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HOW CAN EMOTION-AI HELP UNDERSTAND TRANSLATOR TRAINEES' TECHNOLOGY LEARNING EXPERIENCES?

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Abstract

The present study examines the effectiveness of Sentiment Analysis, also known as Emotion-AI, in analysing translator trainees' learning narratives regarding their experiences with translation memory systems (TMs). Students were asked to describe how they learned and whether the experience was pleasant or unpleasant. The narrative texts were then automatically analysed with Sentiment Analysis, and the emotional component was quantified into a Sentiment score which encompasses both the polarity, i.e., positive vs. negative, and the magnitude (in numerical terms) of emotion. The results showed that narratives about pleasant learning experiences had significantly higher scores than those about unpleasant ones, indicating that Sentiment Analysis can be used to identify learners' emotions while using technology. Our findings suggest that automatic emotion detection tools can be used in combination with human judgments for data triangulation.

Keywords: Sentiment Analysis, translation memory, emotions, human-computer interaction

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1. INTRODUCTION

The translation industry is becoming increasingly dependent on translation technology, and translator trainees must be proficient in a variety of digital tools (Alcina et al., 2007; Doherty & Kenny, 2014; Mellinger, 2017). Multiple translation competence models have also recognized the need to develop technology-related skills (e.g., PACTE, 2003; EMT, 2009, 2017). At first, technology in these models was referred to as digital documentation resources (e.g., dictionaries, corpora, parallel texts) while over the years the scope of technology has been expanded to include translation-specific technology, such as translation memory (TM) suites with machine translation feeds. Most recently, the revised EMT model (2017) recognized that various technologies which are widely used in the industry for managing large volumes of multilingual content are integral parts of the translation process. Consequently, in the face of technological advances and changing industry landscapes, a substantial number of higher-education institutions have begun offering translation-technology courses in their curricula (Rothwell & Svoboda, 2019; Wang et al., 2018; Zhang & Vieira, 2021). Nevertheless, it remains relatively understudied what pedagogical approaches and methods support learners' familiarisation with new technologies (except for Rothwell & Svoboda, 2019; Zhang & Vieira, 2021), as well as how to evaluate systematically their learning progress.

A recent attempt has been made to research cognitive and emotional engagement during the learning process by analyzing narratives elicited from self-reflective writing tasks by student translators (Koskinen & Ruokonen, 2017; Ruokonen & Koskinen, 2017). This letter-writing approach asks translator trainees to compose original and authentic reflections (in the form of a "love" or "hate" letter) concerning their interactions with electronic tools, as well as their pleasant and unpleasant experiences when learning to operate such tools. It has been shown that when conducting these written self-reflections, translator trainees are concerned with multiple aspects of their human-computer-interaction (HCI) experiences (Koskinen & Ruokonen, 2017), including issues related to (1) learnability, e.g., the easiness to accomplish basic tasks, (2) efficiency, e.g., the speed at which tasks can be performed, (3) memorability, e.g., the easiness of re-establishing technical proficiency from a period of not using it, (4) errors, e.g., how to identify, evaluate, and counteract technical errors, and finally, (5) satisfaction, e.g., how much joy or confusion is experienced by the learner during their HCI experiences. It was also reported that trainees' narratives can reveal complex ways in which they engage with the digital tools emotionally: Certain experiences are perceived as being convergent with the learner's agency, and such narratives tend to be emotional positive; on the other hand, when learners perceive their HCI experiences as divergent from their agency, such narratives tend to be negative (Ruokonen & Koskinen, 2017).

However, some methodological concerns require further investigations. It should be noted that in these two previous studies, the emotional colours of learner narratives are primarily determined by the researcher's assessment, and they are defined in discrete and tripartite terms, for example, positive, negative, or ambivalent (Koskinen & Ruokonen, 2017; Ruokonen & Koskinen, 2017). As reported, "love letters" are largely positive in nature, but "hate/break-up letters" tend to be emotionally negative for the most part, while researchers observed that trainees can sometimes adopt a middle ground, showing a complex interplay of both positive and negative emotions. In the current study, we examine a new method for measuring emotional engagement and explore whether emotional colour can be assessed quantitatively and objectively in translator trainees' learning narratives using Sentiment Analysis, a technique that is currently at the forefront of natural language processing (NLP) (Feldman, 2013).

Sentiment Analysis, also known as Emotion AI, is a type of automatic NLP algorithm that is capable of identifying, extracting, and quantifying emotion from text streams without requiring any human intervention (Feldman, 2013). The tool is thus suitable for assessing usability narratives objectively, and it has been widely applied in various research areas such as political opinion mining in social media (Sobkowicz et al., 2012), assessing medical patients' well-being (Denecke & Deng, 2015), and improving teaching environments and educational atmospheres (Rani & Kumar, 2017). In addition to its objectivity, one of the advantages of

Sentiment Analysis is that it provides gradient values (as opposed to discrete labels) for building up an emotional profile of a given text, which enables us to identify and compare not only the emotional polarity (positive or negative) but also its magnitude. Additionally, Sentiment Analysis can evaluate emotional colours at different linguistic levels and can evaluate each sentence in a text, for example. The importance of this feature is apparent since positive and negative emotions can coexist in learners' experiences with HCI (Koskinen & Ruokonen, 2017; Ruokonen & Koskinen, 2017). We aim to replicate the letter-writing task with a group of translator trainees in the present study, and via automatic Sentiment Analysis, to bridge the methodological gap for analyzing the affective component of student translators' narratives. In particular, our research questions (RQs) are:

RQ1: Can Sentiment Analysis effectively identify, extract, and quantify the emotional colour in trainees' learning narratives related to their experiences in HCI? We expect that Sentiment scores will differ significantly between narratives reporting pleasant experiences (i.e., "love letters") and those reporting unpleasant experiences (i.e., "break-up letters").

RQ2: How are positive and negative emotions intermixed in HCI narratives? For example, whether there are negative emotions in reports about pleasant HCI experiences, or positive emotions in reports about unpleasant HCI experiences? We expect these two emotions to be mixed, but the specific proportion should depend on the nature of the narrative ("love letter" vs "break-up letters").

2. METHODS

2.1 Participants and task

This study involved 69 students enrolled in a Master-level English-Chinese translation program at an Australian university. The majority of them (over 90%) were Chinese international students, either in their first semester, second semester, or about to complete their coursework. All participants had not previously been exposed to TM systems in any informed way. At the time of the investigation, they were enrolled in an introductory course that had a three-week technology component. The purpose of this module was not only to encourage the acquisition of abilities to use TM software, but also to assist students in performing a usability analysis and understanding the nuances among different tools. To facilitate such comparison, a range of free-access TM systems were introduced as course material, including Wordfast and Omega-T, CaféTran Espresso, and Google Translator Toolkit (GTT, discontinued in December 2019), MateCat and Smartcat. More advanced TM systems such as Trados and Memsource are not included here due to the introductory nature of this course. Students were required to complete translation exercises using at least one TM system in each of the three classes; an additional TM system was available for students with more advanced computer skills. At the end of this module, students were asked to write a fictional letter to one of the TM systems based on their initial HCI experiences, and they were required to identify the letter as either a "love letter" or a "break-up letter".

A total of 69 letters were collected from participants (English letters: 16; Chinese letters: 53). English letters were collected from L1 speakers and L2 speakers who were confident to describe their nuanced emotions in English. The researcher who is a NAATI- (National Accreditation Authority for Translators and Interpreters) accredited translator translated the collected Chinese letters into English. The majority of participants addressed their letters to a specific TM system, while the six letters that described TM as a whole were excluded from the analysis.

2.2 Procedure

All narrative letters were divided into separate sentences, and then their sentiment scores were calculated. Analysis was conducted in R (R Core Team, 2020) using the package "*sentimentr*" (version 2.7.1) (Rinker, 2019). Table 1 summarizes the descriptive information.

Table 1. Narrative letters collected for each addressed TM system.

TM system	Love	Breakup	Total
CaféTran Espresso	11 (101)	2 (34)	13 (135)
GTT	4 (28)	2 (17)	6 (45)
MateCat	5 (36)	6 (47)	11 (83)
Omega-T	1 (10)	12 (99)	13 (109)

Smartcat	5 (31)	7 (36)	12 (67)
Wordfast	7 (61)	1 (15)	8 (76)
Others	5 (40)	1 (6)	6 (46)
Total	38 (307)	31 (254)	69 (561)
Total (excl. Others)	33 (267)	30 (248)	63 (515)

Contrary to the traditional text-level analysis, the sentence-level sentiment analysis used in the present study is able to consider both word polarity and the context in which the sentiment information is expressed. To interpret the sentiment score, a value close to +1 indicates strong positivity, while a value close to -1 indicates strong negativity; close to zero values indicate emotional neutrality. We have put two examples below to show how the analyses were performed. First, the narrative letter below is a "breakup" letter written to the TM system *Omega-T*. It consists of eight sentences, each enclosed by a pair of square brackets. The sentiment score for each sentence follows the right bracket:

[[Dear Omega-T, maybe you can help me to some extent, but you do not know me at all.]0.12 [I wish we can be in an easy-going mode. You are so complicated; I do not know what you are thinking.]-0.38 [You are not my MR (Mr Right).]0.00 [When I get along with you, I am not happy anymore.]-0.23 [And I even do not go into your heart, and I do not figure out how to use you until now.]0.00 [It is too difficult for me to understand the rules of you.]0.14 [I am scared to use a new

technology, which means that we are two parallel lines and cannot be drawn too close together.]0.08 [So, hope you can meet your MR.]0.19]

In the "breakup" letter above, we see that the second sentence was judged by the algorithm as the most negative sentence (sentiment = -0.38), where the student translator complained about the usability of the TM system; while the last etiquette sentence was judged as the most positive sentence (sentiment = 0.19), where the author expressed their will to terminate the relationship politely. The mean sentiment score for all eight sentences was -0.01. Next, we present a "love" letter written to *CaféTran Espresso*:

[[Dear CafeTran, With just a short moment dating you, I was totally enchanted.]0.61 [I know this is the feelings of love.]0.27 [In my mind, you are the most shining star I have ever seen, compared with other tools.]0.52 [You are a lifesaver for me because you are easy to operate and work fast, which saves me a lot of time.]0.71 [When I import TM, every single second I spent with you flashes in my head.]-0.06 [What you fancy me the most is that you integrate lots of sources of online translation tools to assist me every time I am stuck in a translation problem.]0.06 [These words cannot express all my admiration for you, but I really want to take your hand and create a brilliant future with you.]0.84 [All the best.]0.29]

In this narrative letter, we can see that most of the sentences are positive, whilst there are two sentences with a close to zero sentiment score. The second last sentence has the highest sentiment score (0.84), in which the student translator expressed their admiration for the addressee TM system. There are also eight sentences in this letter, and the mean sentiment score is 0.41. It is worth noticing that not all sentences in "love" letters are positive, and not all sentences in "breakup" letters are negative. To offer an estimate of the proportion of sentiment categories, the raw sentiment scores were further collapsed into tripartite categories: negative (sentiment < -0.1), neutral (-0.1 < sentiment < 0.1), and positive (sentiment > 0.1). The cut-off value of ±0.1 was arbitrarily chosen following previous research (e.g., Teh et al., 2015). When this criterion applies, we conclude that there are six positive sentences and two neutral sentences in the "love" letter, and there is no negative sentence. However, the "breakup" letter shown earlier has two negative sentences, three neutral sentences, and three positive sentences.

2.3 Data analysis and hypotheses

Two types of data were analysed in the present study: numerical data (raw sentiment score) and categorical data (sentiment category). For numerical data, they are analysed using analysis of variance (ANOVA) tests. The distributions of sentiment scores for six TM systems in two types of narrative letters are inspected in density plots to make sure that distributions are roughly symmetric and not severely skewed, and the sentiment scores are checked by a two-way ANOVA test (2 letter types × 6 TM systems). The categorical data are treated as count data in the present study, and they can be collated into contingency tables to analyse whether sentiment is relevant to narrative letter types (3 sentiment categories × 2 letter types), and TM systems (3 sentiment categories × 6 TM systems). These interactions are checked by a series of Chi-squared tests. These statistic tests are conducted using JASP (JASP Team, 2020). The main research question of the present study is whether the automatized sentiment analysis can be used to analyse narrative letters that are qualitatively opposite in terms of usability satisfaction. We aim to test the following two hypotheses:

- *Hypothesis 1*: "Love" letters will have a higher sentiment score than "breakup" letters.
- *Hypothesis 2*: When collapsed into tripartite sentiment categories (i.e., negative, neutral, and positive), "love" letters will have a higher proportion of positive sentences, and a lower proportion of negative sentences, than "breakup" letters.

If both of the hypotheses are confirmed, then it shows that sentiment analysis is an efficient tool for analysing usability narrative in an educational setting. As long as the automatic analysis gives consistent and robust estimates, this method can be potentially used to triangulate and complement qualitative methods in usability analysis.

3. RESULTS

3.1 Sentiment score patterns

The distribution of sentiment scores for sentences in “love” and “breakup” narrative letters was summarized in Figure 1. From data inspection, it is clear that “love” letters generally have a higher sentiment score than “breakup” letters for most of the TM systems. For each density plot, the sentiment score distribution for different letter types should differ concerning the location of the peak value, and the peak for “love” letters should appear to the right of that for “breakup” letters if the first hypothesis is true. This pattern is more salient for *CaféTran Espresso*, *Omega-T*, and *Smartcat*, while for the TM system *Wordfast*, the two distributions seem to have similar mean sentiment scores, which would predict a null effect of letter type. In general, all the scores are unimodally distributed and are not severely skewed. A Levene’s test has confirmed that the assumption of the equality of variances was not violated, $F(5, 509) = 1.902$, $p = 0.092$. These data inspection procedures have validated the applicability of a two-way ANOVA, which is a parametric test that assumes the homoscedasticity of data distributions.

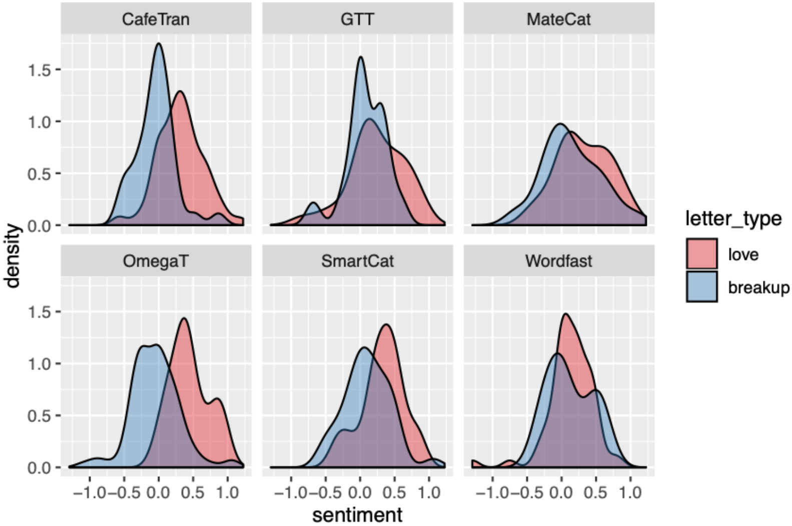

Figure 1. Distribution of sentiment score for sentences in love and breakup letters.

Table 2. Estimated sentiment scores and standard errors (SEs) for TM systems in narrative letters.

TM system	Letter Type	Sentiment	SE
CaféTran Espresso	Love	0.316	0.034
	Breakup	-0.038	0.059
GTT	Love	0.236	0.065
	Breakup	0.086	0.084
MateCat	Love	0.319	0.058
	Breakup	0.144	0.050
Omega-T	Love	0.445	0.109
	Breakup	-0.052	0.035
Smartcat	Love	0.322	0.062
	Breakup	0.103	0.058
Wordfast	Love	0.130	0.044
	Breakup	0.124	0.089
Total (6)	Love	0.295	0.027
	Breakup	0.061	0.027

To address the first hypothesis, a two-way ANOVA (2 letter types × 6 TM systems) revealed that there was a main effect of letter type, $F(1, 503) = 37.674$, $p < 0.001$, but not for TM system, $F(5, 503) = 1.036$, $p = 0.396$, while the letter type * TM system interaction was also significant, $F(5, 503) = 2.963$, $p = 0.012$. The estimated values of the ANOVA model are summarized in Table 2. For all "love" letters the mean estimated sentiment score was above zero, $M = 0.295$, 95% confidence interval (95%CI): [0.241 0.348]. For all "breakup" letters the mean sentiment score was also above zero, $M = 0.061$, 95%CI: [0.009 0.114]. The difference was significant when checked by a post hoc Bonferroni test, $M_{diff} = 0.233$, t

= 6.138, $p < 0.001$. To estimate the effect size of this difference between letter types, an independent t-test was also performed, $t(513) = 7.753$, $p < 0.001$, Cohen's $d = 0.684$, 95%CI: [0.506 0.861]. This result showed that the effect size was likely to be medium to large (Cohen, 1988).

As shown earlier, the distributions are slightly different for letters that take different TM systems as the addressee. In order to examine whether the general pattern is consistent for each TM system, another series of post hoc Bonferroni tests were conducted. It was found that the love-breakup sentiment difference was significant for letters that addressed *CaféTran Espresso*, $M_{diff} = 0.354$, $t = 5.166$, $p < 0.001$, and *Omega-T*, $M_{diff} = 0.497$, $t = 4.335$, $p = 0.001$; while the difference was not significant for other four TM systems. This result has shown that the sentiment difference exists as a general tendency, but individual differences for each TM system may also exist. For certain TM systems, e.g., *Omega-T*, the narrative was highly polarized as the sentiment difference between "love" and "break-up" letters was relatively large (0.497). For some other systems, however, the difference may not reach a significant level. Up to this point, the first hypothesis is confirmed that positive narrative letters generally have a higher sentiment score than negative narrative letters.

3.2 Sentiment category patterns

When classified into tripartite categories, each sentence can be either negative (sentiment < -0.1), or neutral (-0.1 < sentiment < 0.1), or positive (sentiment > 0.1). The categorization results are summarized in Table 3. For "love" letters, there were 188 positive sentences (70.4%), 53 neutral sentences (19.9%), and 26 negative sentences (9.7%); for "breakup" letters, there were 91 positive sentences (36.7%), 124 neutral sentences (24.1%), and 86 negative sentences (34.7%). When these observations were checked by a Chi-squared test, the null hypothesis was rejected, $\chi^2(2) = 67.871$, $N = 515$, $p < 0.001$. This result confirms that the percentages of sentences from each sentiment group were different for the two narrative letter types. The second hypothesis of the present study is confirmed that "love" letters have a higher proportion of positive sentences than "breakup" letters, and the opposite relation holds for negative sentences. In addition, the percentage of neutral sentences seems to be higher in "breakup" letters (28.6%) than in "love" letters (19.9%). However, this difference was only close to significant when checked by a binomial exact test, $N = 124$, $K = 53$ (or 71), $p = 0.063$. For the negative and positive categories, the differences were both significant at 0.001 level when checked by two separate binomial exact tests. In short, the second hypothesis is confirmed.

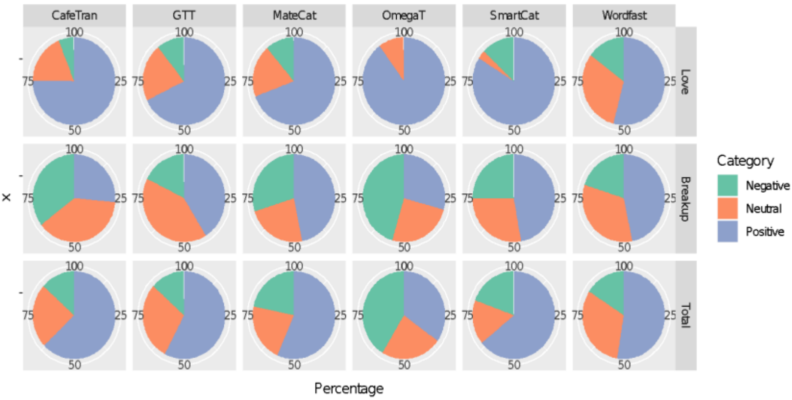

Figure 2. Percentage of sentences of different sentiment categories, i.e., negative, neutral, and positive sentences, for six TM systems.

Table 3. Contingency table of sentence category and letter type for six TM systems.

TM System	Letter Type	Sentiment Category			Total
		Negative	Neutral	Positive	
CaféTran Espresso	Love	6	19	76	101
	Breakup	12	13	9	34
	Subtotal	18	32	85	135
GTT	Love	3	6	19	28
	Breakup	3	7	7	17

	Subtotal	6	13	26	45
MateCat	Love	4	7	25	36
	Breakup	14	11	22	47
	Subtotal	18	18	47	83
Omega-T	Love	0	1	9	10
	Breakup	45	25	29	99
	Subtotal	45	26	38	109
Smartcat	Love	4	1	26	31
	Breakup	9	10	17	36
	Subtotal	13	11	43	67
Wordfast	Love	9	19	33	61
	Breakup	3	5	7	15
	Subtotal	12	24	40	76
Total (6)	Love	26	53	188	267
	Breakup	86	71	91	248

Subtotal	112	124	279	515

It has been shown earlier that the general sentimental pattern may be more salient for certain TM systems than others. To check whether the proportion difference is consistent for narrative letters addressing different TM systems, the whole dataset was divided into six subsets, and the proportion patterns were summarized in a grid of pie charts in Figure 2. The percentage data was the same as in Table 3. For "love" letters, the TM system *Omega-T* had the highest proportion for positive sentences (90%), while *Wordfast* had the lowest proportion (54.1%). For "breakup" letters, the highest negative sentence proportion was found for *Omega-T* again (45.5%), while GTT had the lowest proportion for negative sentences (17.6%). For individual TM platforms, a series of Chi-squared tests revealed that the proportion of different sentiment categories (i.e., positive, neutral, negative sentences) differed significantly in two letter types ("love" and "breakup" letters) in *CaféTran Espresso* ($p < 0.001$), *Omega-T* ($p < 0.001$), *Smartcat* ($p = 0.004$), but not for *GTT* ($p = 0.211$), *MateCat* ($p = 0.072$), and *Wordfast* ($p = 0.083$). Again, we find evidence for both the existence of a general tendency of sentimental difference for "love" and "breakup" letters and also the individual differences among different TM systems. Taken together, the two hypotheses of the present study are both confirmed.

4. DISCUSSION

4.1 Can Sentiment Analysis reveal emotional colour in HCI narratives?

First, this study examines if Sentiment Analysis can be effectively used as an automatic tool for detecting, extracting, and quantifying textual emotions in a manner similar to that of a human judge. Previous research (Koskinen & Ruokonen, 2017; Ruokonen & Koskinen, 2017) reveals that translator trainees' "love letters" primarily report their pleasant HCI experiences, and thus are dominated by positive emotions, whereas "hate/break-up letters" that report unpleasant HCI experiences are dominated by negative emotions. In the present study, we used Sentiment Analysis as an objective assessment tool for detecting such emotions, and the results confirmed our hypothesis showing that Sentiment Analysis indeed can effectively differentiate "love letters" and "break-up letters" based on the measure of Sentiment score alone. This is shown in the distribution charts (Figure 1) and the mean value comparisons (Table 2) where a recurrent pattern was found that "love letters" had significantly higher Sentiment scores as compared to "break-up letters" for all TM systems addressed in the narratives. Based on human judgement, previous research shows that the two types of letters tend to manifest a clear cut in terms of emotionality: Koskinen and Ruokonen (2017) found that 14 out of 18 (78%) "love letters" can be classified as "positive," while four (22%) can be classified as "ambivalent." In contrast, 13 out of 13 (100%) "hate/break-up" letters were classified as "negative". The results of our Sentiment Analysis indicate that the differences tend to be gradient, and there are some areas of overlap between the "love" and "hate" narratives in terms of emotionality. Taking our findings together, our observations are in agreement with previous research (Koskinen & Ruokonen, 2017; Ruokonen & Koskinen, 2017), but our data suggest that differences in emotionality may be more nuanced and gradient, at least from a computational perspective.

4.2 How are positive and negative emotions intermixed in HCI narratives?

Apart from the overlapping distributions of Sentiment scores in "love letters" and "break-up letters", we also carried out a tripartite classification analysis based on a working criterion: A sentence is deemed "negative" if its Sentiment score is lower than -0.1, "neutral" if the Sentiment score is between -0.1 and 0.1, or "positive" if the score is higher than 0.1. In this way, one can easily inspect the proportions of negative and positive sentences in different kinds of emotional narratives (see Table 3, Figure 2). Additionally, our predictions are supported by the quantitative analysis, which indicates that some negative emotions can be found in "love letters", while "break-up letters" also include positive statements. Obviously, the proportion of positive, neutral, and negative sentences varies significantly between the two narrative types. On average, the proportion of the three sentence types was approximately 7:2:1 in "love letters", but 1:1:1 in "break-up letters". Potentially, the balanced proportion in the "break-up letters" reflects the trainees' linguistic knowledge of politeness. For instance, students sometimes express the mixed feelings at the beginning of a "break-up" letter, e.g., "*Dear Omega-T, maybe you can help* *me to some extent, but you do not know me at all. I wish we can be in an easy-going mode…*" (see Section 2.2). Again, this observed pattern contrast clearly with the clear-cut reported in previous research (Koskinen & Ruokonen, 2017; Ruokonen & Koskinen, 2017).

5. CONCLUSION

The present study evaluated Sentiment Analysis as an automated tool for detecting translator trainees' narratives about their HCI experiences. As a methodological study, we compared the commonality and complementarity between Emotion-AI and previous research using human evaluation. There is converging evidence that shows sentiment analysis can serve as an objective and effective tool for classifying narrative sentences that display a positive, neutral, or negative tone. However, it was also found that the differences in Sentiment scores are more likely to be gradient than categorical, which contrasts with human-classified results. We argue that Sentiment Analysis is an effective complementary tool for qualitative classification of textual emotion, or perhaps a potential substitute when a large number of texts are of interest (and consequently perusing all sentences becomes tedious). There is, however, a clear limitation in the automatic method, since Sentiment Analysis is strictly based on the emotional colour of lexical items, and therefore it is not able to detect patterns at the discourse level, such as sarcasm. In addition to narrative letters, Sentiment Analysis can also be applied to other types of educational texts, e.g., teachers' comments on student essays, and students’ comments on class evaluations. By highlighting the role of affective factors in the classroom, Sentiment Analysis may offer educators additional insights for building a positive learning environment.

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