Journal of Languages and Translation (*JLT*)
Vol. 11, Issue 3, pp. 59-81 | July 2024
Print ISSN: 2735-4520 | E-ISSN: 2735-4539
https://jltmin.journals.ekb.eg/

Transcending ambiguities: Enhancing AI-driven Arabic to English translations with human expertise

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Abstract

Given the limitations of AI translation in accurately capturing nuances and cultural subtleties, is it necessary for humans to intervene and refine the translated text? In this research, the exploratory sequence design, a mixed methodology, was used, and a panoptic error analysis was conducted on samples of multicultural translation. The aim is to identify, emphasize, classify, and categorize the ambiguities and translation errors that occur frequently when translating 15 culturally sensitive terms and sentences from Arabic to English in a multicultural setting. This research aimed to identify and classify the ambiguity markers based on their equivalent recommendations. An evaluation of the effectiveness of human translators and AI-based translation apps was carried out through a qualitative analysis. To ensure the validity of these findings, the researcher quantitatively analyzed the responses of 50 bilingual speakers who had a high level of proficiency in both Arabic and English. The study incorporated both quantitative and qualitative data to gain comprehensive insights.

Keywords: AI-driven translation, human expertise, ambiguity in translation, cultural insensitivity

1. Introduction

In an era characterized by unprecedented global connectivity and intercultural exchange, the role of translation has emerged as a vital conduit for facilitating communication across linguistic boundaries. From international business transactions to diplomatic negotiations, from academic collaboration to cultural exchanges, translations have always played a pivotal role in ensuring mutual understanding and collaboration among individuals and communities around the world. A great example would be the United Nations General Assembly (UNGA). Every year, almost 200 world leaders from around the world gather to address global issues such as human rights, peace, and climate change. Given the diverse linguistic backgrounds of these leaders, simultaneous interpretation services are provided in multiple languages to ensure each individual can fully participate in the discussions and understand the various perspectives people bring. The event relies on near-accurate translation and interpretation, highlighting the importance of translation in facilitating collaboration on the world stage.

As people engage in more global collaboration, the landscape of translation is also rapidly evolving with the advent of artificial intelligence (AI) and machine translation technologies.

These innovations promise to revolutionize the translation process by offering faster turnarounds, increased efficiency, and broader accessibility to language services (Khasawneh, 2023). However, they also raise questions about the accuracy and cultural sensitivity of AI-generated translations compared to those that are translated by humans. This study delved into the complexity of multicultural translations by examining both AI and human translation of Arabic to English texts? It examined both AI and human translation to understand their strengths and limitations.

2. Research objectives

The aim of this paper is to identify the roles and negative impacts of ambiguity in multicultural translation assignments, along with the linguistic factors that influence meaning and communication among different speakers. Moreover, the paper also assesses the risk of cultural insensitivity inherent in AI translation processes and develops strategies to address these challenges in multicultural translation projects.

3. Research question

To further understand the dynamics of multicultural translation and achieve the research objectives, the study poses the following research question:

RQ: What are the challenges of ambiguity in language translation and how can we overcome them in multicultural translation? This general question can be further branched into the following sub-questions:

a) What are the major ambiguities occurring during multicultural translation (Arabic to English)?
b) What are the specific ambiguities, and how does ambiguity in language occur when the context or tone is unclear, leading to different interpretations?
c) How does ambiguity arise in language due to translation, context, or tone, and how does this affect the meaning and communication among different speakers?
d) What could be the strategies to avoid ambiguities during multicultural translation?

4. Literature review

Arabic and English, being natural languages, often have multiple meanings because of their inherent ambiguity. Language translation is an intricate process that requires careful consideration of various factors, including linguistic nuances, cultural contexts, and the intended audience (Bazzi, 2022). Despite the impressive advancements in AI that enhance translation speed, human translators remain essential to ensure accuracy and cultural sensitivity. AI's limitations become apparent when it comes to effectively resolving ambiguity in multilingual and multicultural translation tasks. One significant challenge is that AI does not properly grasp the cultural context and historical references, which is crucial for both Arabic and English languages. This poses a major obstacle to achieving quality translations. Translating across cultures involves more than just switching between languages; it also involves transferring styles within a language. To achieve appropriate multicultural translations, it is important to identify the roles and negative impact of ambiguity in multicultural translation assignments. Additionally, linguistic factors that affect the meaning

and communication among different language audiences and speakers must be taken into account.

4.1. Defining ambiguity

Linguistic researchers and scholars have always been interested in the concept of ambiguity and conceptualized the topic of ambiguity in several ways. For instance, Scollon and Scollon (1995, as cited in Kakavá, 2000) described. They effectively illustrate various types of linguistic ambiguity at the word, sentence, and discourse levels. Additionally, they explain the interdiscourse framework, which provides a better understanding of how speakers simultaneously belong to different discourse systems. According to Refaat, depending on where it appears in a sentence, the same word can have different meanings and ambiguity leads to misunderstanding at this point (Refaat, 2023). She further describes ambiguity as the presence of multiple meanings in a single word, phrase, or sentence. They also conceptualized ambiguity as the basic aspect of daily speech and perceived it in the form of external and internal ambiguity.

AI faces challenges in capturing the subtleties and complexities of literary works and idiomatic expressions. The study conducted to Analyze the Scores from Automated Metrics and Human Annotators (Zhang Lv, Qianxi & Jiang, Zhaokun & Zhang, Ziyin., 2024) compares the performance of popular neural machine translation (NMT) engines with ChatGPT's large language models (LLMs) in translating Chinese diplomatic documents into English. That study used statistical modeling as a methodology and found that ChatGPT performs similarly to NMT methods when measured automatically using various prompts but performs significantly better when given examples or contextual knowledge regarding the translation job, according to human annotators. Human translators possess a deeper understanding of language and culture, which is necessary for accurate translations. AI methods also require constant modification and improvement to address various issues. Cultural sensitivity is crucial in translation, as machines struggle to interpret and translate cultural context and emotional cues. Therefore, human intervention and post-editing are necessary for high-quality translations that preserve cultural humor and context.

To draw reliable and consistent conclusions, the audience must create a framework in the face of external uncertainty. On the contrary, internal ambiguity is concerned with figuring out which parts fit together to make a text that makes sense. It is often believed that external ambiguity presents a difficulty for the listeners since it requires cultural context and global knowledge to calculate the extent of ambiguity (Degani et al., 2016).

Meanwhile, Al-Jarrah et al. (2018) conceptualized ambiguity as occurring when the uttered word has multiple interpretations or at least more than a single interpretation. When expressions are ambiguous, it indicates that they might vary in meaning but not in phoneme or in semantics but not in form. When two homonyms appear in the same structural place, such as “The boy is on his way to the restaurant,” ambiguity may ensue due to several potential interpretations based on context, syntax, and semantics. Examples include destination ambiguity, Timing ambiguity, Purpose ambiguity, restaurant ambiguity, and route ambiguity. Depending on their internal structure as well as syntactic location, components in bigger structures may also have many interpretations.

Similarly, Piantadosi et al. (2015) defined ambiguity as a universal occurrence in language that happens in every stage of linguistic analysis. Words can have several meanings and grammatical categories when taken out of context. Therefore, it's up to the listener to figure out which interpretation and sentence structure the speaker meant. Morphemes can also be vague and unclear in some contexts; for instance, in English -'s' indicates the plural (keys), possessive (Mary's), and the present simple third-person singular conjugation (kicks). Similarly, phonological forms can also cause ambiguity in the form of homophones such as “buy,” “by,” and “bye.” When syllables are used alone, they are nearly always ambiguous, which means that the listener may perceive them as offering insufficient context for the terms the speaker is trying to convey. The frequency of syntactic as well as semantic ambiguity poses a significant obstacle to natural language dispensation.

4.2. Ambiguity in a translation and interpreting context

Natural languages have the tendency to significantly increase ambiguity in various ways. Situations of natural language ambiguity arise when a word, phrase, or sentence can be interpreted in various manners, posing a challenge in correctly understanding it. A particular term can have several meanings, grammatical forms, or lexical categories (Basnight-Brown et al., 2018). 'Flying planes may be risky' is an example of a statement that has two core structures, which is known as syntactic ambiguity (Clifton et al., 1994; Bracken et al., 2016). Therefore, a word's intended interpretation might differ significantly depending on the linguistic context in which it is used (Elizaveta, 2022).

Research on psycholinguistics and monolingual language processing has shown that the cognitive system often uses the linguistic context to overcome the challenge of accessing both interpretations of ambiguous terms (Degani et al., 2016; Lee et al., 2022). It is rather unexpected that only lately has experimental research in the field of cognitive psycholinguistics examined the cross-linguistic consequences of word meaning ambiguity and other types of translation ambiguity (Carl & Schaeffer, 2017; Al-Jarrah, et al. 2018; Wei, 2022). Additionally, Tokowicz et al. (2002) gathered multiple translation standards from bilingual Dutch-English speakers, which was also the first study conducted and officially published on translation ambiguity. They discovered that almost 25% of the 562 words were translation ambiguous, meaning that different participants translated the terms differently in one or both ways. Furthermore, according to Eddington, Degani, and Tokowicz (2015), 40% of the identical English terms have several German translations.

According to Degani et al. (2016), there are several reasons why translation equivalents can transfer one to many.

Synonymy:

This occurs when the words considered for translation have a closer meaning with other words in the first language but at the same time, may have only one translation in the second language. For instance, the words in the English language 'close' and 'near' both have a single word translation in French i.e. 'proche', and the Spanish words 'serpiente' and 'culebra' both have a single translation of 'snake' in the English language (Degani et al. 2016).

Polysemy:

Multiple related meanings of a single phrase in the first language can be communicated by distinct words in the second language. For instance, the English translation of the Spanish word *sombra* can mean either shadow (cast by a person) or shade (of an object) (Degani et al., 2016).

Homography, homophony and homonymy:

It is possible for two distinct words to be formed identically due to linguistic "accidents." We refer to these forms as homographs. For instance, Spanish *corteza* (a tree's outer layer) and *ladrido* (a dog's sound) can be mapped to English *bark*. It is possible for homographs to have a similar pronunciation, which is also referred to as homophones. For instance, the word *bark* in the English language has multiple homographs which are also homophones. On the other hand, the term 'row' has multiple homographs, but they are not homophones. In cases where the words are homographs as well as homophones, they are referred to as 'homonyms' (Degani et al., 2016).

Morphological ambiguity:

In languages such as English that have limited morphology, certain lexemes have the same forms in both their derivational and inflectional variations. When those are translated into languages that are rich in morphology, such as Spanish, these variations might correspond to many forms. For instance, the Spanish nouns *paseo, caminata*, and *vuelta* are all possible translations of the English word *stroll*. It may also be translated into over 20 other verb tenses (Degani et al., 2016).

Semantic discrepancy:

The disparities in the conceptual-lexical mappings between the two languages might lead to numerous translations in some situations. The word 'know' in English, which embraces knowing individuals facts, is used in Spanish by two different verbs: 'conocer', which means knowing individuals, and 'saber', which means knowing facts (Degani et al., 2016).

4.3. Multicultural translation assignment

The concept of multiculturalism suggests that there are many opposing cultural voices that are free to define the nation's envisioned community in their own ways. Therefore, it should be interpreted as a challenge to monoculturalism—the desire to force particular cultural norms on all facets of society (Kupriianova & Kupriianova, 2024). In translation, the issue of multiculturalism is very common when the translators focus on cultural terms (Putrawan, 2018). Translators define cultural terms in many disciplines while dealing with cultural challenges. According to Mu'in (2018), the immediate varieties of influential languages are based on ecological words. The use of ecological language is often employed to distinguish geographical elements from cultural concepts for example, the ecological terminology that we encounter and understand in various ecological and geographical environments, such as towns, plains, hills, seasons, wind, flora, and wildlife etc. (Khani et al., 2021). Also, the are terms that refer to cultural items like clothes, cuisine, towns and homes, and modes of transportation. For many individuals, such as those who enjoy sate, coto, sego pecel, and other national dishes, food is the most delicate and significant form of cultural expression. Culturally speaking, clothing might refer to traditional or national garments like kimonos, yukatas, and sarung

(Kazakova & Tamara, 2015). Research conducted by Satisha (2020) pertains to the challenges that translators encounter while converting spoken language sources (SL) into target language (TL) due to linguistic and cultural differences. This covers people's interactions with one another, activities, celebration techniques, and costumes. It also provides answers to these issues. Another study by (Apostolatua & Apostolatua, 2012) highlighted the methods employed by Petru Comărnescu and Margareta Sterian when translating Eugene O'Neill's "Mourning Becoming Electra." into Romanian. This research illustrates the challenges associated with translation and emphasizes the importance of cultural sensitivity in communication.

4.4. Role of cultural sensitivity in AI translation

Given the range of academic fields connected to translation studies, it is inevitable that AI will eventually be included as a topic in cross-cultural language translation (Frąckiewicz, 2023). While AI has certainly revolutionized translation processes in terms of efficiency, maintaining accuracy and cultural sensitivity in translations requires balancing AI's benefits with the critical role performed by human translators. According to Maučec (2019), the difficulties in translation through AI are caused by the subtleties and complexities found in literary works, which call for a deeper comprehension than what is currently possible with machine translation technology. Literary writings frequently contain a wealth of stylistic elements and cultural allusions that are firmly ingrained in the culture of the original language. Accurate translation of these components necessitates not just language proficiency but also a deep comprehension of the culture (Dalibor & Schoening, 2022).

AI translation has several obstacles, such as managing polysemous words, domain mismatch, scarce training data, uncommon terms, lengthy phrases, word alignment, and beam search (Rijeka, 2017). The vagueness of polysemous words and figuring out the right meaning depending on context provide challenges for machine translators (Koehn & Knowles, 2018). Neural machine translation also has to deal with issues such as beam search, domain mismatch, managing uncommon words, translating lengthy phrases, word arrangement, and the nonexistence of data training (Bracken et al. 2016). These difficulties show how AI translation methods must be constantly modified and improved.

Translation across cultures does not only mean translating between languages; it may also refer to the transfer of styles within a language. Pretrained language models (PLM) represent some sociolects more than others, according to Zhang et al. (2021). For instance, morphosyntactic differences between the Spanish language spoken in Argentina and Spain are significant, but they are not taken into account independently (Cañete et al., 2023b). Likewise, native German speakers frequently employ a directness that would be deemed disrespectful in English (Hovy & Yang, 2021). Ringel et al. (2019) used remote supervision in response to the discovery that these discrepancies exist. They did this by generating labels for English formality and sarcasm detection depending on the language—in this example, German and Japanese, respectively.

Cross-cultural translation evaluation is difficult, as the work is not usually clearly defined. Briakou et al. (2021) found that while human assessment is more dependable than automatic

evaluation, it is still subject to non-standard evaluation techniques, especially when it comes to style transmission. Because the premise that there is only one (or a few) right translations is allegedly broken, reference-based automatic assessment systems are especially problematic in this situation (Reiter, 2018). This emphasizes the significance of culturally appropriate human assessment, as stated by (Zhou et al., 2023). The following table provides a review of the studies that highlighted the role of culture in AI translations compared to human translations.

Table 1: Review of the studies

Author	Objective	Methodology	Findings
Jiang & Zhang (2024)	This study compares the popular neural machine translation (NMT) engines with ChatGPT's large language models (LLMs) to see how well they translate Chinese diplomatic documents into English.	Statistical Modelling	ChatGPT performs similarly when measured automatically using various prompts and NMT methods, but ChatGPT performs significantly better when given examples or contextual knowledge regarding the translation job, according to human annotators.
Kunst & Bierwiaczonek (2023)	The practicality of translating survey materials with AI help for cross-cultural and intercultural research, contrasting the accuracy of machine translations with that of conventional human translations.	By using HEXACO personality inventory, the researchers used GPT-3.5 and Google translation to convert the original English inventory into thirty-three languages that have verified human translations available.	Although the disparities between the four machine translations and the human translation were not very great, the human translation was judged as being of superior quality considering the cultural sensitivity in translations.
Alsubhi (2023)	With an emphasis on Saudi Arabia, this study looks into how translation services and qualified translators feel	The design of the study was predicated on an extensive mixed-methods strategy that deliberately blended	Despite having a number of benefits, the study established that AI does not properly understand the cultural context and historical references in both Arabic and English languages which makes it the biggest challenge for the quality.

	about integrating and using TMS.	quantitative and qualitative processes to provide a wide range of outcomes.	
Muñoz-Basols (2023)	The study focused on understanding the potentialities of AI translation and the role of cultural insensitivity	Qualitative review	Cultural insensitivity is made worse by underrepresentation or the lack of specific cultural groups in training datasets. Additionally, cultural quirks pertaining to decorum and politeness might provide difficulties for AI translations.
Ardi et al. (2022)	With regard to translating cultural jokes related sentences from English to Indonesian, the research compared the accuracy and output of three well-known machine translation services: Yandex, Bing and Google Translate.	Qualitative descriptive method	While machine translation services can translate amusing texts, the quality is still either average or not quite there. It also demonstrates that when compared to Bing and Yandex, Google Translate yielded superior translation results. Nonetheless, several mistakes pertaining to lexical, syntactic, semantic, and pragmatic faults were detected. These results suggest that human post-editing is still necessary for machine translation to achieve a comparable effect and maintain cultural humor.
Akorbi (2022)	The study highlights the risk of cultural insensitivity of AI translations.	Qualitative review	The major issue in AI translations can occur when emotional cues and cultural quirks are ignored or misinterpreted. Some languages have unique ways of addressing delicate subjects or expressing emotions that are difficult to translate exactly.
Almaaytha (2022)	The research focused on AI based translation of Idiomatic Expressions from the Arabic language to English	Qualitative review	There are a few idioms in the Arabic language that do not have equivalent translations available in the target language; hence, the quality of translation is poorly affected as the machine is unable to capture the cultural context.
Hershcovich et al. (2022)	The study focused on understanding challenges and strategies in cross-	Qualitative review	Despite the close relationship between language and culture, there are nevertheless significant distinctions. Similar to multilingual and cross-

	cultural NLP		lingual NLP, multicultural and cross-cultural NLP takes these distinctions into account to provide improved support for NLP system users.
Kalda (2023)	The study identified linguistic, cultural, and social implications of AI translations.	Empirical research	Several elements might facilitate or obstruct translation. Above all, context facilitates the translation of metaphors that are particular to one culture and those that are cross-cultural.
Dai (2019)	The study focused on a philosophical analysis on the challenge of cultural context to AI translation.	Qualitative review	Although AI systems may collectively have a far greater command of terminology than various human translators, it cannot be philosophically possible that they comprehend human culture as better as human translators can.

5. Research methodology

This research utilizes a mixed-method approach involving the collection and analysis of both quantitative and qualitative data. This methodology is called exploratory sequential design, where the qualitative data was gathered first, and then the quantitative method was used to triangulate the data (Doyle et al., 2016). During the first part of the research, qualitative methodology is employed to comprehend various types of ambiguities by coding and highlighting them. This enables a comparison between AI and human translations in real-time translation assignments. To draw inferences from the findings and compare the performance of AI and human translations, data is collected, transformed into codes, correlated, and then empirically evaluated to ascertain any potential connections. The following sections elaborate on both qualitative and quantitative data collection and analysis, starting with the qualitative sections first.

5.1. Qualitative analysis of real-time translation: AI vs human

The major question at hand is whether AI translation performance is, in reality, inferior to that of humans; without real-time analysis of both performances, it is impossible to provide an answer. Our process involves real-time analysis of qualitative data to catch translation errors, followed by relying on post-test measures to collect quantitative data. The qualitative data was collected through real-time multicultural translation questionnaires and error analysis, while the quantitative data was collected through post-test measures. The qualitative data was analyzed to gain insights and understanding into the experiences, perceptions, and attitudes of the participants. The quantitative data, on the other hand, was analyzed to identify patterns, trends, and statistical relationships among variables (Lee, 2021). This dual-analysis approach allowed for a more comprehensive and nuanced understanding of the participants' perspectives and provided a solid foundation for drawing meaningful conclusions and making informed recommendations based on the findings (Ramanadhan et al., 2021). Barker's (1990) notation symbols were used to show the relationships between the variables and factors between the

qualitative data and the quantitative data and vice versa. Barker's notation symbols, a graphical representation of relationships between variables and factors, were utilized to demonstrate the interconnectedness between the qualitative and quantitative data in this study.

5.2. The variables and aligned factors

The ambiguities discussed above can have a direct impact on how different speakers understand and engage with each other, possibly resulting in miscommunication and misinterpretations in a multicultural environment. The research methodology involves an initial qualitative analysis, followed by a quantitative analysis. The main purpose is to investigate the ambiguities that arise in multicultural translation assignments and recommend strategies to mitigate the risk of miscommunication. Barker's notation symbols and arrow notation symbols are utilized to indicate relationships between Factors, Variables, and Entities (items) in questionnaires. By using arrow notation symbols, complex concepts and processes can be represented in a more streamlined and organized manner (Ghosh et al., 2023). They allow for a concise and standardized representation of logical operations, making it easier to communicate and manipulate complex expressions (Gloning, 2019). To indicate the relationships, a mandatory attribute is denoted by an asterisk (*), while the other attributes are represented differently. By examining recommendations for translation, this research seeks to identify and categorize ambiguity markers across various languages. It is important to adhere to these recommendations, as failure to do so may result in significant translation ambiguities, particularly in multicultural translation assignments. The recommendations for minimizing ambiguities are being organized and classified as follows.

1. TFP -Translated term must fit perfectly.
2. TFC -Translated term can have different interpretations depending on the context or tone of the sentence.
3. TSDCOL -Translated term can have synonymous relevance based on the identical context, the origin of the term, and/or the first language of the term user.
4. TEMT- translated term has evolved into a more modern term.
5. TMN- Translated term is a misnomer or “no longer used”.
6. TDC-Translated term changes due to collocations.

Figure 1 illustrates the existence of various types of relationships, including one or many relationships, zero or many relationships, one and only one relationship, and zero or one relationship. When translating 15 culturally sensitive terms from Arabic to English, we need to find and categorize the most repeated ambiguous terms and translation errors.

1. Ambiguity occurs because of TFP (-) Negative when the translated term does not fit perfectly.
2. Ambiguity arises because of TFC (-) Negative when the translated term can have different interpretations depending on the context or tone of the sentence.
3. Ambiguity occurs because of TSDCOL (-) Negative when the translated term does not have synonymous relevance based on the identical context, the origin of the term, and/or the first language of the term user.
4. Ambiguity arises because of TEMT (-) Negative when the translated term has not evolved into a more modern term but is translated incorrectly.

5. Ambiguity occurs because of TMN (-) Negative when the translated term is not a misnomer or "no longer used" but is translated incorrectly.
6. Ambiguity arises because of TDC (-) Negative when the translated term does not change due to collocations but is translated incorrectly.

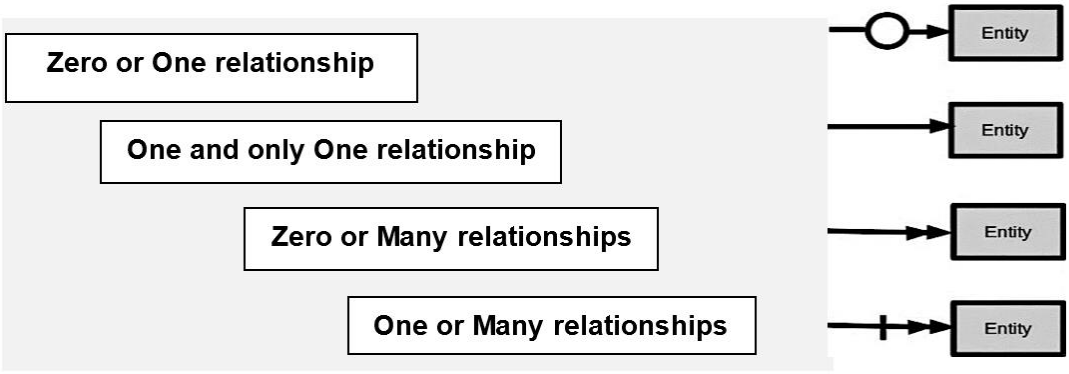

Figure 1. Multiple relationship possibilities between Qualitative and GEMTA Quantitative data

Moreover, a questionnaire named GEMTA (Grid for Evaluating Multilingual Translation and Ambiguity) has been developed as a research instrument to evaluate the performance of translators, including both human and AI translators. The adequacy of the translations is assessed on a scale of 1-5, with 5 representing the highest level and 1 representing the lowest level. The major ambiguities in multicultural translation can be identified by analyzing the translation assignments from Arabic to English. In multicultural translation, there are several major ambiguities that one needs to be aware of. As shown in Figure 2, The TFP -Negative (Term doesn't fit perfectly) is aligned to Item numbers COM1*, COM2*, COM3*, and COM4*. The ambiguity arises when the translated term doesn't seamlessly match the intended meaning, interpretations, and connotations.

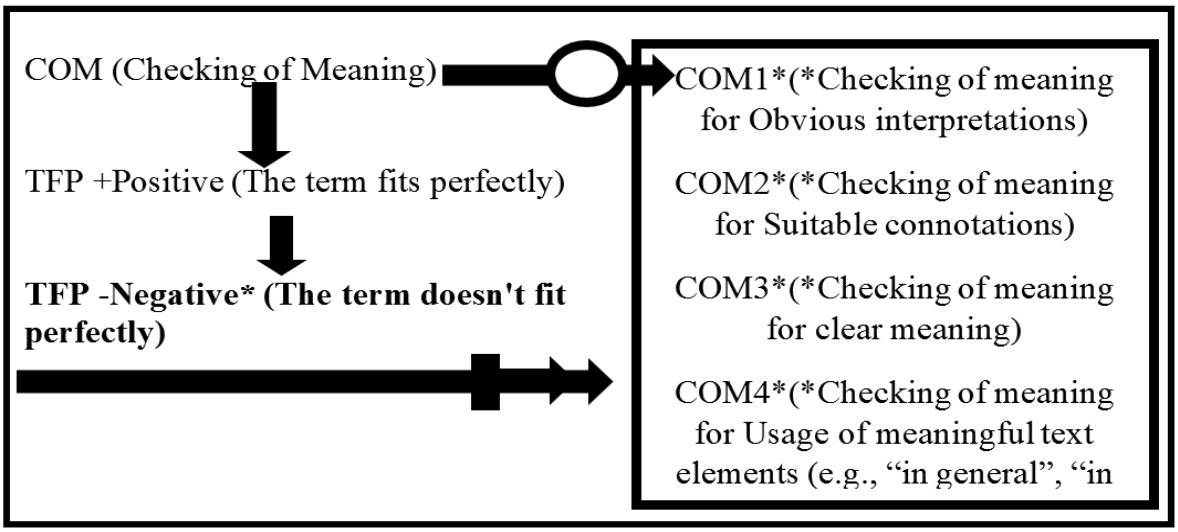

Figure 2. Ambiguity arises when the translation doesn't match the intended meaning

As shown in Figure 3, TFC—Negative (Term fits with different meanings depending on context) is aligned to item numbers CCA1* and CCA2*. Ambiguity arises when the translated term can have different interpretations depending on the context or tone of the sentence.

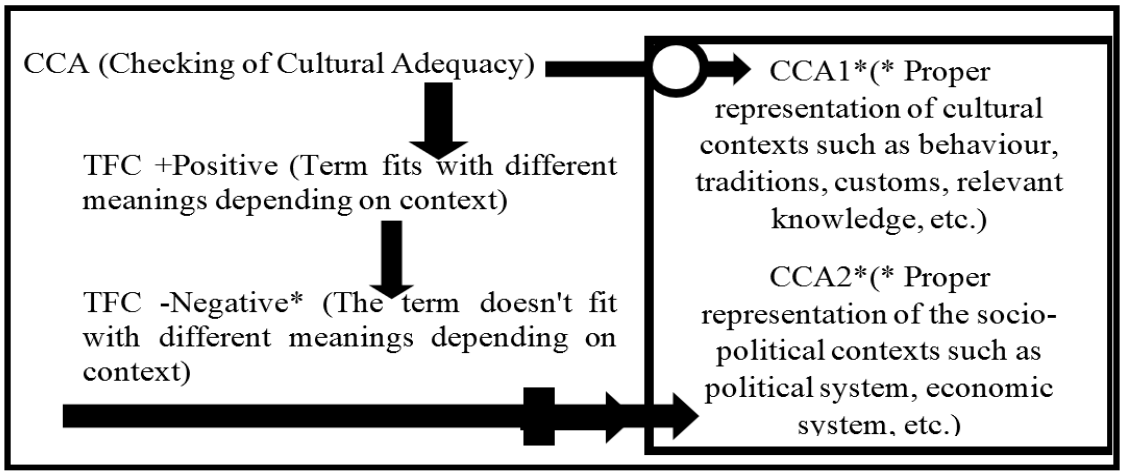

Figure 3. The translated term can be ambiguous due to contextual variations

As shown in Figure 4, TSDCOL -Negative (Term doesn't have synonymous relevance based on context, origin, and/or language) of the translator is aligned to item number CCA1* and CCA2*. This kind of ambiguity occurs when the translated term does not have synonymous relevance based on the identical context, origin of the term, and/or the first language of the term user.

As shown in Figure 5, the TDC -Negative (Term does not change because of collocations yet translated incorrectly) is aligned to Item number COSLC5*. This Ambiguity arises when the translated term does not change due to collocations but is translated incorrectly.

As shown in Figure 6, in addition to the variables, factors, and entities, there are instances where a term has not been updated to a modern version and is wrongly translated, resulting in ambiguity. Furthermore, there are occasional instances of incorrect translation of the term, which can create confusion despite its continued relevance and usage.

TSDCOL -Negative* (The term doesn't fit with different meanings depending on context)

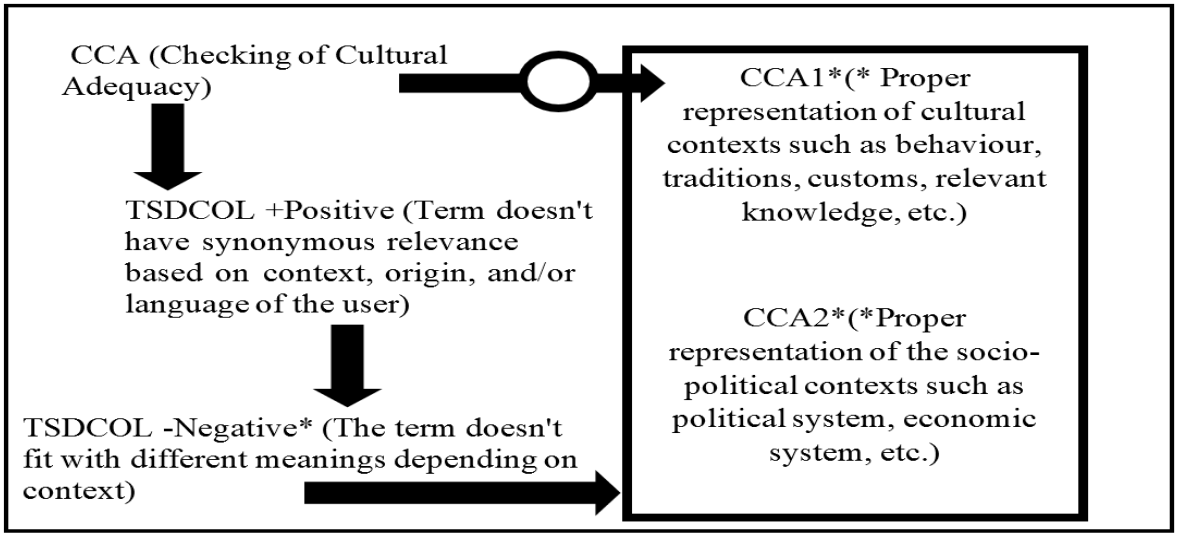

Figure 4. Ambiguity happens when a translated term lacks synonymous relevance in context or origin

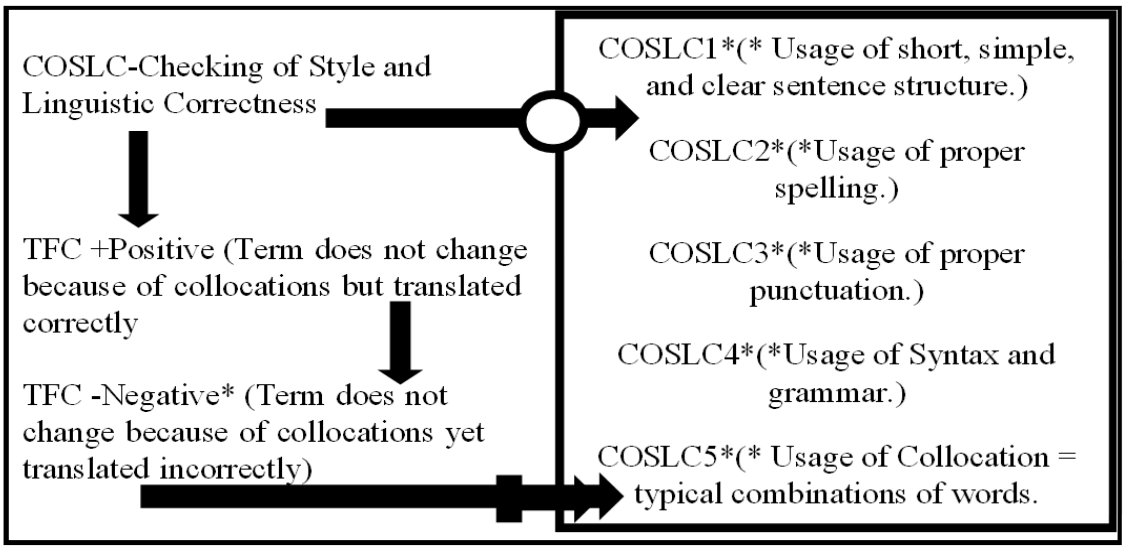

Figure 5. Ambiguity arises when collocations are not accurately translated

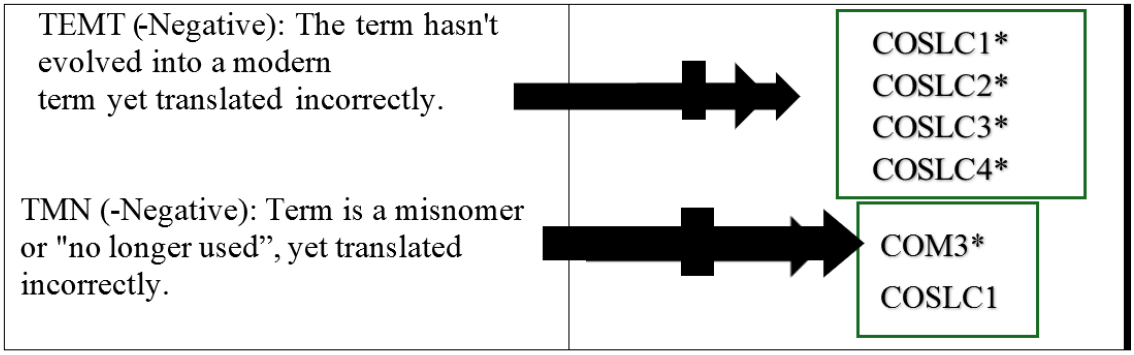

Figure 6. The term's incorrect translation causes ambiguity despite its still valid status

6. Data analysis and interpretation

Since the research utilized an exploratory sequential design, a mixed methodology, the following sections of data analysis will describe the qualitative and quantitative data individually.

6.1. Qualitative analysis: ambiguity markings in AI and human translation

The major ambiguities in multicultural translation were identified by analyzing the translation assignments from Arabic to English. The purpose of the study was to identify and classify ambiguity markers by examining the suggested recommendations for each.

Artificial intelligence-based translation samples illustrated more ambiguity-oriented occurrences, with a count of 18 TFP negatives, as the translated terms do not fit perfectly with the meaning, interpretations, and connotations. On the other hand, human translation performance shows a count of 10 TFP negatives, indicating fewer mistakes in interpretations, meaning, and connotations. Additionally, instances of misunderstanding the context or tone of the sentence were also less frequent during the human translation assignment, with a count of 12 TFC negatives, which is slightly but evidently less than the 13 TFC negative errors made by AI-oriented translation apps.

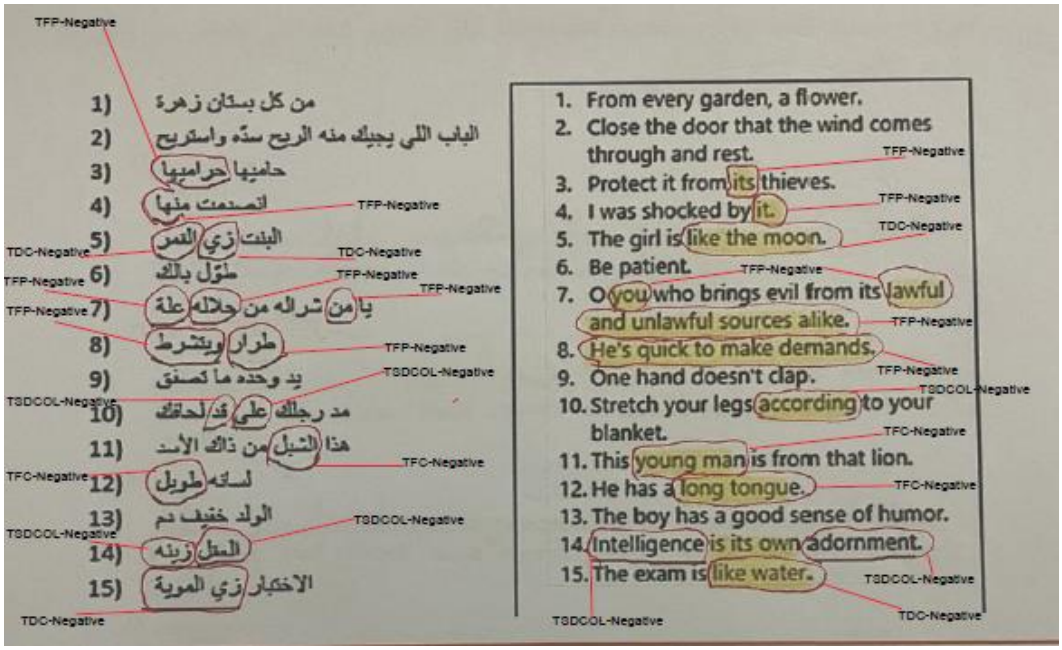

Figure 7. AI translation sample 1–translation ambiguity marking and observations

AI-based Translation Apps have made a substantial number of mistakes, particularly when there is a need to understand terms in relation to their synonymous relevance based on the context, origin, and/or language of the user. In qualitative samples, it is observed that TSDCOL negative mistakes in AI translations amount to eleven instances. On the other hand, Human Translators have not made any mistakes related to the context, origin, and/or language of the user. They have excelled in the bilingual translation process, with only four mistakes related to ambiguity caused by incorrect translations of terms that remain unchanged despite collocations.

In comparison, AI-based translation apps have made two more mistakes regarding collocations and ambiguity compared to the four mistakes made by human translators in the same 15 sentences. Neither AI translation applications nor human translators have shown any mistakes regarding ambiguity and incorrect bilingual translation due to etymons and semantics in this research project. However, it is worth noting that AI translation models struggle to fully understand cultural subtleties, resulting in potentially inaccurate translations. It is evident that biases are present in AI models as they are trained on subjective data, which leads to more ambiguity during bilingual translation.

These ambiguities can impact the meaning and communication between different speakers, potentially leading to miscommunication and misunderstanding. Based on our analysis of the ambiguities mentioned above, we developed several strategies that can effectively minimize the risk of miscommunication in multicultural translation assignments.

To sum up, our qualitative analysis of Arabic-to-English translation samples demonstrates that we can effectively deal with ambiguity concerns in multicultural translation projects and devise strategies to minimize the risk of miscommunication in the age of AI translation through the formulation of precise rules. To achieve accurate and culturally inclusive translation of languages, the translation strategies should be focused on preserving the context, translate metaphors and slang, and avoid unnecessary mechanical processes that can distort the intended and precise meaning.

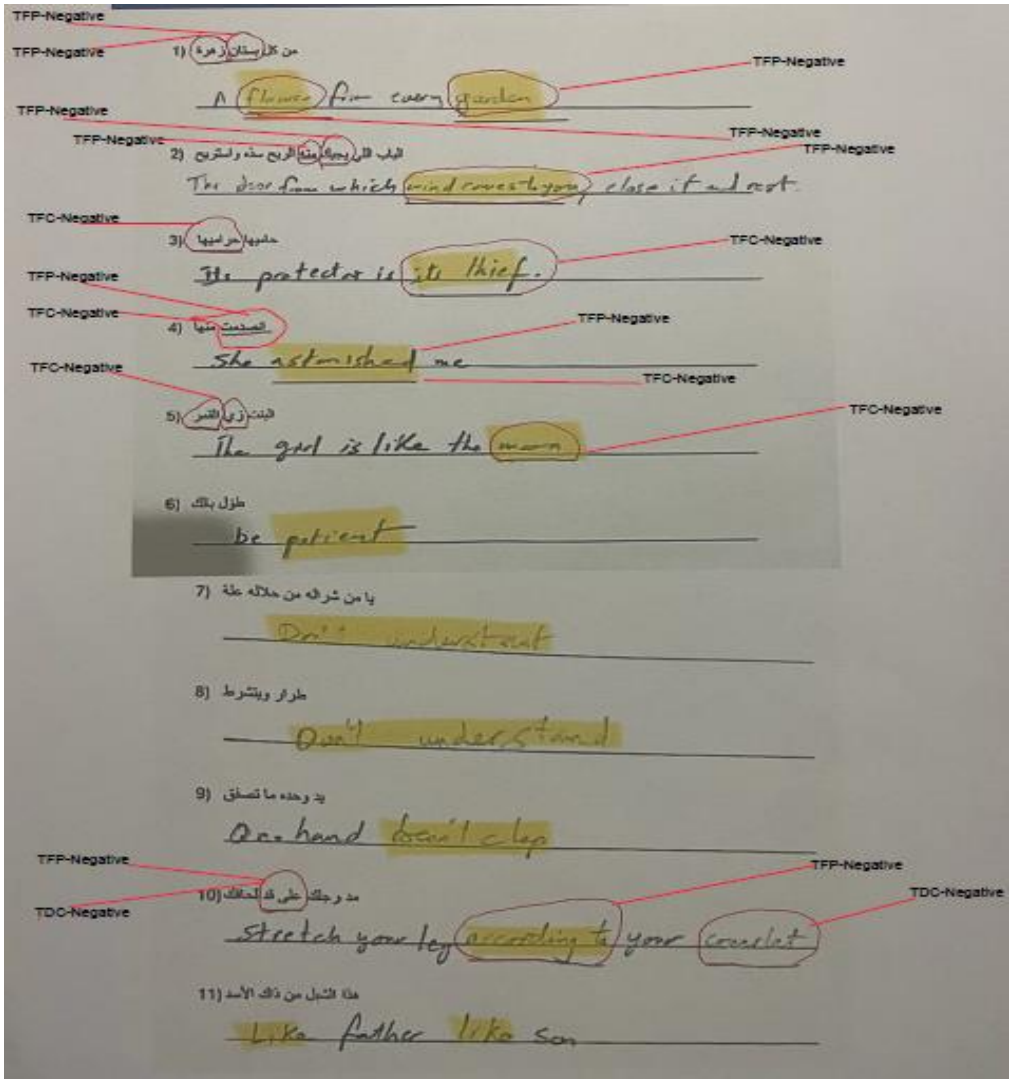

Figure 8. Human translation sample 1–translation ambiguity marking and observations.

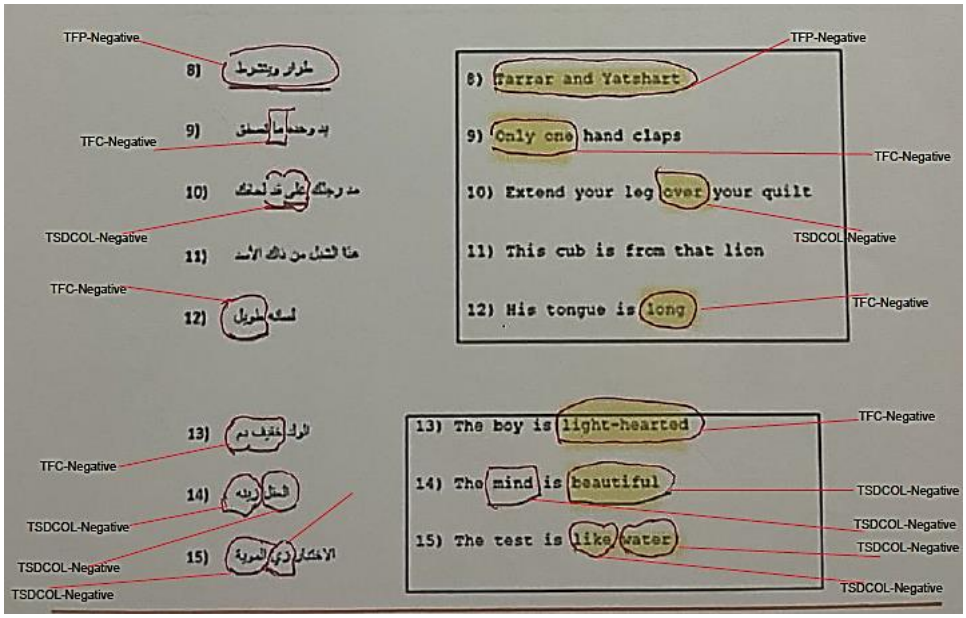

Figure 9. AI translation sample 2–translation ambiguity marking and observations.

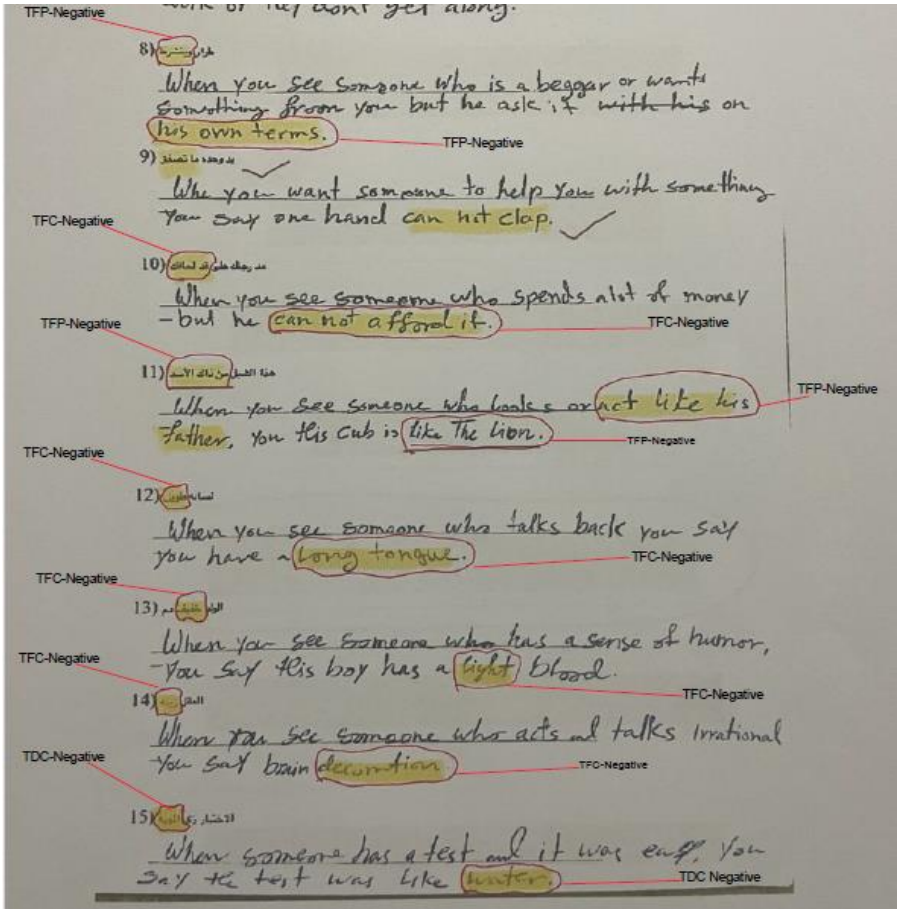

Figure 10. Human translation sample 2–translation ambiguity marking and observations.

6.2. Quantitative analysis: affirming results from AI and human translation

Drawing from the research approach utilized by Zhang (2023), the analysis of the qualitative data provided rich insights into the experiences, perceptions, and attitudes of the 50 bilingual speakers, which proved to be essential to determine the strategies to analyze possible AI-based ambiguities in multicultural translation assignments. Additionally, the quantitative part of the analysis proposes strategies to minimize the risk of miscommunication during the multicultural translation of Arabic to English. The quantitative data, on the other hand, provided statistical evidence to support and validate the findings from the qualitative analysis.

Table 2. Variables and items for Quantitative analysis

Variables	Number of items	Items	
COM-Checking of Meaning	4	(Obvious Interpretations): Ratings for clarity of explanations.	التفسيرات واضحة
		(Suitable Connotations): Ratings for the appropriateness of connotations.	الدلالات المناسبة
		(Clear Meaning): Ratings for clarity of meaning.	المعنى واضح
		(Use of Meaningful Text Elements): Ratings for the use of	استخدام عناصر نص ذات مغزى

		meaningful text elements.	
CCA-Checking of Cultural Adequacy	2	(Proper Representation of Cultural Contexts): Ratings for the appropriateness of cultural background representation.	التمثيل مناسب للخلفية الثقافية
		(Proper Representation of the Socio-political Contexts): Ratings for the appropriateness of social and political background representation.	التمثيل مناسب للخلفية الاجتماعية والسياسية
COSLC-Checking of Style and Linguistic Correctness	5	(Usage of Short, Simple, and Clear Sentence Structures): Ratings for the use of short, simple, and clear sentence structures.	استخدام هيكل جمل قصير وبسيط وواضح
		(Usage of Proper Spelling): Ratings for the use of correct spelling.	استخدام إملاء صحيح
		(Usage of Proper Punctuation): Ratings for the use of correct punctuation.	استخدام علامات الترقيم الصحيحة
		(Usage of Syntax and Grammar): Ratings for the use of grammar and linguistic rules.	استخدام النحو والقواعد اللغوية
		(Usage of Collocation): Ratings for the use of typical linguistic constructions.	استخدام التراكيب اللغوية النموذجية

The given table includes the means for each variable from each group and their combined average. The "Combined Mean Across Groups" column in the table represents the average of the mean scores from all three groups for each linguistic quality variable.

Table 3. A comparison of AI translation versus Human translation ratings across a variety of translation quality metrics.

AI Translation Evaluation		**Human Translation Evaluation**	
Variable	**Combined Mean Across Groups**	**Variable**	**Combined Mean Across Groups**
Obvious Interpretations	3.173	Obvious Interpretations	3.53
Suitable Connotations	2.753	Suitable Connotations	3.21
Clear Meaning	3.200	Clear Meaning	3.40
Use of Meaningful Text Elements	3.163	Use of Meaningful Text Elements	3.50
Proper Representation of Cultural Contexts	2.260	Proper Representation of Cultural Contexts	3.42
Proper Representation of the Socio-political Contexts	2.89	Proper Representation of the Socio-political Contexts	3.293
Usage of Short, Simple, and Clear	2.373	Usage of Short, Simple, and Clear	3.25

Sentence Structures		Sentence Structures	
Usage of Proper Spelling	3.617	Usage of Proper Spelling	3.45
Usage of Proper Punctuation	3.540	Usage of Proper Punctuation	3.29
Usage of Syntax and Grammar	3.260	Usage of Syntax and Grammar	3.36
Usage of Collocation	3.276	Usage of Collocation	3.50

The table compares the performance of AI and human translation evaluations across various metrics indicative of translation quality. It reveals that AI has more weaknesses compared to human translation evaluations.

AI Translation Evaluation excels notably in "Usage of Proper Spelling" with a score of 3.617, and “Usage of Proper Punctuation” with a score of 3.540, surpassing the human translation score. This suggests that AI is particularly expert at recognizing and applying standard spelling and punctuation, possibly due to its programming and vast databases of correct spelling patterns.

However, the Human Translation Evaluation betters AI in remaining critical areas, such as "Use of Meaningful Text Elements" and "Proper Representation of Cultural Contexts" with scores of 3.50 and 3.42, respectively. These are substantial components in translation where contextual understanding and the details of language are important sections that require empathy, cultural insight, and a nuanced scope of language that AI currently struggles to match.

Overall, while AI shows promise in technical aspects, humans exhibit a superior ability to navigate the complexities of language that are essential for reducing ambiguity in multicultural translation. The human touch remains critical in understanding the depth and nuance of language, especially when it comes to cultural and contextual relevance. This comparison underscores the need for AI to evolve in dealing with complex, exact linguistic tasks. It suggests that human oversight is crucial in translation, especially in a multicultural context with high risk of miscommunication.

7. Research findings

The research has uncovered a spectrum of errors and discrepancies in multicultural translation, particularly in Arabic-to-English translations. The data analysis has shown that the ambiguity often originates from the ambiguity of the original text, where the context or tone is obscure. It leads to divergent interpretations by both AI and human translators. This lack of clarity poses significant challenges as it contributes to variability in translations, which could potentially compromise the intended meaning. It hinders effective communication across diverse linguistic communities.

Additionally, the comparison between the AI and human translation samples depicts distinct patterns of errors and inaccuracies. While AI-based translation systems demonstrate proficiency in certain technical aspects, such as spelling and punctuation, they falter when it comes to contextual understanding and cultural nuances. On the other hand, human translators exhibited a more nuanced grasp of contextual intricacies. This is supported by the data that indicated that human translators make fewer errors when translating Arabic sentences into

English. However, it is also important to note that both AI and human translation encountered challenges in accurately translating culturally sensitive terms, which calls for refined translation methodologies.

The comparison between AI and human translation samples in this research has shed light on the multifaceted nature of translation ambiguities, which are impacted by contextual, cultural, and linguistic factors. Moreover, the findings bring attention to the discrepancies in error frequencies that provide valuable insights into areas where each translation method excels and where improvements are needed. The comprehensive understanding emphasizes the importance of developing strategies that address these complexities to enhance the accuracy and effectiveness of multicultural endeavors.

7.1. Strategies to enhance translation accuracy

To effectively address the major ambiguities in multicultural translation, especially Arabic to English, it is important to begin by acknowledging the various factors that contribute to the ambiguity due to the complexities that exist within the original text. Though human translation outperformed AI in certain key areas, it is important to note that both translations face the challenges of ambiguity in varying degrees, especially with context or tone. Therefore, strategies should be implemented to mitigate ambiguity that stems from unclear context or tone. It could be addressed through contextual analysis and linguistic interpretation to ensure that translators understand the nuances of the original contexts.

Additionally, the research has shown that the major factor and entity responsible for translation ambiguity is the lack of cultural and contextual understanding. This factor affects the meaning and communication among different speakers, which highlights the importance of cultural and linguistic proficiency in translation. While both AI and human translators face challenges in this regard, the human translator often has an edge due to their innate ability to comprehend and interpret cultural nuances. They could draw from their personal experiences, cultural backgrounds, and language expertise to navigate these complexities more effectively (Amini et al., 2024). Moreover, human translators could engage in ongoing professional development activities, such as cultural immersion programs and intercultural communication workshops that could assist in improving their cultural sensitivity and linguistic skills (Navidinia et al., 2019). By investing in continuous learning and development, human translators could stay abreast of evolving cultural dynamics and ensure more accurate and culturally sensitive translations.

7.2. Discussion

The major issue with cultural insensitivity risk that arises from ambiguous translation in the era of AI is the potential for miscommunication and misunderstanding. To address this challenge, leveraging advanced neural machine translation models trained on diverse and culturally rich datasets could significantly improve the AI translation process. These models, equipped with sophisticated algorithms, could better capture the nuances of language and culture. Through this training, it is possible to reduce the cultural insensitivity and ambiguity in AI translation. Moreover, ongoing refinement and adaptation of AI translation systems through a continuous feedback loop and human oversight mechanisms are essential to improve

their cultural sensitivity and accuracy over time iteratively.

These different strategies show that the quest for translation accuracy in multicultural settings demands a multifaceted view that allows us to address the intricacies inherent in language and culture. While human translators possess innate advantages in understanding cultural nuances, AI systems offer promising avenues for improvement through advanced training and refinement. Together, these strategies offer a path toward reducing ambiguity, minimizing miscommunication, and fostering greater cross-cultural understanding in translation endeavors.

8. Conclusion

This research has unveiled a nuanced understanding of ambiguities in Arabic to English translation. It shed light on the intricate discrepancies prevalent in multicultural translations, particularly between human and AI translators. This study has supported the findings of previous research findings that underscored the multifaceted nature of the challenges caused by factors such as cultural and contextual understanding. By interrogating the complexities of linguistic interpretation of Arabic to English translation, this research advocates for a paradigmatic re-evaluation of translation methodologies. It emphasizes the imperative of integrating cultural and contextual insights into translation processes, thereby fostering more accurate, inclusive, and culturally sensitive translations. This study not only answers the research question but also advocates for a paradigmatic re-evaluation of translation approaches to better navigate the complexities of cross-cultural communication in our increasingly interconnected world.

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