Emoji is the New Politeness: Primary Language's Richness of Polite Elements in Relation to Emoji Use to Communicate Politely in English

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Abstract

Investigating the computer-mediated communications (CMCs) in an online community that specialized in communications for gamers, this paper successfully replicates the prior results of politeness function of emoticons on emoji. In addition, this paper demonstrates that when a speaker whose primary language has richer elements for politeness communicates politely in English, that speaker is more likely to use emoji and emoticons than a speaker whose primary language has less rich elements for politeness. The paper also simulates a simple listener model which suggests that the presence emoji or emoticons may increase the likelihood of perceiving an utterance as more polite.

1 Introduction

Emoji, a form of ideograms, support computer-mediated communications (CMCs) in the same way nonverbal cues–such as facial expression, gesture, and tone of voice (Tang and Hew, 2019)–support face-to-face (FTF) communications. According to prior literature on emoticons (the predecessor of emoji), one way that emoji can support CMCs is to convey politeness. Since some languages have richer linguistic elements for politeness (e.g., honorifics in Japanese, sentence-final particles in Thai) than the others (e.g., English), it is possible that when a speaker whose primary language has richer elements for politeness needs to communicate politely through texts in foreign language with less rich elements for politeness, the speaker may resort to emoji due to the lack of linguistic elements for politeness as well as nonverbal cues to convey politeness as in FTF. This paper investigates such possibility by studying speakers with various primary languages communicating in English within an online community. The specific hypotheses are:

1. A speaker, regardless of one's primary language, is more likely to use emoji when communicates politely than when does not. (This hypothesis serves a purpose of replicating prior results on politeness function of emoticons on emoji.)
2. A speaker whose primary language has richer elements for politeness is more likely to use emoji than a speaker whose primary language has less rich elements for politeness when communicates politely in English.

2 Related Works

A number of research have linked the use of emoticons–the predecessor of emoji–with politeness strategies.

Sampietro (2016) proposed that one of the pragmatic function of emoticons was to mitigate possible face-threats. For example, emoticons were used with requests and orders to soften these speech acts (Dresner and Herring, 2010; Darics, 2012; Skovholt et al., 2014). Specifically, Darics (2012) found that emoticons were mainly used to mitigate or to clarify the message, usually to reach a successful cooperation. Here are two example sentences mitigated by emoticons from Dresner and Herring (2010):

> I would like a noncircumventing solution ;->
>
> I wonder if you could recommend me some good readings related to conversational data. We just collected some IM data and are about to conduct some analysis on it. Since I've never worked on this kind of data before, I am writing for some suggestions.:)

Furthermore, Sampietro (2019) proposed that emoticons may contribute to politeness in CMCs.

Specifically, Skovholt et al. (2014) found emoticons to be positive politeness markers and rapport building devices, and Vandergriff (2013) found emoticons to be mostly used in the service of politeness and to mitigate disagreement.

One of this paper's goal is to replicate these prior results on politeness function of emoticons on emoji.

In terms of cross-language analysis, prior works have studied emoticon usages for politeness across different languages. Komrsková studied emoticons in Czech and English, and found that phrases of greeting and thanks were very often accompanied by emoticons in both languages. Kavanagh (2016) studied emoticon as a medium for channeling politeness within American and Japanese online blogging communities and found that Japanese used emoticons significantly more than Americans.

In contrast to these works which investigated the use of emoticons for politeness in each speaker's primary language, this paper investigates the use of emoji for politeness in a speaker, regardless of the speaker's primary language, communicating in English.

3 Method

The goals of this paper are to replicate prior results on politeness function of emoticons on emoji and to investigate whether a speaker whose primary language has richer elements for politeness is more likely to use emoji than a speaker whose primary language less rich elements for politeness when communicates politely in English. To do so, an ideal dataset would be an English CMC that is a product of speakers with different primary languages where each speaker's primary language as well as the intention to communicate politely are explicitly coded.

In this paper, the next best ideal data is used because it is not feasible to conduct a controlled experiment. In particular, the ideal dataset is approximated from an English CMC where some speakers' preferred languages other than English are known. The intention to communicate politely is approximated from how polite the utterance is as well as whether that utterance is a direct mention to another speaker. Lastly, each language's degree of richness in polite elements is approximated from the politeness distinctions in pronouns feature from WALS (Dryer and Haspelmath, 2013).

In terms of statistical test, logistic regression is used in a binary classification task predicting whether an utterance contain any emoji. Independent variables that are inputs of the logistic regression are a speaker's primary language's degree of richness in polite elements, how polite the utterance is, and whether the utterance is a direct mention to another speaker. In addition, according to **?**, there are some cultural differences in the use of emoji between the East and the West. Hence, a binary feature indicating whether the speaker's primary language is from the East or the West is used as a control variable in the logistic regression.

3.1 Data

The data of an English CMC was obtained from the official Discord server of Tsuki Adventure, a free-to-play mobile game. Discord is a proprietary freeware VoIP application and digital distribution platform designed for video gaming communities that specializes in text, image, video and audio communication between users in a chat.

What is special about Tsuki Adventure Discord is that each user in the community is asked to tag the user profile with what language other than English the user prefers to communicate in. Although the preferred language tag is not mandatory, there is a significant number of the users in this community that do so. Hence, there is sufficient data to investigate the research questions. Nevertheless, using this data requires a strong assumption that the language tagged is the primary language of that user. If this assumption is not true, the results from testing the second hypothesis should be more conservative. Hence, this assumption should make it harder to get significant results. Also note that testing the first hypothesis doesn't require the user's primary language, while testing the second hypothesis requires one. Therefore, all utterances are used in testing the first hypothesis, while only utterances from users with language tags are used in testing the second hypothesis.

In term of the data collection, the data was scraped from the official discord server of Tsuki Adventure on 02/21/2020 using a Python Discord scraper from Dracovian (2019). The total number of scraped utterances was 3,371, of which 1,622 utterances came from users with language tags. There were 12 different languages being tagged: 7 are Eastern languages (Bahasa, Chinese, Japanese, Korean, Tagalog, Thai, and Vietnamese) and 5 are Western languages (French, German, Portuguese, Russian, and Spanish).

3.2 Approximating an intention to communicate politely via an utterance's Polite Level and Direct Mention

3.2.1 Polite Level

One way to approximate the intention to communicate politely is to see how polite the produced utterance is. In order to quantify such quality, a maximum entropy classifier–which is commonly used in several text classifications–predicting an utterance's polite level is trained from a human-annotated corpus created and used by **?**.

?'s corpus has more than 10,000 utterances annotated by humans via Amazon Mechanical Turk (AMT) and these utterances came from two large online communities: Wikipedia and Stack Exchange. According to **?**, this corpus was thus far "the largest corpus with politeness annotations". Each utterance was labeled by five different annotators. The standard z-score normalization was applied to each worker's scores to account for subjectivity, and finally, the politeness score of an utterance was defined as the average of the five normalized scores assigned by the annotators

To convert the corpus' continuous politeness score into a categorical variable to be predicted by the maximum entropy classifier, the corpus is binned into 5 equal percentile width bins which are labeled as $-2, -1, 0, 1$, and 2 respectively (henceforth polite level). A maximum entropy classifier with the polite level as the target labels is then trained on a 80-20 train-test split of the corpus with the utterance's bag-of-words as the input features. The total number of iterations is 100 with the training accuracy of 0.953 and the testing accuracy of 0.947.

The trained maximum entropy classifier is then applied on the current dataset to classify the polite level of each utterance. The input features are the bag-of-words of each utterance after removing any emoji contained. The polite level variable is treated as an ordinal categorical variable in the analysis.

Even though the logic behind approximating the intention to communicate politely from how polite the produced utterance is is intuitive, there are some problems to be aware of. First, the polite level is quantified from the utterance with emoji removed. Thus, only the function of emoji as the supplement but not as the substitute of polite elements can be investigated in the current study. This limitation, nevertheless, makes the results more conservative. Second, the intention to communicate politely is the main independent variable that should drive the use of emoji, according to the paper's hypotheses. However, using polite levels of utterances to mediate between such intentions and the use of emoji weakens the possible claims. It is to be noted that only correlations but not causations can be concluded about possible relationships between intention to communicate politely and the use of emoji.

3.2.2 Direct Mention

Since the polite level is measured automatically, there could be some cascading errors from the training corpus (which is the least likely given the reliability of the corpus), training the classifier, or applying the trained classifier on the current data. In addition, there could still be some aspect of politeness that the trained classifier fails to capture. Therefore, direct mention, which is defined as when an utterance contains Discord's mentioning users feature to mention the other user(s), is used as another proxy of an intention to communicate politely that does not suffer from possible cascading errors like the polite level does. Note that direct mention is not equivalent to a private chat between users. Similar to other social media and online community platforms, utterances contain Discord's mentioning users feature are publicly accessible to all users.

The logic behind using direct mention as a proxy of an intention to communicate politely comes from **?**'s theory of politeness. The theory explains that all persons are concerned with their face and recognize that others also have face wants, and it is generally in everyone's interests to maintain each other's face. The risk of failing to maintain the other's face (or being not polite) is then highest when there is a particular other's face to maintain. That is if a user produces a not so polite utterance without directly mentioning any other user, it is less clear whose face is not maintained and hence it is less likely that any other user's face will not be maintained at all. On the other hand, if a user produces a not so polite utterance and directly mentions the other user(s), it is definite that the other user(s)'s face(s) will not be maintained. Hence, when there is a direct mention, the user should be more likely to communicate politely.

Similar to the concern about polite level, using direct mention to mediate between intention to communicate politely and the use of emoji limits the possible conclusions to only correlations but not causations.

3.3 Approximating a language's degree of richness in polite elements via WALS' politeness distinctions in pronouns

Politeness distinctions in pronouns feature from WALS (Dryer and Haspelmath, 2013)–The World Atlas of Language Structures–is used as a proxy for each language's degree of richness in polite elements. This feature has been used in some prior social science research. For example, **?** studied relationship between politeness distinctions and egalitarianism, and found that this politeness distinctions feature from WALS was more reliable than the others.

The scope of this feature is restricted to politeness distinctions in second person pronouns. Below are the 4 categories of this politeness distinctions in pronouns feature with corresponding descriptions from WALS and **?**:

1. *No politeness distinctions* - Languages that were assigned this value have no personal pronouns in their paradigms which are used to express different degrees of respect or intimacy toward the addressee. For example, there is no politeness distinction in English, in which "you" is used for both formal and familiar forms of address.

2. *Binary politeness distinctions* - Languages that were assigned this value have a paradigmatic opposition between one intimate or familiar pronoun of address and another one expressing respectful address. The binary politeness distinction is found in many Indo-European languages, such as "du" and "Sie" in German or "tu" and "vous" in French.

3. *Multiple politeness distinctions* - Languages that were assigned this value have two or more degrees of politeness within a pronominal paradigm. For example, In Marathi, "tu" is used for family members and friends, "te" and "he" are used for people with higher social status, and an extra polite form "apan" is used for priests and teachers and in very formal contexts. Note that these systems are rare cross-linguistically.

4. *Pronoun avoidance* - The term "pronoun avoidance" describes a strategy of pronoun usage which has an effect on the overall shape of the paradigm. Languages of East and Southeast Asia such as Japanese, Burmese and Thai have a strong sensitivity to politeness in language usage and within their grammars. Speakers have to account for a variety of social distinctions linguistically. Social distinctions between speaker and hearer may reflect relative age, kinship, social ranking, intimacy, and other social features. From a linguistic point of view, one of the most important strategies of being polite is to avoid of addressing people directly.

Politeness Distinctions in Pronouns	**Languages**
Pronoun avoidance	Japanese, Korean, Thai, Vietnamese
Multiple politeness distinctions	Tagalog
Binary politeness distinctions	Bahasa, Chinese, French, German, Portuguese, Russian, Spanish
No politeness distinctions	English

Table 1: The polite level classification for the languages present in the data

Table 1 summarizes the politeness distinctions in pronouns of the languages present in the data.

Since, in the data, there is no language besides English that has no politeness distinction and no preferred language tag for English, this category is omitted from the analysis. Also, since there is only Tagalog that is multiple politeness distinct in the data, using this category as it is in the analysis could lead to a scenario where the results from this category are due to Tagalog itself and not due to having multiple politeness distinctions. Thus, multiple politeness distinctions and binary politeness distinctions are combined into a single category in the analysis. The reason to combine multiple politeness distinctions with binary politeness distinctions instead of pronoun avoidance is because according to WALS and **?**, the pronoun avoidance is an indication of politeness that goes beyond the use of formal pronouns. Hence, linguistically, multiple politeness distinctions are closer to binary politeness distinctions than to pronoun avoidance. In sum, there are 2 categories of politeness distinctions used in the analysis: binary/multiple politeness distinctions and pronoun avoidance. This simplification in the politeness distinctions in pronouns feature is actually desirable. The validity of using this feature to approximate a language's degree of richness in polite elements is limited by the scope of the feature being restricted to politeness distinctions in second person pronouns. However, opting to distinct only pronoun avoidance from the rest helps ameliorate this limitation due to the fact that pronoun avoidant languages are classified by their intensive polite strategies that extend beyond second person pronouns.

4 Results

Before testing the hypotheses, there are some properties of the data that needed to be checked:

1. There should be no difference in the use of emoji, polite level, and direct mention between utterances produced by users with and without language tags.

2. There should be no difference in polite level and direct mention between utterances produced by users speaking binary/multiple distinct and pronoun avoided languages.

Between utterances produced by users with and without language tags, there is no difference in polite level, but there are slight differences in the use of emoji and direct mention. For polite level, utterances produced by users with language tags ($M = 0.2775, SD = 1.5304$) compared to utterances produced by users without language tags ($M = 0.2449, SD = 1.4473$) demonstrates no difference in average polite level, $t(3318.1) = 0.6363, p = 0.5246$. For the use of emoji, utterances produced by users with language tags ($P = 0.1286, SD = 0.3349$) compared to utterances produced by users without language tags ($P = 0.0993, SD = 0.2992$) demonstrates significantly higher proportion of utterances with emoji, $t(3260.9) = 2.6737, p = 0.0075$. For direct mention, utterances produced by users with language tags ($P = 0.1440, SD = 0.3512$) compared to utterances produced by users without language tags ($P = 0.1176, SD = 0.3222$) demonstrates significantly higher proportion of utterances with direct mention, $t(3289.8) = 2.2726, p = 0.0231$. These differences suggest that there could be some selection bias from language tagging being optional. Nevertheless, even though the differences in emoji use and direct mention are significant, the magnitudes of differences are quite small.

Between utterances produced by users speaking binary/multiple distinct and pronoun avoided languages, there is no difference in both polite level and direct mention. For polite level, utterances produced by users speaking binary/multiple distinct languages ($M = 0.2996, SD = 1.5259$) compared to utterances produced by users speaking pronoun avoided languages ($M = 0.0654, SD = 1.5630$) demonstrates no difference in average polite level, $t(183.42) = 1.7681, p = 0.0787$. For direct mention, utterances produced by users speaking binary/multiple distinct languages ($P = 0.1481, SD = 0.3553$) compared to utterances produced by users speaking pronoun avoided languages ($P = 0.1046, SD = 0.3070$) also demonstrates no difference in proportion of utterances with direct mention, $t(196.88) = 1.6429, p = 0.1020$. Hence, there doesn't seem to be systematic differences between utterances produced by users speaking binary/multiple distinct and pronoun avoided languages.

4.1 Replicating prior results on politeness function of emoticons on emoji

If emoji also serve politeness function as prior works found emoticons do, utterances with higher polite level or with direct mention should be more likely to contain emoji, regardless of the users' primary languages. If emoji also serve politeness function as prior works found emoticons do, utterances with higher polite level or with direct mention should be more likely to contain emoji, regardless of the users' primary languages. Table 2 shows the proportion of utterances that contain emoji by polite level and direct mention, using all utterances produced by users both with and without language tags. The most distinct case is when polite level is highest (polite level = 2) and there is direct mention where 25.4% of utterances contain emoji, doubling to tripling the proportions of utterances containing emoji in the other cases.

Fitting a logistic regression model, with polite

Polite Level	Direct Mention	Not Direct Mention
-2	0.0769	0.0940
-1	0.1160	0.0748
0	0.1080	0.0891
1	0.0806	0.1200
2	0.2540	0.1390

Table 2: Proportion of utterances containing emoji by polite level and direct mention, using all utterances produced by users both with and without language tags.

	Model 1 (AIC = 2366.9)	Model 2 (AIC = 2365.6)
(Intercept)	-2.1792*** (0.0632)	-2.1642*** (0.0630)
Polite Level	0.1750*** (0.0381)	0.1467*** (0.0410)
Direct Mention	0.3501* (0.1474)	0.2218 (0.1704)
Polite Level x Direct Mention	-	0.1979 (0.1118)

Table 3: Logistic regression models predicting whether an utterance contains emoji on utterances produced by users both with and without language tags ($* : p < 0.05$, $** : p < 0.01$, $*** : p < 0.001$).

level and direct mention as input features, and whether an utterance contains any emoji as the outcome variable, there are significant effects of both polite level ($p < 0.001$) and direct mention ($p < 0.05$) (Table 3, Model 1). One step upward in polite level increases the odds of containing emoji by 19%, while the presence of direct mention increases the odds by 42%. Table 3, Model 2 shows another logistic regression model with an additional input of interaction between polite level and direct mention. The effect of polite level remains significant ($p < 0.001$), but the effect of direct mention becomes insignificant. The interaction effect of polite level and direct mention is close to significant ($p = 0.0777$) with an increasing of the odds by 22%.

Discussion

The first hypothesis, that a speaker, regardless of one's primary language, is more likely to use emoji when communicates politely than when does not, is supported. Both the utterance's polite level and direct mention, which serve as the proxies for the speaker's intention to communicate politely, significantly increase the probability of using emoji in the utterance. The result also suggests that polite level and direct mention might capture different dimensions of politeness since there is an almost significant positive effect of the interaction term between the two. In addition, emoji seems to play an obvious role only when the intension to communicate politely is strong (when both the utterance's polite level is highest and direct mention is presence). These findings lead to further research questions about the exact roles of emoji for politeness: whether emoji is a substitution or a supplement of the traditional politeness markers, whether the presence of emoji is perceived to serve the politeness function that the production side intends, etc.

4.2 A user whose primary language has richer elements for politeness is more likely to use emoji when communicates politely

To test the second hypothesis, a logistic regression model is fitted with polite level, direct mention, the language's politeness distinctions, and whether the language is Eastern or Western (as a control for possible cultural differences) as input features, and whether an utterance contains any emoji as the outcome variable (Table 4, Model 3). In addition, all possible interactions (up to three-way interaction) among polite level, direct mention, and politeness distinctions are added as input features to the model. Then, the best fit model (Table 4, Model 4) is chosen by AIC in a stepwise selection started from the full model. In the best fit model and after controlling for possible differences in Eastern/Western cultures, there are significant effects of polite level ($p < 0.001$), politeness distinctions ($p < 0.05$), and interaction between politeness distinctions and direct mention ($p < 0.01$), but there is no significant effect of direct mention alone. One step upward in polite level increases the odds of containing emoji by 26%, the language being pronoun avoided increases the odds by 67%, while the interaction between direct mention and the language being pronoun avoided increases the odds further by 564%. Also note that the effect of the control variable is close to significant ($p = 0.0524$) with the language being Eastern increases the odds by 55%.

Since utterances with both direct mention and the language being pronoun avoided are quite low

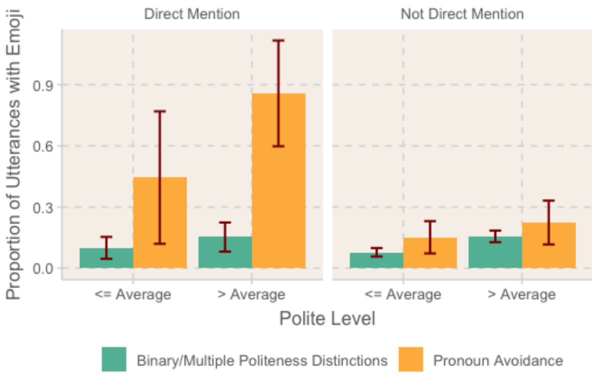

Figure 1: Proportion of utterances containing emoji by polite distinctions, direct mention, and the simplified polite level.

	Model 3 **(AIC = 1212.6)**	**Model 4** **(AIC = 1208.5)**
(Intercept)	-2.4954*** (0.2152)	-2.4980*** (0.2139)
Polite Level	0.2297*** (0.0616)	0.2339*** (0.0526)
Direct Mention	0.0656 (0.2490)	0.0909 (0.2253)
Pronoun Avoidance	0.5338* (0.2488)	0.5127* (0.2432)
Polite Level x Direct Mention	0.0406 (0.1622)	-
Polite Level x Pronoun Avoidance	-0.0661 (0.1553)	-
Direct Mention x Pronoun Avoidance	1.8125** (0.6646)	1.8933** (0.6105)
Polite Level x Direct Mention x Pronoun Avoidance	0.6118 (0.5500)	-
Eastern Language	0.4360 (0.2246)	0.4355 (0.2245)

Table 4: Logistic regression models predicting whether an utterance contains emoji on utterances produced by users with language tags (* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$). Model 4 is the best fit model resulted from performing a stepwise selection by AIC on Model 3.

in number in comparison to utterances in the other conditions, further post-hoc analysis beyond logistic regression is conducted to ensure there is no effect undetected by the logistic regression alone. To reduce the variance from insufficient data, polite level $-2, -1$, and 0 are grouped together forming utterances that are not more polite than average, while polite level 1 and 2, are grouped together forming utterances that are more polite than average. Figure 1 shows proportion of utterances containing emoji by polite distinctions, direct mention, and the new polite level. Note that the variances around utterances with both direct mention and the language being pronoun avoided are still high in comparison to the others, but these are already improved hugely by reducing polite level into only two categories. It seems that only when there is direct mention and the utterances are more polite than average, proportion of utterances containing emoji is significantly higher when the language is pronoun avoided $(P = 0.8571, SD = 0.3780)$ than when the language is binary/multiple politeness distinct $(P = 0.1481, SD = 0.3619)$, $t(6.8097) = 4.7747, p = 0.0022$. This seems to suggest the three-way interaction effect among polite level, direct mention, and the language's politeness distinctions that logistic regression might have missed due to insufficient number of observations.

Discussion

The second hypothesis, that a speaker whose primary language has richer elements for politeness is more likely to use emoji than a speaker whose primary language has less rich elements for politeness when communicates politely in English, is partially supported. Controlling for possible cultural differences, a speaker whose primary language is pronoun avoided is more likely than a speaker whose primary language is binary/multiple politeness distinct to use emoji regardless of the intention to communicate politely, and the difference in the likelihood increases further when the intention to communicate politely is presence in the form of direct mention. Unfortunately, likely due to insufficient data, there is no significant interaction between language's politeness distinctions and the intention to communicate politely in the form of utterance's polite level. However, after recategorizing the polite level to reduce noises from insufficient data, the post-hoc analysis reveals a three-way interaction effect among polite level, direct mention, and the language's politeness distinctions, which supports the second hypothesis.

4.3 Combining emoji and emoticons together (Post-hoc analysis)

Since the first hypothesis–that emoji also serve politeness function like emoticons do–was supported, as a post-hoc analysis, it is logical to examine the second hypothesis again considering both emoji and emoticons together. Doing so will yield a more complete picture of the second hypothesis than considering emoji and emoticons separately since they could be substitutes of one another.

To do so, a list of common emoticons is constructed from the List of emoticons page on Wikipedia (**?**). The same analysis as before is conducted on the utterances collected from Tsuki Adventure Discord but now with emoticons in the list are also treated as emoji.

Table 5 confirms that the first hypothesis still holds when considering both emoji and emoticons together. The results are similar to when considering only emoji, but with stronger effects of direct mention.

In terms of the second hypothesis, the logistic regressions considering both emoji and emoticons together also supports the second hypothesis the same way the analysis considering only emoji did as demonstrated by Table 6. Moreover, additionally considering emoticons yields a stronger effect of direct mention in both full model (Model 7) and stepwise-selected model (Model 8). Also, the controlling variable for possible cultural differences seems to be unimportant when considering both emoji and emoticons.

	Model 5 (AIC = 2366.9)	**Model 6 (AIC = 2365.6)**
(Intercept)	-1.9606*** (0.0579)	-1.9477*** (0.0578)
Polite Level	0.1656*** (0.0348)	0.1396*** (0.0377)
Direct Mention	0.5231*** (0.1313)	0.4280** (0.1464)
Polite Level x Direct Mention	-	0.1657 (0.0973)

Table 5: Logistic regression models predicting whether an utterance contains any emoji or emoticons on utterances produced by users both with and without language tags (* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$).

After simplifying polite level into only two categories, the result also supports possible three-way interaction effect among polite level, direct mention, and the language's politeness distinctions as when considering emoji alone. Only when there is direct mention and the utterances are more polite than average, proportion of utterances containing emoji and emoticons is significantly higher when the language is pronoun avoided ($P = 0.8571, SD = 0.3780$) than when the language is binary/multiple politeness distinct ($P = 0.2577, SD = 0.4397$), $t(7.2247) = 4.0049, p = 0.0048$.

Discussion

The second hypothesis, that a speaker whose primary language has richer elements for politeness is more likely to use emoji than a speaker whose primary language has less rich elements for politeness when communicates politely in English, is still supported when considering both emoji and emoticons. Additionally considering emoticons also yields clearer effect of direct mention and negligible possible cultural differences. Given that people may use emoji as a substitute of emoticon and vice versa and that emoji seem to serve politeness function like emoticons do, it may be more desirable to combine emoji and emoticons together rather than separate them when investigating their politeness function.

	Model 7 (AIC = 1375.2)	Model 8 (AIC = 1369.6)
(Intercept)	-2.0100*** (0.1774)	-1.9377*** (0.0887)
Polite Level	0.2216*** (0.0567)	0.2339*** (0.0526)
Direct Mention	0.4387* (0.2071)	0.4817* (0.1894)
Pronoun Avoidance	0.4776* (0.2402)	0.4849* (0.2326)
Polite Level x Direct Mention	0.0777 (0.1360)	-
Polite Level x Pronoun Avoidance	-0.0497 (0.1497)	-
Direct Mention x Pronoun Avoidance	1.3457* (0.6479)	1.4055* (0.5958)
Polite Level x Direct Mention x Pronoun Avoidance	0.5662 (0.5418)	-
Eastern Language	0.1004 (0.1875)	-

Table 6: Logistic regression models predicting whether an utterance contains any emoji or emoticons on utterances produced by users with language tags (* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$). Model 8 is the best fit model resulted from performing a stepwise selection by AIC on Model 7.

4.4 Simulating a listener model (Post-hoc analysis)

Up until this point in the paper, the politeness function of emoji and emoticons is only investigated from the language production side: whether the users use emoji and emoticons as elements for politeness when they intend to produce polite utterances. However, it has not yet been investigated from the language comprehension side if the users perceive utterances with emoji and emoticons as more polite.

Admittedly, the current dataset is not suitable for investigating the politeness function of emoji and emoticons from the language comprehension side. However, it is still possible to simulate a very simple listener model from the current dataset as a post-hoc analysis and use the result as a guide to future work.

To do so, a logistic regression is fitted with whether an utterance contains any emoji and emoticons, direct mention, and the language's politeness distinctions as input features, and the simplified polite level (whether an utterance is more polite than average) as the outcome variable. The polite level used here is classified by the same trained maximum entropy classifier, but the input features are the bag-of-words of each utterance without removing any emoji and emoticons contained. This is because, practically, when the listeners perceive the politeness of the utterances, they take the whole utterances, including emoji and emoticons, into consideration. The control variable whether the language is Eastern or Western is omitted because it was shown to be negligible in the prior analysis considering both emoji and emoticons.

Table 7 (Model 9) shows the simulated listener model. Only the effect of containing some emoji or emoticons is significant, where containing some emoji or emoticons increases the odds of the utterance being more polite than average by 78%. In terms of the model's performance, its accuracy (54.88%) is slightly better than the baseline model that always predicts an utterance to be more polite than average (48.15%).

Discussion

As expected, since the current dataset is not exactly suitable for investigating the politeness function of emoji and emoticons from the language comprehension side, the simulated listener

	Model 9 (AIC = 2232.4)
(Intercept)	-0.1214*
	(0.0594)
Presence of emoji or emoticons	0.5768***
	(0.1400)
Direct Mention	-0.1123
	(0.1432)
Pronoun Avoidance	-0.2852
	(0.1734)

Table 7: Simulating a listener model with a logistic regression model predicting whether an utterance is more polite than average (* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$).

model does only slightly better than the baseline model. However, the model suggests that emoji and emoticons might play some roles in perceiving politeness. Interestingly, an utterance being a direct mention and the speaker's primary language's degree of polite elements do not affect the perception of politeness. This is different from the results on the language production side where both variables influence the use of emoji. Combined with prior results, it suggests that emoji and emoticons may serve the politeness function for both production and comprehension sides. On the other hand, direct mention may only play the role on the production but not on the comprehension side. Since the simulated listener model is a very simple one where individual differences between listeners were not taken into account, it cannot be concluded whether the listener's primary language's degree of polite elements interacting with the presence of emoji and emoticons affects the perception of politeness like the speaker's primary language's degree of polite elements does on the production side.

All in all, these interpretations should not be taken as final conclusions. As already mentioned, the current dataset is not entirely suitable, and the simulated listener model is very simple. Hence, these results should only be usedd to guide the directions of future works.

5 Limitations and Future Work

There are several limitations in the current study needed to be concerned due to the nature of observational study.

First of all, several variables of interest are approximated. The primary languages of the speakers are inferred from the self-reported preferred languages, the languages' degrees of richness in polite elements are approximated from WALS' politeness distinctions in pronouns, and the intentions to communicate politely are approximated from the utterances' polite levels and direct mention. In addition, the utterances' polite levels are labelled by a classifier trained on an existed annotated corpus. Future work will benefit greatly from having a more complete dataset where none of these variables needed to be approximated. Such data might be best obtained via controlled experiments such that the speakers' primary languages could be directly inquired and the intentions to communicate politely could be manipulated.

In terms of generalizability, the current study suffers from insufficient data, possible selection bias, and representative sample problem. There is no speaker whose primary language is in the no politeness distinction category, and there is only one language represent the multiple politeness distinctions category such that it has to be combined with the binary politeness distinctions category. In order to obtain a more complete answer to the second hypothesis, a dataset with more unique primary languages sufficient to represent the full WALS' politeness distinctions is needed. Also, the small size of the current dataset may mask some possible significant results, so future work will benefit greatly from having a bigger dataset as well. In addition, even though the differences between the users who tag and who don't tag their preferred languages are small, there could be a selection bias. Obtaining the data from a controlled experiment or from a platform which requires all users to declare their primary languages would be more desirable. Lastly, the current data is a convenient sample obtained from a single online community for the gamers of a specific game. It cannot be guaranteed that this sample is a representative sample of the general population. Future work should expand the study such that the results could be broadly generalized.

Lastly, this paper primarily investigates the politeness function of emoji (and emoticons in the post-hoc analysis) from the language production side. To understand the politeness function of emoji and emoticons better and completely, a well-designed study of the language comprehension side is needed. The results from the post-hoc simulation of the simple listener model could be used as a guide for future works.

6 Conclusion

This paper, using the computer-mediated communications (CMCs) in an online community that specialized in communications for gamers, successfully replicates the prior results of politeness function of emoticons on emoji. In addition, this paper demonstrates that when a speaker whose primary language has richer elements for politeness communicates politely in English, that speaker is more likely to use emoji and emoticons than a speaker whose primary language has less rich elements for politeness. The paper also simulates a simple listener model which suggests that the presence emoji or emoticons may increase the likelihood of perceiving an utterance as more polite.

Nevertheless, there are still several limitations and generalizability issues in the current study, and future works should attempt to solve these issues to understand the politeness function of emoji and emoticons better. In addition, the current results lead to further questions about emoji and emoticons and their politeness functions. Are emoji and emoticons substitutions or supplements of the traditional politeness markers? How does one's primary languages' degree of richness in polite elements affect the comprehension side of the politeness function of emoji and emoticons? Future work should aim to improve the present limitations and generalizability and to expand the scope of research on politeness function of emoji and emoticons in CMCs.

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