – No meaning preserved

Manchu: miyoose tusy labdu tacin umesi oshon ehe

Reference: There are many chieftains of the Miao, whose customs are cruel and wicked in the extreme.

Translation: The third month after the harvest is very difficult.

→ Almost none of the source meaning is captured. An extremely low score is appropriate.

- 33% – Some meaning preserved

Manchu: bayara be beise gaifi morin ulebumbi

Reference: The Beise led the bayara guards to feed the horses.

Translation: The prince, taking joy, rides the horse.

→ A few words are correctly translated (e.g., "beise", "morin"), but the overall meaning is not.

- 66% – Most meaning preserved

Manchu: emu inenggi ududu morin gabtabumbi

Reference: In a single day many horses were shot.

Translation: One day, several horses shone forth.

→ Most of the meaning is preserved, but there is a key error ("gabtabumbi" mistranslated).

- 100% – Adequate translation, all meaning preserved

Manchu: bi gemun hecen i baru genembi

Reference: I'm going to Beijing (the capital).

Translation: I go toward the capital city.

→ The system output preserves the full meaning, even if the wording differs from the reference.

Please try to be consistent in your use of the scale across all items. Your valuable evaluation will help improve the quality of machine translation for endangered languages like Manchu.

I Output Examples

	Retrieved Dictionary Entries (Input Sentence: <i>se udu oho</i>)	Translation
$\pi(\mu(\mathbf{x}))$	morphological segmentation: se udu oho/o-ho. (<i>alternative analyses are separated by ‘/’</i>)	It happened to be the time.
+D ¹	+lexical entries: se: 1. year (said of age), age 2. raw silk, unprocessed silk 3. the juncture of the stem and root on the ginseng plant 4. (plural suffix) udu: 1. “How many?”, “How much?” 2. several 3. although oho: armpit o-: 1. to become, to change into 2. to be, to exist 3. to be proper, to be permissible	How many are the years?
Ground Truth		How many years old?

Table 11: Comparison between the outputs of $\pi(\mu(\mathbf{x}))$ and D¹. The LLM selects the most appropriate sense, interpreting *se* as “year” and *udu* as “How many”. Additionally, the LLM correctly identifies that *oho* is better analyzed as *o-ho*, where *o-* means “to be”, rather than as *oho* (“armpit”) which does not fit in this context.

	Retrieved Dictionary Entries (Input Sentence: <i>gvsai ejen jiha...</i>)	Translation
D ¹	lexical entries: gvsai: banner ejen: master, ruler ji-: to come	the ruler of the banner comes...
D ^{1+s}	+suffixes: -i: it is used to indicate possession (Genitive) or the means by which something is accomplished (Instrumental) -ha: Perfect participle: ara- 'to do', ara-ha 'he.did, who has done, what was done'	the ruler of the banner came...
D ^{1+s+c}	+collocations: gvsai-i ejen: Lieutenant-General (of a banner)	the Lieutenant-General came...
Ground Truth		Lieutenant-general came...

Table 12: Comparison of the outputs for D¹, D^{1+s} and D^{1+s+c}. As the example shows, the additional information about suffixes and collocations helps the model to correctly translate the tense of the verb and the phrase *gvsai ejen*.

	Retrieved Parallel Examples (Input Sentence: <i>geli emu hvlha be we waha be sarkv.</i>)	Translation
$\pi(\mu(\mathbf{x}), D^{1+s+c})$	-	Still, <u>it is unknown</u> who has killed one bandit.
+P ^r	...	Also, one bandit, who has killed, <u>is not known</u> .
+P ^d	...	Also, who has killed one bandit <u>without knowing it?</u>
+P ^{bm}	Manchu: wede hvlhame gamabuha be inu sarkv. English: I don't know who stole it. ...	Still, I <u>do not know</u> who killed one bandit.
Ground Truth		Who killed the other rebel, <u>I do not know</u> .

Table 13: Comparison between the outputs of the baseline $\pi(\mu(\mathbf{x}), D^{1+s+c})$ and the variants of adding parallel examples retrieved by different ways (+P^r, +P^d and +P^{bm}). As the example demonstrates, when using the BM25 algorithm, the retrieved parallel example helps the model to recover the subject ‘I’, which is often omitted in Manchu but can be inferred from the context.

	Retrieved Grammar Excerpts (Input Sentence: <i>muke <u>be</u> genekini</i>)	Translation
$\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$	lexical entries: be: accusative particle	go <u>by</u> water
+G ^s	+grammar excerpts: An object of a verb having definite or specific reference is shown with the particle be.	go <u>to</u> the water
+G ^l	+grammar excerpts: ...The accusative may express space within and means of conveyance by which the motion is going on.	go <u>by</u> water
+G ^{l+p}	+grammar excerpts +example: ...The accusative may express space within and means of conveyance by which the motion is going on. jugvn be yabu-me road ACC go-CONV “to go along the road;”	go <u>by</u> water
Ground Truth		travel <u>by</u> water

Table 14: Comparison between the outputs of the baseline $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ and the variants of adding grammar excerpts (+G^l, +G^{l+p} and +G^{s+p}). With the more detailed long grammar excerpt explaining a specific function of Manchu accusative as *expressing space within and means of conveyance by which the motion is going on*, the model correctly selects the English preposition ‘by’. In contrast, when provided with the short grammar excerpt of G^{s+p}, the model chooses the preposition ‘to’ as the translation for the accusative particle. This likely stems from the model’s broader knowledge of the accusative case, including its usage in other languages such as German, where it can correspond to the English preposition ‘to’. However, in the case of Manchu, such a translation is incorrect. Notably, in the baseline $\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm})$ without any grammar excerpts, the model also translates the preposition correctly, either by chance or through contextual inference.

	Translation (Input Sentence: <i>nikan coohiyan tob seme emu dulin</i>)	Model Response
$\pi(\mu(\mathbf{x}), D^{1+s+c}, P^{bm}, G^{1+p})$	Chinese and Korea are exactly in one middle	...
+C ^a	Halfway between China and Korea	Now, let's analyze ... "emu dulin" modifies the action, indicating the manner or status as "one middle" or "a middle stage" contextually suggesting halfway or middle grounds ...
+C ^{a+s}	The statement or identity concerning the Chinese and Korea is exactly as described in the middle.	Step 2: Analyze the sentence structure ... The sentence implies a direct identification or explanation regarding the entities "Chinese" (<i>nikan</i>) and "Korea" (<i>coohiyan</i>) with respect to something being exactly in the middle or balanced ("emu dulin") described as "just" or "right" ...
Ground Truth	Chinese and Korean each just one half.	

Table 15: The translations and some of the model responses involving CoT steps, comparing the baseline with the variants of adding CoT prompting instruction(+C^a and +C^{a+s}). As shown in the model responses, the CoT prompting makes the model engage in multiple iterative reasoning steps. While these steps are intended to help the translation, it may also introduce errors at each turn, leading to a worse final translation.

	Retrieved Dictionary Entries (Input Sentence: <i>mini morisa be ganabufi...</i>)	Translation
D ^l	lexical entries: mini: my, of me morin: horse be: 1. we (exclusive) 2. (accusative particle) ganabu-: (causative of gana-); gana-: to fetch	After my <u>horses</u> were fetched...
D ^{l_e}	lexical entries: (enciphered sentence: <i>nopo nusote ci hepecago</i>) nopo: my, of me nusop: horse ci: 1. we (exclusive) 2. (accusative particle) hepeca-: (causative of hepe-); hepe-: to fetch	My <u>horse</u> was caused to fetch...
D ^{l+s}	+suffixes: -fi: Perfect converb: ara- 'to do', ara-fi 'having done, he did and (then did something else)'. -sa: (-sa/-se/-so) Plural: <i>sakda</i> 'old man', <i>sakda+sa</i> 'old men'.	My <u>horses</u> having been fetched...
Ground Truth		I had my <u>horses</u> fetched and...

Table 16: Comparison of the outputs between D^l, D^{l_e} and D^{l+s}. This example suggests that the LLM already has some prior knowledge about the Manchu plural suffix so that even when the information about plural suffix *-sa* is not included in the prompt of D^l, the model is still able to identify the plurality. In contrast, when the Manchu tokens are enciphered, there is no clue for plurality in the context, leading the model to incorrectly identify the noun as singular.

Model	Translation (Input Sentence: <i>ere uthai tere gucu inu</i>)	BLEU	chrF	SBERT
Llama3-1B	te=re/tere inu uju be tongki	0.0	7.75	1.67
Llama3-3B	This friend and that one are the same, at the same time, or both are friends.	2.86	27.46	42.74
Llama3-8B	Even though he/she/it sits, a friend.	6.77	31.36	42.81
Llama3-70B	This one, then, is also living with a friend.	8.05	35.86	46.97
GPT-4o	This immediately is that friend too	19.3	45.72	70.88
DeepSeek-V3	This is also that friend	20.8	45.26	81.96
Ground Truth	This is that very friend.			

Table 17: Comparison of outputs across different LLMs, along with their **sentence-level** BLEU and chrF scores, as well as SBERT scores. We **bold** the best score for each metric. In this example, Llama3-1B fails to follow the instructions, generating a sentence in Manchu. This illustrates a clear trend that as models become larger and/or more advanced, the translation quality consistently improves.