Compilation and Translation Review
Vol. 14, No. 2 (September 2021), 125-166
DOI: 10.29912/CTR.202109_14(2).0004

Re-Looking Into Machine Translation Errors and Post-Editing Strategies in a Changing High-Tech Context

Chung-ling Shih

This article re-looks into machine translation (MT) errors and proposes a function-oriented MT post-editing (MTPE) typology in a new technological context. Driven by the technological advances of the neural machine translation (NMT) system over the past several years, the author thinks that we should re-examine MT errors created by NMT systems, and understand whether the NMT system can resolve the issues the rule-based MT (RBMT) and statistical MT (SMT) systems have encountered. A mixed-methods approach is used to complete this study, and technical texts, journalistic texts and web-based company texts are chosen as analytical materials. The three-phased procedure consists of (1) cross-checking the differences between source texts (STs), MT outputs and corresponding human translations (HTs) to identify MT errors, (2) proposing a three-tier MTPE typology to supplement the current binary MTPE typology and (3) exploring empirical and theoretical implications of this research. The findings differ from previous MTPE studies in three aspects: (1) amending linguistic, pragmatic and affective MT errors with the strategies of "accurate-enough editing," "clear-enough editing" and "attractive-enough editing," not the strategies of light editing and full editing; (2) replacing the existing editor-driven MTPE typology with a function-driven MTPE typology; and (3) using a progressive, flexible MTPE typology to meet the textual functions of different types of MT texts. Overall, this article re-examines MT errors and MTPE strategies, and raises an alternative MTPE typology from the perspective of textual functions in the framework of the NMT scenario. It expects to add some novel insights to contemporary MT studies.

Keywords: MT errors, MT post-editing (MTPE) strategies, a cross-checking method, a three-tier MTPE typology, textual functions

Received: October 6, 2020
Revised: January 12, 2021, February 19, 2021
Accepted: June 24, 2021

Chung-ling Shih, Professor, Department of English, National Kaohsiung University of Science and Technology, E-mail: clshih@nkust.edu.tw
The author deeply appreciates Taiwan MOST, 108-2410-H-992-006-, for a grant and her research assistants, Ellie, Garry, Johnson, Yen, and Susan, for helping her conduct this research.

編譯論叢
第十四卷　第二期（2021年9月），125—166

高科技變動情境下的再出發——重新審視機器翻譯錯誤和後編輯策略

史宗玲

本論文重新審視新型神經機器翻譯系統產生的翻譯錯誤，並提出功能導向的機譯後編輯類型學。由於近幾年來神經機器翻譯系統的技術大幅進步，作者認為有必要重新檢視神經機譯系統產生的翻譯錯誤類型，以了解是否有所突破與改進。本論文採用混成研究方法，並選擇技術文本、新聞文本及公司網頁為分析樣本。研究過程包含：（1）交叉分析比對原文、機器翻譯及人工譯文之差異，以辨識及歸納神經機譯錯誤類型；（2）提出「三層級的機譯後編輯類型學」，以補充目前二元對立局部與全部機譯後編輯類型學；（3）探討本研究在實證及理論層面所透露的意涵。最終分析結果證實本研究與過去機譯後編研究有三處差異：（1）本論文採用足夠正確、足夠清晰、足夠吸引的三層級機譯後編輯策略，來修正語言、語用及情感的機器翻譯錯誤；（2）本論文提出功能導向的機譯後編輯類型學，不是依照編輯的程度而定；（3）建議採用彈性、漸進式後編輯，俾各種文類的機器翻譯可達成不同的文本功能。簡言之，本研究在神經機譯科技的框架下，從文本功能視角來探究機譯的錯誤類型、後編輯策略，並提出三層級功能導向的機譯後編輯類型學，期能為當代翻譯研究提供一些嶄新的洞見。

關鍵詞：機器翻譯錯誤、機器翻譯後編輯策略、交叉分析方法、三層級後編輯類型學、文本功能

收件：2020 年 10 月 6 日
修改：2021 年 1 月 12 日；2021 年 2 月 19 日
接受：2020 年 6 月 24 日

史宗玲，國立高雄科技大學應用英語系教授，E-mail: clshih@nkust.edu.tw。

Introduction

Driven by the technological advances of the neural machine translation (NMT) system[1] over the past several years, web audiences have increasingly used online machine translation (MT) systems and web-based MT Apps to help reduce cross-border and inter-lingual communication barriers. This promising hope and optimistic wish is, however, damaged after the unsatisfying quality of MT outputs is shortly found. MT errors remain discovered, varying with different text types and different language pairs. However, according to the diagram of multi-lingual translations in an online report (TechOrange, 2016), Google NMT's English (En)-Chinese (Ch) translation quality has improved about 58% and English-Spanish translation quality has improved about 87% when compared to Google's phrase-based MT (PBMT).[2] In a joint study, Brussel et al. (2018) investigated some English-Dutch MT errors, including mistranslation, omissions, untranslated words, addition, omission and mechanical errors. Their findings showed that rule-based MT (RBMT)[3] produced 1,309 errors; Google's PBMT, 741 errors, and Google's NMT, 472 errors. Thus, NMT performs better than RBMT and PBMT.

The above information triggered the author's curiosity, so she conducted a small-scale research by comparing the MT outputs produced by RBMT, statistical

---

1 The online NMT systems have improved their translation quality over time using the techniques of artificial intelligence.

2 The PBMT system finds the matched phrases of the highest probability from the corpus that saves millions of bilingual phrase-pairs (Cheng, 2008). The statistical MT (SMT) system finds the match of the segments of the highest probability from bilingual translation corpuses and combines the extracted target-language fragments into a translation sentence (Cheng, 2008).

3 The RBMT system builds a parallel corpus of dictionary and grammatical rules to generate translations. Later, knowledge of neither grammar nor syntax is required, and statistical techniques to measure the highest probabilities for target language (TL) strings or phrases are used to develop the SMT system (Koehn, 2009; Stix, 2006).

MT (SMT) and NMT systems. One English sentence, "We welcome the new year with a renewed spirit and enthusiasm," was translated by the RBMT system (TransWhiz) as "*Women huanying xin de yi nian yi xin de jingshen he reqing* 我們歡迎新的一年以新的精神和熱情" (Shih, 2006, p. 112). The MT error is the use of incorrect word order. In Luo's (2014) article, "The AFS ECU receives signals indicating the height of the vehicle from the rear height control sensor" was translated by the SMT system (*Huajian* 華建) as "*AFS ECU shoudao xinhao cong hou gaodu kongzhi ganceqi zhuming cheliang de gaodu* AFS ECU 收到信號從後高度控制感測器注明車輛的高度" (p. 116). The error of incorrect word order remained detected in the SMT output. However, when the two sentences were translated using Google's NMT system, their automated translations were correct: "*Women yi xin de jingshen he reqing huanying xin de yinian* 我們以新的精神和熱情歡迎新的一年" and "*AFS ECU cong hou gaodu kongzhi chuanganqi jieshou zhishi cheliang gaodu de xinhao* AFS ECU 從後高度控制傳感器接收指示車輛高度的信號." The above comparison illustrates that the NMT output has improved much in the aspect of word order, but other linguistic aspects need to be explored. The above two sentences are short, so it remains a question whether long sentences can be handled accurately by the NMT system. The author also wonders if the NMT system can resolve some issues that cannot be resolved by RBMT and SMT systems. To find answers to above questions, the author conducted the present research and investigated NMT errors through the analysis of the En-Ch and Ch-En MT outputs of technical, instructional, journalistic and web-based company texts. Some MT post-editing (MTPE) strategies are also proposed to amend the NMT errors.

Much literature has been devoted to MT errors. It mainly features: (a) analysis of the machine-produced translations from English into other Indo-European or Romance languages, not En-into/from-Ch MT outputs, (b) use of MT outputs produced by RBMT or SMT systems, not by the NMT system, and (c) analysis of MT samples of technical and informative texts, not non-technical, evocative and hybrid types of texts. Depraetere's (2010) MT study used English-to-French MT texts; Belam's (2003) MT study used German-to-English MT texts. Regarding the MT systems used to handle En-Ch translations, Shih's (2006) MT examples were produced by TransWhiz, an RBMT system, developed by OTek company in Taiwan. Luo's (2014) MT examples were produced by an SMT system, developed by Huajian company in China. As to the text types of En-Ch translations, Yang's (2018) study used user's manuals for 3C devices; Zhang and Zhang (2018) used a book of biological science; Shih (2006) used product instructions and user's manuals. All the analytical MT errors were collected from a single type of MT texts produced by RBMT or SMT systems.

On the other hand, much attention has been dedicated to MTPE study. MTPE strategies are discussed in a binary form—light editing and full editing (Flanagan & Christensen, 2014; Massardo et al., 2016). Much-discussed literature puts its focus on the editor's effort to achieve the binary function of translation products—to publish or not to publish. The binary typology revolves around two MTPE types: light editing for inbound translation and heavy editing for outbound translation. However, MT accuracy produced by the NMT system has improved and the NMT system can be used to handle the translations of non-technical texts, such as journalistic texts and company web texts, so we may start to explore the variation in MTPE strategies across text types in terms of different textual functions. We can explore how MTPE strategies are used to achieve the textual functions of different types of MT texts.

Moving towards a new direction, this research analyzes En-into/from-Ch MT errors that are produced by Google NMT (GNMT) system. It also explores to what extent Ch-En GNMT errors differentiate from En-Ch GNMT errors across different types of texts. The author also proposed a host of MTPE strategies and remodeled the existing binary MTPE typology using a more flexible model to meet desirable purposes of different types of MT texts. Thus, this research unfolds on three thematic routes: re-identifying MT errors produced by the GNMT system and proposing corresponding MTPE strategies, remodeling the current MTPE typology, and exploring empirical and academic significance of this research.

To guide the investigation, three research questions are raised:

1. What are common MT errors produced by the GNMT system and what MTPE strategies can be used to amend the errors?
2. How can the existent MTPE typology be modified from the perspective of textual functions?
3. What are practical and theoretical implications of this research?

Analyzing En-Ch MT outputs of various text types produced by Google Translate allows us to identify whether MT errors produced by the NMT system are different from those found in RBMT or SMT outputs and understand whether the NMT system can resolve the issues SMT and RBMT systems have encountered. Re-looking into MT errors and re-modeling MTPE typology aims to relax the binarism of the existing MTPE typology and invests it with more flexible and progressive features.

Literature Review

Since this research addresses MT errors and MTPE strategies, some relevant literature will be reviewed. Notably, some articles on MTPE deal with the benefits of translation productivity and efficiency (Arenas, 2009; Carl et al., 2011; Koehn, 2012; Zhechev, 2012), but this research focuses on the literature addressing MTPE types and strategies (Belam, 2003; Depraetere, 2010; Doherty & Gaspari, 2013). More details are provided as follows.

MT Errors

In Kliffer's (2008) survey, the criteria for analyzing MT errors include: (a) agreement (e.g., incorrect morphological concord between subject and verb), (b) anaphora (e.g., lack of object pronoun), (c) article (e.g., use of definite article when not necessary), (d) literal (word-for-word translation), (e) mistranslation (e.g., carless translation), (f) omission (e.g., missing content words/noun, verb, adjective, adverb), (g) preposition (e.g., incorrect or missing preposition), (h) punctuation (e.g., lack of a comma), (i) spelling (a typo error), (j) structure (syntactic errors), (k) tense (incorrect verb tense or mood), (l) word choice (e.g., error in polysemy or homonymy), and (m) words order (e.g., failure to invert subject and communication verb). The findings show that ambiguous and synonymous words are most common English-French MT errors produced by the Power Translator Pro (PTP) system. Niño's (2008) study probes four domains of MT errors: vocabulary, grammar, discourse and spelling. He provides a number of assessment items for each domain. For example, vocabulary errors include "mistranslated proper noun, different meanings, nonsense, wrong sense, false friend, collocation/idiom, words not interchangeable in context, and incorrect cultural equivalent" (p. 48).

Luo (2014) analyzes En-Ch MT errors, covering noun phrases, verb phrases, prepositional phrases, infinitive phrases, and participle phrases. Her findings show that MT error of prepositional phrases account for the highest percentage (13.3%) with noun phrase (6.95%) as the second highest, and infinitive phrase (1.45%) as the lowest. In her study of En-Ch MT errors, Shih (2006) analyzes MT outputs of technical texts and has identified some common MT errors in the lexical-semantic aspect: (a) mistranslated homonyms (multi-meaning words; e.g., the word "charge") and homographs (words whose spellings are the same but whose pronunciations and meanings are different; e.g., the word "live"), (b) mistranslated subject-specific lexical items, (c) mistranslated proper nouns (e.g., the names of companies), (d) mistranslated idioms, metaphors and colloquial expressions. In the syntactic/grammatical aspect, Shih (2006) also identifies some frequently occurring MT errors, including (a) mistranslated long compound nouns, noun groups or compound subjects (e.g., "Use of controls, adjustments and performance of procedures other than specified herein"), (b) mistranslated "that"/"which"-led relative clauses, (c) incorrect word order resulting from mistranslation of prepositional phrases, (d) mistranslated passive voices, (e) mistranslated articles, (f) mistranslated past participles, (g) mistranslated infinitive-led phrases, (h) mistranslated negative auxiliaries and (i) mistranslated verb phrases.

In their error analysis of English-Spanish and En-Ch MTs of the source texts (STs) collected from European Parliament Sessions corpora and broadcast news corpora, Vilar et al. (2006) find that common MT errors included missing words, incorrect word order, incorrect-meaning words, unknown words, and incorrect punctuation marks. The preceding error analyses use the MT outputs of technical texts produced by the RBMT systems or/and SMT systems. In a different manner, this research reinvestigates MT errors using the MT outputs of technical, journalistic and web-based company texts produced by the GNMT system.

Literature on MTPE Strategies

MT errors need to be fixed following some MTPE guidelines or/and using appropriate MTPE strategies. Before we review some articles that address MTPE strategies, we can look at how MTPE is defined. According to Melby (1987), MTPE means "the process of revising a translation after the draft translation has been completed" (p. 146). It is also defined as "the adaptation and revision of a machine translation either to eliminate errors which impede comprehension or to make the output like a natural language" (Sager, 1994, p. 327). For some scholars

(Allen, 2003; Veale & Way, 1997), MTPE refers to human linguist/editor's correction of MT or the use of minimal labor to improve MT process (Translation Automation User Society [TAUS], 2010).

Our primary concern with MTPE strategies can be a set of guidelines developed by the TAUS in collaboration with the Centre for Global Intelligent Content (CNGL). Their guidelines for creating good-quality post-editing include the use of semantically correct translation, no need of omitting or adding some information, use of culturally acceptable content, correct spelling, no need to deal with stylistic problems, and no need to restructure sentences for natural flow (TAUS, 2016). When the post-edited output expects to be like human translation, the guidelines involve the use of semantically, syntactically and grammatically correct translations, correct punctuation, correct key terminology, addition or omission of any information, use of culturally acceptable content, correct formatting and a fine style (TAUS, 2016). Loffler-Laurian divides MTPE into fast and conventional types. Fast MTPE requires quick correction of basic MT errors, but conventional MTPE offers slower turnaround with elaborate correction or fine-tuning (Loffler-Laurian, 1994, as cited in Doherty & Gaspari, 2013). Fast MTPE is often used for audiences to get main ideas of the translation, but conventional MTPE is used to publish the translation. Svěrák (2014) claims that the above classification fails to cover all possible MTPE types, so he proposes no MTPE for inbound translation (for personal reference), and uses minimal and full MTPE for outbound translation (for public release and publication).

As aforementioned, many articles address light and full MTPE. The article published by United Language Group (Shofner, 2021) indicates that light MTPE needs to be good enough in accordance with its intended purposes of information scanning or getting the gist of the text (TAUS, 2016). In contrast, full MTPE must be error-free with the human-translation quality (TAUS, 2016). The fully-edited translation also needs to notice consistency in style and terminology (Shofner, 2021). In Depalma's (2013) report, the Common Sense Advisory Inc. has proposed light and full MTPE guidelines using the metrics of the Localization Industry Standards Association (LISA) quality assurance (QA) model. The principles for light MTPE include the amendment of mistranslations, lexical omission, lexical addition, and adherence to domain-specific terminology glossary, use of correct spelling, and terminological consistency. For full MTPE, in addition to meeting the above guidelines, accurate cross-references, correct headers and footers, accurate grammar, semantics, punctuation, spelling, and a register-specific good style need to be used. Furthermore, the post-edited text needs to be in compliance with country-wide wording standards, company standards, and local terms.

Densmer's MTPE guidelines are also divided into light and full types with the former emphasizing accurate facts, terminological consistency, correct grammar, correct semantics, rewriting of confusing sentences, and correction of other MT errors (such as machine-generated unnecessary or extra words) (Densmer, 2014, as cited in Hu & Cadwell, 2016), and the latter, focusing on accurate messages, terminological consistency, appropriate terminology, correct grammar, semantics, punctuation, spelling, modification of incorrect syntactic structure, correct formatting and correction of other MT errors (such as machine-generated unnecessary or extra words). This type of post-edited output assures human translation quality. Furthermore, in a joint study (Massardo et al., 2016), MTPE guidelines are similarly recommended for creating good-enough quality (i.e., light post-MT editing) and human translation quality (i.e., full post-MT editing). These guidelines are the same as those recommended by TAUS (2016).

The preceding literature shows that MTPE strategies recommended for professional translators generally follow the framework of binary division, comprising light MTPE and full MTPE. This division considers the editor's efforts and the degree of editing, but does not attend to the textual functions of different types of MT texts. In addition, existing research on MTPE strategies does not have a classification of mandatory and optional strategies based on their practice. To make up for the shortcomings, this research proposes a "function/audience-oriented MTPE typology" that presents a more flexible MTPE model in the function-driven direction.

Methodology

Collected Data and Development of a Small Parallel Corpus

This research develops one parallel En-to-Ch-translation corpus and one parallel Ch-to-En-translation corpuses to analyze, identify MT errors and infer corresponding MTPE strategies. Each parallel corpus comprises three sub-corpuses with one sub-corpus, containing 45 news reports, 45 web-based company texts and 45 technical texts, and the other two, containing the corresponding MTs (a total of 211,232 words) and corresponding human translations (HTs). The web-based journalistic texts are retrieved from the websites of *NOW News* (https://www.nownews.com/news), *Taipei Times* (https://www.taipeitimes.com/News/lang/archives), *Taiwan News* (https://www.ttv.com.tw/news), *Liberty Times Net* (https://news.ltn.com.tw/news/life/breakingnews), *FTV News* (https://www.ftvnews.com.tw/news) and others; company texts, from the websites of famous companies in Taiwan, including ASUS Company (https://www.asus.com/tw/About-ASUS-History), TSMC Company (https://investor.tsmc.com/chinese/fundamentals), H2O Hotel (http://www.h2ohotel.com.tw/en/about), Trend Micro Company (https://www.trendmicro.com/en_us/business.html), HTC company (https://www.htc.com/tw/about) and others. Technical texts cover a wider range of topics, such as iPhone's user manual, China airline's instructions and others. Notably, some Chinese news texts are pretty short and their average word count reaches 657. Most of technical, instructional texts and web company texts are longer with the average word count of 840. Thus, the total word counts of 45 journalistic texts and their MTs are lower than those of other two text types. Since this article only measures type/token ratios of MT errors, the size difference among various sets of data would not affect the results. All collected texts are randomly chosen, not targeting at the company web and journalist texts that contain many metaphors and cultural references. The time span for collecting the texts ranges from 2018 to 2021. One important point is that the ratios of MT errors would change when the contents of the collected texts of the same text-type have changed.

The scope of MT data for present analysis has been expanded when compared to the data used in Shih's (2006) study of Chinese MT errors. The data include MTs of texts translated not only from Chinese into English but also from English into Chinese. Furthermore, the data cover not only technical MT texts but also journalistic MT texts and web-based company MT texts. All these MT outputs are produced by online neural Google Translate from 2019 to 2020 because their semantic and grammatical accuracy is better than the MT outputs of online Baidu Translate.

It is difficult to cover all key words and specific grammatical types for inquiries using the concordance function supported by a translation memory tool. Thus, the author did not develop parallel translation memories using Trados or other translation memory tools. All data are saved in digital files using the Microsoft Word system and so it is convenient to cross-check STs, MTs and their corresponding HTs one sentence after another. This way of cross-checking is safer and will not overlook some MT errors though the process is time/energy-consuming. In the process of error analysis, the author worked together with her research assistants. Joint assessment through discussion and views exchange is expected to enhance the validity of evaluation.

Research Methods

A mixed-methods approach is adopted to conduct this investigation throughout three phases. In the initial phase, the author and her three research assistants cross-checked STs, MTs and HTs, and identified MT errors. The cross-checking used semantic, grammatical accuracy as basic-level criteria, target language conventions as middle-level criteria, and emotional touch as advanced-level criteria. If the MT does not meet any of the above criteria, it is identified as an MT error. The type/token ratio is measured to indicate variation of errors in Ch-En and En-Ch MT outputs across three types of texts. Type means the number of each type of MT error; token means the total word count of each MT text. The same word that is mistranslated by Google Translate is only calculated one time no matter how many times it is shown in the entire MT text. After the identification of MT errors, corresponding MTPE strategies are proposed to amend the errors.

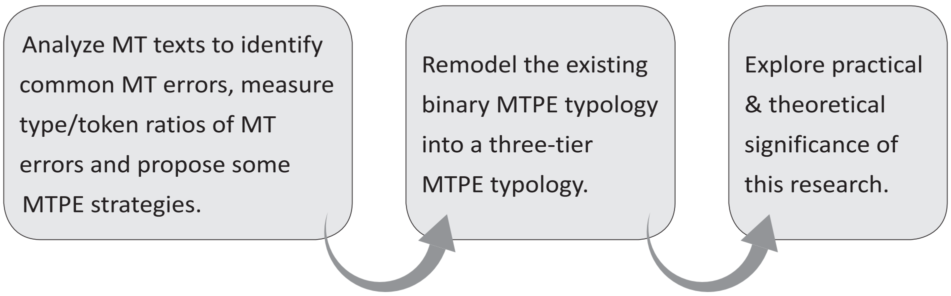
In the second phase, a new MTPE model is proposed to supplement the existing one from the perspective of textual functions of various types of MT texts. The textual functions of technical texts, journalistic texts and company texts are defined based on Reiss's (1971/2000) text typology theory. Reiss proposes the classification of texts into "informative texts which convey information, expressive texts which communicate thoughts in a creative way and operative texts which persuade" (Reiss, 1976, as cited in Hatim, 2001, p. 77). In addition, Reiss (1976) emphasizes that there is a hybrid text that combines the features of two or three text types. Defined from Reiss's (1976, 1971/2000) views, technical, instructional texts are informative texts that aim to inform users of the procedures of operating a device, performing a function, applying for subsidies and relevant others.

Journalistic texts and company texts belong to hybrid texts because they not only report news and introduce company products, but try to catch audiences' attention.

The third phase conducts a probe into the practical and theoretical implications of this research. Figure 1 shows how this research proceeds using the mixed-methods approach:

Figure 1

A Mixed-Methods Approach Adopted to Complete This Research



As demonstrated above, the present research proceeds from an empirical study of identifying NMT errors and proposing MTPE strategies to a theoretical study of exploring empirical and theoretical implications.

Findings and Discussions

This section reports the findings of common types of MT errors through the analysis of MT outputs of technical, instructional, journalistic and company web texts. Subsequent to it is a proposal of corresponding MTPE strategies to amend the NMT errors and the recommendation of an audience-oriented three-tier MTPT typology that serves as an add-on to the existing binary MTPE typology. Finally, the significant implications of this research are discussed.

Re-Identification of MT Errors and MTPE Strategies

Linguistic MT Errors and MTPE Strategies

In reply to RQ1, the findings of cross-checking STs, MTs and HTs show that there are three major types of MT errors produced by Google Translate: linguistic errors, pragmatic errors and affective errors. Notably, the NMT errors that are singled out in the present research are the common ones shown in both Ch-En and En-Ch NMT outputs. The errors of punctuations and quantifiers are not discussed because they are only seen in En-Ch NMT outputs, and orthographic and morphological errors are mostly found in Ch-En NMT outputs.

Linguistic errors mean the language-specific inaccurate translations, including the words without correct meanings, metaphorical expressions without accurate meanings, cultural references without accurate meanings, incorrect grammar and incorrect word order. The list of linguistic NMT errors in the present research are identical with Densmer's (2014) SMT errors of incorrect semantics, inaccurate facts, inaccurate cultural references, incorrect grammar, and incorrect word order. However, they do not include the mistranslations of infinitive, prepositional and noun phrases, as shown in Luo's (2014) study of En-Ch SMT errors. It is a breakthrough for the NMT system to be able to handle the translations of many noun phrases, infinitive-led phrases and prepositional phrases accurately. Additionally, the present research does not find the errors of mistranslated articles, mistranslated past participles, mistranslated infinitive-led phrases and incorrect "wh"/"that"-led phrases in En-Ch MT outputs, but these errors are found in the translations produced by the RBMT system (Shih, 2006). Thus, the NMT system outperforms the RBMT and SMT systems when dealing with the above linguistic features.

To amend the linguistic MT errors, the author proposes some MTPE strategies including: (a) use of words with correct meanings based on the context, (b) adaptation of metaphorical expressions, (c) adaptation of cultural references, (d) use of correct grammar, and (e) use of correct word order. The proposed MTPE strategies are partially identical with Densmer's (2014) full MTPE guidelines of the use of correct semantics, accurate facts, adaptation of all cultural references, correct grammar, and rewriting of confusing sentences with the correct word order. They are also identical with Shih's (2006) MTPE strategies of change of words, change of word order, and Depalma's (2013) MTPE strategies of amending mistranslations, accurate grammar, and accurate semantics. Thus, we know that the current NMT system still cannot translate all words accurately based on the context and produce the correct word order. Nor can it handle the translation of metaphorical and idiomatic expressions accurately without semantic and grammatical errors. Some issues RBMT and SMT systems cannot resolve are still found in the NMT outputs. To illustrate the linguistic MT errors and their MTPE strategies, some examples are provided as Table 1 shows.

Table 1

Examples of Linguistic MT Errors and MTPE

Error/MTPE	Source texts	MT errors	Post-editing
(1) Incorrect words/ (a) Use of accurate words	To find out which features are $\boxed{\text{supported}}$ in your area, see	*Yao liaojie nin suozai diqu* $\boxed{\textit{zhichi}}$ *naxie gongneng, qing canyue* 要了解您所在地區$\boxed{\text{支持}}$哪些功能，請參閱 (lit: To know the functions supported in your area, please see)	*Ruoyao chakan nin de suozai diqu* $\boxed{\textit{zhiyuan}}$ *naxie gongneng, qing canyue* 若要查看您的所在地區$\boxed{\text{支援}}$哪些功能，請參閱 (lit: If you want to check out the functions achievable in your region, please see)

(continued)

Table 1

Examples of Linguistic MT Errors and MTPE (continued)

Error/MTPE	Source texts	MT errors	Post-editing
(2) Incorrect metaphorical expressions/ (b) Adaptation of metaphors	*Ge guo shanggu, zhengyao mingliu, duo ru guojiangzhiji*. 各國商賈、政要名流，多如過江之鯽。(lit: As much as the fish crossing the river.)	The merchants and political figures from all over the world, like the rivers and rivers.	Numerous merchants and political figures from all over the world.
(3) Incorrect cultural references/ (c) Adaptation of cultural references	*Xinbeishi Jiufen laojie jinqi chuxian "jibao" huamian, kan zai luyou renci "xuebeng" de Kending diqu yezhe yan li wuxian xixu*. 新北市九份老街近期出現「擠爆」畫面，看在旅遊人次「雪崩」的墾丁地區業者眼裡無限唏嘘。(lit: Visitors flux into Jiufen old street of New Taipei city, but the number of visitor in Kenting drops like an avalanche. This contrast makes the tourism operators feel much distress.)	The recent "extrusion" scene in Jiufen Old Street, New Taipei City infinitely flawed in the eyes of the tourists in the Kenting area of the tourist avalanche.	The recent tourist "explosion" in Jiufen Old Street, New Taipei City, adds much sorrow to Kenting tourism operators who see the number of tourist visitors to Kenting is plummeting like an avalanche.
(4) Incorrect grammar/ (d) Use of correct grammar	*Dui nan Taiwan juyou buke momie de gongxian.* 對南臺灣具有不可抹滅的貢獻。(lit: For Southern Taiwan, there is indelible contribution.)	Have an indelible contribution to South Taiwan.	Have an indelible contribution to Southern Taiwan.
(5) Incorrect word order/ (e) Use of correct word order or correct syntactic structure	Elite benefits . . . earned after completing 25 eligible stays or 50 eligible nights in a calendar year.	*Zai wancheng 25 ge fuhe tiaojian de zhusu huo zai yi ge rilinian nei wancheng 50 ge fuhe tiaojian de zhusu hou.* 在完成 25 個符合條件的住宿或在一個日曆年內完成 50 個符合條件的住宿後。(lit: After completing 25 eligible stays or in one calendar year completing 50 eligible nights.)	*Zai yi ge rilinian nei wancheng 25 ge fuhe tiaojian de zhusu huo wancheng 50 ge fuhe tiaojian de zhusu hou.* 在一個日曆年內完成 25 個符合條件的住宿或完成 50 個符合條件的住宿後。(lit: In a calendar year, if you complete 25 eligible stays or 50 eligible nights.)

In Example (1), "support" has several meanings, and Google Translate mistranslates it as *zhichi* 支持 without considering the context. This MT error, *zhichi* 支持 (lit: give support), needs to be edited as *zhiyuan* 支援 (lit: back up) and so the meaning of MT can be accurate. Example (2) shows that the metaphorical expression, *duo ru guojiangzhiji* 多如過江之鯽 (lit: as much as the fish crossing the river) is literally mistranslated as "like rivers and rivers." This MT error needs to be edited as "numerous." Example (3) shows that the idiomatic expressions, *kan zai . . . yan li wuxian xixu* 看在……眼裡無限唏噓 (lit: feel upset when looking at . . .) is literally mistranslated by Google Translate as "infinitely flawed in the eyes." This mistranslated cultural reference needs to be edited as "feel helpless and upset." Example (4) shows a grammar error because *nan Taiwan* 南臺灣 should be translated as "Southern Taiwan," not "South Taiwan." In Example (5), *zai yi ge rilinian nei* 在一個日曆年內 (lit: in a calendar year) should be put at the beginning of the sentence, not in the middle of the sentence, so it is the MT error of incorrect word order.

All above examples suggest that despite an overall upgrade in the quality of the NMT outputs, some linguistic errors that are already found in SMT outputs cannot be resolved by the NMT system. Some MTPE strategies proposed for SMT or RBMT errors are needed to edit NMT outputs. Notably, Massardo (2019) claimed that SMT errors were different from NMT ones; the former were predictable and easy to spot but the latter, hard to identify because the fluency of NMT outputs veiled their accuracy. However, the author learned from her MT error analysis that En-Ch MT errors produced either by SMT or NMT systems were similarly easy to identify. Thus, the types of MT errors differ by language pair and content type.

Pragmatic MT Errors and MTPE Strategies

The second type is pragmatic MT errors. According to online Collins Dictionaries (n.d.), the word "pragmatic" means the way of dealing with something based on actual practice, not the theory. In this article, the pragmatic MT errors refer to the incorrect expressions or presentations that do not meet the real conditions or the real circumstances in which the target language is used.[4] In many cases, word-for-word literal translations produced by the NMT system result in redundant, mechanical and incomplete translations, which do not meet the normal way the target audiences use their native languages in daily communication although some of them do not hinder the audiences' understanding of the messages. The pragmatic NMT errors identified in the present research include the use of redundant, mechanical words, inconsistent specialized terms, incomplete sentences, some expressions that do not meet the pragmatic norms of the target language and professional terms that do not meet the terminological convention of the target language. These pragmatic errors are identical with Densmer's (2014) SMT errors of inappropriate terminology, extra words, confusing sentences and Depalma's (2013) SMT errors of redundant words, incomplete information, and incorrect domain-specific terminology that do not comply with local linguistic presentations. Thus, we know that the current NMT system still cannot resolve some pragmatic issues that cannot be resolved by the SMT system. However, SMT errors analyses

4 Halliday (1978), and Halliday and Hasan's (1985) register theory can be used to explain why it is important to identify pragmatic MT errors. According to Halliday (1978), and Halliday and Hasan (1985), speakers need to consider three variables—tenor (audience), field (subject matter) and mode (manner of presentation) for effective communication. All thematic messages must be appropriately presented by addressors to meet the way addresses expect to get the information. Only when the content of communication is contextually relevant to the audience's cognitive assumptions, can it be easily understood by the audience. Thus, when an automated translation produced by Google Translate cannot comply with the linguistic conventions of a certain genre used by target audiences in their real communication situations, it can be identified as a pragmatic error.

conducted by some Chinese scholars (Li & Zhu, 2013; Zhao & Liu, 2014) did not discuss the pragmatic errors. One major reason is that their samples are limited to technical texts, not including company web texts and journalistic texts.

To amend the pragmatic errors, some MTPE strategies are recommended, including (f) elimination of redundant, mechanical and repetitive words, (g) use of consistent words, (h) supplementation of additional words or information, (i) rewriting or paraphrasing of the entire clause or sentence, and (j) use of well-established, register-specific terms of the target language. The recommended MTPE strategies are identical with Densmer's (2014) MTPE guidelines of terminological consistency, correction of machine-generated unnecessary or extra words, and rewriting of confusing sentences. The strategies are also similar to Depalma's (2013) MTPE strategies of lexical omission and lexical addition, and Shih's (2006) MTPE strategies of adding words, "restoring implicit information" and using "pragmatically-appropriate phrases" (pp. 121, 125). Table 2 shows some examples of pragmatic MT errors and their MTPE strategies.

Table 2

Examples of Pragmatic MT Errors and MTPE

Errors/MTPE	Source texts	MT errors	Post-editing
(6) Redundant words/ (f) Elimination of redundant words	*Women* *buduan di* *tansuo weizhi de fanchou,* *chixu* *tupo xianzhi.* 我們不斷地探索未知的範疇，持續突破限制。 (lit: We continue exploring the unknown areas, and continuously make some breakthroughs.)	We continue to explore the unknown, continue to break through the limits.	We continue to explore the unknown, break through the limits.

(continued)

Table 2

Examples of Pragmatic MT Errors and MTPE (continued)

Errors/MTPE	Source texts	MT errors	Post-editing
(7) Lexical inconsistency/ (g) Use of consistent words	Otherwise, the buttons control the volume for the ringer, alerts, and other sound effects. Lock the ringer and alert volumes.	*Fouze, anniu jiang kongzhi lingsheng, jingbao he qita yinxiao de yinliang. Suoding lingsheng he tixing yinliang.* 否則，按鈕將控制鈴聲，警報和其他音效的音量。鎖定鈴聲和提醒音量。(lit: Otherwise, buttons will control the volume of the ringer, alert and other sounds. Lock the ringer and the alert volume.)	*Fouze, anniu hui kongzhi lingsheng, tishisheng he qita yinxiao de yinliang. Suoding lingsheng he tishisheng yinliang.* 否則，按鈕會控制鈴聲、提示聲和其他音效的音量。鎖定鈴聲和提示聲音量。(lit: Otherwise, the buttons controls the volume for the ringer, alert and other sound effects. Lock the ringer and alert volumes.)
(8) Incomplete sentences/ (h) Adding words or information	From weddings to meetings to family reunions.	*Cong hunli dao huiyi zai dao jiating juhui.* 從婚禮到會議再到家庭聚會。(lit: From weddings through meetings to family reunions.)	*Bulun shi hunli, huiyi naizhiyu jiating juhui jie shiyong*. 不論是婚禮、會議乃至於家庭聚會皆適用。(lit: We meet your demands from weddings, meetings to family gatherings.)
(9) Expressions without meeting the pragmatic norms of target language/ (i) Rewriting or paraphrasing	If a standard room is available, it's yours.	*Ruguo you biaozhun fangjian, na shi ni de*. 如果有標準房間，那是你的。(lit: If there is any standard room, that is yours.)	*Ruo you biaozhun kefang, women jiu hui wei nin baoliu*. 若有標準客房，我們就會為您保留。(lit: If there is any standard room, we will reserve it for you.)
(10) Professional terms without meeting the linguistic convention of the target language/ (j) Use of well-established, register-specific terms of the target language	Please request the agency to affix the stamp on this warranty card.	*Qing yaoqiu dailishang zai ci baoxiuka shang gaizhang.* 請要求代理商在此保修卡上蓋章。(lit: Please ask the agent to put their stamp on the maintenance -repair card.)	*Qing yaoqiu jingxiaoshang zai ben baoguka gaizhang.* 請要求經銷商在本保固卡蓋章。(lit: Please ask the agent to put their stamp on the warranty card.)

Example (6) shows that "continue" is used two times in the English MT output. The correct English writing will not use that way of presentation, so the second "continue" can be omitted. In Example (7), the first "alert" is rendered as *jingbao* 警報 (lit: an alarming call) and the second "alert" as *tixing* 提醒 (lit: reminding). This terminological inconsistency might cause audiences to be disoriented and view both "alerts" as two different things. The translation of the same professional terms should be kept consistent through the entire MT output. In Example (8), the Chinese MT output, *cong hunli dao huiyi zai dao jiating juhui* 從婚禮到會議再到家庭聚會 (lit: from wedding through meeting to family gathering), cannot communicate the message clearly. The words *jie shiyong* 皆適用 (lit: fit all) should be added to make the revised MT sentence communicate clearer meanings. In Example (9), "it's yours" is literally rendered as *na shi ni de* 那是你的 (lit: that's yours) without conveying a clear message. This error can be edited as *women jiu hui wei nin baoliu* 我們就會為您保留 (lit: we will reserve it for you). Example (10) shows that "warranty card" is translated as *baoxiuka* 保修卡 (lit: the maintenance-repair card). Native speakers in mainland China are familiar with the professional term, but many Taiwanese are not. Since the automated translation does not meet the register-specific norms in Taiwan, it is identified as a pragmatic MT error and needs to be edited as *baoguka* 保固卡 (lit: the warranty card). Many native Taiwanese audiences can understand the meaning of *baoguka* 保固卡 easily.

The above examples suggest that pragmatic MT errors occur because the GNMT system cannot automatically omit repeated words, and cannot keep terminological consistency. Nor can it add words to explicate the implicit meanings of messages and cannot adapt some segments or clauses to meet the pragmatic norms of the target language. It cannot also choose right expressions to meet the linguistic conventions of a specific discipline in the target language. These issues have been discovered in the SMT outputs (Densmer, 2014; Depalma, 2013) and RBMT outputs (Shih, 2006). The advanced NMT system still cannot find good solutions. One point worth notice is that Shih's (2006) En-to-Ch RBMT samples used short sentences, so she did not propose the MTPE strategies of paraphrasing entire segment/clause and using consistent professional terms.

Affective MT Errors and MTPE Strategies

Often overlooked but notable are affective MT errors. This type of MT errors happens due to the lack of an emotional appeal. We all know that incompetent human translators have the difficulty creating an emotional touch in their translations. The author's emphasis on this type of MT errors aims to remind post-MT editors that the challenging problem that SMT cannot resolve remains unresolved by the advanced NMT system, which cannot automatically use rhetorical devices to create the aesthetic effect. Nor can it rewrite or adapt the source sentence to help achieve the marketing function. This suggests that despite a huge improvement in its accuracy and fluency, NMT outputs cannot get rid of affective errors. What cannot be done by the NMT system can only be done by human editors. Thus, the author pointed out affective MT errors and proposed some MTPE strategies. She tried to attract people's attention that only humans could edit NMT outputs to achieve the marketing function. However, compared to linguistic and pragmatic MT errors, affective ones have higher error tolerance. The marketing effect of revised MT outputs can be downplayed when the customer does not ask about it.

To fix affective MT errors, we can use some MTPE strategies: (k) rewriting the sentence with a new thematic focus, and (l) using catchy description. Table 3 shows some examples of affective MT errors and MTPE strategies.

Table 3

Examples of Affective MT Errors and MTPE

Error/MTPE	Source texts	MT errors	Post-editing
(11) Lack of emotional appeal without using literary devices/ (k) Rewriting the sentence with a new thematic focus	*HTC yi gegu dingxin de lingdao zhi zi zi zhangshangxing diannao jinru zhihuixing shouji chanye*. HTC 以革故鼎新的領導之姿自掌上型電腦進入智慧型手機產業。(lit: HTC takes the position of a leader by moving into the industry of smart phones from handheld computers.)	HTC has entered the smart phone industry from handheld computers with a new leadership position.	We act as a reformative leader by using smart phones to replace handheld computers.
(12) Inadequate marketing function without sentential rewriting/ (l) Use of catchy descriptions	*Xianzai ze xun zhe tongyang de chuangxin moshi, jinru zhihui lianjie yu xuni shijing de lingyu*. 現在則循著同樣的創新模式，進入智慧連結與虛擬實境的領域。(lit: Now, we move into the area of smart links and virtual reality following the similar innovative paradigm.)	The mobile phone industry is now following the same innovative model and entering the field of smart links and virtual reality.	Now we are moving towards the industry of smart links and virtual reality following the initial innovative model.

In Example (11), the literal MT, "with a new leadership position," does not highlight the role of HTC as an innovative creator. The MT output cannot attract web audiences' much attention because it does not emphasize that HTC is an innovative developer of computing technology. To create an emotional touch or/and persuasive effect, "with a new leadership position" can be paraphrased as "We act as a reformative leader," and is put at the beginning of the sentence. In Example (12), the MT segment, "entering the field of smart links and virtual reality," is not appellative to web audiences because it does not describe HTC as an inventor of digital/smart connections and virtual reality. To catch the audience's attention, "entering the field of smart links and virtual reality" can be edited as "Now we are moving towards the industry of smart links and virtual reality," so it helps promote the status of the company and achieve the marketing function.

The above affective MTPE strategies are identical with Densmer's (2014) MTPE guideline for stylistic appropriateness. This suggests that affective errors have been found in SMT errors. However, the affective MTPE strategies are not suggested by Depraetere (2010) and Belam (2003). One reason is that technical MT texts analyzed in Depraetere's (2010) and Belam's (2003) studies describe only facts and use the functional language. No appellative expressions are used to boost the marketing effect in technical texts. However, the present research investigates MT errors of web-based company texts, so some affective MTPE strategies are proposed to help achieve the marketing function.

A Comparison of MT Errors Across Text Types

Variation of Errors in Ch-En and En-Ch MTs

To show how MT errors vary across text types, type/token ratios are measured. The findings show that in the Ch-En MT outputs, the expressions that do not meet English linguistic conventions take up the highest type/token ratio, 1.26% and 1.40% respectively in technical/instructional texts and journalistic texts. In contrast, the use of incorrect words holds the highest type/token ratio, 1.30%, in web-based company texts.

Chinese instructions often use long sentences, so their English MTs produced through literal translation are odd and awkward, not meeting the conventional English presentations. The same problem about journalistic texts shows that the English MTs of many segments do not present clear meanings and thus need to be paraphrased. Regarding the highest ratio of incorrect words in the English MTs of web-based company texts, a major reason is the use of many boastful, exaggerative words, but these words refer to different things, not what their surface meanings suggest. For example, *zonghe da chang* 綜合大廠 and *qiangshi chengzhang* 強勢成長 are mistranslated by Google Translate as "integrated manufacturer" and "grow strongly." They should be edited as "leading conglomerate" and "grow rapidly."

Table 4 shows the type/token ratios of MT errors in Ch-En MT outputs. "A" stands for technical/instructional texts; "B," company web texts, and "C," journalistic texts. Type (1) represents the MT error of incorrect words; type (2), incorrect metaphors; type (3), incorrect cultural references; type (4), incorrect grammar; type (5), incorrect word order; type (6), redundant, mechanical information; type (7), terminological inconsistency; type (8), insufficient information/incomplete sentences; type (9), the expressions that do not meet the linguistic conventions of a target language; type (10), incorrect professional terms

Table 4

The Type/Token Ratios in Ch-En MTs

Ch-En MTs						
Error Type	A		B		C	
Type (1)	460/38,060	1.2%	488/37,488	1.30%	344/29,572	1.16%
Type (2)	3/38,060	0.00%	16/37,488	0.04%	24/29,572	0.08%
Type (3)	28/38,060	0.07%	112/37,488	0.29%	140/29,572	0.47%
Type (4)	188/38,060	0.49%	372/37,488	0.99%	248/29,572	0.83%
Type (5)	28/38,060	0.07%	32/37,488	0.08%	40/29,572	0.13%
Type (6)	116/38,060	0.30%	104/37,488	0.27%	48/29,572	0.16%
Type (7)	20/38,060	0.05%	36/37,488	0.09%	8/29,572	0.02%
Type (8)	132/38,060	0.34%	116/37,488	0.30%	104/29,572	0.35%
Type (9)	480/38,060	1.26%	396/37,488	1.05%	416/29,572	1.40%
Type (10)	140/38,060	0.36%	68/37,488	0.18%	68/29,572	0.22%
Type (11)	8/38,060	0.02%	28/37,488	0.07%	8/29,572	0.02%
Type (12)	1/38,060	0.00%	44/37,488	0.11%	4/29,572	0.01%
Total		4.16%		4.77%		4.85%

or the terms that do not meet the expectation of the target audience; type (11), misplaced focal points; type (12), lack of the rhetorical skills applied to achieve the marketing function.

The overall type-token ratios of Ch-En MT errors in web-based company texts and journalistic texts are similar, 4.77% and 4.85%, which are higher than 4.16% in the technical/instructional texts. The statistical result justifies that the NMT system is better used to translate technical/instructional texts than other two types of texts from Chinese to English.

The results of error analysis of En-Ch MT outputs are also reported. The findings show that the use of incorrect words takes up the highest type/token ratio, 0.95% and 0.86%, in the web-based company texts and journalistic texts. The results are attributable to the use of multi-meaning English words in the English STs. As of today, the advanced NMT system still has the difficulty of handling the translation of the words that have several different meanings. This finding does not deny that the outputs of RMT and SMT do not have the same error. Rather, it highlights that despite a huge improvement in its accuracy and fluency, the NMT system still cannot translate all words accurately based on the context.

Furthermore, the errors of professional terms take up the highest type/token ratio, 0.98%, in the En-Ch NMT outputs of technical, instructional texts. There are two reasons for the result. One is that the current size of professional terms translations is not huge; the other is that Google’s translation corpora store many professional terms used in mainland China, not used in Taiwan. Taiwanese audiences are not familiar with the NMT outputs of professional terms. Table 5 shows the type-token ratios in the En-Ch MT outputs.

Since journalistic texts have an overall lower type-token ratio, 2.95%, than other two types of texts, the NMT system is better used to translate journalistic texts from English into Chinese than technical/instructional and web-based

Table 5

The Type/Token Ratios in En-Ch MTs

	En-Ch MTs					
Error Type	A		B		C	
Type (1)	292/37,916	0.77%	360/37,628	$\boxed{0.95\%}$	264/30,568	$\boxed{0.86\%}$
Type (2)	2/37,916	0.00%	12/37,628	0.03%	8/30,568	0.02%
Type (3)	8/37,916	0.02%	12/37,628	0.03%	72/30,568	0.23%
Type (4)	36/37,916	0.09%	24/37,628	0.06%	40/30,568	0.13%
Type (5)	20/37,916	0.05%	64/37,628	0.17%	64/30,568	0.20%
Type (6)	28/37,916	0.07%	72/37,628	0.19%	100/30,568	0.32%
Type (7)	12/37,916	0.03%	8/37,628	0.02%	8/30,568	0.02%
Type (8)	188/37,916	0.49%	316/37,628	0.83%	100/30,568	0.32%
Type (9)	208/37,916	0.54%	256/37,628	0.68%	216/30,568	0.70%
Type (10)	372/37,916	$\boxed{0.98\%}$	189/37,628	0.50%	36/30,568	0.11%
Type (11)	2/37,916	0.00%	3/37,628	0.00%	8/30,568	0.02%
Type (12)	1/37,916	0.00%	3/37,628	0.00%	8/30,568	0.02%
Total		3.04%		3.46%		2.95%

company texts. However, the overall type-token ratio of technical, instructional texts is similar to that of journalistic texts with the gap of 0.09, so the NMT system is also suited for translating technical texts from English into Chinese. Interestingly, in Luo's (2014) analysis of the En-Ch MT outputs of car repair texts created by the SMT system, the findings show that errors of preposition-led phrases take up the highest rate 13.3%; noun phrases, 6.95%, and infinitive-led phrases, 1.45%. The errors of the above three linguistic features are all higher than the type/token ratio of each type of MT error in the present research. This comparison suggests that no matter what types of errors are produced, the accuracy rate of En-Ch NMT outputs is higher than En-Ch SMT outputs.

To understand better the strength and weakness of NMT systems, we may compare Ch-En and En-Ch type/token ratios. In the Ch-En MT outputs, the overall (A + B + C) ratio is 13.78%, higher than 9.45% in the En-Ch MT outputs. Thus, the GNMT system performs better in the translation from English to Chinese than from Chinese to English. Table 6 shows the gap between Ch-En and En-Ch type-token ratios.

Table 6

A Comparison of Type/Token Ratio Gaps Between Ch-En and En-Ch MTs

Error Types	Ch-En MT		En-Ch MT	Gaps
	A + B + C	Comparison	A + B + C	
Type (1)	3.66%	>	2.58%	1.08%
Type (2)	0.12%	>	0.05%	0.07%
Type (3)	0.83%	>	0.28%	0.55%
Type (4)	$\boxed{2.31\%}$	>	$\boxed{0.28\%}$	$\boxed{2.03\%}$
Type (5)	0.28%	<	0.42%	-0.14%
Type (6)	0.73%	>	0.58%	0.15%
Type (7)	0.16%	>	0.07%	0.09%
Type (8)	0.99%	<	1.64%	-0.65%
Type (9)	3.71%	>	1.92%	1.79%
Type (10)	$\boxed{0.76\%}$	<	$\boxed{1.59\%}$	$\boxed{-0.83\%}$
Type (11)	0.11%	>	0.02%	0.09%
Type (12)	0.12%	>	0.02%	0.10%
Total	13.78%	>	9.45%	4.33%

When each type is assessed, type 9, type 4, and type 1 have higher type/token ratios in Ch-En MT outputs than in En-Ch MT outputs. We can infer that English sentences emphasize grammatical accuracy, but Chinese sentences do not, so the type/token ratio of type 4 is much higher in Ch-En MTs than En-Ch MTs.[5] Furthermore, the literal translations of headline, topics or headings[6] have caused Ch-En MTs to have a higher ratio of type 9. For example, two news topics, *ba da changsuo mei dai zhao zui gao fa 15,000 yuan* 八大場所沒戴罩 最高罰 1 萬 5 千元 and *"Atimisi" dengyue jihua puguang Taiyi taikongren jiang feiwang yueqiu* 「阿提米絲」登月計畫曝光 臺裔太空人將飛往月球 are literally translated by Google Translate as "Eight places without a cover, the maximum fine is 15,000 yuan" and "'Artemis' moon landing plan exposed, Taiwanese astronauts will fly to the moon." The two automated translations are not presented in the ordinary way native English speakers present the messages in their daily communication, so the two MT outputs should be edited as "Failing to wear a mask in public spaces now involves fines of NT$15,000" and "Taiwan-born astronaut chosen for Artemis lunar mission." With regard to the much higher ratio of type 1 in Ch-En MTs, its major reason is that the current NMT system still cannot translate multi-meaning words based on the context.[7]

We cannot overlook type 8 and type 10—the two higher ratios in the En-Ch NMT outputs than in the Ch-En NMT outputs. Since western writing style tends to

---

5 Incorrect English grammar takes up a very high ratio in the Ch-to-En MT outputs. For example, "a" or "the" is not put before a noun accurately and a subject is missing in a clause/sentence. Also, singular or plural nouns and verb tenses are incorrect.

6 The MT system translates Chinese headlines and headings literally without paraphrasing or adapting them, so the English MT output tends to be awkward. The odd, unnatural MT outputs are also produced when NMT system translates a very long Chinese sentence and automatically split it into two or three ones.

7 For example, *jihua* 計畫 can be translated as "plan" or "project," but *hezuo jihua* 合作計畫 must be translated as "cooperative project," not "cooperative plan." However, the translation produced by Google Translate is "cooperation plan."

be concise, literal rendition from English into Chinese easily causes information inadequacy and thus type 8 shows a higher ratio in the En-Ch MT output. The reason for type 10, as aforementioned, comes to be that Google Translate's database of professional terms is built up by collecting many terms from China, not from Taiwan, and native Taiwanese and Chinese speakers use different professional terms. Additionally, the size of the database is not huge.

The above findings suggest that each text type uses specific linguistic components to achieve its textual function and tries to meet the expectations of different groups of target audiences, so its NMT output shows different type-token ratios of errors. Since different types of texts would produce different type/token ratios of MT errors, the efforts put into editing MTs would vary even though the editor's linguistic competence and experiences are the same. Furthermore, the NMT system can produce fewer errors than the SMT system, so MTPE effort for NMT output would be less than for SMT outputs. Some English-Russian professional translators had ranked NMT as more fluent after they post-edited the outputs of PBMT and NMT outputs (Castilho et al., 2017). They claimed that "NMT produced more correct sentences, contained fewer inflectional and word order errors and needed less effective post-edits" (Brussel et al., 2018, p. 3800; Castilho et al., 2017). Thus, MT error variation, which is in large part determined by text types and MT systems, would affect the editor's MTPE efforts.

Remodeling MTPE Strategies

In response to RQ2, this research recommends a function-oriented three-tier MTPE typology as an add-on to the existing MTPE typology. The preceding literature on MTPE strategies emphasizes the efforts taken by post-editors to complete light or full editing. In a different vein, this research focuses on adoption of varied MTPE strategies to help achieve the textual functions of different types of

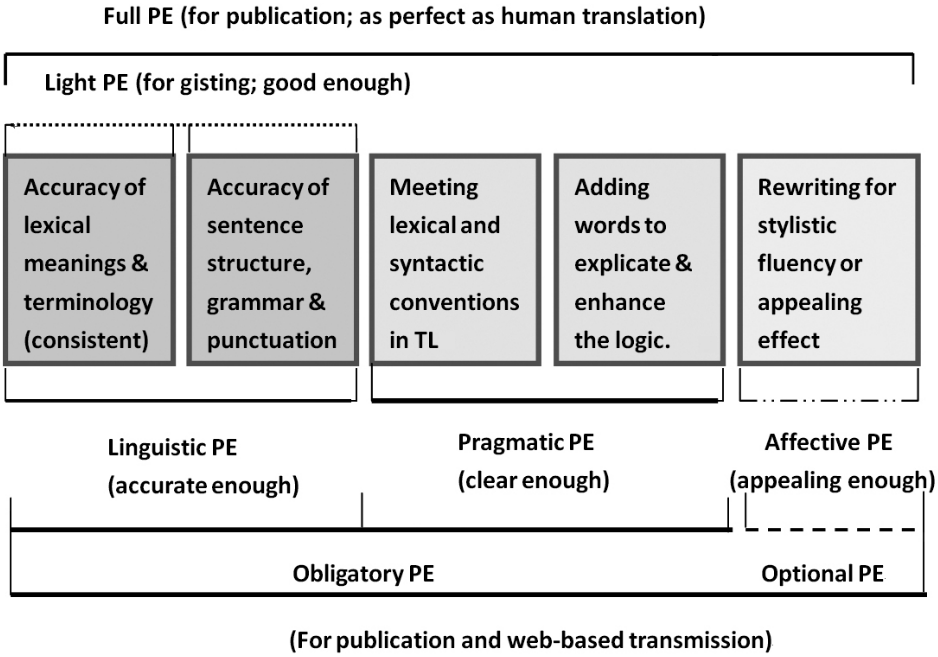
NMT texts. For the product instructions and user's manuals that aim to convey accurate information, the post-edited MT texts need to be semantically and grammatically accurate; for the journalistic texts that aim to present the clear, comprehensible content, the post-edited NMT texts need to be as clear and communicative as possible; and for web-based company texts that aim to inform and attract audiences, the post-edited NMT texts need to be as communicative and appellative as possible. Taking into consideration varied textual functions of different types of NMT texts, the author proposes using different MTPE strategies to help achieve the goal.

When previous literature on MTPE attends to the editor's efforts, the present research opens up a new path with a focus on the concern of web audiences. After re-investigating the situation where new NMT errors are produced by Google Translate, flexible, progressive MTPE strategies are raised. In practice, MTPE moves from the basic-level (essential) fixation of linguistic errors, through the intermediate-level fixation of pragmatic errors, and further to the advanced-level amendment of affective errors. This framework leads to the up-building of a function-oriented MTPE typology that starts with mandatory linguistic correction, ascends into the mandatory pragmatic modification, and finally arrives at the non-mandatory affective rewriting. The first and second types are mandatory because whatever types of NMT texts need to provide accurate and communicative information. No audiences want to read inaccurate and unclear information. However, the third type is optional, for it aims to enhance the marketing function or/and create emotional, aesthetic value. Figure 2 shows the differences between the three-tier MTPE typology and the binary MTPE typology.

Since current NMT systems have greatly improved the translation accuracy, only basic-level linguistic MTPE is needed for the publication of technical texts. However, journalist texts and company web texts require pragmatic MTPE to

Figure 2

The MTPE Typology: Then vs. Now



produce clear, communicative translations. Affective MTPE helps create an emotional appeal to achieve the marketing function, but it is optional. Due to a great improvement in the recent NMT quality, NMT application may extend to non-technical and hybrid texts. Thus, we need to consider how to edit NMT outputs of different text types to achieve their desired textual functions. A progressive, three-tier MTPE typology helps achieve the objective.

Implications of the Present Research

This article has shed new light on MT and MTPE study. The research implications can be explored from the aspects of re-identifying NMT errors and the corresponding MTPE strategies in a changing high-tech context, use of a poly-

MTPE typology to achieve diverse textual functions, and the expansion of the scope of MTPE strategies.

Re-Identifying MT Errors and MTPE Strategies in a New Context

MTPE strategies need to be re-investigated to understand how to edit the NMT errors. It has been justified that some errors identified in the present research are found in RBMT and SMT outputs, but some errors are not. There are still some issues the advanced NMT system cannot resolve. However, if we compare the automated En-Ch translations of short sentences created by RBMT, SMT and NMT systems, we can immediately find that NMT systems outperform the other two. For example, the English sentence, "Shoulder all the blame for the mistake and face it with no fear," was translated in 2006 by TransWhiz (a RBMT system) as *Jianbang suoyou zebei wei chacuo he lian ta meiyou kongju* 肩膀所有責備為差錯和臉它沒有恐懼 (lit: Use the body shoulder to take all the blame for the mistake and use one's face to touch it with no fear). To amend this MT error, we need to use two MTPE strategies: change of the word order and conversion of nouns into verbs. The two nouns, *jianbang* 肩膀 (lit: shoulder) and *lian* 臉 (lit: face), were edited as two verbs, *chengdan* 承擔 (lit: take the responsibility) and *miandui* 面對 (lit: confront). The original word order was revised by moving *wei chacuo* 為差錯 (lit: for mistakes) and *meiyou kongju* 沒有恐懼 (lit: without fear) to the initial positions of two clauses respectively. Thus, the post-edited sentence was *Wei chacuo chengdan suoyou zebei he meiyou kongju miandui ta* 為差錯承擔所有責備和沒有恐懼面對它 (lit: For the mistake take all the blame and have no fear to face it).

Nowadays, the translation of the same English sentence produced by Google neural MT system in 2020 is *Jianfu suoyou cuowu de zeren, bing haobu kongju di miandui ta* 肩負所有錯誤的責任，並毫不恐懼地面對它 (lit: Take the responsibility for all mistakes and face it fearlessly). This MT sentence is fully comprehensible and so we do not have to correct it. If we want to make it more communicative, we may add words "*ni bixu* 你必須" (lit: you need to) at the beginning of the entire sentence, and so the post-edited sentence is "*Ni bixu jianfu suoyou cuowu de zeren, bing haobu kongju di miandui ta* 你必須肩負所有錯誤的責任，並毫不恐懼地面對它" (lit: You need to take the responsibility for all mistakes and face it fear lessly). Overall, the NMT outputs of shorter sentences in technical texts are better than SMT and RBMT outputs. They only need light editing to achieve the publication purpose, but the SMT or RBMT outputs of technical texts need full-editing. Thus, NMT outputs need to be re-examined to help us understand how far the NMT system has improved.

A Progressive, Three-Tier MTPE Typology

Current MTPE guidelines have a clear-cut division between light and full editing, but do not define clearly what types of MT errors should be amended with what types of MTPE strategies. Depalma (2013) raised the guidelines for the register-specific good style created with language variants and slang, and compliance with country standard, company standard and legal suitability. But, MTPE beginners have difficulty guessing what the country and company standards refer to. Some other MTPE guidelines are oversimplified and inadequate. For example, Depraetere (2010) mentioned that post-editing guidelines cover a change of word order, a change of sentence structure and no waste of time for the style. These guidelines might be too brief to be abided by. In contrast, the MTPE strategies raised in the present article are mapped out step by step, moving from the basic-level fixation of linguistic MT errors to the inter-mediate level modification of pragmatic MT errors and the advance-level amendment of affective MT errors. The three-tier MTPE typology points out three types of MT errors in line with three types of MTPE strategies in a progressive, ascending order.

More Flexible Applications of MTPE Strategies

The existing MTPE typology presented in the binary form of light and full editing emphasizes the scale and efforts of editing. It lacks flexibility because not all text types need to use full MTPE for the purpose of publication. Nowadays, the translations of some technical texts created by the GNMT system have reached the high accuracy level, and only light editing is adequate for publication. Thus, it is risky to cut MTPE strategies into only two types in accordance with the objectives of either publication or non-publication. To make MTPE classification more flexible, the present research proposes the strategies based on different types of MT texts that are intended to achieve different textual functions. Some MTPE strategies can be used to fix NMT errors that mainly occur at lexical, grammatical, syntactic levels, and so the NMT output provides accurate information. Some strategies can be used to amend NMT errors that mainly occur at the pragmatic level, so the MT output presents clear and communicative information. Other strategies are used to amend MT errors that mainly occur at the affective level, so the NMT output delivers attractive, persuasive, attention-catching information. The updated MTPE strategies allow for more flexible applications to meet diverse situations, lifting the functions of NMT products beyond the clear-cut division between publication and non-publication.

Conclusion

Despite a small sample size, this research has revealed its sociological, practical and theoretical significance. The sociological contribution is justified as this research re-examines MT errors and updates corresponding MTPE strategies by using the GNMT system and using samples of technical and non-technical texts, meeting the increasing demand for using the NMT system to translate non-technical texts too in the era of global communication. Practical significance is shown as a more flexible MTPE typology provides mandatory and optional strategies for the editor's consultation when they edit different types of NMT texts. This point means that specific, updated MTPE strategies can be consulted when the NMT outputs of journalistic texts and web-based company texts are asked to be post-edited. Theoretical significance is shed on the proposal of a function-oriented three-tier MTPE typology that supplements the existing editor-oriented binary MTPE typology.

Remodeling the current MTPE typology does not criticize that the existent MTPE typology fails to live up to the function of translation products. All identified NMT errors are not exhaustive and the identification of NMT errors does not deny the absence of the errors in the SMT and RBMT outputs. Instead, it emphasizes that the advanced NMT system still cannot resolve some linguistic, pragmatic and affective issues that cannot be resolved by SMT and RBMT systems. This research simply explores whether new wine is stored in the old MT bottle. If new wine is produced by a new machine in a changing high-tech context, its ingredients should be different and need to be examined again.

References

Allen, J. H. (2003). Post-editing. In H. Somers (Ed.), *Computers and translation: A translator's guide* (pp. 297-317). John Benjamins. https://doi.org/10.1075/btl.35

Arenas, A. G. (2009, August 30). *Productivity and quality in MT post-editing* [Paper presentation]. MT Summit XII-Workshop: Beyond Translation Memories: New Tools for Translators MT, Ottawa, ON, Canada.

Belam, J. (2003, September 27). *"Buying up to falling down": A deductive approach to teaching post-editing* [Paper presentation]. MT Summit IX Workshop on Teaching Translation Technologies and Tools (T^4), New Orleans, LA, United States. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.132.1973&rep=rep1&type=pdf#page=5

Brussel, L. V., Tezcan, A., & Macken, L. (2018, May 7-12). *A fine-grained error analysis of NMT, PBMT and RBMT output for English-to-Dutch* [Paper presentation]. 11th Edition of the Language Resources and Evaluation Conference, Miyazaki, Japan. https://www.aclweb.org/anthology/L18-1600.pdf

Carl, M., Dragsted, B., Elming, J., Hardt, D., & Jakobsen, A. L. (2011). The process of post-editing: A pilot study. *Copenhagen Studies in Language*, *41*, 131-142.

Castilho, S., Moorkens, J., Gaspari, F., Calixto, I., Tinsley, J., & Way, A. (2017). Is neural machine translation the new state of the art? *The Prague Bulletin of Mathematical Linguistics*, *108*, 109-120. https://doi.org/10.1515/pralin-2017-0013

Cheng, S. Y. (2008). Understanding and improving online statistical translation method. *Sino-US English Teaching*, *5*(9), 38-44.

Collins Dictionaries. (n.d.). Pragmatic. In *Collins*. Retrieved December 2, 2020, from https://www.collinsdictionary.com/dictionary/english/pragmatic

Densmer, L. (2014, August 19). Light and full MT post-editing explained. *RWS*. Retrieved August 19, 2014, from https://www.rws.com/insights/rws-moravia-blog/bid-353532-light-and-full-mt-post-editing-explained

Depalma, D. (2013, December). Post-editing in practice. *Tcworld*. https://www.tcworld.info/e-magazine/translation-and-localization/post-editing-in-practice-459

Depraetere, I. (2010, May 27-28). *What counts as useful advice in a university post-editing training context? Report on a case study* [Paper presentation]. EAMT 2010—14th Annual Conference of the European Association for Machine Translation, Saint Raphaël, France. https://aclanthology.org/2010.eamt-1.11

Doherty, S., & Gaspari, F. (2013, December 5). *Effective post-editing in human & machine translation workflows: Critical knowledge & techniques* [PowerPoint slides]. QTLaunchPad. http://www.qt21.eu/downloads/QTLaunchPad-Post-Editing-Webinar.pdf

Flanagan, M., & Christensen, T. P. (2014). Testing post-editing guidelines: How translation trainees interpret them and how to tailor them for translator training purposes. *The Interpreter and Translator Trainer*, *8*(2), 257-275. https://doi.org/10.1080/1750399X.2014.936111

Halliday, M. A. K. (1978). *Language as social semiotic: The social interpretation of language and meaning.* Edward Arnold.

Halliday, M. A. K., & Hasan, R. (1985). *Language, context, and text: Aspects of language in a social-semiotic perspective.* Deakin University.

Hatim, B. (2001). *Teaching and researching translation*. Pearson Education.

Hu, K., & Cadwell, P. (2016). A comparative study of post-editing guidelines. *Baltic J. Modern Computing*, *4*(2), 346-353. https://doi.org/10.13140/RG.2.1.2253.1446

Kliffer, M. D. (2008). Post-editing machine translation as an FSL exercise. *Porta Linguarum*, *9*, 53-67. https://doi.org/10.30827/Digibug.31745

Koehn, P. (2009). *Statistical machine translation*. Cambridge University. https://doi.org/10.1017/CBO9780511815829

Koehn, P. (2012, September 7). *Computer aided translation.* CiteSeerX. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.639.9206&rep=rep1&type=pdf

Li, M., & Zhu, X. M. (2013). Error patterns and statistical analyses of an English-Chinese machine translation corpus. *Journal of University of Shanghai for Science and Technology*, *35*(3), 201-207.

Luo, J. M. (2014). Analyses of syntactic errors in machine translation. *Journal of Tongji University (Social Science Section)*, *25*(1), 111-118, 124.

Massardo, I. (2019, April 16). 5 effective strategies for post-editing MT. *Wordbee*. https://www.wordbee.com/blog/localization-industry/5-effective-strategies-for-post-editing-of-machine-translation

Massardo, I., Meer, J. V. D., O'Brien, S., Hollowood, F., Aranberri, N., & Drescher, K. (2016). *MT post-editing guidelines*. TAUS Signature Editions.

Melby, A. (1987). On human-machine interaction in translation. In S. Nirenburg (Ed.), *Machine translation: Theoretical and methodological issues* (pp. 145-154). Cambridge University.

Niño, A. (2008). Evaluating the use of machine translation post-editing in the foreign language class. *Computer Assisted Language Learning*, *21*(1), 29-49. https://doi.org/10.1080/09588220701865482

Reiss, K. (1976). *Texttyp und übersetzungsmethode: Der operative text* [Text type and translation method: The operative text]. Scriptor Verlag.

Reiss, K. (2000). *Translation criticism—The potentials and limitations: Categories and criteria for translation quality assessment* (E. F. Rhodes, Trans.). St. Jerome. (Original work published 1971)

Sager, J. C. (1994). *Language engineering and translation: Consequences of automation*. John Benjamins. https://doi.org/10.1075/btl.1

Shih, C. L. (2006). *Helpful assistance to translators: MT & TM*. Bookman Books.

Shofner, K. (2021, January). Post editing 101. *United Language Group*. https://unitedlanguagegroup.com/blog/post-editing-101/

Stix, G. (2006). The elusive goal of machine translation. *Scientific American*, *294*(3), 92-95. https://doi.org/10.1038/scientificamerican0306-92

Svěrák, M. M. (2014). *Translator as a text editor: From pen and paper to automated translation* [Master's thesis, Masaryk University]. MUNI. https://is.muni.cz/th/mnqwx

TechOrange (2016, September 29). *No need to learn English anymore; Google Translate introduces neuron-like machine learning; Miss Google is now very smart!* Buzzorange. https://buzzorange.com/techorange/2016/09/29/google-translation-gnmt/

Translation Automation User Society. (2010, November). *MT post-editing guidelines*. TAUS—The Language Data Network. https://www.taus.net/academy/best-practices/postedit-best-practices/machine-translation-post-editing-guidelines

Translation Automation User Society. (2016, January 20). *TAUS post-editing guidelines*. TAUS—The Language Data Network. https://www.taus.net/insights/reports/taus-post-editing-guidelines

Veale, T., & Way, A. (1997, January). *Gaijin: A bootstrapping, template-driven approach to example-based MT* [Paper presentation]. Recent Advances in Natural Language Processing (RANLP 1997), Tzigov Chark, Bulgaria. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.59.1971&rep=rep1&type=pdf

Vilar, D., Xu, J., D'Haro, L. F., & Ney, H. (2006, May 22-28). *Error analysis of statistical machine translation output* [Paper presentation]. 5th Edition of the International Conference on Language Resources and Evaluation (LREC 2006), Genoa, Italy. http://www.lrec-conf.org/proceedings/lrec2006/pdf/413_pdf.pdf

Yang, D. H. (2018). *A comparative study of strategic differences in Chinese-English bidirectional post-MT editing: Use of 3C user manual as samples* [Unpublished master's thesis]. National Kaohsiung University of Science and Technology.

Zhang, J. Z., & Zhang, S. L. (2018). Analysis of online machine translation errors of informative texts. *Overseas English*, *13*, 135-136.

Zhao, H. M., & Liu, Q. (2014, November 4-6). *Common error analysis of machine translation output* [Paper presentation]. The 10th China Workshop on Machine Translation (CWMT 2014), Macau, China. https://doi.org/10.13140/2.1.4160.7360

Zhechev, V. (2012, October 28). *Machine translation infrastructure and post-editing performance at Autodesk* [Paper presentation]. AMTA 2012 Workshop on Post-Editing Technology and Practice (WPTP 2012), San Diego, CA, United States. https://aclanthology.org/2012.amta-wptp.10