Morphological Error Analysis of Machine Translation Output: A Case Study on Kurdish Texts Translated by OpenAI ChatGPT

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***Abstract*—Evaluation of machine translation output is an effective step to develop the quality of any automated translation project. This step has been taken by different researchers in a variety of methods, most of them lead to holistic findings without targeting the main causes of deficiencies. The current study is an attempt to address morphological errors that affect the quality of an automatic translation system that has recently been used as the most popular platform (OpenAI ChatGPT) among Kurdish individuals and institutions to translate texts from English into Kurdish (Sorani) and vice versa. To target the aims of the study, 30 sentences from different text types defined by Reiss (2000) were selected among a 100-sentence corpus as the data of the study and translated by a practiced human translator, taking the role of reference translation and the same source sentences translated by the understudy ChatGPT system. Based on the integrated model of error categorization proposed by Popović and Arcan (2015) and the multidimensional quality metrics model developed by Lommel et al. (2014), problems related to lexical choice were by far the most common and followed by inflectional, syntax-morphology, and derivational errors, respectively. At the same time, weak semantic discrimination related to choosing the right equivalents has greatly affected the quality of the Kurdish output of the understudy system.**

***Keywords*—Classification and identification of errors, Kurdish (Sorani) language, Machine translation, Morphological error analysis, OpenAI ChatGPT**

I. Introduction

Evaluation of machine translation (MT) outputs is a challenging task that accomplished to develop the quality of the outputs of MT systems and to meet different requirements assigned by the real users of the systems. Different methods and metrics have been proposed to assess the automatically translated texts that mostly are general in nature and provide scores based on comparison between the source text (ST) and target text (TT). It is believed that evaluation of MT output through holistic scores and interpretations does not lead to very clear and focused results and cannot highlight the systems' weaknesses fully; consequently, do not help the system designers to evolve their systems successfully (El Kholy and Habash, 2011).

One way of evaluating MT performance is to evaluate the translation project by human evaluators who understand both the source language (SL) and the target language (TL). The main criteria of such assessments are usually adequacy and fluency of translated texts. Taking into account the reality that there is no single correct translation of a text, human evaluation measures, most of the time, do not lead to specific and meaningful results (Popovic, 2018).

Concentrating on the shortcomings of human evaluation methods, researchers have proposed automatic evaluation models of MT outputs that usually lead to more consistent results (Rasouli, 2018). The automatic models such as Bleu based on words n-gram precision (Papineni et al., 2002), TER based on the number of error corrections or edit distance (Snover et al., 2006), METEOR that is designed by Banerjee and Lavie (2005) based on unigram precision, recall and extra linguistic knowledge are significantly cheaper and faster than human evaluations, and proposed based on different goals.

Despite valuable data and information provided by the mentioned models of MT evaluations, researchers, designers, and users of MT systems are more interested in getting detailed information that highlights the system's weaknesses and identifies errors that help them to reach more reliable outputs and to focus their efforts as well (Vilar et al., 2006).

To identify the specific strengths and weaknesses of MT systems and to compare their performance, developing

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a clear error taxonomy and conducting systematic error analysis are highly valuable (El Marouani et al., 2020). MT outputs to the main approaches of quality assessments can be applied, which are the evaluation of the translated text by human experts in the field or the examination of the output automatically. The essential shortcomings of human assessment approaches are their high cost and the extent of time that must be consumed to assess the quality of the translated text, meanwhile as Popović (2018) notes, different human evaluators judge the output subjectively, which can lead to inconsistent results across. In contrast, to avoid the mentioned shortcomings of the human evaluation methods, most researchers are interested in evaluating MT outputs automatically which are generally more efficient and produce more consistent outcomes.

Posner (1975) has defined morphology as a branch of grammar that works on the structure of words and has classified morphology into three subcategories of inflections, derivations, and compounds. According to Aronoff and Fudeman (2011), morphology examines how morphemes combine to produce complex word forms and grammatical distinctions. In addition, Spencer and Zwicky (1998) maintain that a language's morphological system plays a key role in showing how word meaning connects with both its grammatical behavior and its broader semantic patterns.

Existing research often used human or automatic evaluation metrics to identify the quality of the translated texts by MT in general terms; consequently, taxonomy and evaluation of errors and their types have been ignored in the majority of related works. OpenAI ChatGPT has been increasingly used by Kurdish individuals and academic institutions as an automated translation platform; therefore, identification, taxonomy, and analysis of morphological errors made by the understudy platform can significantly improve the quality of translated texts in the Kurdish language.

Answering the following research questions can shed light on the main area of difficulties in translation of different types of texts from English into Kurdish languages, and at the same time, it can help systems' designers to concentrate on major issues to improve the accuracy and fluency of the translated texts:

1. What are the most frequent types of morphological errors in Kurdish translation of understudy ChatGPT systems?
2. How identifying morphological errors can affect the quality of automatic translation of English texts into Kurdish?

II. Literature Review

A. Assessment and Classification of Errors

Translation studies have considered errors as a crucial device for improving the quality of the TT (Van der Wees et al., 2015). Identification and categorization of errors in automated translated texts can put the specific problems and challenges of MT systems into the sight of investigators and MT system designers. Error analysis can fill the gap of assessment of MT systems, which are difficult to evaluate by automatic metrics like Bleu (Papineni et al., 2002) or ranking the understudy systems manually (Callison-Burch et al., 2007). To detect and classify the types of errors generated by MT systems when producing translations for the selected dataset, researchers are interested in comparing a translated text to one or more reference translations that are produced by practiced human translators. However, because a single ST can legitimately yield multiple acceptable translations, the process of comparing versions is not always clear-cut or straightforward (Vilar et al., 2006).

Comparison and analysis of errors of MT outputs have been made based on different criteria, and different researchers worked on the case by putting the errors into distinct classification models that mainly caused more specific and usable results (Rasouli, et al. 2024, 2026). Farr´us et al. (2010) presented a five-class scheme of MT error analysis of translation from/into Spanish: Morphological errors, lexical errors, orthographic errors, syntactic errors, and semantic errors. To analyze automated translated texts, Federico et al. (2014) grouped translation errors into four main categories: (1) Morphological errors, (2) Lexical choice issues such as additions and omissions, (3) Casing and punctuation problems, and (4) Word-order errors. Vilar et al. (2006) proposed a hierarchical model for classifying MT errors that largely follows the framework introduced by Llitjos et al. (2005), with only minor modifications to the structure and categorization. The model has divided the first-level error into five main classes of "Missing words," "Wrong Word Order," "Incorrect Words," "Unfamiliar Words," and those errors that may happen due to the misuse of "Punctuation" rules. Costa et al. (2015) in an innovative model proposed a linguistically grounded taxonomy of translation errors that builds upon and expands earlier classifications. The proposed model, based on major linguistic domains, classifies errors to provide necessary information for identifying errors more accurately. This taxonomy of errors has been widely used to evaluate online systems such as Google Translate and Systran and another system that was developed with Moses technology (ibid).

Koehn (2005) defines Moses technology as an open-source statistical MT system widely used in MT research internationally. It enables the automatic training of translation models for any language pair, provided that a parallel corpus is available.

Two principal types of morphological difficulty in MT have been identified by Burlot et al. (2017), the first stems from morphological variation in the SL, which results in the system encountering word forms that fall outside its stored vocabulary and therefore cannot be translated reliably. The second arises in the TL, where the system must produce morphologically appropriate forms that may not exist in its training data, making accurate generation of new word forms challenging.

In Popović (2018), morphological errors are subdivided into inflectional, compounding, and derivation types; in addition, he added some more distinctive details to his categorization about verb-related errors including person, mood, and tense. Annotatively, the latter category of errors can be labeled as a separate type of error.

In general, errors are identified either manually or automatically (Massoudi et al., 2024). Manual interpretation of errors can reach more specific details that cannot be achieved by automated systems, but it necessitates a remarkable attempt and consistent applying of this method of identification without strict coding protocols is difficult. As Popović (2018) notes, although a detailed taxonomy of errors leads to more acceptable descriptions of translation error, this detailed error causes mounting disagreements among interpreters. Particularly, evaluators who are not practiced and have not received specialized training probably find it challenging to make a differentiation between major inflectional errors and some agreement violations. Accordingly, to ensure consistent, valuable, and effective use of human evaluation, creating a well-organized and language-specific classification of errors is central to this model of MT error analysis.

Identifying errors automatically serves as a helpful supplement to manual annotation (Massoudi et al., 2024). Relying on word alignment data and edit-distance measures, systems such as Hjerson and Addicter detect different types of errors. Contrasting Word Error Rate (WER) with Position-Independent Error Rate (PER) at both the surface and lemma levels, Popović and Ney (2007, 2011) explained that many errors are rooted in inflectional problems rather than incorrect lexical selection. Taking into account this principle, Hjerson group errors in translation output into categories include morphological, lexical, omission, addition, and reordering. Access to accurate lemmatized forms effectively influences the capability of the system to identify true morphological mismatches; however, when such resources are unavailable, the system must resort to innovative approaches. By flagging untranslated material, Addicter expands the range of error labels but to differentiate between morphological errors and more general translation errors, Addicter also needs lemmatized inputs.

Undoubtedly, to detect morphologically related errors on a large-scale, automatic tools are useful, but their effectiveness depends on the quality of the reference data and the accuracy of lemmatization. Popović (2018) enumerates the effectiveness of automated approaches of identifying morphological errors; due to the weakness of the systems in distinguishing error types clearly, he believes that precise human assessment remains essential for effective and valuable evaluation of MT outputs.

Taking into consideration the practical and theoretical background in the field, the present study evaluates the translated sentences from English into Kurdish (Sorani) to identify any morphological errors including problems in derivation, word formation, and inflectional endings for number and person agreement that affected the quality of translation.

III. Materials And Methods

A. Data Selection

The materials of this study are selected rigorously among a large corpus of English-Kurdish texts produced by AI ChatGPT. To analyze the understudy's platform performance on translating English texts into the Kurdish language, 30 sentences have been selected based on text typology (informative, expressive, and vocative) proposed by Reiss (2000). This is done to cover a variety of morphological categories across different communicative contexts. Each sentence consists of an original English ST, a humanly translated sentence as the study's reference sentence in Sorani Kurdish, and a corresponding AI-generated translation of ChatGPT-4 that has been increasingly used as a translation aid platform. The whole data of the study is presented in Appendix I of the current paper.

The reference sentences of the study were translated by an academist and native speaker of the Kurdish language who teaches translation studies at Cihan University, Erbil, Iraq, and also works as a certified translator. This strategy provides a solid and dependable model of correct and natural Kurdish language morphological standards.

B. The Framework of Identification and Taxonomy of Errors

A combined and adjusted framework based on the multidimensional quality metrics (MQM) model developed by Lommel et al. (2014), and the morphological error classification proposed by Popović and Arcan (2015), has been applied to identify and analyze collected data. The MQM framework offers a structured way of identifying translation errors made by MT's and organizes them into clear categories related to accuracy (fidelity toward ST meaning) and fluency (stylistically and grammatically natural). Targeting the following four morphological aspects is the main aim of applying this integrated model of error analysis:

1. Errors that relate to the morphological agreement such as number, gender, case, and person that are labeled herein study as MQM: Accuracy/Fluency and Grammar.
2. Incorrect formation of words that are labeled (MQM: Fluency and Grammar), and divided into two types:
    - Inflectional errors: incorrect application of mood, aspect, number, case, etc.,
    - Derivational errors: wrong use of derivational affixes that affect the meaning and word class.
3. Selection of wrong equivalence for ST words in the ChatGPT output that affects the accuracy of translation (MQM: accuracy- wrong translation).
4. Errors that are rooted in incorrect morphological forms and grammatical structure such as ungrammatical word order and calques which are referred to this type of errors, in this study, as Syntactic-Morphological interaction (MQM: Fluency and Grammar. syntax).

Based on Popović's and Arcan's (2015) framework of error analysis, five different types of errors can be identified at the level of lexicon in ChatGPT outputs:

1. Morphological errors: Selection of correct word but the form of it is incorrect grammatically
2. Lexical errors: Selected word is entirely wrong
3. Syntactic errors: Errors in word order or structurally incorrect sentences
4. Reordering errors: Relate to the correct selection of words

but in an incorrect order
5. Derivational errors: Relate to the different parts of speech of a word that has been used incorrectly. For instance, noun is used instead of an adjective.

C. Analytical Procedure

The methodology of the study was conducted in three stages of providing English texts as the ST of the study, translating the sentences by a practiced translator into Kurdish (Sorani) as the reference sentences of the study, and systematically and precise comparison between ST and reference sentences to identify and taxonomize morphological errors.

Sentence 1

- Source: The water supply was interrupted yesterday.
- Human reference: دوێنێ دابین کردنی ئاو وەستاندرا (dowe-ne daa-been kird-nee aw was-tan-dra)
- GPT translation: ئاو دوێنە وەستاندرا (aw dwen-e wus-tan-dra).
- Error analysis: MQM: Accuracy – wrong translation, Popović: Lexical Error – the inability of the system to realize the root of the word. The compound noun "water supply" is not translated. "Supply" is omitted, demonstrating a fundamental failure in recognizing the correct nominal root that in the reference sentence has been translated by a verbal compound ("دابین کردنی") and, in case of omitting it, affects both accuracy and fluency of the translation.

Sentence 2

- Source: The report includes recent statistics
- Human reference: ڕاپۆرتەکە ئاماری ئەم دواییەی لەخۆگرتووە (ra-por-ta-ka -amaree- am doo-a-ya-y le-kho-gir-tu-wa)
- GPT translation: ڕاپۆرتەکە ئامارە نوێکان لەخۆ دەگرێت (ra-por-ta-ka a-ma-ra nwe-kan le-kho da-gret)
- Error analysis: MQM: Fluency - Grammar (Aspect) & Accuracy - Mistranslation
- Popović: Morphological error (Aspect)
- Inflectional error: The present perfect aspect ("لەخۆگرتووە" - has included) is reduced to simple present ("دەگرێت" includes).

Sentence 3

- Source: When I remember her, I feel sad
- Human reference: کاتێک ئەوم بیر دێتەوە خەمبار دەبم (ka-tek -awum -beer -detwa -khambar -da-bim)
- GPT translation: کاتێک لەبیر دەکەم، غەمگین دەبم (ka-tek le-beer da-kam, gham-geen da-bim)
- Error analysis: MQM: Fluency - Grammar (Syntax) and Accuracy – Mistranslation Popović: Syntactic-morphological error and lexical error

1. The construction which is experiencer-subject "بیر دێتەوە," is changed to an agentive construction "لەبیر دەکەم" (I forget). Syntactic-morphological error.

Sentence 4

- Source: I really enjoyed the dinner
- Human reference: بەڕاستی خواردنی ئێوارەم بەدڵ بوو (be-ras-tee khuard-ni e-wa-ram ba-dil boow)
- GPT translation: ڕاستەوخۆ خۆشحاڵ بووم لە خۆراکەوە (ras-ta-w-kho khosh-hal boowm le kho-ra-ka-wa)
- Error analysis: MQM: Accuracy - Mistranslation (Double) Popović: Lexical error multiple lexical errors
- "بەڕاستی" (truly) → "ڕاستەوخۆ" (directly)
- "خواردنی ئێوارە" (dinner) → generic "خۆراک" (food). The error happened due to the failure in contextual understanding by the AI system.

Sentence 5

- Source: Please before sending, check the document
- Human reference: تکایە پێش ناردنی بەڵگەنامەکە بپشکنە (tka-ya pesh nard-nee bel-ga-na-ma-ka bpish-ki-na)
- GPT translation: تکایە پێش ناردنی پەڕگەکە بپشکنە (tka-ya pesh nard-nee par-ga-ka bpish-ki-na)
- Error analysis: Based on MQM: mistranslation that affects accuracy happen accuracy through wrong equivalent selection for English word of document. At the same time, Popović: Lexical Error (Register/Specificity) can be elicited from the Kurdish text that the AI system was not able to differentiate between the level of formality in the selection of "پەڕگە" instead of "بەڵگەنامە."

IV. Findings and Discussion

The administration of integrated model of MQM and Popović's taxonomy of errors highlights the types of morphological errors produced by the understudy A Platform in the translation of English sentences into the Kurdish Language. The clear trends of errors show that the selection of lexical equivalence represents the largest group of errors that appear in 24 out of 30 sentences (80%). Through the interpretation of this class of errors, we can reach the point that the main difficulty for Kurdish ChatGPT does not lie in forming the grammar correctly but in choosing the right equivalent for the intended ST word for a given context. The system often picks words that are close in meaning but do not fit the intended sense, which significantly changes the message.

Inflectional errors are the second most common type, found in 7 sentences (23.3%). Mainly, these groups of errors include incorrect use of verb tense or aspect, and problems that refer to the noun - adjective agreement, specifically in relation to number and definiteness. The repetition of these types of errors highlights the system's inability to manage the agglutinative structure of the Kurdish language.

It seems that the understudy system has followed the English syntactic pattern rather than Kurdish grammatical norms; as a result, syntactic–morphological errors happened in 7 sentences (23.3%). By contrast, derivational errors were rare and could only be seen in one sentence (3.3%), which suggests that the system avoids generating more complex word formation. The error distribution is visualized by the following Table 1 in detail:

The following charts depict the findings of the study in a

TABLE I
Distribution of Different Errors Based on the Integrated Model of the Study

Error category	Model	No. occurrence	Percentage of 30 sentences	Sentences found
Accuracy	MQM	25	83	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 20, 22, 24, 25, 26, 27, 28, 29
Fluency	MQM	17	57	2, 4, 5, 6, 7, 8, 10, 15, 18, 19, 20, 21, 23, 26, 27, 29, 30
Lexical	Popović	24	80	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16, 17, 20, 22, 24, 25, 26, 27, 28, 29
Inflectional	Popović	7	23.3	2, 8, 10, 15, 21, 26, 29
Syntactic – Morphological	Popović	7	23.3	5, 15, 18, 19, 20, 27, 30
Derivational	Popović	1	3.3	30

MQM: Multidimensional quality metrics

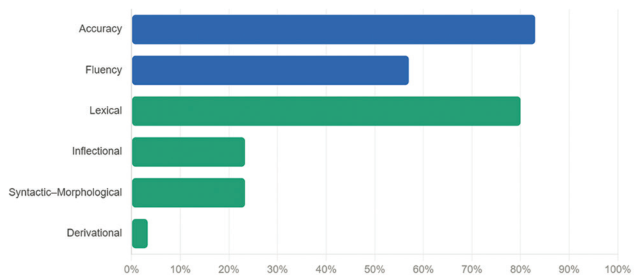

Chart 1: Percentage rate of identified errors based on both multidimensional quality metrics and Popović model.

more detailed way:

The findings of the study are depicted in greater detail (see Figures 1 and 2). Accuracy and Lexical errors are clearly the biggest problems; they show up in more than 80% of the 30 sentences. Appearing in about half the sentences, fluency errors are also quite common. The other three error categories (inflectional, syntactic–morphological, and derivational) are much less frequent, all below 25%.

Chart 2 tells the same story but with actual numbers. Accuracy errors were found in 25 sentences and lexical errors in 24, which is a lot out of only 30. Derivational errors are almost not there at all and are found just in 1 sentence. Therefore, if someone wants to fix the translation quality, the best place to start is clearly with accuracy and lexical issues, since they cause the most trouble.

The system's tendency to use Persian loan words in the translation of ST where native Kurdish equivalence is more acceptable, is another type of wrong lexical choice by the system that can be traced in translating sentences 4, 28, and 30. These types of errors highlight the systematic shortcomings of the system in avoiding the selection of an accurate equivalent that directly affect semantic accuracy and stylistic appropriateness.

Based on the findings of the study, most of the inflectional errors relate to the verbal aspect and agreement inside noun phrases which underline the system's problem in dealing with the agglutinative nature of the Kurdish language.

V. Discussion

The functional characteristics and shortcomings of ChatGPT, as identified through its performance in translating texts from English into Kurdish, indicate deficiencies in the system's ability to select appropriate semantic equivalents for English lexical items when translating into the Kurdish (Sorani) language. The system's inability to generate correct translation semantically is probably due to this reality that it has not been designed properly to process the morphological system of agglutinative languages like Kurdish.

Based on the MQM framework, both accuracy and fluency-related errors are at a significant level and can affect the quality of the translated text under question. Accuracy errors appeared in 25 sentences at 83% which followed by fluency errors at 57%. This shows that the system could not pass the standards determined by MQM framework.

The high rate of inflectional errors reveals that the system is not able to analyze grammatical features referring to the verb aspect and nominal agreement elements in the Kurdish language and it faces limitations in this area. The attribution of this limitation may be due to the lack of training resources and the availability of the inflectional data in Kurdish, which is a morphologically rich language.

Syntactic-morphological errors highlight broader structural constraints in the system's performance. Evaluation of such errors indicates that the notable existence of structural differences between English and Kurdish affects the fluency and accuracy of the output due to the inadequate programming and definition of these structural diversities for the understudy system.

The limited number of derivational Errors implies that the system operates mainly at the lexicon level instead of involving generative morphological processes. Even though this cautious method of dealing with derivational structures leads to a low number of these types of errors, it may affect the system's capability in offering and generating new morphological constructions whenever needed.

The use of Persian loan words in the translation of ST is another issue that can be seen among translated texts and shows the tendency of the system in these cases, where native Kurdish equivalence is semantically more acceptable; this kind of wrong lexical choice can be traced in translating sentences 4, 28, and 30. The existence of these types of errors highlights the systematic shortcomings of the system to consider both semantic accuracy and stylistic appropriateness in their selection of equivalent elements in TL. Practically, this preference distorts the accuracy of the translation and, in some cases, subtly changes the meaning when the borrowed word does not express exactly the intended Kurdish concept.

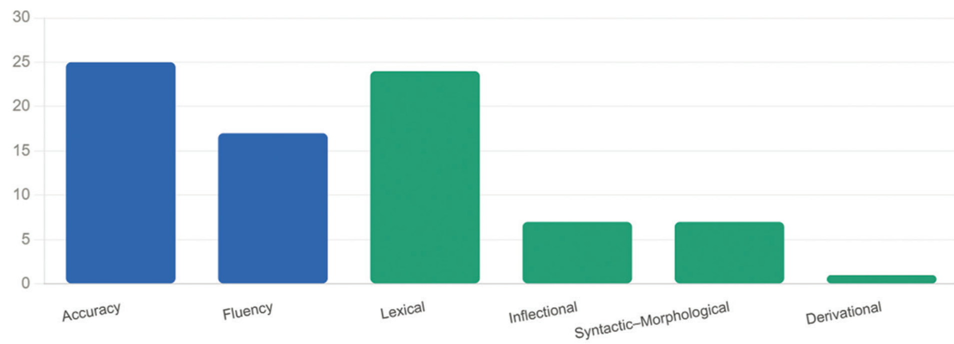

Chart 2: Frequency of errors based on the integrated model of the study.

Instead of producing translations that adhere to Kurdish linguistic rules, the exhibition of a consistent pattern in terms of selection of optimal equivalence, morphological, and syntactic issues represents the reality that understudy automated translation platform mainly relies on vocabulary and structure of the ST, as well as the statistical trends in the data used for training. These results provide valuable information on the system's shortcomings in processing morphological structures of low SLs such as Kurdish (Sorani) with complicated lexicon structure.

VI. Conclusion

Regarding morphological errors in Kurdish MT, this research investigates the following questions:

- Research Question 1: What types of morphological errors are most prevalent in the Kurdish translations generated by the analyzed MT systems?

In responding to the first query, a variety of errors have been spotted through analysis of the collected data. Based on the MQM framework, both accuracy and fluency-related errors are at a significant level and can affect the quality of translated text under question. Accuracy errors appeared in 25 sentences at 83% which followed by fluency errors at 57%. This shows that the system could not pass the standards determined by the MQM framework. Comprising around 80% of all documented instances, the selection of appropriate equivalents and correct words was the most common issue in translation from English into Kurdish. Automatic inflectional mistakes came next, but at a significantly lower rate of 23.3%. Errors that arise at the junction of syntax and morphology followed closely at 23.3%. Derivational errors were rare, contributing only 3.3% to the overall total. The related statistics to the most common errors reveal that the main source of errors lies not in handling the Kurdish morphological structures but the system mainly shows inappropriate selection of words that convey the intended meaning within the context by which the semantic aspects of the output have been affected and distorted.

- Research Question 2: To what extent identification of morphological errors can affect the quality of translated text by ChatGPT systems' translation of English texts into Kurdish (Sorani)?

During the current study, through classification of different morphological errors, a clear framework has been offered to highlight the ChatGPT system's failure of processing Morphological structure of the Kurdish language. Most importantly, the overall quality of the translated text that presents the correctness and acceptability of the generated texts by MT has been achieved through identification of the system's weaknesses and should be prioritized in the system refinements. This happened by evaluating the frequency and distribution of every error type. According to the analyzed data, inadequate semantic differentiation is the crucial obstacle to achieve acceptable Kurdish ChatGPT output. As discussed, the understudy system faces more difficulties in selecting the appropriate equivalents of words that are suitable for the correct context than it does in offering accurate Kurdish equivalent morphologically. In addition, there are considerable issues related to factors including: Agreement, aspect, and other inflectional characteristics. Even though these sorts of problems that are connected to syntax and morphology are important, they have a comparatively lesser impact on the quality of translation semantically.

Based on the findings of the study, a balanced approach to improve the system's performance can be recommended through the following steps. First, the semantic issues that are common among errors made by the system assessed in the current study should be addressed; second, the control over the selection of inflectional morphology must improve, and finally, syntactic generation that has a direct impact on morphological correctness must improve as well. Each of these steps plays a crucial role in addressing the needs of generating translations for Kurdish users of OpenAI ChatGPT.

VII. Acknowledgment

It should be noted that the collected materials of the study have been translated by OpenAI ChatGPT and this can affect the AI composition rate in general.

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APPENDIX I
ANALYZED DATA OF THE STUDY

No.	English source	Human reference (Kurdish)	AI (GPT) translation	Error analysis (Integrated MQM-Popović framework)
1	The water supply was interrupted yesterday.	ێنیۆد وائ یندرک نیباد اردناتسەو daabeen- kirdnee -aw Doweene-wustan-dra.	ئاو دوێنە وەستاندرا aw -dwen-e- wustan-dra.	MQM: Accuracy - Mistranslation Popović: Lexical error - Root recognition failure Mistranslation of the compound noun "water supply" is incorrectly parsed. "Supply" is "yesterday" ("ەنێود"); this demonstrates a fundamental failure of the system in recognizing the correct verbal root ("یندرکنیباد") within the phrasal context.
2	The report includes recent statistics.	ڕاپۆرتەکە ئاماری ئەم دواییەی لەخۆگرتووە Raporta-ka -amaree- am -dooayay la-kho-girtu-wa.	ڕاپۆرتەکە ئامارە نوێکان لەخۆ دەگرێت raporta-ka -amara- nwekan la-kho- dagret.	MQM: Fluency - Grammar (Aspect) and Accuracy - Mistranslation Popović: Morphological error (Aspect) and lexical error 1. Inflectional error: The present perfect aspect ("ەووترگۆخەل" - has included) is reduced to simple present ("تێرگەد" - includes). 2. Lexical error: The temporally specific adjective "یەییاود مەئ" (recent) is replaced with the generic and plurality in AI-generated translation as "کانێون" (new).
3	The new policy was implemented last month.	مانگی پێشووتر سیاسەتێکی نوێ جێبەجێ کردرا Mangi- peashooter- siyasete-ki- nwe jebeje -kird-ra.	سیاستی تازە لە مانگی پێشووتر جێبەجێ شد si-ya-se-tee ta-za le man-gi pesh-oo-ter jeb-e-je shud.	MQM: Fluency - Grammar (Register/Word Form) Popović: Morphological error (Voice/Register) Inflectional/Register error: The native Kurdish passive morphological construction ("کردرا") is replaced by the Persian word "شد." This represents a non-native morphological choice that causes mistranslation and specifically affects the register.
4	The plane landed safely.	فرۆکەکە بە پارێزراوی نیشت fro-ka-ka be pa-rez-ra-wee neesht.	فڕۆکەکە بەسەلامەتی کەمارد fro-ka-ka be-se-la-ma-tee ka-mard.	MQM: Accuracy - Mistranslation and Fluency - Grammar (Register) Popović: Lexical error and morphological interference Two lexical/register error: Mis translation of landed into: "درامەک" that must be "تشین" (land), and "یتەمالەسەب" (Persian) versus native "یوارزێراپ ەب" (safely). Shows preference of the system in selection and register.
5	The company released its annual report.	کۆمپانیاکە راپۆرتی سالانەی بڵاوکردەوە kom-pan-ya-ka ra-por-ti sa-la-nay blaw-kird-a-wa.	کۆمپانیا راپۆرتی ساڵانەی خۆی بەدروست کرد kom-pan-ya ra-por-ti sa-la-nay khoy be-drust kird.	MQM: Accuracy - Mistranslation Popović: Lexical error - Semantic Lexical semantic error: The verb "ەوەدرکواڵب" (published) is incorrectly translated as "درک تسوردەب" (made/fabricated). The system disability to provide a correct equivalent.
6	The festival will start next week.	هەفتەی داهاتوو ڤیستیوالەکە دەست پێدەکات haf-tay da-ha-too ves-ti-wa-la-ka dest pe da-kat.	فێستیڤاڵەکە هەفتەی داهاتوو دەستپێدەکات fes-ti-va-la-ka haf-tay da-ha-too dest-pe-da-kat.	MQM: Fluency - Terminology (Minor) Popović: Orthographic variation Transliteration difference for the loanword "festival" ("لاویتسیڤ" vs. "ڵاڤیتسیف"). This is a low-impact error in the morphological integration of borrowing words that do not affect the text semantically.
7	The museum displays ancient artifacts.	مۆزەخانەکە ئاسەواری کۆن نمایش دەکات mo-za-kha-na-ka a-sa-wa-ree kon num-ayesh da-kat.	ەینات‌ساب ەناخەزۆم تاکەد شەکشێپ نۆک mo-za-kha-na bas-ta-ni-ya kon pesh-kesh da-kat.	MQM: Accuracy - Mistranslation and Fluency - Collocation Popović: Lexical error (Collocation) and Redundancy 1. Lexical/Collocation error: The verb "تاکەد شیامن" (displays) is replaced with "تاکەد شەکشێپ" (offers), display equivalent is more suitable for the context in this sentence. 2. Redundancy: "نۆک ەینات‌ساب" (ancient old) is morphologically redundant. 3. The system deleted artifacts and did not present any equivalent for it in the Kurdish text.
8	The internet is down again.	ئینتێرنێت دووبارە دابڕاوە in-ter-net doo-ba-ra da-bra-wa.	ئینتەرنێت جارێکی تر دابڕاوە in-ter-net ja-re-ki ter da-bra-wa.	MQM: Accuracy - Mistranslation (Minor) Popović: Lexical error (Synonym) Lexical Synonym Error: "ەرابوود" (again) is replaced with "رت یکێراج" (another time). Both words are acceptable but the selected word by AI represents a stylistic preference error with minimal impact on accuracy.
9	The project will take three months.	ئەم پرۆژەیە سێ مانگ دەخایەنێت am pro-zhay-e se mang da-kha-ya-net.	پرۆژەکە سێ مانگ دەڕێژێت pro-zha-ka se mang da-re-zhet.	MQM: Accuracy - Mistranslation Popović: Lexical error (Aspectual Nuance) Lexical error with aspectual impact: "تێنەیاخەد" (will take time) is replaced with "تێژێڕەد" (will last). This alters the aspectual perspective on the temporal event and has affected the understanding of the TT semantically.
10	The road to the village is being repaired.	نەژۆن ەکەدنووگ یاگێڕ ەوەتەوارک re-ga-y goon-da-ka no-zhen kir-a-wa-ta-wa.	ڕێگای گوند ڕێکخراوە re-ga-y gund rek-khra-wa.	MQM: Accuracy - Mistranslation and Fluency - Grammar (Aspect) Popović: Lexical error and morphological error (Aspect) 1. Lexical error: "ەوەتەوارک نەژۆن" (is being repaired/renewed) is mistranslated as "ەوارخکێڕ" (is organized). 2. Aspectual error: The progressive passive aspect is lost in the TT.
11	I'm tired of waiting.	ماندووم لە چاوەروان کردن man-doowm le cha-wa-ra-wan kird-in.	من خەستەم لە چاوەڕوانبوون min khas-tam le cha-wa-rra-wan-boon.	MQM: Accuracy - Mistranslation Popović: Lexical error (Register/Semantic) Lexical register error: "ماندووم" (exhausted/worn out - mental state) is replaced with "خەستەم" (sick/tired - primarily physical). This is not common in Kurdish and is mostly borrowed from Persian.
12	I feel sad when I remember her.	ەوەتێد ریب مەوئ کێتاک مبەد رابمەخ ka-tek a-wum beer det-wa kham-bar da-bim.	،مەکەد ریبەل کێتاک مبەد نیگمەغ ka-tek le-beer da-kam, gham-geen da-bim.	MQM: Fluency - Grammar (Syntax) and Accuracy - Mistranslation Popović: Syntactic-Morphological error and lexical error 1. Syntactic-Morphological error: The experiencer-subject construction "ریب ەوەتێد" (memory comes to me) is changed to an agentive construction "مەکەد ریبەل" (I forget).

(Contd...)

APPENDIX I
(Continued)

No.	English source	Human reference (Kurdish)	AI (GPT) translation	Error analysis (Integrated MQM-Popović framework)
13	His words touched my heart.	نکەد مشۆخڵد یناکەشو wsha-ka-nee dil-khosh-am da-kan.	درک تسەه مڵد یەکەشو wsha-kay dil-m hast kird.	MQM: Fluency - Grammar (Agreement) and Accuracy - Mistranslation Popović: Morphological error (Number) and lexical error (Idiom) 1. Agreement error: Plural possessive suffix "-یناک" is incorrectly replaced with singular "-یەک" for "words. 2. Lexical/Idiomatic error: The conventional idiom "کنەد مشۆخڵد" is replaced by a literal, unidiomatic calque "کرد تسەه مڵد." That provided an unclear sentence semantically.
14	I was overwhelmed by emotions.	نقوومی هەستەکانم بووم nqoo-mee has-ta-kan-am boowm.	هەستەکانم زۆر بارەم کرد has-ta-kan-am zor ba-ram kird.	MQM: Accuracy - Mistranslation Popović: Lexical error (Metaphorical vs. Literal) Lexical error: The metaphorical expression "مووب .یمووقن" (I was drowned) is replaced with a literal, less expressive phrase "کدر مەراب" (burdened me). The accuracy of translated text is under question and not acceptable.
15	Her voice is very calming.	دەنگی زۆر ئارامبەخشە dang-ee zor a-ram-ba-kh-sha.	دەنگەکەی زۆر ئاسودەیە dang-a-kay zor a-soo-da-ya.	MQM: Accuracy - Mistranslation Popović: Lexical error (Agentive vs. Stative) Lexical error: The agentive adjective "مشخەبمارائ" (calming/peace-giving) is replaced with the stative "یەدوسائ" (is peaceful), altering the semantic role of the subject.
16	I really enjoyed the dinner.	بەڕاستی خواردنی ئێوارەم بەدڵ بوو be-ras-tee khuard-ni e-wa-ram be-dil boow.	راستەوخۆ خۆشحاڵ بووم لە خۆراکەوە ras-ta-w-kho khosh-hal boowm le kho-ra-ka-wa.	MQM: Accuracy - Mistranslation (Double) Popović: Lexical error Multiple lexical errors: 1. "یتسارەب" (truly) → "ۆخوەتسار" (directly). 2. "مراوێئ ینردراوخ" (dinner) → generic "ارکۆخ" (food). Unacceptable translation in the target Language
17	I'll never forget your kindness.	زیگرەه ۆت ینەبەرەیم مەکان ریبەل mi-h-ra-ba-nee to har-geez le-beer na-kam.	هەرگیز مەهربانی تۆ فرامۆش ناکەم har-geez mah-ra-ba-nee to fra-mosh na-kam.	MQM: Accuracy - Mistranslation (Minor) Popović: Lexical error (Synonym) Spelling error: "یەنەبەرەیم" and "ینابرەەم" are synonyms for "kindness." This is an acceptable stylistic variation with minimal impact.
18	I love the smell of fresh coffee.	زۆرم بۆنی قاوەی تازە پێخۆشە zor-im bo-nee qa-way ta-za pe-kho-sha.	خۆشم دەوێت بۆ بۆنی قەهوەی تازە khosh-im da-wet bo bo-nee qa-h-way ta-za.	MQM: Fluency - Grammar (Syntax) Popović: Syntactic-Morphological error Syntactic-Morphological error: The concise, adjectival construction "مرۆز. مشۆخێپ" (it is very pleasant to me) is replaced with a heavier, full verbal clause "تێوەد مشۆخ" (I love it), which is less idiomatic. The equivalent of "love" is not accepted in the target text contextually.
19	I don't feel like talking right now.	ئێستا حەزم لە قسەکردن نیە es-ta haz-im le qi-sa-kird-in ni-a.	هەستم نییە ئێستا بۆ قسەکردن has-tim ni-ya es-ta bo qi-sa-kird-in.	MQM: Fluency - Grammar (Syntax/Preposition) Popović: Syntactic-Morphological error Syntactic-Morphological error: The native construction with "ەل" ("مزەح ەل. نیە") is replaced with an unidiomatic calque using "ۆب" ("ەیین متسەه ۆب"), violating Kurdish prepositional usage and unusual sentence in Kurdish semantically.
20	I feel lucky to have friends like you.	خۆم بە بوونی هاورێی وەک تۆ بەختەوەر دەزانم khom be boo-nee ha-wa-ray wak to bekh-ta-wer da-zan-im.	ەک مرایتخب مەکەد تسەه ەیەه ۆت اکەو ێرواه hast da-kam bekh-ti-yar-im ke ha-w-re wa-ka to ha-ya.	MQM: Fluency - Grammar (Syntax) and Accuracy - Mistranslation Popović: Syntactic-Morphological error and lexical error 1. Syntactic-Morphological error: The structure shifts from a complement clause with "بەختەوەر دەزانم" to a different complementation pattern with "هەست دەکەم". 2. Lexical error: "رەوەتخەب" (fortunate) vs. "امریتخب" (lucky) - a semantic shift that affects the understanding of the text in Kurdish.
21	Please check the document before sending.	تکایە پێش ناردنی بەڵگەنامەکە بپشکنە tka-ya pesh nard-nee bel-ga-na-ma-ka bpish-ki-na.	تکایە پێش ناردنی پەڕگەکە بپشکنە tka-ya pesh nard-nee par-ga-ka bpish-ki-na.	MQM: Accuracy - Mistranslation Popović: Lexical error (Register/Specificity) Lexical register error: "بەڵگەنامە" (formal/official document) is replaced with "پەڕگ" (file, often digital), which affects both formality and understanding of the sentence by Kurdish speakers.
22	Call me when you arrive.	کاتێک گەییشتی تەلەفونم بۆ بکە ka-tek ga-yish-tee te-le-fo-nam bo bi-ka.	کاتێک گەیت، پێم زەنگ بێنە ka-tek gayt, pem zang be-na.	MQM: Accuracy - Mistranslation (Double) and Fluency - Register Popović: Lexical error and register error 1. Lexical error: "ەکب ۆب منوفەلەت" (call my phone) → colloquial "ەنێب گنەز" (ring me).The compound verb used by AI is totally wrong in the Kurdish language. 2. Aspectual/Register Error: "گەییشتی" (completive "arrive") → simple "گەیت," mixing registers and orthographically wrong.
23	Wear a mask in crowded places.	لە شوێنە قەرەباڵغەکان دەمامەک بەکاربێنە le shwe-na qa-ra-bal-gha-kan da-ma-mak be-kar-be-na.	لە شوێنە گەڕاوپەڕدا ماس بپێبڕەک le shwe-na ga-ra-w-par-da mask bpeeb-ra.	MQM: Accuracy - Mistranslation (Double) Popović: Lexical error Multiple Lexical errors: Different lexical choices for "crowded" ("قەرەباڵغ" vs. "("غلابەرەق"), "mask" ("دەمامک" vs. "ماسک"), and "wear" ("بەکاربێنە" vs. "بپێبڕە"). Shows variability but not necessarily inaccuracy. گەڕاوپەر is not an acceptable word in the Kurdish language provided by the AI system.

(Contd...)

APPENDIX I
(CONTINUED)

No.	English source	Human reference (Kurdish)	AI (GPT) translation	Error analysis (Integrated MQM-Popović framework)
24	Save your work frequently.	ئیشەکەت زوو زوو خزن بکە i-sha-kat zoo zoo khizn bi-ka.	کار بکە مکەت زۆرجار پاشەکەوت ka-ra-kat zor-jar pa-sha-kawt bi-ka.	MQM: Accuracy - Mistranslation Popović: Lexical error (Aspectual Nuance) Lexical error with aspectual implication: "زوو زوو" (frequently and promptly) is replaced with "زۆرجار" (many times). "خزن بکە" is also a specific term for "save/store." And the AI sentence provided the wrong equivalent in TT.
25	Don't leave the door open.	دەرگاکە بە کراوەیی بە جێ مەهێڵە dar-ga-ka be ki-ra-we-yee be je ma-hee-la.	دەرگا بۆراو مەبە dar-ga bo-raw ma-ba.	MQM: Fluency - Grammar (Syntax/Word ForDm) and Accuracy Popović: Syntactic-Morphological error and morphological omission 1. Syntactic-Morphological error: "بۆراو مەبە" is a grammatical calque from Persian, violating Kurdish syntax, and semantically the word is abnormal in the TT. 2. Morphological omission: The definite object marker "-کە" is omitted from "دەرگاکە."
26	Take your medicine on time.	دەرمانەکەت لە کاتی خۆی دا بخۆ dar-ma-na-kant le ka-tee khoy da bik-ho.	دەرمانی خۆت لەکات وەرگرە dar-ma-nee khoot le-kat wer-gi-ra.	MQM: Fluency - Grammar (Agreement) and Accuracy - Mistranslation Popović: Morphological error (Number) and lexical error 1. Lexical Error: The specific verb "بخۆ" (consume, for medicine) is replaced with the generic "وەرگرە" (receive/take). 2. Register Error: "دەرمانەکەت" (your medicine) has been translated to " دەرمانی خۆت" which is contextually improper here in this sentence.
27	Put your phone on silent mode.	مۆبایلەکەت لەسەر بێدنگ دابنێ mo-ba-ee-la-kat le-ser be-dang [da-bin-ne].	مۆبایلت لە مۆدی بێدەنگ ببە mo-ba-ee-let le mo-dee be-dang bi-ba.	MQM: Fluency - Grammar (Syntax/Lexical) and Accuracy Popović: Syntactic-Morphological error AND LEXICAL Borrowing 1. Syntactic-Morphological error: The native phrase "لەسەر بێدنگ" is replaced with the borrowed structure "لە مۆدی بێدەنگ."
28	Don't forget to lock the door.	لە بیرنەکەی دەرگاکە دابخەیت le beer-na-kay dar-ga-ka da-bik-khayt.	فرامۆشت مەکە دەرگا قفل بکە fra-mosht ma-ka dar-ga qif-il bi-ka.	MQM: Accuracy - Mistranslation (Double) Popović: Lexical error (Borrowing) Lexical borrowing error: The native verb construction "لەبیرنەکەی. دابخەیت" is replaced with the Persian borrowing "فرامۆشت مەکە," and the native locking action is replaced with the noun "قفل" (lock). The Persian borrowed construction has been used even wrongly and is not accepted.
29	Wash your hands before eating.	پێش خواردن دەستەکانت بشۆ pesh khuard-an das-ta-kant bi-sho.	پێش خۆردن دەستەکانت بشوورە pesh khord-an das-ta-kant bi-shoo-ra.	MQM: Fluency - Grammar (Inflectional) and Accuracy Popović: Morphological error (Verb Form) and Lexical Variant 1. Inflectional/Verb form error: The imperative "بشۆ" is replaced with the variant "بشوورە." This may not affect the meaning seriously but still it is unusual in Kurdish. 2. Lexical variant: "خواردن" vs. "خۆردن" for "eating." Represents a dialectal/ formal variant choice. It seems system is taking it from more relevant language. (Persian)
30	Please don't be late.	تکایە دوا مەکەوە tka-ya dawa ma-ka-wa.	تکایە دێر مەبە tka-ya der ma-ba.	MQM: Fluency - Grammar (Word Formation and Syntax) Popović: Derivational error and syntactic error 1. Derivational error: "دێر" appears to be a non-standard, incorrectly derived form for "late." Which is common in the Persian language not in Kurdish. 2. Syntactic-Morphological error: "مەبە" is an ungrammatical syntactic calque for the negative imperative.

AI: Artificial intelligence, MQM: Multidimensional quality metrics