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Machine Translation and Automatic Post-Editing in Translation of Business Letters and Contracts

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Abstract

In this article the feasibility of the translation of the business letters and contracts through Google Translate as the web-based machine translation program and Grammarly and LanguageTool as the automatic post-editors and also the quality level of the final output of the machine translation and automatic post-editing in comparison with the human translation are studied. The researchers conducted a careful comparative content analysis with both a qualitative and a quantitative design. After comparing the final output of the machine translation and post-editing with the reference materials, the researchers found that the above-mentioned texts can be translated through machine translation and post-editing only under the supervision of a professional translator, and testing the null hypothesis by using t-test indicated that there was a significant difference between this kind of translation and human translation based on the data obtained from this research.

Key Terms: Business Letters, Business Contracts, Machine Translation, Post-Editing

Introduction

The genesis of thoughts related to machine translation (MT) can be tracked to 17th-century theories about global languages and dictionaries, but the initial respective experimental recommendations emerged in the 20th century. Optimum translation output quality is still the most important aspect in the field of machine translation. Today, the two major discussions for achieving this goal are ameliorating the MT processing system or ameliorating the final MT output, called post-editing. Improvement of MT output is extensively limited to editing the output manually, or in an advanced method, to an automatic post-editing procedure in order to ease the tiresome act of manually-operated post-editing with the assistance of a computer program for correcting the most obvious faults of translation. The study of the application of the web-based translation and post-editing programs to business letters and contracts and comparison of the output with the respective human translation and the reference books will reveal the advantages and disadvantages of machine translation and automated post-editing. This will serve as a research translation paradigm to translation agencies, freelance translators, translation teachers, vocational translation institutes and business companies and will enlighten the involved people about the most effective and economically-efficient method of

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translation of texts with specific structures.

To make the best use of MT, human translators are urged to perform post-editing efficiently and effectively. Development of automatic post-editing software is considered to alleviate the burden of manual post-editing. However, the quality of the automatically post-edited MT output should be evaluated. Due to the low number of computerized programs for translating from Persian to English or vice versa and the respective editing, the researchers chose Google Translate which has higher practicality for translation and Grammarly and LanguageTool as web-based programs for editing part of the research. They intended to choose texts which follow denotative formal lexicons and are recognizable for electronic devices. Therefore, the researchers chose the business letters and contracts as a specific type of text with definite structures. MT evaluation is aimed at measuring the quality of a candidate translation by comparing it with a reference translation. Therefore, the researchers decided to find the answers to the following questions:

1. To what extent Google Translate as a computerized web-based translator and Grammarly and LanguageTool as automatic post-editors contribute to a sound translation of business letters and contracts based on the Waddington's method C?

2. Is it possible to translate business letters and contracts by using Google Translate, Grammarly and LanguageTool?

3. Is there any significant difference between the machine translation of the business letters and contracts using Google Translate, Grammarly and LanguageTool and translation of human translator?

Based on the second and third research questions, the researchers proposed the following null hypotheses:

H_{01}: It is not possible to translate business letters and contracts by using Google Translate, Grammarly and LanguageTool. H_{02}: There is not any significant difference between the machine translation of the business letters and contracts using Google Translate, Grammarly and LanguageTool and the translation of human translator.

Review of Literature

To process any translation, human or automated, the meaning of a text in the original (source) language must be fully restored in the target language, i.e., the translation. While on the surface, this seems straightforward, it is far more complex. The human translation process, for instance, may be described as:

1. Decoding the meaning of the source text; and
2. Re-encoding this meaning in the target language (Okpor, 2014)

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Okpor (2014) adds that behind this ostensibly simple procedure lies a complex cognitive operation. To decode the meaning of the source text in its entirety, the translator must interpret and analyze all the features of the text, a process that requires in-depth knowledge of the grammar, semantics, syntax, idioms, etc., of the source language, as well as the culture of its speakers. The translator needs the same in-depth knowledge to re-encode the meaning in the target language. Since natural languages are highly complex, MT becomes a difficult task. Many words have multiple meanings, sentences may have various readings, and certain grammatical relations in one language might not exist in another language. The following diagram shows all the phases involved in the process of Machine Translation.

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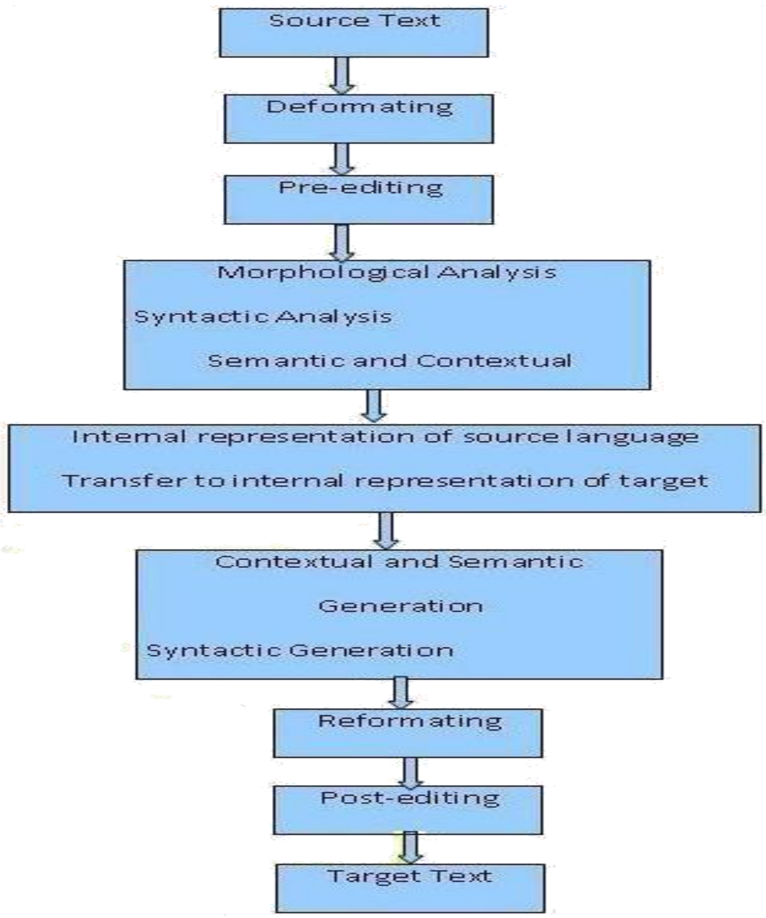

A Typical Machine Translation Process

(Okpor, 2014, p. 160)

A machine translation (MT) system first analyses the source language input and creates an internal representation. This representation is manipulated and transferred to a form suitable for the target language. Then at last output is generated in the target language. On a basic level, MT performs simple substitution of words in one natural language for words in another, but that alone usually cannot produce a good translation of a text because recognition of whole phrases and their closest counterparts in the target language is needed. Therein lies the challenge in machine translation: how to program a computer that will “understand” a text as a person does, and that will “create” a new text in the target language that “sounds” as if it has been written by a person (Okpor, 2014).

There is now no doubt that computer-based translation systems are not rivals to human translators, but they are aids to enable them to increase productivity in technical translation or they provide means of translating material which no human translator has ever attempted. In this context we must distinguish (1) machine translation (MT), which aims to undertake the whole translation process, but whose output must invariably be revised; (2) computer aids for translators (translation tools), which support the professional translator; and (3) translation systems for the ‘occasional’ non-translator user, which produce only rough versions to aid comprehension. These differences were not recognised until the late 1980s. The previous assumption had been that MT systems, whether running on a mainframe or a microcomputer, could serve all these functions with greater or lesser success. In part, this failure to identify different needs and to design systems specifically to meet them has contributed to misconceptions about translation technology and its impact for the professional translator (Hutchins J. , 2001).

It is important to clarify that the term “post-editing” (also often written non-hyphenated as “post-editing”) has been used within different subfields of natural language processing, including MT, automated error correction, optical character recognition, translation memory, and even controlled language. Post-editing is by far most commonly associated as a task related to MT and has been previously defined as the “term used for the correction of machine translation output by human linguists/editors” (Veale & Way, 1997). Another good summary statement indicates that “post-editing entails correction of a pre-translated text rather than translation “from scratch” (Wagner, 1985). In basic terms, the task of the post editor is to edit, modify and/or correct pre-translated text that has been processed by an MT system from a source language into (a) target language(s) (Allen, 2003).

Koponen (2012) examined the relationship between human assessment of post editing efforts and objective measures such as post-editing time and number of edit operations. She found that segments that require a lot of reordering are perceived as being more difficult, and that long sentences are considered harder, even if only few words changed.

Above all, post-editing should be seen as a process of improving through modification (rather than revision) a machine-generated translation, often eyeing a minimum of effort on behalf of the post-editor. The quicker the turn-around needs of a translation, the more likely the post-edited machine translation effort will be a fast one, also known as ‘light post-editing’. More thorough modifications, with less urgency, aim to produce a better quality and are often known as ‘full post-editing’. The latter category is the more common one, not least because it aims to obtain a quality level that is the same as if the entire text had been translated from scratch by a human translator (Declercq, 2015).

Current machine translation systems usually employ a human post-editor to transform the MT output into usable, quality text. If the post-editor can do this transformation in less time than it takes to translate from scratch, then the MT system is economically viable. Many commercial systems exist on this principle. Improving a particular MT system often means automating something that the post-editor is doing. The system gets further, leaving the post-editor with less to do. And usually, the improvements are coded into the internals of the MT system, becoming part of a black box. Another way to think about automating post-editing tasks is to build automated post-editing modules that are detachable and independent of any particular MT system. The advantage of detachable post-editors is that they are portable across MT systems. They accomplish their tasks without reference to the internal algorithms and representations of particular systems (Knight & Chander, 1994).

According to Kristen Parton et al. (2012), the advantage of automatic post-editing is that the automatic post-editors can adapt any MT output to the needs of each task without having to re-train or re-tune a specific MT system (Isabelle et al., (2007)). Acquiring parallel text, training and maintaining an MT system is time-consuming and resource-intensive, and therefore not feasible for everyone who wishes to use MT in an application. Ideally, an automatic post-editor can adapt the output of a black-box MT system to the needs of a specific task in a light-weight and portable manner. Since automatic post-editors are not tied to a specific MT system, they also allow application developers flexibility in switching MT systems as better systems become available.

Childs (1999) states that the body of a business letter is written in formal language, unlike the casual language of a friendly letter. As a general rule, most business letters should be short and to the point; a busy person does not have time or interest in wading through extra words or confusing details. Each letter must be absolutely perfect in spelling, grammar, sentence structure, appearance, and format.

The tone of a business letter should always be appropriate for the selected audience or a certain purpose. Apparently, letters intended to a business partner with whom the writer has worked closely for years will have a warm and friendly tone. Still, the sender has to bear in mind the very first attribute of a business letter which is courtesy and politeness, no matter what the occasion or attitude towards the recipient. Sentence structure, level of formality, preciseness and selection of vocabulary, all contribute to the final tone of a letter. The language of a business letter is frequently quite formal and succinct (Hardošová, 2014).

Abdul (2013) has discussed the language and translation qualities of a good business letter as follows:

(i) Simplicity - Simple and easy language should be used for writing business letters. Difficult words should be strictly avoided, as one cannot expect the reader to refer to the dictionary every time while reading letter.

(ii) Clarity - The language should be clear, so that the receiver will understand the message immediately, easily and correctly. Ambiguous language creates confusion. The letter will serve the purpose if the receiver understands it in the same manner in which it is intended by the sender.

(iii) Accuracy - The statements written in the letter should be accurate to the best of the sender's knowledge. Accuracy demands that there are no errors in the usage of language - in grammar, spellings, punctuations, etc. An accurate letter is always appreciated.

(iv) Completeness - A complete letter is one that provides all necessary information to the users. For example, while sending an order we should mention the desirable features of the goods, i.e., their quality, shape, colour, design, quantity, date of delivery, mode of transportation, etc.

(v) Relevance - The letter should contain only essential information. Irrelevant information should not be mentioned while sending any business correspondence.

(vi) Courtesy - Courtesy wins the heart of the reader. In business letters, courtesy can be shown/expressed by using words like please, thank you, etc.

(vii) Neatness - A neat letter is always impressive. A letter either handwritten or typed, should be neat and attractive in appearance. Overwriting and cuttings should be avoided.

A distinction needs to be made between machine translation (MT) and computer-aided translation (CAT). Where MT tries to replace a translator to a certain extent, CAT tools support the translator by preventing repetitive work, automating terminology lookup activities, and re-using previously translated texts (Esselink, 2003).

CAT systems fundamentally enable the reuse of past (human) translation held in so-called translation memory (TM) databases, and the automated application of terminology held in terminology databases. These core functionalities may be supplemented by others such as alignment tools, to create TM databases from previously translated documents, and term extraction tools, to compile searchable term bases from TMs, bilingual glossaries, and other documents. CAT systems may also assist in extracting the translatable text out of heavily tagged files, and in managing complex translation projects with large numbers and types of files, translators and language pairs while ensuring basic linguistic and engineering quality assurance (Garcia, 2015).

Methodology

In this research, seven authentic business contracts and five genuine business letters were used as the corpus of the study. The contracts were obtained from one of the most significant domestic manufacturers and the letters from National Library and Archives of the Islamic Republic of Iran. To assess the quality level of the translation of the machine translator and automatic post-editors, the researchers used Christopher Waddington's Model C, the description and criteria of which is as follows:

According to Waddington (2001), Method C is a holistic method of assessment. The scale is unitary and treats the translation competence as a whole, but requires the corrector to consider three different aspects of the student's performance, as shown in the following table. For each of the five levels there are two possible marks, so as to comply with the Spanish marking system of 0 - 10; this allows the corrector freedom to award the higher mark to the candidate who fully meets the requirements of a particular level and the lower mark to the candidate who falls between two levels but is closer to the upper one.

Christopher Waddington's Model C

Level	Accuracy of transfer of ST content	Quality of expression in TL	Degree of task completion	Mark
Level 5	Complete transfer of ST information; only minor revision needed to reach professional standard.	Almost all the translation reads like a piece originally written in English. There may be minor lexical, grammatical or spelling errors.	Successful	9, 10
Level 4	Almost complete transfer; there may be one or two insignificant inaccuracies; requires certain amount of revision to reach professional standard.	Large sections read like a piece originally written in English. There are a number of lexical, grammatical or spelling errors.	Almost completely successful	7, 8
Level 3	Transfer of the general idea(s) but with a number of lapses in accuracy; needs considerable revision to reach professional standard.	Certain parts read like a piece originally written in English, but others read like a translation. There are a considerable number of lexical, grammatical or spelling errors.	Adequate	5, 6
Level 2	Transfer undermined by serious inaccuracies; thorough revision required to reach professional standard.	Almost the entire text reads like a translation; there are continual lexical, grammatical or spelling errors.	Inadequate	3, 4
Level 1	Totally inadequate transfer of ST content; the translation is not worth revising.	The candidate reveals a total lack of ability to express himself adequately in English.	Totally inadequate	1, 2

Procedure

In order to answer the research questions of the present study, after obtaining the most appropriate business letters and contracts, the researchers inputted them first into Google Translate and then into Grammarly and LanguageTool one by one respectively. Then they compared the final output of the web-based machine translation and post-editing tools of the business contracts with their respective official translation and analyzed the final output of both business letters and contracts according to two widely-accepted reference books. The next step was recognizing the errors and classifying them and then assessing the translation quality level of the final output according to Christopher Waddington's Model C. Some samples are presented in the following part.

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Table 1. Sample of analysis

No.	Persian contracts	Machine Output	Errors	Type of errors
1	**۲- موضوع تفاهم‌نامه:** همکاری بازرگانی-تجاری و فنی شامل بازاریابی، تبلیغات، فروش و ارائه خدمات پس از فروش محصولات طرف اول توسط طرف دوم در کشور .... و همسایگان آن می‌باشد. همچنین طرف دوم پذیرفت که در ابتدا برای تسهیل در امر بازاریابی یک دستگاه .... به عنوان نمونه طبق پیش فاکتور شماره ...... پیوست خریداری نموده وجه آن را حداکثر ۶ ماه پس از تحویل به حساب طرف اول واریز نماید.	**2. The subject of the agreement:** Commercial-business and technical collaboration, including marketing, advertising, sales and after-sales service products first hand by the second party in the country is .... and its neighbors. The two sides agreed initially to facilitate the marketing of a device attached .... for example, the invoice number, purchase it at a maximum of 6 months delivery to the first account deposit.	Service of Of the first party .... - second party - to initially no sense	Prep. Prep./ Word choice Redundant word - Word choice & form – structure sense
	تبصره ۱: طرف دوم باید چک تضمینی به ارزش .... ریال به تاریخ / / که توسط .... به عنوان تأیید ظهرنویسی شده است، قبل از تحویل به طرف اول تحویل دهد و در صورت عدم واریز، فروشنده حق برداشت از حساب خریدار را در تاریخ سررسید خواهد داشت.	**Note 1:** The second side must guarantee the value .... rials Czech Date / / as approved by .... endorsements, before the first delivery to delivery and in case of failure deposit, the seller will be entitled to withdraw from the buyer's account on the maturity date.	party no sense endorsed Extra word no sense failure of transfer	Word choice sense Word choice Redundant word sense Prep.
	تبصره ۲: چنانچه کالای موضوع قرارداد زودتر از ۶ ماه فروخته شود، طرف دوم موظف است حداکثر یک ماه پس از تاریخ معامله وجه آن را به حساب فروشنده واریز نماید.	**Note 2:** If the goods are sold earlier than six months, the second side shall, one month after the date of the transaction means it will be paid to the sellers account.	party no sense	Word choice sense

Examples of Qualitative Data Analysis

In the previous example, the first sentence and the title of Article 1 of the contract have been translated well by Google Translate because of their shortness, but the sense of Paragraph 1.1. has not been conveyed in the target language.

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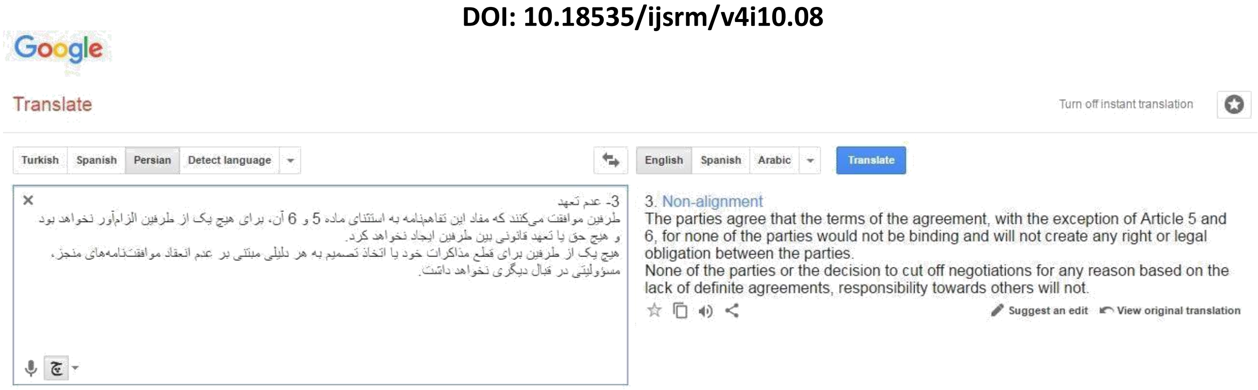
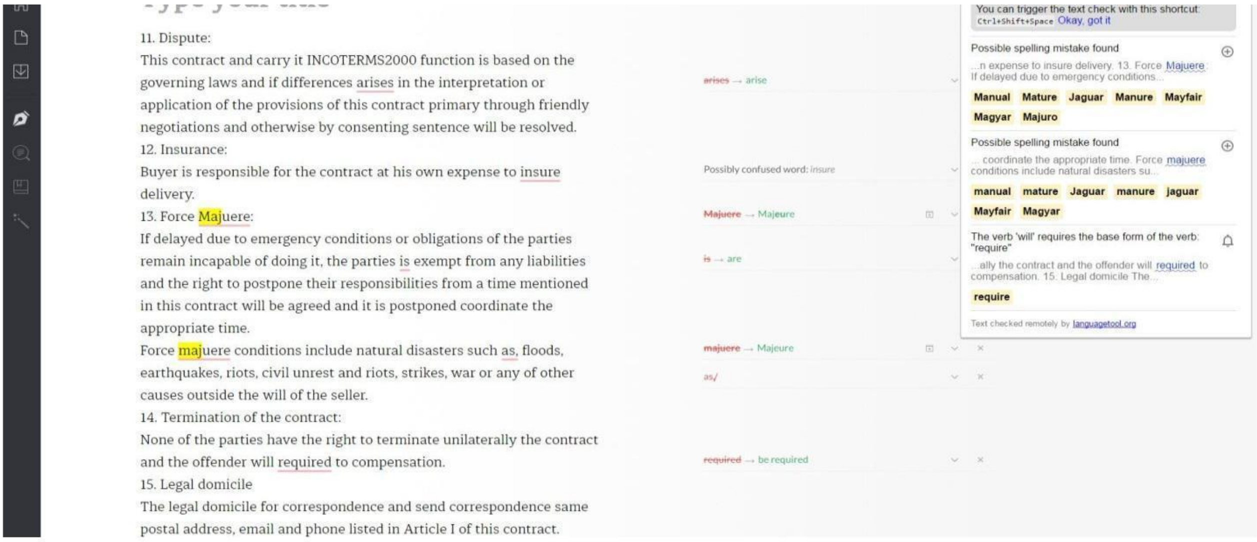


The image above contains continuous structural and grammatical errors and an inappropriate equivalent (Non-alignment for عدم تعهد) that lead to the meaningless translation of the text.



Strength of Post-editors	Weakness of Post-editors
• Disagreement between subject (differences) and verb (arises) • Spelling error (Majuere) • Comma misuse (should be omitted) • Verb form (will required)	• Continuous structural and grammatical errors, inappropriate equivalents and meaningless sentences in the whole passage and the lack of verb in Article 15

Then the frequency of the types of error recognition performed by human and automatic post-editors on the machine translation of business contracts was calculated (table 2). Finally, by using descriptive and inferential statistics, the researchers analyzed the obtained data.

Difference of the Types of Error Recognition Performed by Human and Automatic Post-editors on the Machine Translation of Business Contracts

Recognized by the Post editors		Recognized by the Researcher	
Type of Errors	**Frequency**	**Type of Errors**	**Frequency**
Determiner Use (a/an/the/this, etc.)	8	Determiner Use (a/an/the/this, etc.)	9
Incorrect Noun Number	2	Wrong or Missing or Redundant Preposition	25
Faulty Tense Sequence	3	Punctuation	0
Wrong or Missing Prepositions	1	Spelling	0
Incorrect Verb Forms	0	Word Choice	100
Faulty Subject-Verb Agreement	0	Misspelled Word	10
Misuse of Semicolons, Quotation Marks, etc.	89	Sense	104
Punctuation in Compound/Complex Sentences	6	Incomplete Sentence	5
Comma Misuse within Clauses	5	Misplaced Word or Phrase	14
Commonly Confused Words	1	Structure	96
Misspelled Words	2	Redundant Word	20
Confused Words	6	Missing Word	67
Word Choice	51	Form	14
Wordy Sentences	42	Part of Speech	2
Improper Formatting	16	Subject-Verb Non-agreement	1
Passive Voice Misuse	37	Colloquial Word	1
Unclear Reference	0	Total	468
Inappropriate Colloquialisms	0		
Misplaced Words or Phrases	5		
Incomplete Sentences	1		
Total	269		

According to the previous table, the number of error categories prepared by human and the post-editors is 16 and 20 respectively. The number of errors recognized by human being under some fundamental categories such as "sense", "structure", "word choice" and "missing word" is significantly high, while the frequency of errors detected by the applications under the categories "Misuse of Semicolons, Quotation Marks, etc.", "word choice", "wordy sentences" and "passive voice misuse" is remarkably high. The frequency of other items identified through human and non-human post-editing methods is in a moderate range and in some cases quite similar to each other. However, the total number of faults recognized by human is much higher than the web-based programs.

The analysis of the data obtained from the qualitative part shows that the two automatic post-editing tools can be reliably used when just spelling and punctuation of a text is the main focus of attention. But when the whole structure of sentences and clauses need to be rectified, these tools are incapable of making the main required corrections. In fact, the effectiveness of the function of these two programs in terms of grammatical and lexical amendments is just limited to some minor and superficial suggestions which rarely help the improvement of the nature of a text. However, the number of error categories prepared by human and the post-editors is 16 and 20 respectively. This shows that the faults have been sorted in more detail by the tools. Since the applications are programmed based on a specific framework, when they encounter a certain type of error defined by the programmers, they record it as a fault unconditionally. It is, in fact, the reliable aspect of the nature of the computerized programs. But human being may unconsciously disregard or ignore some errors of a specific kind. In this regard, the performance of the tools is considered to be preferable to human being.

Quantitative Data Analysis

Descriptive Statistics of Business Letters

Comparing General Errors in Machine Translation of the Business Letters from Automatic Post-editor vs. Human's Points of View

General Types of Errors	Automatic Post-editor Recognition	Human Recognition
Grammar	2	11
Punctuation	7	0
Spelling	0	9
Enhancement	17	15
Style	17	77
Sentence Structure	1	3
Total	44	115

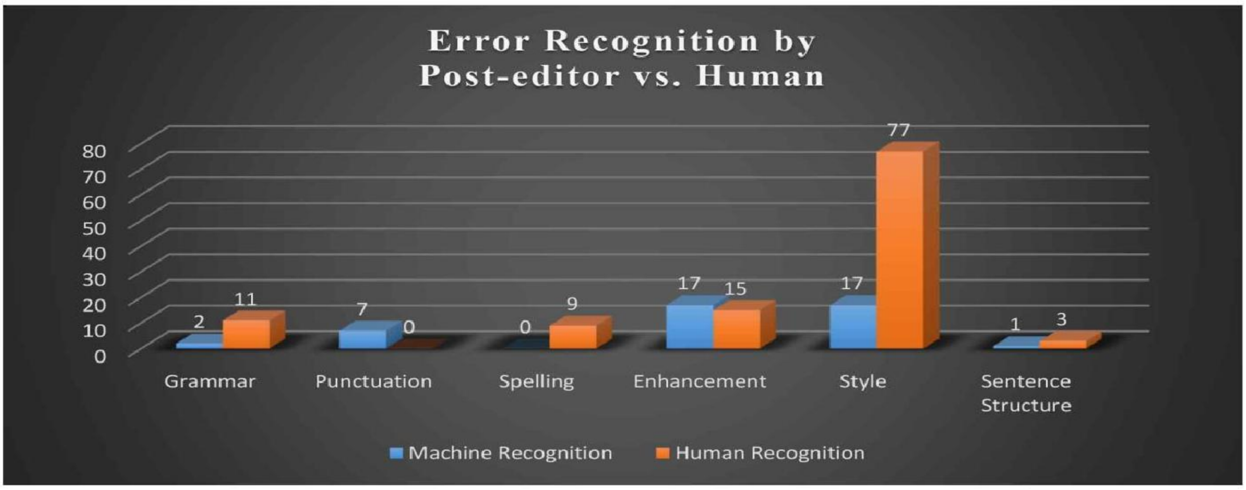


Table 3 and the related figure showed that grammar, spelling and style errors have been detected among general problems more precisely by human being in comparison with the automatic post-editors. But the post-editing tools have been

able to identify 7 punctuation problems which were disregarded by human. The performance of both human and non-human proofreaders is the same in terms of enhancement and sentence structure. However, the total number of faults recognized by human is much higher than the ones detected by the applications.

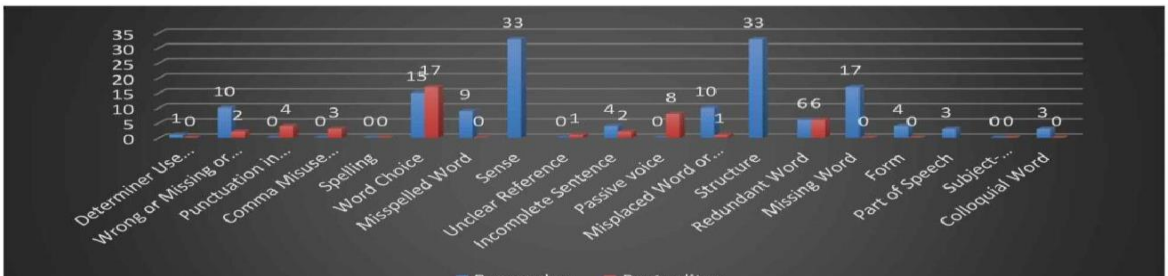
Table 4. Descriptive Statistics of General Errors in Machine Translation of the Business Letters from Automatic Post-editor vs. Human's Points of View

	N	Minimum	Maximum	Mean	Std. Deviation
Machine recognition	6	0	17	7.33	7.866
Human recognition	6	0	77	19.17	28.847
Valid N (listwise)	6				

Table 4 shows that from human's point of view, the general errors in machine translation of the business letters are more than the errors recognized by the automatic post editors. And the scattering of the errors was more than the ones recognized by machine which indicates the ability of human beings in vast linguistic and textual directions

5. Comparing Detailed Errors in Machine Translation of the Business Letters from Automatic Post-editor vs. Human's Points of View

Type of Error	Recognized by the Researcher Frequency	Recognized by the Post-editor Frequency
1. Determiner Use (a/an/the/this, etc.)	1	0
2. Wrong or Missing or Redundant Preposition	10	2
3. Punctuation in Compound/Complex Sentences	0	4
4. Comma Misuse within Clauses	0	3
5. Spelling	0	0
6. Word Choice	15	17
7. Misspelled Word	9	0
8. Sense	33	0
9. Unclear Reference	0	1
10. Incomplete Sentence	4	2
11. Passive Voice Misuse	0	8
12. Misplaced Word or Phrase	10	1
13. Structure	33	0
14. Redundant Word	6	6
15. Missing Word	17	0
16. Form	4	0
17. Part of Speech	3	0
18. Subject-Verb Non-agreement	0	0
19. Colloquial Word	3	0
Total	148	44

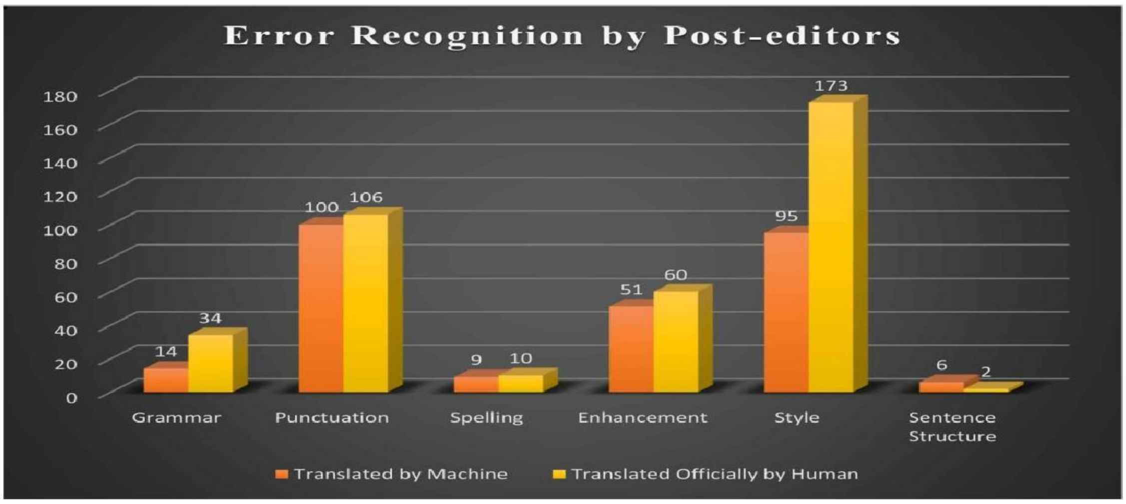


The most frequent errors found by the researchers in the machine translation of the business letters were related to the most fundamental and effective error categories, namely sense, structure, word choice and missing word. Except for some word choice problems, the post-editors were unable to detect any of the faults under the said categories. Even the number of faults discovered by the tools under the other error classes is less in most cases in comparison with the human evaluation. Based on this, the researchers come to the conclusion that the post-editing tools are unable to recognize the extensive syntactic and semantic problems of machine translation. Once again, it should be emphasized that the tools were used on the business texts with the specific characteristics to reach a higher degree of translation quality.

Descriptive Statistics of Business Contracts

Table 6. General Evaluation of the Machine and Official Human Translations through the Post-Editing Tools

General Types of Errors	Translated by Machine	Translated Officially by Human
Grammar	14	34
Punctuation	100	106
Spelling	9	10
Enhancement	51	60
Style	95	173
Sentence Structure	6	2
Total	275	385



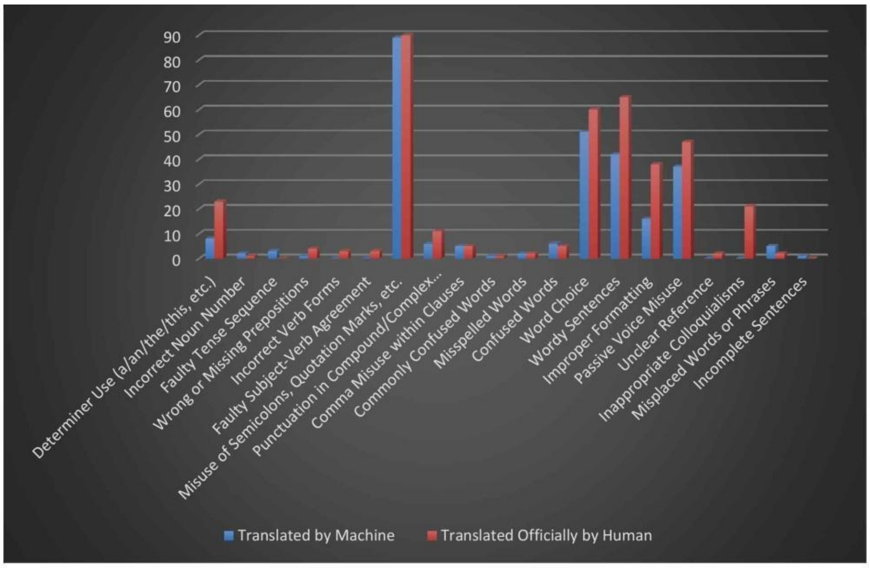
The previous table and figure showed that the errors recognized by the automatic post-editors under the categories “punctuation”, “spelling”, “enhancement” and “sentence structure” are more or less equal in both machine and official human translations in terms of their frequency. But the number of faults under the categories “grammar” and “style” in the official human translation is apparently higher than the machine translation. Therefore, the total number of problems recognized by the applications in the official translation is seemingly higher than the ones found in the machine translation.

Table 7. Descriptive Statistics of General Evaluation of the Machine and Official Human Translations of the Business Contracts through the Post-Editing Tools

		Minimum	Maximum	Mean	Std. Deviation
Translated by machine		6.00	100.00	45.8333	43.20841
Translated officially by human		2.00	173.00	64.1667	65.30059
Valid N (listwise)					

As it can be seen, the mean and standard deviation of the general errors in machine vs. human translation which were indicated by the automatic post-editors show that the human translation has seemingly more errors and the dispersion among the errors are apparently more (65>43).

Detailed Evaluation of the Machine and Official Human Translations of the Business Contracts through the Post-Editing Tools



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Detailed Evaluation of the Machine and Official Human Translations of the Business Contracts through the Post-Editing Tools

Specific Type of Errors	Recognized by Automatic Post-editors	
	Translated by Machine	Translated Officially by Human
Determiner Use (a/an/the/this, etc.)	8	23
Incorrect Noun Number	2	1
Faulty Tense Sequence	3	0
Wrong or Missing Prepositions	1	4
Incorrect Verb Forms	0	3
Faulty Subject-Verb Agreement	0	3
Misuse of Semicolons, Quotation Marks, etc.	89	90
Punctuation in Compound/Complex Sentences	6	11
Comma Misuse within Clauses	5	5
Commonly Confused Words	1	1
Misspelled Words	2	2
Confused Words	6	5
Word Choice	51	60
Wordy Sentences	42	65
Improper Formatting	16	38
Passive Voice Misuse	37	47
Unclear Reference	0	2
Inappropriate Colloquialisms	0	21
Misplaced Words or Phrases	5	2
Incomplete Sentences	1	0

The result showed seemingly a slightly higher number of faults in the human translation, especially under some categories. In this regard, the researchers conclude that the formal and definite structure and wording of the business letters and contracts have not been properly defined for the web-based programs. Therefore, when the tools encounter unfamiliar words and grammatical rules which may not be commonly used in the routine discourse, they regard them as errors and faults. This conclusion is supported when it is taken into account that the official and authentic human translations, like those used for assessment of the present corpus, are widely accepted and used in the international level. The above facts, therefore, have made the researchers deduce that in machine translation programming, the linguistic-based approach should be replaced with

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the text-based approach. At the present time, the machine translation and post-editing tools cannot distinguish the appropriate manner of writing or translating within a definite type of context. The researchers think that the possibility of choosing the type of context should be embedded in the applications.

Table 9. Descriptive Statistics of the Specific Type of Errors of the Machine and Official Human Translations of the Business Contracts through the Post-Editing Tools

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Translated by machine	20	89.00	.00	89.00	13.7500	23.32353
Translated officially by human	20	90.00	.00	90.00	19.1500	26.58903
Valid N (listwise)	20					

As it can be seen, the mean and standard deviation of the specific type of errors in machine vs. human translation which were indicated by the automatic post-editors show that the human translation has seemingly more specific errors and the dispersion among the errors are somehow more (26>23).

Inferential Statistics for Testing the Null Hypotheses

T-Test for Finding the Difference between the Mean of Errors Recognized by the Post-editors vs. Human in Machine Translation of Business Letters

Table 10. Descriptive Statistics of One-Sample: Machine vs. Human Recognition

	N	Mean	Std. Deviation	Std. Error Mean
Machine recognition	6	7.33	7.866	3.211
Human recognition	6	19.17	28.847	11.777

Table 11. Difference between Means of the Errors Recognized by Automatic Post-editors vs. Human

Difference between Means of the Groups	Observed t	df	Critical t Probability level			Difference
				95%	99%	Tobserved>Tcritical
				α=0.05	α=0.01	
Automatic Post-Editor Recognition vs. Human Recognition	2.284	5	One tailed distribution	2.015	3.365	Yes
	1.627	5	Two tailed distribution	2.571	4.032	No

Since the observed t is greater than the critical t at the probability level of 95%., therefore, the researchers can conclude that there is a significant difference between the error recognition performed by the automatic post-editors and human being. But since the same result has not been repeated at the other level of significance and two tailed distributions, the researchers conclude that more data should be processed to come to a more exact conclusion. In this research, at the significant level of α=.05 with the probability level of 95%, the first null hypothesis was rejected and the researchers can claim that it is possible to translate business letters and contracts by using web-based translation tools. However, since these programs have some deficiencies, they should be used under the supervision of a professional translator.

T-Test for the Mean of the Errors Recognized by Post-editors in the Machine Translation of the Business Texts vs. the Human Translation

Table 12. Descriptive Statistics of One-Sample: Machine vs. Human

	N	Mean	Std. Deviation	Std. Error Mean
Translated by machine	6	45.8333	43.20841	17.63976
Translated officially by human	6	64.1667	65.30059	26.65885

Table 13. Difference between Means of the Errors Recognized by Automatic Post-Editors in Machine Translation and Human Translation

Difference between Means of the Groups	Observed t	df	Critical t Probability level			Difference
				95%	99%	Tobserved>Tcritical
				α=0.05	α=0.01	
in Machine Translation vs. Official Human Translation	2.598	5	One tailed distribution	2.015	3.365	Yes
	2.407	5	Two tailed distribution	2.571	4.032	No

Since the observed t is greater than the critical t at the probability level of 95%., therefore, the researchers can conclude that there was a significant difference between the machine translation of the business letters and contracts using Google Translate, Grammarly and LanguageTool and the translation of human translator. But since the same result has not been repeated at the other level of significance and two tailed distributions, the researchers conclude that more data should be processed to come to a more exact conclusion.

Conclusion

In order to answer the first research question, the researchers conducted the required comparisons with the reference materials and assessed the final output of the web-based applications and concluded that Google Translate as a computerized web-based translator and Grammarly and LanguageTool as automatic post-editors produce a translation which is ranked at Level 1, Mark 2 according to Christopher Waddington's holistic method C.

In order to answer the second research question regarding the feasibility of translation of business letters and contracts through Google Translate as the web-based translator and Grammarly and LanguageTool as the automatic post-editors, an inferential statistical analysis was carried out using t-test which indicated that such business texts can be translated by the applications only under the comprehensive supervision of a professional translator.

In order to answer the third research question and decide if there is any significant difference between the machine translation of the above programs and human translation, another inferential statistical analysis was carried out using t-test which showed that there is a significant difference between the two types of translation according to the available data but more data should be evaluated for a more precise conclusion.

It can finally be deduced that translators can provide the machine translation programmers with incomparable feedback about the advantages and deficiencies of different types of machine translation or automatic post-editing tools. This will help the programmers to trace, analyze and rectify the existing faults.

References

Abdul, D. (2013, 10 2). *National Institute of Open Schooling.* Retrieved 12 22, 2015, from National Institute of Open Schooling: old.nios.ac.in/Secbuscour/cc14.pdf

Allen, J. (2003). Post-editing. In H. Somers, *Computers and Translation: A translator's guide* (pp. 297-319). Philadelphia: John Benjamins.

Childs, L. (1999, 02 12). *Support Materials and Exercises for Writing Letters.* Retrieved 12 22, 2015, from National Adult Literacy Database: http://www.nald.ca/CLR/search

Declercq, C. (2015). Editing in translation technology. In C. Sin-wai, *The Routledge Encyclopedia of Translation Technology* (pp. 480-494). New York: Routledge.

DePalma, D. A. (2013, April 30). *Post-Edited Machine Translation Defined*. Retrieved November 24, 2014, from Common Sense Advisory: http://www.commonsenseadvisory.com/AbstractView.aspx?ArticleID=5499

Esselink, B. (2003). Localisation and translation. In H. Somers, *Computers and Translation: A translator's guide* (pp. 67-87). Philadelphia: John Benjamins.

Gamble, J. (2015). *Business Letters Definition*. Retrieved May 02, 2015, from eHow: http://www.ehow.com/list_7535468_10-types-business-letters.html

Garcia, I. (2015). Computer-aided Translation: Systems. In C. Sin-wai, *The Routledge Encyclopedia of Translation Technology* (pp. 68-88). New York: Routledge.

Hardošová, M. (2014). Appropriate Tone in Business Letter Communication. In A. Štulajterová, *Teória a prax prípravy budúcich translatológov a učiteľov anglického jazyka* (pp. 133-137). Banská Bystrica: Vydavate stvo Univerzity Mateja Bela - Belianum.

Hutchins, J. (2001). Machine translation and human translation: in competition or in complementation? *International Journal of Translation*, 5-20.

Hutchins, W. J. (1995). Machine Translation: A Brief History. *Concise history of the language sciences: from the Sumerians to the cognitivists*, 431-445.

Isabelle, P., Goutte, C., & Simard, M. (2007). Domain adaptation of MT systems through automatic post-editing. *MT Summit XI.*

Knight, K., & Chander, I. (1994). Automated postediting of documents. *Proceedings of the Twelfth National Conference on Artificial Intelligence*, (pp. 779-784). Seattle.

Koponen, M. (2012). Comparing human perceptions of post-editing effort with post-editing operations. *Proceedings of the 7th Workshop on Statistical Machine Translation* (pp. 181-190). Montreal: Association for Computational Linguistics.

Newmark, P. (1988). *A TEXTBOOK OF TRANSLATION.* Hertfordshire: Prentice HaH International vUIO Ltd.

Okpor, M. D. (2014). Machine Translation Approaches: Issues and. *International Journal of Computer Science Issues*, 159-166.

Okpor, M. D. (2014). Machine Translation Approaches: Issues and Challenges. *International Journal of Computer Science Issues*, 159-166.

Parton, K., Habash, N., McKeown, K., Iglesias, G., & de Gispert, A. (2012). Can Automatic Post-Editing Make MT More Meaningful? *Proceedings of the 16th EAMT Conference.*

Thomas, C. (2015). *Definition of a Business Contract*. Retrieved 09 22, 2015, from eHow: http://www.ehow.com/about_5054609_definition-business-contract.html

Veale, T., & Way, A. (1997). A Bootstrapping Approach to Example-Based Machine Translation. In N. Nicolov, & R. Mitkov, *International Conference, Recent Advances in Natural Language Processing* (pp. 239-244). Philadelphia: J. Benjamins.

Waddington, C. (2001). Different Methods of Evaluating Student Translations: The Question of Validity. *Meta: Translators' Journal*, 311-325.

Wagner, E. (1985). Post-editing Systran — A Challenge for Commission Translators. *Terminologie et Traduction*.