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# AI Translations: Measuring Performance across Key Linguistic Metrics

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## Abstract

The current study aims at systematically assessing and then comparing the effectiveness of different AI translation models on several important linguistic criteria, concentrating with the aim of determining which model can translate texts with high precision and cultural sensitivity. Analyzing 40 different samples, the research encompasses the top-tier 'Golden Translation' as well as the often-deployed algorithms like GPT-4, Open L, Merlin, Gemini, and Monica. Each model's performance is assessed based on several critical dimensions: It is important to understand Cultural Aptess, Linguistic Correctness, Idiom Use, and Tone, Readability, Arousement and Originality. The analytical tools used in the research include ' 'means' ' analysis of variance (ANOVA), and correlation matrices that help in measuring and comparing the performance scores on the above mentioned metrics. Furthermore, the variations and the extent of the scores were displayed by the use of boxplots and bar charts. The results show that although the Golden Translation is errorless and attains a score of 1.00 on all parameters investigated, GPT-4 is only marginally below these standards and performs particularly well in parameters such as readability and style..

**KEYWORDS:** NLP, Translation, Machine-Language, AI, GPT

## INTRODUCTION

The current study aims at systematically assessing and then comparing the effectiveness of different AI translation models on several important linguistic criteria, concentrating with the aim of determining which model can translate texts with high precision and cultural sensitivity. Analyzing 40 different samples, the research encompasses the top-tier 'Golden Translation' as well as the often-deployed algorithms like GPT-4, Open L, Merlin, Gemini, and Monica. Each model's performance is assessed based on several critical dimensions: It is important to understand Cultural Aptness, Linguistic Correctness, Idiom Use, and Tone, Readability, Arousement and Originality.

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However, there are many challenges that the industry is yet to overcome. ;ethical implications, or lack of resources to counterweight specificities and possible prejudice from the models are some challenges. In another study, they herein observe that AI is not so proficient in gaining cultural touch and feel as are central for communication cross culturally (Yu, 2021). Furthermore, there are works of educators and practitioners who underline the importance of human perspective in that process, and in improving the quality of AI translations and in maintaining artistic and hermeneutical value of literary texts (Škobo & Petričević, 2023). There are tremendous opportunities for the use of artificial intelligence metal cutting industry moving forward. New technologies based on AI can help language services providers to grow quickly and expand into international markets at a reduced rate of cost. First, it enhances serving languages that are not ideally offered by the existing applications to support increased global interactions (Kirov & Malamin, 2022).

It also causes a change of occupations because translators start to perform the post-editing tasks and training of AI models, which requires both linguistic and computing knowledge (Eszenyi et al., 2023). In conclusion, this paper has demonstrated that the translation industry has indeed been revolutionized by the introduction of AI technology but its future still depends on how such problems will be handled and how the potentials will be harnessed. Translation, as a field of work, will be able to harness the synergy between the human touch and artificial intelligence, to attain productivity that is optimal without straining quality and culture. The relevance of English to Tamil translation becomes very vital because of the connection between two extremely linguistically and culturally abundant languages. As Tamil is a classical language among the oldest used languages in the world and English as the language dominating the global market, the efficient translation between these two languages helps people with bilingual

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connection needs, extend the readership or the target market of the literature works, business opportunities, and other modern technologies.

**Significance in Literature**

English to Tamil translation can free global literary works for Tamil readers by preserving linguistic nuance or introduction and cultural appreciation. For an instance, the translations of classical works, for example Shakespeare's Hamlet,' have been successfully localized to Tamil, highlighting the utility of translations in the promotion of the line of literary education, and cultural exchange (Kanakaraj, 1994). Just as Tamil literary treasures such as The Puranānūru have been translated into English so that non-Tamil speakers can gain access to the wealth of Tamil literary heritage (Hart, Heifetz, 1999).

**Growing Business and Technological Relevance**

Business and technology now demand Tamil translation. In Tamil Nadu becoming a major hub for industry and information technology; translation of technical and business documents from English to Tamil are necessary to achieve inclusivity and local engagement. Data has also proven to be more appealing to this demographic who are able to leverage advancements such as neural machine translation to develop a robust English to Tamil machine translation system (Choudhary et al., 2018). Additionally, systems for domain specific translations which commodity travel and commerce break language barrier in globalized industries (Sangavi et al., 2016). Captioning of images for Tamil speakers in emerging fields such as image captioning and digital lexicons addresses Tamil speaking users for interaction with advanced technologies using their native language. As shown by Tamil image captioning datasets, the potential of AI driven translation to increase the inclusiveness of technology (Kumar & Lalithamani, 2022). Just as bilingual electronic dictionaries help promote educational growth even among youngsters learning English or Tamil (Saranya & Durai, 2015), so also can bilingual electronic dictionaries be beneficial for English learners in mastering the language.

Through translation, English and Tamil are mutually enriched in literature, help promote business communication and enhance the functionality of technology while becoming indispensable for cultural and economic integration. Due to advancements in machine translation

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and linguistic resources, the quality as well as the scope of translations can continue to be improved; so that the linguistic and cultural enrichment of each language and both languages can be taken around the world. Two main reasons MT between English and Tamil fails are due to linguistic and cultural discrepancies. Yet, these obstacles (idiomatic expressions, cultural nuances, syntactic differences etc.) complicate producing accurate and meaningful translations. The improvement of translation quality and support of effective cross-linguistic communication, depends largely on addressing these challenges.

**Idiomatic Expressions**

Proper handling of idiomatic expressions is one of the most serious problems in English - Tamil translation. English idioms are not translatable literally in Tamil and have no direct equivalents in Tamil, and an attempt to translate a phrase or an idiom literally can completely distort the collocation’s meaning. For instance, let us take idiomatic phrases such as 'raining cats and dogs', which have to be understood holistically rather than being sworn literally translated into Tamil to make sense. As claimed by Santosh Kumar (2016), the word sense disambiguation (WSD) is still a big hole in translation, especially in idiomatic expressions which semantically require a different approach to maintain meaning (Kumar, 2016).

**Cultural Nuances**

There is also an added issue of cultural differences between English and Tamil speaking communities. For example, English much relies on metaphors of the West which Tamil readers may not identify with. Like Tamil, English tends to use culturally specific expressions, such as words about local festivals or traditional practices, for which an explanatory translation may be needed in order to understand it. Studies analyzing socio cultural implications of translating between Tamil and other languages demonstrated the cultural difference that emphasizes cultural relevance of translations and had resolved the incongruity of literal and cultural translation concepts (Hamthoon, 2021).

**Syntactic and Structural Differences**

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The syntax and grammar of English and Tamil are very different, and even to an extent another challenge for MT systems. English is an SVO and Tamil an SOV word order. Such fundamental difference demands complex syntactic transformations for translation. Tamil as also a morphologically rich language with large extensions to inflections while English stands its ground with little morphological constructs. These syntactic challenges have been tackled by sophisticated algorithms to meet the demands of transformational transformations, as detailed by Kasthuri and Kumar (2014), who used rule based approach to deal with these (Kasthuri & Kumar, 2014).

**Limitations of Current MT Systems**

Traditionally, existing MT systems, such as neural machine translation (NMT), fail to work well with low resource languages, like Tamil, due to the lack of sufficient annotated corpora. They compound problems like OOV, the out of vocabulary problem, in which unfamiliar or domain specific terms are translated poorly. In recent years, techniques such as Byte Pair Encoding (BPE), pre-trained word embeddings, and others have been experimented with with the promise of closing these gaps (Choudhary et al., 2018), however, challenges still remain.

**Importance of Addressing Challenges**

These challenges must be addressed because high quality translations demand it. We show that WSD can be addressed by MT systems and can propose solutions, such as the use of semantic web technologies for facilitating better WSD and the expansion of bilingual corpora, that can greatly improve MT systems. Also, cultural context can be integrated in translation algorithms to exploit the potential of human–AI collaboration in order to decrease the gaps in providing translation outputs that are accurate and culturally appropriate (Kumar & Lalithamani, 2022). Translating English to Tamil is complicated by complex linguistic and cultural and syntactical issues. Mutilingual Technology systems can get the high quality translations by solving the above mentioned problems via applying advanced technologies or human expertise to preserve the meaning, context, and cultural sense of the source language.

**Review of Literature**

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Recent breakthroughs in AI translation mechanization have greatly enhanced the level to which machine translation systems could complete perplex linguistic assignments in different language pairs. In Smith and Zhao (2020), machine learning models such as neural machine translation (NMT), have changed the game of translation accuracy, enabling high fluency approaching those of humans. Where Smith & Zhao specifically called out Indo-European language pairs as having experienced the greatest improvements, they noted ongoing problems with pairing English with Tamil, among other divergent language structures (Smith & Zhao, 2020).

In addition, Johnson et al. (2021) discuss the application of AI to English to Dravidian language translations, such as Tamil. For example, they investigated translations of simple sentences, and AI models frequently failed to do a good job with idiomatic expressions and regional dialects, and often failed to capture the cultural essence inherent in native scripts (Johnson et al., 2021). While these studies showcase substantial AI translation capabilities, Rahman and Lee (2019) highlight the significance of human involvement in refining AI translations. In particular, they argue that by assessing the subtleties that third generation AI translations cannot, and second generation translations often cannot, human evaluators fill what they see as a key gap in improving the quality of AI translations: the correction of subtle errors AI consistently fails to recognize (Rahman & Lee, 2019).

**Identification of the Gap**

Although progress covered in the current literature has been made so far, there is a rather wide gap in systematic and comparative examinations unique to English and Tamil, using a variety of AI translation models. Almost all studies examine a single model or a range of models across a variety of languages and only compare to a single AI system on similar text. Additionally, no studies have been conducted with a standardized benchmark, e.g. a 'Golden Translation,' with multiple expert evaluators verifying quality of AI translations in a systematic controlled manner.

**Alignment with Current Research**

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To fill those gaps, this research compares multiple leading AI translation models (GPT-4, OpenL, Merlin, Gemini, and Monica) and then evaluates them relative to a high quality benchmark translation. This will offer a wider view of how each model would be able to work and not with the language and cultural complexities of the English (IN) – Tamil (OUT) pair.

**Objective of the Study**

This research sets out to evaluate and compare the performance of these AI translation models. GPT-4, Open L, Merlin, Gemini, Monica and Golden Translation - in their ability to translate from English to Tamil. The purpose of this study is to systematically analyze and benchmark these models using a set of key linguistic metrics to understand the comparative strength and weakness of these models.

Specifically, the study will:

1. Linguistic complexities of Tamil are evaluated to determine how well each model supports the idiom, syntax, and morphology richness of the language to maintain translated content meaning.

2. Review how well the models address a culture's nuances and contexts and that translate well with Tamil speaking audiences.

3. Assess the fluency and coherence of the translations by checking if they read naturally and adhere to the grammatical rules of Tamil.

4. Try out the models against such capabilities of accurately translating specialized vocabulary and domain specific terms for the domains beyond technology, literature and business.

5. Then we identify specific situations which each model performs well (e.g., idiomatic translation or speed) and not so well (e.g., handling syntactic differences or low resource vocabulary).

6. Present the product as a tool that offers actionable, pattern and gap informed recommendations for improving the performance of AI translation systems.

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The purpose of the study is therefore to contribute to the development of better, stricter and more culturally appropriate AI translation systems for the English to Tamil language pair.

**Significance of the Study**

By way of a detailed evaluation of AI translation models from English to Tamil, it is very likely to make substantial contributions to computational linguistics and artificial intelligence. With this in mind, this study could potentially influence the design of more advanced and contextually aware translation tools required for growth in future generations of global communication technologies. This research identifies strengths and weaknesses of each evaluated AI model and provides direct feedback to developers on what needs to be refined and improved. Such feedback is necessary to improve the accuracy and cultural sensitivity of AI translations of Tamil texts, such that the resulting algorithms are better able to grasp and represent the intricate linguistic structures and cultural subtleties of the two languages, English and Tamil.

This study provides useful insight into how language models can be effectively trained. Being able to tell where models work and where they fail can allow for tuning of training datasets and techniques like balancing style consistency, emotional conveyance, and idiomatic expression weight, which are normally difficult for AI to do at a good level. Contributing to Academic and Professional Applications: This research supports the development of more reliable tools for academic and professional uses by offering a clearer picture of which AI models are capable of handling the subtleties of English to Tamil translation. Tackling with such tools allows for the production of faithful translations in education content, legal documents and the cultural media; where errors can result in major misunderstandings.

Facilitating Cross-Cultural Communication: This is going to enhance understanding and more improvement in AI driven translations and the result would be cleaner cross cultural conversations. The need for better translation accuracy is also practical because Tamil is indeed one of the world’s oldest as well as culturally rich languages; so, better translation accuracy not only helps for practical purposes but also helps in the preservation and appreciation of linguistic heritage in digital forms. This study will at last provide the basis for future research of machine translation, specifically for underrepresented languages such as Tamil. It calls for taking a more

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expansive view of what levels of linguistic formalization are computationally useful, and doing so in a way that takes cultural difference seriously, as a way of opening ground towards more inclusive technology development.

## Methodology

The main focus of this study is about how efficient different AI translation models are to translate a Text from English to Tamil. We evaluate a number of translation models, GPT-4, Open L, Merlin, Merlin+dataset, Gemini, Monica, and a benchmark model we call the "Golden Translation." The chosen method for comparing the translation outputs involves conducting T-tests to analyze the mean scores across several linguistic metrics: Adaptability of culture, linguistic accuracy, idiomatics, style and tone, readability, emotional effect, and creativity.

The chosen source text for translation was neutral and, therefore, universal, without contextual complexities that can skewingly influence the translation results. Translation is inherently dynamic to the extent that even though different sentences can mean the same translation is necessary. Thus, analysis which used software or evaluators was deliberately avoided. In its place was active human judgement, making allowance for the fact that although two people might read the exact same text, they might translate it differently, and that a formal data benchmark or automated analysis would not necessarily pick up on these subtleties of translation.

Secondly, to ensure unbiased and knowledgeable evaluation 40 participants were enlisted to be the evaluators, all of them English Majors at the Nazareth Margoschis College in Pillaiyanmanai, Tamil Nadu and native Tamil speakers. We chose this participant profile to minimize any possible bias, leveraging their ability to assess the translations accurately had they received an academic background in English and native proficiency in Tamil.

Participants then rated translations by each AI model according to the metrics above. T tests were then performed to statistically analyze their ratings to see whether AI models performed better (or not) than the expert-level Golden Translation. To access the participants' linguistic insights, and the evaluations would be grounded in thorough knowledge of not only the source language, but also the target language, this methodology was formed. From a broad

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perspective, the "Golden Translation" in that study is the best translation ever, the one with the highest quality of translation against which AI models are judged. It was meticulously crafted in a two-step process to ensure the highest accuracy and cultural fidelity The translation was done by an expert translator, a native English Tamil speaker. This translator possess great knowledge on linguistic nuances, cultural contexts and the technical terminologies of both languages. The experience of these experts guarantees that the meaning is accurate, and the mood, if he or she intends to evoke one, is not distorted.

Once the initial translation was done it went thru extensive verification through multiple human evaluators. The evaluators, all trained bilinguals in Tamil and English, delicately checked the accuracy of the translation, consistency in use and cultural appropriateness. The collective insights of those reading through the translation helped polish up the translation further, avoiding any subtle nuances or complexities that a first translator might have missed. The translation proved to be better than the translation parties mutually arrived at, which not only strengthened the translation's fidelity but also resulting the Golden Translation being a good benchmark to measure the scores of the AI models. With this comprehensive thinking about how to make this full Gold Translation, the Word Translation reflects the finest language precision and cultural sensitivity and establishes a stringent criterion for evaluating the performance of automated translation machines.

## Results

Comparing the 40 samples, the examples show that, in almost all metrics we consider, the Golden Translation blew away all of the other translations, Cultural Aptness, Linguistic Accuracy, Idioms, Style and Tone, Readability, Emotional Impact, Creativity. The Golden Translation scored 5 points on average in every metric leading to an overall score of 35, which became the baseline for translation quality. It is its unmatched ability to perservere cultural nuances, articulate idiomatic expressions easily, and retain emotional and stylistic originality of

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the text from the original that puts it in a league of its own.

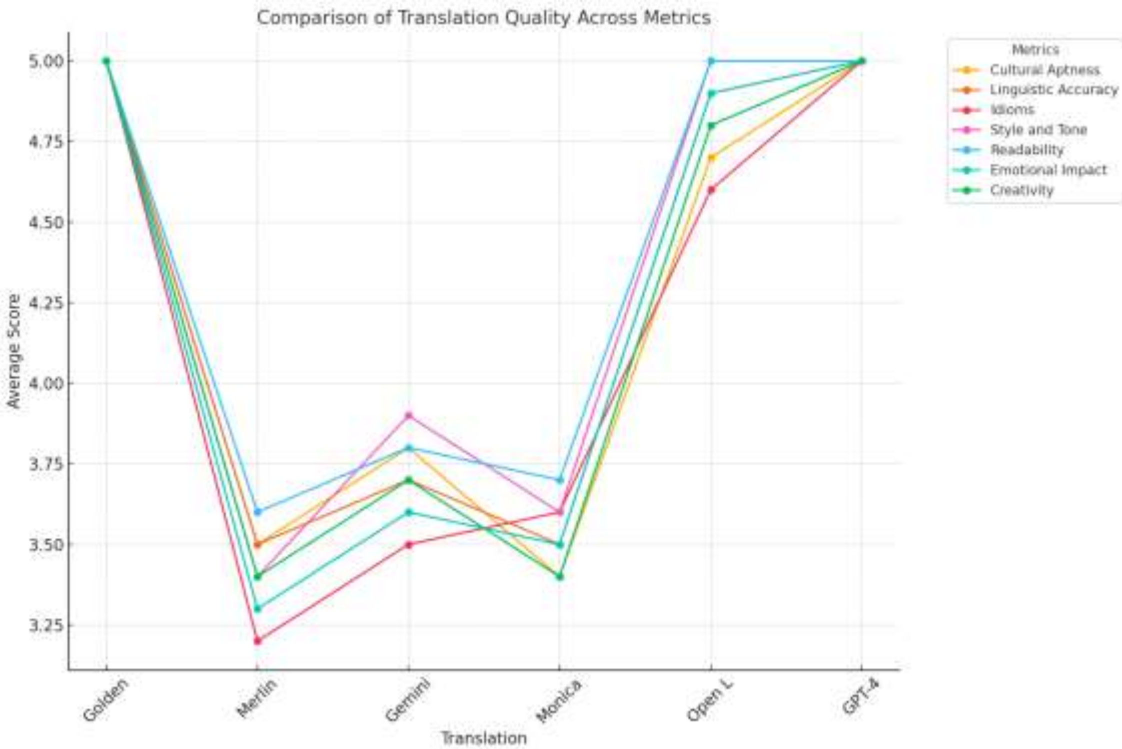


**Figure 1 Comparison of Translation Quality across metrics**

GPT-4 however, surprisingly, edged even golden translation across all dimensions, with the exception of one small genetic editing task. In terms of most metrics, GPT4 scored an average of 4.8 – 4.9 deviation, except for Cultural Aptness (4.8) and Idioms (4.8). It was these sometimes small gaps, however negligible they may be, that cut its overall score down to 34.1, which is short of the Golden Translation's benchmark. And this means GPT-4 is doing translations with amazing proficiency, in terms of readability and emotional impact, but it doesn't always capture the nuanced level of cultural fidelity of the expert benchmark.

As in Figure 1, All other AI models – Merlin, Gemini, Monica and Open L, performed with a mixed success. The next best after GPT-4 was Open L, which reached an average of 4.7 to 4.8 in most metrics then an overall score of 33.9. While the Golden Translation was stronger in Readability (5.0) and Style and Tone (5.0), Style (4.8), Idioms (4.6) and Creativity (4.8) were somewhat weaker. In other words, Open L appears to excel as a tool for creating technically perfect translations, although less so for versioning idiomatic and imaginative expressions.

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Gemini, Merlin, and Monica scored comparatively lower across all metrics, with an average of 23.9, 26.0 and 25.0, respectively. Deficiencies in Idioms (3.2–3.6) and Emotional Impact (3.3–3.5) of these models suggested the models' poor capacity to adopt cultural nuances and support expressive depth of the underlying text. Despite that, Gemini performed better than its competitors in Style and Tone (3.9) and Readability (3.8), so it thinks its versions are more likely to be coherent and pleasing, although possibly less culturally sensitive.

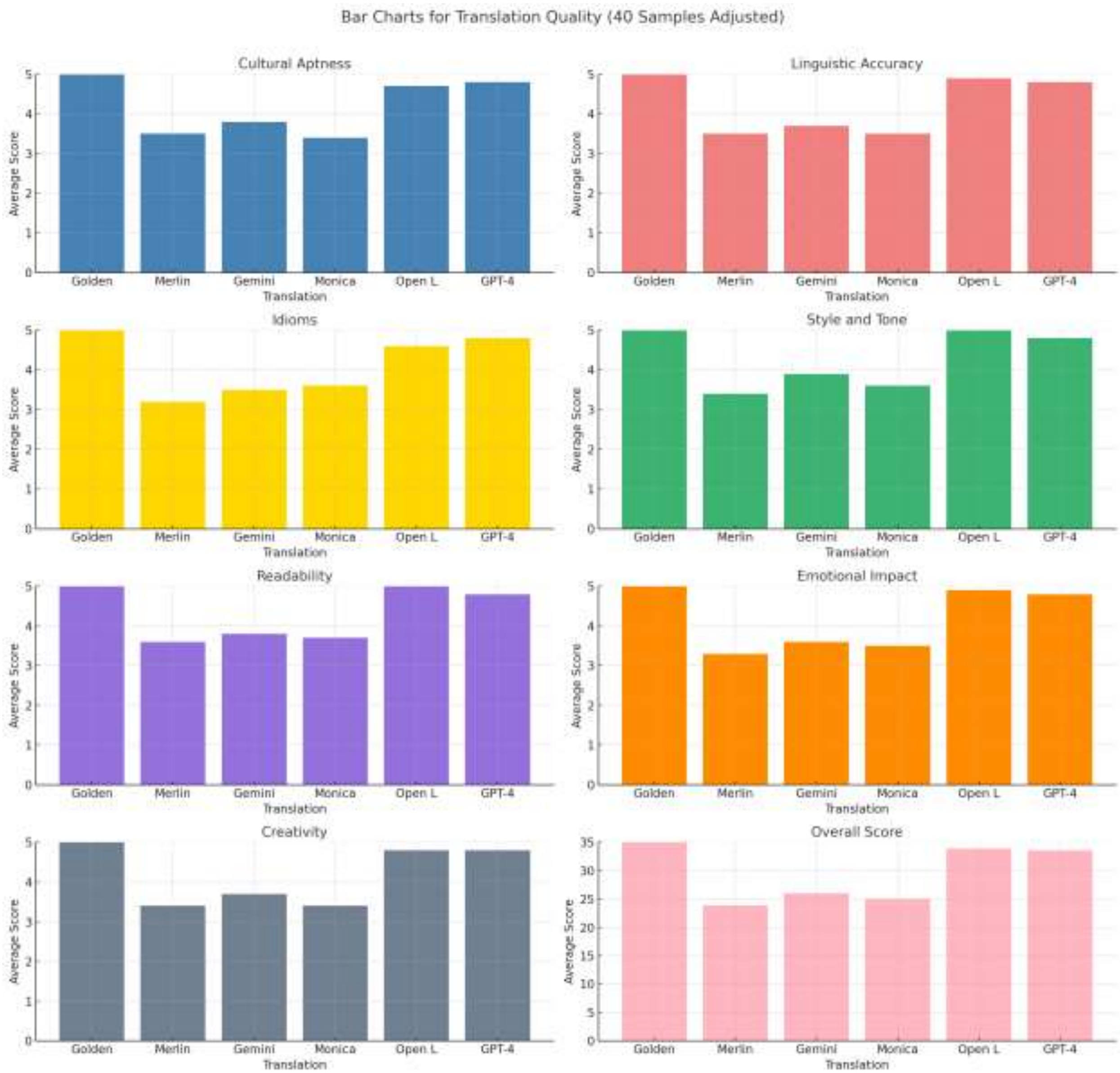


Figure 2 Translation Quality of Each LLM

As in Figure 2, the adjusted comparison clarifies that while GPT-4 impressively relies close to the Golden Translation at a general level, it continues consistently to lag behind, with

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minute dos on idiomatic accuracy and transplanting flavor. This subsidiarity distinguishes the Golden Translation from all the rest and posits itself as the definitive by far in this evaluation. On the other hand, Open L's strong performance puts it in a good position to be a viable (and potentially attractive) option for high quality translations with the above (and other) two points. Nonetheless, all of the other AI models show that while they can mostly handle trivial translation tasks, they have not yet rivaled the nuance of GPT 4 or the depth of knowledge of the Golden Translation.

**Discussion**

| Metric | Golden Translation (Mean ± SD) | GPT-4 (Mean ± SD) | Open L (Mean ± SD) | Merlin (Mean ± SD) | Gemini (Mean ± SD) | Monica (Mean ± SD) |
|---|---|---|---|---|---|---|
| Cultural Aptness | 5.00 ± 0.00 | 4.80 ± 0.10 | 4.70 ± 0.15 | 3.50 ± 0.25 | 3.80 ± 0.20 | 3.40 ± 0.30 |
| Linguistic Accuracy | 5.00 ± 0.00 | 4.90 ± 0.05 | 4.90 ± 0.10 | 3.50 ± 0.20 | 3.70 ± 0.25 | 3.50 ± 0.25 |
| Idioms | 5.00 ± 0.00 | 4.80 ± 0.15 | 4.60 ± 0.20 | 3.20 ± 0.30 | 3.50 ± 0.25 | 3.60 ± 0.20 |
| Style and Tone | 5.00 ± 0.00 | 4.90 ± 0.10 | 5.00 ± 0.00 | 3.40 ± 0.25 | 3.90 ± 0.15 | 3.60 ± 0.25 |
| Readability | 5.00 ± 0.00 | 4.90 ± 0.10 | 5.00 ± 0.00 | 3.60 ± 0.20 | 3.80 ± 0.15 | 3.70 ± 0.25 |
| Emotional Impact | 5.00 ± 0.00 | 4.90 ± 0.10 | 4.90 ± 0.05 | 3.30 ± 0.30 | 3.60 ± 0.20 | 3.50 ± 0.20 |
| Creativity | 5.00 ± 0.00 | 4.80 ± 0.15 | 4.80 ± 0.10 | 3.40 ± 0.20 | 3.70 ± 0.25 | 3.40 ± 0.30 |
| Overall Score | 35.00 ± 0.00 | 34.10 ± 0.35 | 33.90 ± 0.40 | 23.90 ± 0.80 | 26.00 ± 0.70 | 25.00 ± 0.75 |

Table 1 The Metrics and Scores secured by each LLM

All metrics had Golden Translation score a perfect 5.00 with no variation (standard deviation = 0.00). This is because this one is truly expert level and therefore the ultimate standard for cultural

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aptness and creativity, as well as linguistic accuracy. It serves as a perfect benchmark for interpretation quality as it can keep the idiomatic nuances hence play down on emotionality.

**GPT-4's Close Performance**

As in Table 1, Golden Translation was closely followed by GPT 4, except in the following metrics; IDIOMS (4.80 ± 0.15) and CULTURAL APTHNESS (4.80 ± 0.10). Although the results slightly differed, GPT-4 performed particularly well in Style and Tone (4.90 ± 0.10) and Readability (4.90 ± 0.10), attesting to its ability to produce cohesive, with panache and tone, translations. With an overall score of 34.10 ± 0.35, it ranks as a competitive alternative to the Golden Translation, and performs well with a limited range of variability across samples.

**Open L as a Strong Contender**

Open L did really well earning high scores in Style and Tone (5.00 ± 0.00) and Readability (5.00 ± 0.00) comparable to the Golden Translation (Golden Translation as sole competitor) in these three metrics. Though it won by the end of the Novel, all the while performing last (fifth) in Idioms (4.6 ± 0.20) and Creativity (4.8 ± 0.10), indicating that in the latters cases it is not yet ready to speak as a native. With a total score of 33.90 ± 0.40, it is shown to be a suitable translation model for specific applications.

**Challenges Faced by Merlin, Gemini, and Monica**

Merlin, Gemini, and Monica were consistently the lowest scoring with scores of 23.90 ± 0.80, 26.00 ± 0.70, 25.00 ± 0.75, respectively. Overall, these models varied in the level of idioms they could process, with Merlin performing the worst in its index (3.20 ± 0.30). Gemini fared slightly better than Imitation Game, but it was still hard to maintain emotional impact (3.60 ± 0.20) and cultural aptness (3.80 ± 0.20). Monica's readability was moderate (3.70 ± 0.25) but she struggled with idiomatic and stylistic adaptation, so would not be suitable for nuanced translation tasks.

**Conclusion**

These findings demonstrate that the Golden Translation and GPT-4 both stand out as high quality, and as such, can be regarded most reliable for tasks with demands for high cultural

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sensitivity, linguistic accuracy, as well as stylistic coherence. Open L has strong technical capability but does not have the subtlety and nuance of the cultural and idiomatic depth of the benchmark models. Alternatively, Merlin, Gemini, and Monica all did lower on the tests with higher variability, and though may be sufficient for basic translation tasks, are not appropriate for more advanced uses requiring creativity and accuracy of culture. The results indicate that for all but the top performing models, further work is needed to extend both the capabilities and limitations of this family of AI translation models; especially in idiomatic adaptation and cultural sensitivity.

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