Investigating Quality in the Translation of Cultural Items through an AI-based Machine Translation from Arabic into English

تقييم مدى جودة ترجمة العناصر الثقافية من خلال الترجمة الآلية القائمة على الذكاء الاصطناعي من العربية إلى الإنجليزية

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Abstract

Computer-based translation, which is believed to enjoy rapidity, readability, and translatability of various types of texts as they become more artificially intelligent, has begun to be discussed on the different issues of accuracy and intercultural comprehension. This study is based on House's quality assessment model to evaluate how an AI-based translation system operates. A variety of extracts from the cultural travelogue of Ibn Battuta's *Rihla* are used as a measure of exposure of cultural translation. Notably, the study found that AI-based translation does not have a similar effect as human translations do, which are less likely to drop the actual meanings delivered in the original texts. These findings indicate that, contrary to what has been assumed on computer translation, AI-based translation does not enjoy accuracy with regards to intercultural translation. Rather, human translation, which draws on different aspects of translation strategies and background knowledge, delivers more accurate and acculturated translations.

Key words: Artificial Intelligence, Computer-based Translation, Cultural Translation,

الملخص

بدأت الترجمة الحاسوبية ، والتي يُعتقد أنها تتمتع بالسرعة وسهولة القراءة وقابلية الترجمة لأنواع مختلفة من النصوص عندما تصبح أكثر ذكاءً مصطنعًا، في المناقشة حول قضايا مختلفة تتعلق بالدقة والفهم بين الثقافات. تستند هذه الدراسة إلى نموذج تقييم الجودة الخاص بـ House لتقييم كيفية عمل نظام الترجمة القائم على الذكاء الاصطناعي. تُستخدم مجموعة متنوعة من المقتطفات من رواية الرحلات الثقافية لرحلة ابن بطوطة كمقياس لعرض الترجمة الثقافية. والجدير بالذكر أن الدراسة قد خلصت إلى أن الترجمة القائمة على الذكاء الاصطناعي ليس لها تأثير مماثل للترجمة البشرية، والتي تقل احتمالية إسقاط المعاني الفعلية الواردة في النصوص الأصلية. تشير هذه النتائج إلى أنه، على عكس ما تم افتراضه في الترجمة الحاسوبية، لا تتمتع الترجمة القائمة على الذكاء الاصطناعي بالدقة فيما يتعلق بالترجمة بين الثقافات. بدلاً من ذلك، تقدم الترجمة البشرية، التي تعتمد على جوانب مختلفة من استراتيجيات الترجمة والمعرفة الأساسية، ترجمات أكثر دقة وثقافة

الكلمات الدالة: الذكاء الإصطناعي، الترجمة الحاسوبية، الترجمة الثقافية.

1. Introduction

Recent advances in translation technology, also known as using translation software, have shown considerable results in translation practice. It was notable for scholars to witness that translation industry, which has existed for very long time, is seeing a rapid growth. More explicitly, Erik Chan believes that

> Globalization is real and as organizations around the world continue to transaction across borders and make their products and services available in more languages, the translation industry market continues to increase in size. (www.syncedreview.com/neural-network-ai-is-the-future-of-the-translation-industry; retrieved 6 October 2020)

The terms to be gleaned from the above-mentioned statements are "technology," "translation software," and "translation practice". Most of these elements practically operate through "machine translation". Thus, a general description of this revolutionized means of translation, i.e. machine translation, is deemed necessary. According to Lynne Bowker and Jairo Buitrago Ciro, machine translation "is an area of research and development where computational linguists try to find ways of using computer software to translate text from one natural language to another natural language" (2019, 37). On the basis of this definition, one may then argue that machine translation is by no means a tool that attempts to imitate human performance. However, what appears to be problematic is: How can machine translation software perform human-like intelligent tasks, such as critical thinking, understanding meanings, and selecting contextual words in language transfer? This is why Artificial Intelligence was integrated to enhance the systematic performance of machine translation. Thus, a review of this aspect is necessary.

2. Review of Literature

2.1. Artificial Intelligence-based Machine Translation

Different definitions on artificial intelligence created variant perceptions of how this technology operates in different fields. More explicitly, Bernard Marr (2018, para, 1) holds that "we are not operating from the same definition of the term and while the foundation is generally the same, the focus of artificial intelligence shifts depending on the entity that provides the definition". Accordingly, in a broader sense of understanding what AI is, we shall consider some of the most prominent definitions and deduce how some industries are focusing on their AI research and function.

John McCarthy, in a seminal workshop entitled 'the Dartmouth Summer Research Project on Artificial Intelligence' in the early 1950s, was the first to coin the term 'Artificial Intelligence' and to further discuss what would become the field of AI. The proposal of this workshop states that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (1955, 1). Notably, in a modern conceptualisation of what Artificial Intelligence is, different dictionaries generally define AI as being a sub-branch of computer science that develops machine performance to imitate human intelligence. More fundamentally, the *Oxford English Dictionary* defines AI as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages".

Moreover, *Encyclopaedia Britannica* differently defines Artificial Intelligence as "[t]he ability of a digital computer-controlled robot to perform tasks commonly associated with intelligent beings". The terms to be gleaned from the aforementioned definitions are "computer systems," "simulate," "machine performance," and "human-like intelligence." As each definition indicates, it could be inferred that AI systems shift their performance upon the purposes that are assigned to them. Thus, Bernard Marr (2018) holds that

> people invest in AI development for one of the following objectives: building systems that think exactly like humans do ("strong AI"); just getting systems to work without figuring out how human reasoning works ("weak AI"); or, using human reasoning as a model but not necessarily the end goal. (www.forbes.com/the-key-definitions-of-artificial-intelligence; retrieved 23 October 2020).

According to Bernard Marr (2018), "the bulk of the AI development happening today by industry leaders falls under the third objective". That is to say that researches on Artificial Intelligence attempt to 'imitate' human reasoning to provide better services. Interestingly, scientists working on AI and machine translation have found that MT requires similar qualities to human knowledge and reasoning to say that it 'understands'. More fundamentally, Bar-Hillel (1971) elaborates further that "it is now almost generally agreed upon that high-quality MT is possible only when the text to be translated has been understood, in an appropriate sense, by the translating mechanism" (qtd. in Wilks, 2009, 12).

In accordance to what has been mentioned earlier, translation practice developed to include machine translation, where computational systems try to find ways to use software to transfer texts from one language to another. Yet, since human languages are complicated, it makes it more difficult for machine translation to operate in the most effective manner. In view of such complexity, machine translation evolved to adopt different approaches to enhance its performance. According to Bowker and Jairo (2019, 39) "prior to the year 2000, the main approach that had been used to develop machine translation systems was known as rule-based machine translation (RBMT)". For them, this approach attempted to function "in a way that resembles how human beings process language by incorporating grammar rules and large dictionaries" (2019, 39).

Nevertheless, in the course of time, machine translation systems have witnessed a shift in language processing whereby scientists have adopted new approaches that allowed machine translation to improve its efficiency. These new approaches include 'corpus-based approaches' (which consist of example-based MT and phrase-based statistical MT). To illustrate, the key concept behind corpus-based approaches (also known as data-driven approaches) is that "instead of being based on linguistic rules, translation is based on a very large database of examples of texts that have been translated by professional human translators" (Bowker and Jairo, 2019, 42). Thus, example-based machine translation consults parallel corpus in an attempt to figure out how sentences have been previously translated. However, this form of translation still faces contextual meaning issues (as words, phrases, and even sentences are differently perceived from one context to another). On this basis, phrase-based statistical machine translation was introduced as a second approach of corpus-based machine translation. This approach is systemised based on parallel texts (translated texts) and statistical calculations. According to Bowker and Jairo (2019, 43), the fundamental phases undertaken by this approach are as follows: "First, the source text is segmented into phrases, which for statistical machine translation system can be any sequence of words, even if the combination is not linguistically motivated" then, in the next stage, "each of these phrases is translated into target language", and finally, in the last stage, "the phrases are reordered". As mentioned earlier, phrase-based statistical machine translation is based on 'probability calculations'; hence, Bowker and Jairo (2019) hold that it is based on algorithms that provide a sequence of suggests that are probable to the translation of the source-text items.

2.2. Where Are We with Machine Translation?

In the very recent development of machine translation, neural machine translation was introduced. This approach processes information the way human nervous systems do (which includes learning through examples). Neural machine translation is acknowledged for being able to identify and detect complex items that can hardly be noticed by humans. Accordingly, as Bowker and Jairo (2019, 45) purport, the fundamental difference between neural MT and statistical MT is that "when researchers present training material to the deep learning algorithms in a neural network, they do not necessarily tell them what to look for"; instead, "the neural machine translation system finds patterns itself, such as contextual clues around the source sentence". Quite justifiably of course then, the preliminary results suggest that neural machine translation functions best in specialized texts. Yet, it still struggles to deal with rare words and various language structures (Koehn and Knowles, 2017).

Notwithstanding the fact that neural MT reflects highly developed information processing, Castilho et al. (2017) contend that this approach still did not surpass statistical machine translation in terms of functionality. Bowker and Jairo (2019, 46) assert that "regardless of the approach employed, machine translation systems continue to grapple with the fact that language is inherently ambiguous". Thus, machine translation, in an effort to minimize irrelevant outcomes, incorporates hybrid techniques from each of the alluded approaches.

Having acknowledged some of the ways through which computer-based translation attempts to resolve the challenges of transferring texts from one language to another, it seems necessary to look at some of the human approaches to translation and look at some of the complexities of language, taking into account how humans (specifically translators), as texts generators and intercultural communicators, interact with textual and intertextual elements of a given text.

2.3. Human Approaches to Translation

One of the basic principles of translation efficiency is the use of different theories, methods, and strategies for transferring meanings from the source text to the target text. Given the fact that linguistic and cultural differences raised much debate among translation theorists and practitioners, there has been a great deal of interest in studying the approaches to various challenges in translation practice. With the objective of ensuring the contextual transfer of meanings of texts through translation, some of the approaches have been established to serve the source text, while others were inclined towards the target text conventions. Accordingly, different translation theories are categorised according to different approaches to translation. Chief among them are linguistic approaches, sociolinguistic approaches, functional approaches, interpretative approaches, and cultural approaches.

Each of these approaches present theories in the form of opposing (but interrelated) dichotomies through which human translators deal with texts in the process of translation. To illustrate, in the linguistic approaches, Catford (1965) distinguishes between textual equivalence and formal correspondence, Nida (1964) (in sociolinguistic approaches) between dynamic and formal equivalence, Newmark (1981) between communicative and semantic translation (in functional approaches), and Venuti (1995) between domestication and foreignization in cultural approaches.

2.4. Quality in Translation

The rapid growth of translation practice in nowadays globalized world has turned translation quality and assessment into subjects of significant interest. Besides, among the basic concepts underpinning translation research is the notion of 'equivalence'. Accordingly, in an attempt to assess meanings across two different languages and cultures, Juliane House asserts that evaluating translations has always been both academic and popular undertakings, "as philologists and philosophers, journalists and essayists, poets and novelists, and all manner of lay people have expressed opinions on what makes a good translation" (2009, 43). Notably, House maintains that the processes that provide credible results for translation quality rely on identifying a model that makes evaluative statements on whether a translation is "good" or "bad" (House, 2001, 254).

2.5. Translation Assessment

As this study aims to conduct an evaluation of the translation of an AI-based machine translation, it needs to apply a structuring systematic methodology for purposes of conferring credibility upon its findings. The data is going to be examined on the basis of a well-defined model. Accordingly, this part will briefly provide a comprehensive overview of House's Translation Quality Assessment model and reflect on how this model systematically functions. House (2001, 247) holds that "functional pragmatic equivalence— a concept which has been accepted in contrastive linguistics for long time— is the type of equivalence which is most appropriate for describing relations between original and translation".

In her seminal article 'Translation Quality Assessment: Linguistic Description versus Social Evaluation', House (2001) visually displays the individual textual function in a scheme for ST and TT analysis:

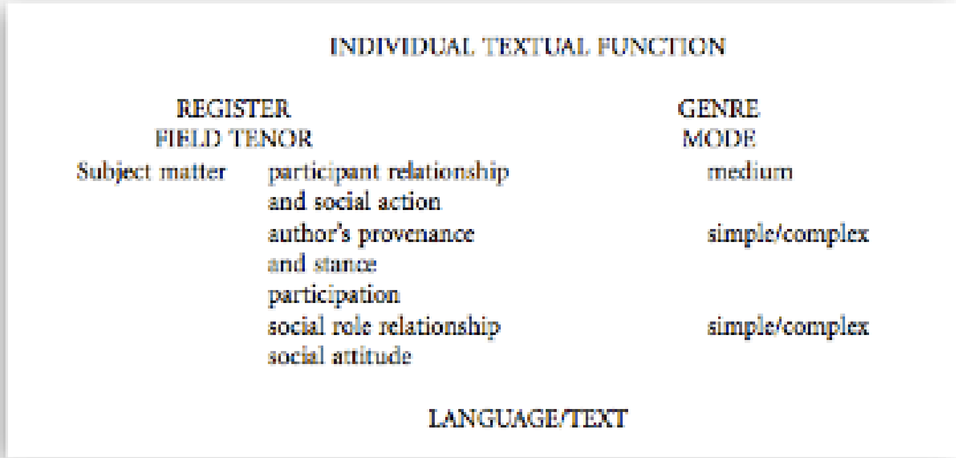

Figure 1. *House's Scheme for Analyzing and Comparing Original and Translation Texts.* Reproduced from 'Translation Quality Assessment: Linguistic Description versus Social Evaluation', by J. House (2001, 249).

Functional equivalence, according to House, is made operational by two criteria, namely *register* and *genre,* which are structured to capture the situational characteristics of the source text (House, 2001, 105-110). Furthermore, while House considers *genre* to be a socially established category, she further subdivides *register* (following Halliday's systematic approach) into *field*, *tenor*, and *mode* and correlates them with syntactic and lexical elements of the text (House, 1977, 42).

House, however, assumes that the textual analysis in which linguistic features are identified in the source text and its translation, under the notions of field, tenor, and mode, does not lead directly to "a statement of individual, textual function" and that the descriptions of these categories are basically limited to capturing "individual features" on the linguistic surface only (House, 2001, 248). Thus, in order to thoroughly elicit a text's function and the language required, House introduces the category of *genre*, which enables "to refer any single textual exemplar to the class of texts with which it shares a common purpose or function"; that is to say, such a new different conceptualization helps to set a deeper framework of text analysis (House, 2001, 248).

3. Methodology

The overall objective of this paper is to carry out an empirical study of (cultural) translation issues in the assessment of an AI-based machine translation; this study is empirical in the sense that it is based on a systematic functional approach to the analysis of the data (the source text and the translation) and points to matches and mismatches committed by the AI-based machine translation system in comparison with a human translation of the excerpts, particularly at the cultural level.

For the sake of establishing credible findings and accurate results, both qualitative and quantitative methods have been chosen in this study. Besides, both of these methods allow listing and tabulating the data collected in order to identify the type of translation strategy involved and disaggregate this date into source-oriented and target-oriented translation (in the light of house's model of translation quality assessment). Consequently, this methodology would allow providing answer to the following questions:

> 1-To what extent has AI-based machine translation system (in comparison to human translation) been inclined towards the source culture and the target culture?
> 2-Which translation procedure or strategy has been more frequently used in both translations?

4. Data Collection

As far as the analytical, comparative, and descriptive procedures are concerned, the study is based on an analysis of a selection of excerpts, which have been chosen according to different sub-cultural categories, including religion, geography, customs, and social status. It is worth noting that the researcher has deliberately concentrated on extracting the excerpts from the book of *Rihla* (specifically from chapters I, II, III, IV, and V), for they are the ones that represent the Muslim culture. This allows for the researcher (who belongs to an Arab Muslim society) to analyse the cultural characteristics of each extract.

5. Procedure

As this study is fundamentally based on a descriptive-analytical framework, it merely compares the source text with the translations generated by the human translator and an AI-based machine translation to identify the matches and mismatches in terms of handling the culture-specific elements. Hence, the procedure is divided into the following phases:

1- Simultaneous reading of the source text in Arabic and the English translation of the excerpts by the human translator (Alexander Gibb) and AI based machine translation;

2- Analysing and comparing the translation of the excerpts identified in the first phase according to the sub-cultural categories;

3- Identifying the main strategies used and developing a statement of quality of the AI-based machine translation.

6. Analysis

Various excerpts from Ibn Battuta's *Rihla* have been selected as the data of the study for their portrayal of the Arab Muslim world (since it displays a variety of cultural items that meet the requirements of the subject of this study), and for the popular narratives that drove many translators to transfer it into other languages (including English). The main reason for selecting Alexander Gibb's translation is that it reflects how human translators deal with culture-specific elements through a range translation strategies.

On the other hand, there are several (free) machine translation engines that provide AI-based translation services and their trade-off being more accurate. Among those engines is 'Google Translate'. According to Elad Plotnik (2020), this translation engine system (in the very beginning) was highly reliant on the statistical translation system; yet, from 2016 onwards, Google altered its machine translation to a neural machine translation system. Thus, considering its existing development and evolution, Google Translate is selected to fulfil the requirements of this study.

Example 01

Source Text (ST)

"وأهل مكة لهم ظرف ونظافة في الملابس وأكثر لباسهم البياض فترى ثيابهم أبدا ناصعة ساطعة. ويستعملون الطيب كثيرا و**يكتحلون** ويكثرون السواك **بعيدان الأراك الأخضر**" (87)

Human Translator

"The Meccans are very elegant and clean in their dress, and most of them wear white garments, which you always see fresh and snowy. They use a great deal of perfume and **Kohl** and make free use of **toothpicks of green arak-wood**" (76)

AI Machine Translation

"The people of Makkah have cleanliness in their clothes, and their clothes are more white, so their clothes will never be seen bright. And they use perfume a lot, and they wear and multiply the **toothpicks** with the **green Arak sticks**".

Commentary

The source text, in example 01, has a descriptive function, as it provides and gives information about the people of Mecca. In human translation, Alexander Gibb opted for free translation (semantic translation), transposition, and borrowing to render the meanings delivered in the source text excerpt; the translation, thus, appears to be contextually cohesive. On the other hand, AI-based machine translation appears to transfer the source text excerpt through word for word translation (which resulted in repetition of words) and omission (as in the case of the word Kohl). The translational choices, therefore, seem to create ambiguous meanings in the target text. The translation, therefore, tends to be ineffective in preserving the descriptive function of the source text.

Example 02

Source Text (ST)

"فقام الإمام المذكور وقال :نماز، ومعناها الصلاة، براي حد او براي طرمشيرين، أي الصلاة لله أو لطرمشيرين .ثم أمر **المؤذن بإقامة الصلاة** .وقد جاء السلطان، وقد صلي منها **ركعتين**، فصلى **الركعتين الأخريين** حيث انتهى به القيام، وذلك في الموضع الذي تكون فيه أنعلة الناس عند باب المسجد" (216)

Human Translator

"**The imam** said in Persian 'Is prayer for God or Tarmashirin?' **and ordered the muezzin** to recite **the second call**. The sultan arrived when the service was half over, and made the remaining two **prostrations** at the end of the ranks, in the place where the shoes are left near the door of the mosque" (173)

AI Machine Translation

”So the aforementioned imam stood up and said: Namaz, meaning prayer, according to a hadd or with the opinion of Tarmashirin, meaning prayer to God or to Tarmashirin. Then the muezzin ordered **the establishment of the prayer**. And the Sultan came, and he had prayed two **rak'ahs** of it, and he prayed the last two **rak'ahs** where he finished standing, and that was in the place where the soles of the people were at the door of the mosque”

Commentary

Alexander Gibb, in the translation of culture-specific elements in example 02, has employed a variety of strategies through literal translation, borrowing, and cultural adaptation. Those translation strategies seem to be specifically used to make the religious custom more explicit for the target readers; this consequently reflects the effort of the translator to transfer cultural meanings delivered in the contextual situation in example 02. However, the AI-based machine translation tends to be source-text oriented via transliteration and borrowing. Besides, the translation follows a word for word structure that does not assure the transfer of correct contextual meanings in the target text. This is reflected in the mistranslation of فقام الإمام المذكور . . . ثم أمر المؤذن بإقامة الصلاة , which contextually denotes that ‘the imam’ is the one who ordered for the second call and not ‘the muezzin’.

Example 03

Source Text (ST)

“فتوجهنا جميعا إلى **متيجة** نحو جبل **الزان**، ثم وصلنا إلى مدينة **بجاية**” (10)

Human Translator

“we went on together through the **Mitija** to the mountain of Oaks **[Jurjura]** and so reached **Bijaya [Bougie]**.[6]” (43)

AI Machine Translation

“So we all headed to **Mitidja**, towards the mountain of **Zan**, and then we reached the city of **Bejaia**”

Commentary

Notwithstanding the fact that the names of the places mentioned in the book of *Rihla* reflect the cultural background of different societies, both translations have opted for various translation strategies. In Alexander Gibb's translation, the geographical items have been transferred using transliteration, amplification (to provide referential meanings in TT), and semantic translation (as in the case of ‘the mountain of Oaks’). The transliteration delivered in the AI-based Machine Translation seems to be slightly different from that of human translation (as it lacks amplification). Thus, the transliteration in this situation does not cater for the needs of the target readers unless they understand Arabic (given the fact that each geographical name has a cultural background).

Example 04

Source Text (ST)

"و خرجنا من تونس في أواخر شهر **ذي القعدة** سالكين طريق الساحل" (12)

Human Translator

"We left Tunis early in **November**, following the coast road" (45)

AI Machine Translation

"We left Tunisia at the end of **the month of Dhu al-Qi'dah**, on the coast road"

Commentary

Culture-specific items involve different aspects of identity, religious background, and social status. Accordingly, the names of the *Hijri* calendar (i.e. Islamic calendar) are important as they determine significant Islamic events (such as the month of pilgrimage 'Hajj' and the month of fasting 'Ramadan'). Besides, the *Hijri* calendar is eleven days shorter than the Gregorian one (as there are either 29 or 30 days per month). In example 04, the name **ذي القعدة** stands for the 'master of truce', as Muslims are prohibited from waging wars in محرم،رجب and ذي القعدة. The translator, Alexander Gibb, has opted for the strategy of cultural adaptation to render ذي القعدة by its conventional correspondent 'November'. Although this word could be transliterated, the translator has made an effort to make such rendition more cohesive in the target text. The transliteration in AI-based Machine Translation seems to be problematic, as it might not be conveniently interpreted in the light of the religious reference of the source text item.

Example 05

Source Text (ST)

"و أما المارستان الذي بين القصرين عند **تربة** الملك المنصور قلاوون فيعجز الواصف عن محاسنه" (23)

Human Translator

"As for the **Maristan [hospital]**, which lies 'between the two castles' near the **mausoleum** of Sultan Qala'un, no description is adequate to its beauties" (50)

AI Machine Translation

"As for the **Maristan**, which is between Kasserine by the **soil** of King Al-Mansur Qalawun, Al-Wasif is incapable of his virtues"

Commentary

The word تربة in Arabic literally means soil; yet, in the Arab culture, it denotes a tomb or a grave. The architecture of such graves varies from one culture to another. Thus, having realized that the literal translation of the word تربة might not convey the exact contextual meaning of the source text, the translator, Alexander Gibb opted for the strategy of substitution to make the rendition more friendly in the target text. Contrary to the human translation, the literal rendition of the word تربة , in AI-based Machine Translation, seems to result in ambiguous rendition in the target text. Besides, given that the target text follows a word for word translation, the target excerpt inevitably involves faulty renditions, as in القصرين/ Kasserine and فيعجز الواصف عن محاسنه/ Al-Wasif is incapable of his virtues.

Example 06

Source Text (ST)

"وكان دخولنا عند الزوال أو بعده إلى القسطنطينية العظمى، **وقد ضربوا نواقيسهم حتى ارتجت الآفاق لاختلاط أصواتها**" (202)

Human Translator

"Our entry into Constantinople the Great was made about noon or a little later and **they rang their bells until the very skies shook with the mingling of their sounds.**" (157)

AI Machine Translation

"Our entry was at midday or after it to the Great Constantinople, and **they blew their bells, until the horizons shook as their voices mixed**."

Commentary

What marks the specificity of this excerpt is that it delivers the descriptive expressions of the events in Ibn Battuta's *Rihla* in a stylistic way. Alexander Gibb, in his translation, resorted to the strategy of semantic translation in an attempt to reflect the same stylistic flavour of the source text. On the other hand, the AI-based Machine Translation seems to follow a literal translation in the rendition of the descriptive items of the source text. Yet, it could be noticed that delivering the original expression through literal translation has caused the target text to lose its stylistic flavour. AI-based Machine Translation is source text-oriented, with tendency lying closer to word for word translation. Under such translational choice, the stylistic features are ambiguously represented in the TT.

8. Findings and Discussion

In order to distinguish the type of translation applied by the human translator and the AI-based Machine Translation, the strategies used in each translation will be classified according to source text-oriented translation and target text-oriented translation (i.e. overt and covert). One of the fundamental roles of this step is to identify the distinctive features of each translation (i.e. human verses AI-based Machine Translation). The results should enable the researcher to determine whether AI-based translation has been overtly or covertly translated. The number of strategies in each translation is presented as follows:

Table (1)

The excerpts	**Strategy Adopted**			
	Human Translation		**AI-based Machine Translation**	
	Overt Tr	**Covert Tr**	**Overt Tr**	**Covert Tr**
Excerpt 01	Borrowing	Free Translation, Transposition	Word for word	Omission
Excerpt 02	Literal Translation, Borrowing	Cultural Adaptation	Transliteration, Borrowing, Word for word	
Excerpt 03	Transliteration, Amplification	Semantic Translation	Transliteration	
Excerpt 04		Cultural Adaptation	Transliteration	
Excerpt 05		Substitution (cultural adaptation)	Literal Translation, Word for word	
Excerpt 06		Semantic Translation	Word for word	

Table (2)

	Source text-oriented Strategies	**Target text-oriented Strategies**
Human Translation	**05**	**07**
AI-based Machine Translation	**09**	**01**

To address the question (*To what extent has AI-based machine translation (in comparison to human translation) been inclined towards the source culture and the target culture?*) and after analysing the excerpts in Table (1) and (2) above, the findings indicate that human translation is mostly inclined towards target text translation approaches, whereas AI-based Machine Translation is mostly inclined towards source text translation approaches. The explanation behind such results is that the strategies used reflect the intent of each translation. To put it differently, Table (1) highlights that while the human translator (Alexander Gibb) has applied target-text oriented strategies in all excerpts, AI-based Machine Translation has implemented source-text oriented strategies in transferring cultural elements. Thus, the tendencies of each translation are highly reflected in the results obtained.

For the sake of answering the question (*Which translation procedure or strategy has been more frequently used in both translations?*), different translation strategies have been identified under the framework of source text-oriented and target text-oriented translation (i.e. overt and covert). Based on Table (1), the results indicate that cultural adaptation is the most frequently used strategy in human translation; while on the other hand, the strategies of transliteration (borrowing) and word for word translation are mostly used in AI-based Machine Translation. The predominance of cultural adaptation in human translation might be due to the awareness of the translator that the target readers might not be familiar with the cultural elements of the source text (if they were borrowed or literally translated). However, the explanation behind the frequent use of transliteration and word for word strategies in AI-based Machine Translation could be due to the lack of interpretation and word matching (causing faulty renditions) in both languages (i.e. source language and target language).

9. Conclusion

This study attempted to evaluate AI-based translation of culture-specific items from Arabic into English. The study purported to identify the translation strategies that have been employed in the translation (in comparison to a human translation), and to evaluate the implications of both translations in the target text. To achieve this aim, both qualitative and quantitative methods have been adopted in order to address the questions raised by this study. Accordingly, based on the assessment of rendition carried out in the above-mentioned analysis, several conclusions have been drawn.

To begin with, an in-depth knowledge of culture (i.e. translation memory for AI-based Machine Translation) is a fundamental prerequisite for ensuring 'accuracy' in the target text. Second, the strategies of transliteration and word for word translation sometimes lead to mistranslation and create ambiguous meanings (especially when they lack amplification). Lastly, in the course of evaluating the translation of cultural items from Arabic into English, it could be inferred that human translation was inclined towards the cultural conventions of the target readers, while AI-based Machine Translation was highly inclined towards the source text's cultural conventions (which consequently led to poor quality translation in the target text). Overall, the study found that AI-based machine translation is more likely to drop the actual meanings of the original text. The analysis and results contend that this type of translation does not assure high levels of accuracy in dealing with intercultural translation.

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