# Conversational Analysis of Daily Dialog Data using Polite Emotional Dialogue Acts

**Chandrakant Bothe[†] and Stefan Wemter[‡]**

[†]Foviatech GmbH

chandrakant.bothe@foviatech.com

[‡]Knowledge Technology, Department of Informatics, University of Hamburg

stefan.wermter@uni-hamburg.de

## Abstract

Many socio-linguistic cues are used in conversational analysis, such as emotion, sentiment, and dialogue acts. One of the fundamental cues is politeness, which linguistically possesses properties such as social manners useful in conversational analysis. This article presents findings of polite emotional dialogue act associations, where we can correlate the relationships between the socio-linguistic cues. We confirm our hypothesis that the utterances with the emotion classes Anger and Disgust are more likely to be impolite. At the same time, Happiness and Sadness are more likely to be polite. A less expectable phenomenon occurs with dialogue acts Inform and Commissive which contain more polite utterances than Question and Directive. Finally, we conclude on the future work of these findings to extend the learning of social behaviours using politeness.

**Keywords:** Politeness, Emotion, Dialogue Act, Conversational Analysis, Artificial Intelligence

## 1. Introduction

Conversational analysis can potentially be enhanced with socio-linguistic politeness cues along with other linguistic cues (Kasper, 1990; Russell and Barrett, 1999; Danescu-Niculescu-Mizil et al., 2013). Literature suggests that analysis and use of social cues is beneficial for human-robot interaction (Salem et al., 2014; Barros et al., 2015; Castro-González et al., 2016; Bothe, 2020). Our article focuses on an experiment by primarily adding linguistic politeness cues, expressed using polite phrases, to conversational analysis along with emotional states and dialogue acts where we aim to discover correlations between these cues.

For our experiment, we will explore DailyDialog dataset (Li et al., 2017), a multi-turn dialogue dataset, which is pre-annotated with emotion and dialogue act labels. Furthermore, the dataset will be augmented with politeness labels ranging from 1 to 5 by leveraging a pre-trained model (Bao et al., 2021). By analyzing the correlation between politeness and emotional states, we discover that utterances with certain emotion classes are more polite or impolite than others. At least frequently, it appears natural to use polite utterances in a happy emotional state, whereas to use impolite utterances in an angry state. This phenomenon is precisely the motivation behind this experiment and we can find such utterance examples illustrated in Figure 1. The conversation in this example shows how an impolite utterance is used in the Anger emotion state and then shifts with a polite utterance to the Happiness emotion state. The results show this phenomenon statistically occurring significantly in the given dataset.

The conversational behaviours learned with these cues might be beneficial to drive the dialogue flow in complex polite human-robot interaction setup, which was
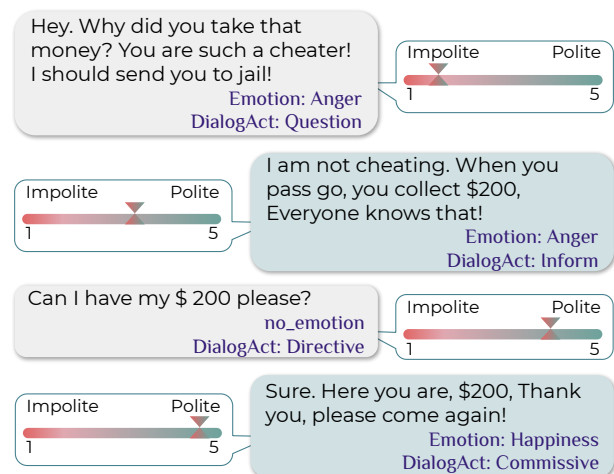


Figure 1: Polite Emotional Dialogue Act labels from the DailyDialog dataset showing the utterances with emotion Anger is very Impolite while with emotion Happiness is very Polite in the bi-turn dialogue flows (Emotion and DialogAct labels are from the already annotated DailyDialog dataset)

not possible in a straightforward dialogue-based navigation system (Bothe et al., 2018a). Additionally, the results could also be applied in pragmatic conversational analysis where politeness strategies could assist in dialogue flow (Bao et al., 2021) and theoretically analyse the core affect study (Russell and Barrett, 1999). The politeness annotated data and the results are available in the GitHub repository *bothe/politeEDAs*[1].

---

[1]https://github.com/bothe/politeEDAs

| | Emotions | | | Dialogue Acts | | | |
|---|---|---|---|---|---|---|---|
| | Utterances | % total | % Emotion | Inform | Question | Directive | Commissive |
| Anger | 1022 | 1.00 | 5.87 | 615 | 174 | 132 | 101 |
| Disgust | 353 | 0.34 | 2.03 | 291 | 30 | 18 | 14 |
| Fear | 174 | 0.17 | 1.00 | 106 | 27 | 21 | 20 |
| Happiness | 12885 | 12.61 | 74.02 | 7830 | 2158 | 1476 | 1421 |
| Sadness | 1150 | 1.13 | 6.61 | 809 | 190 | 95 | 56 |
| Surprise | 1823 | 1.78 | 10.47 | 1122 | 565 | 72 | 64 |
| no_emotion | 85572 | 83.78 | – | 36316 | 26549 | 15542 | 7165 |
| Total | 102979 | – | – | 47089 | 29693 | 17356 | 8841 |

Table 1: Statistics of the number of utterances in Emotion and Dialogue Act classes in the DailyDialog dataset

## 2. Related Work

Perceiving emotions in conversation provides affective information of the conversation partners; similarly, perceiving politeness in conversation provides cues about their social manners/behaviours. The emotion and dialogue act relationships are presented by (Bothe et al., 2020) for Emotional Dialogue Acts using previous work on emotion and dialogue act recognition (Lakomkin et al., 2017; Bothe et al., 2018c). For example, Accept/Agree and Thanking dialogue acts often occur with the Joy emotion, Apology with Sadness, Reject with Anger, and Acknowledgements with Surprise. Similarly, the relationship of politeness and emotion are evidently discussed much in the literature as some of the most critical social cues (Langlotz and Locher, 2017; Renner, 2020; Culpeper and Tantucci, 2021). A computational linguistic study shows how machines learn politeness, for example, the words *please* and *could you* signal on the heatmaps of sentences (Aubakirova and Bansal, 2016). Contrary, prosodic information provides an additional dimension to politeness as the exact phrase might be uttered differently (Culpeper, 2011). In fact, (Brown and Levinson, 1987) mention the display of emotions or lack of control of emotions as positive politeness strategies or potentially face-threatening acts of politeness.

Thus, this study presents an analysis of linguistic politeness by understanding how "appropriate levels of affect" are conveyed in the conversational interaction (Holmes and Stubbe, 2015; Langlotz and Locher, 2017; Kumar et al., 2021). In human-robot interaction, politeness as a social cue plays a vital role to foster socially engaging interaction with robots (Steinfeld et al., 2006; Srinivasan and Takayama, 2016; Bothe et al., 2018a). However, this article explores relations between the socio-linguistic cues, finding out how polite the utterances are against their respective emotion and dialogue act classes.

## 3. Approach

Our goal is to analyze the socio-linguistic cues to find meaningful correlations between them. First, we explore the dataset, DailyDialog, which is pre-annotated with emotion and dialogue act labels. Second, we annotate the utterances with politeness values using a po-

liteness analyzer, more precisely each utterance with a degree of politeness. Finally, we analyze the annotated utterances with politeness against the emotion and dialogue act classes in the dataset to identify their associations. Eventually, we conclude with the results and findings and provide future conversational analysis work to extend this experiment.

### 3.1. DailyDialog Dataset

The DailyDialog dataset contains conversation topics of daily life such as ordinary life and financial topics. It contains bi-turn dialogue flows like Question-Inform and Directive-Commissive dialogue acts. Thus,
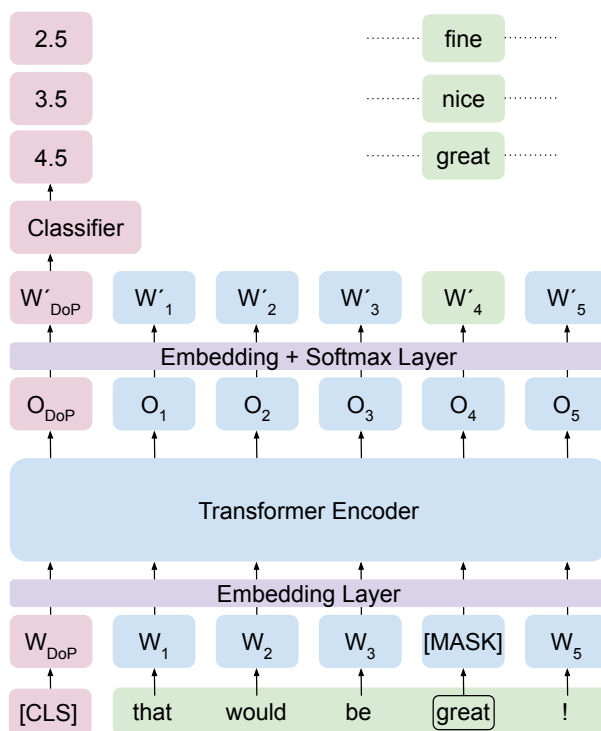


Figure 2: BERT-based masked language model in a classification setup for degree-of-politeness (DoP) recognition on the scale of range between 1 and 5 where a lower value indicates impolite while higher indicates polite whereas around 3 indicates neutral

| DoP | Dialogue Act | Emotion | Utterance |
|---|---|---|---|
| 4.63 | Inform | Happiness | OK! Thank you very much! |
| 4.63 | Inform | Happiness | Sure, that would be great! Thank you! |
| 4.63 | Commissive | Happiness | That would be great! Thanks a lot! |
| 4.62 | Inform | Happiness | Thank you, thank you, thanks again. |
| 4.62 | Inform | Happiness | This is exciting! Thank you so much! |
| 3.67 | Question | no_emotion | That's right. What do you think we should do as a hobby? |
| 3.67 | Inform | no_emotion | Mr Jurgen, yes, the remittance has been successful. |
| 3.67 | Inform | no_emotion | Yes. We all loved the celebration of our city's birthday. |
| 3.67 | Inform | no_emotion | Ok, I'll pay by card then. |
| 3.67 | Commissive | no_emotion | Ok. I won't get into trouble. |
| 3.34 | Inform | Happiness | I went to the tutoring service centre on campus today and got a job. |
| 3.34 | Inform | Happiness | I never knew there were so many fun things to do on a farm. |
| 3.34 | Inform | no_emotion | Just a minute. It's ten to nine by my watch. |
| 3.34 | Inform | no_emotion | You may check out books or videos. |
| 3.34 | Question | no_emotion | That's a small fee? |
| 2.95 | Commissive | Anger | Mike, you're late again. |
| 2.95 | Inform | no_emotion | Ha! It's not like you've ever been one to beat around the bush. |
| 2.94 | Inform | no_emotion | My rear bumper is messed up. |
| 2.94 | Inform | no_emotion | No, they won't. They are shrink proof. |
| 2.94 | Question | no_emotion | Why don't you wear a scarf? |
| 1.59 | Inform | Disgust | Don't dress like that. You'll make fool yourself. |
| 1.51 | Commissive | Anger | Make it work, Geoff. You would say that, wouldn't you. |
| 1.47 | Directive | no_emotion | Get up, you lazybones! |
| 1.46 | Directive | Surprise | You idiot! Don't say that! Do you want this job, or not? |
| 1.37 | Directive | Anger | Get out of my store, you jerk! |

Table 2: Examples from the DailyDialog dataset showing five utterances in the selected ranges of DoP (degree of politeness) with highest values (first block), middle values (three blocks) and lowest values (last block) annotated by the politeness analyzer, which provides a sense of the annotated utterances with different levels of politeness

the dataset is annotated with those four fundamental dialogue acts to follow unique multi-turn dialogue flow patterns (Li et al., 2017). This dataset is manually labelled with six emotion classes and a no_emotion class. The statistics of the dataset is presented in Table 1, we can see that the no_emotion class dominates the total number of utterances. However, Happiness dominates within the emotion classes, whereas Fear contains the least number of utterances. Further, Table 1 also presents the number of utterances for the four dialogue act classes in the dataset for their corresponding emotion classes.

### 3.2. Politeness Analyzer

To annotate the utterances, we will use a politeness analyzer from the recent work of (Bao et al., 2021), where they combine two datasets from (Danescu-Niculescu-Mizil et al., 2013) and (Wang and Jurgens, 2018). The politeness regressor model is obtained on these datasets by pre-training a BERT-based model (Devlin et al., 2019) on Reddit data using masked language modelling, as shown in Figure 2. The word embeddings are encoded with the transformer encoder, which later is used to classify the politeness values. As the words are masked, various words can be detected given different levels of the degree of politeness (DoP). Similarly, given different words, the classifier model can determine various levels of DoP. This model can also be useful to apply utterance-level context-based politeness learning using hierarchical recurrent neural networks (Bothe et al., 2018b).

The encoder is pre-trained on the target dataset and fine-tuned on the above mentioned two politeness datasets. The final model is obtained at an average Pearson correlation of 0.66 with human judgments from both the datasets and made available online at the GitHub repository *wujunjie1998/Politenessr*[2]. The model provides a degree of politeness on a scale between 1 and 5 (presented as float values), where around 3 indicates a neutral state: neither polite nor impolite. In this way, we achieve a very fine-grained annotation to each utterance in the given dataset.

## 4. Experiments and Results

We annotate all utterances in the DailyDialog dataset for politeness values in the range between 1 and 5 using the politeness analyzer. The annotated utterances are arranged in decreasing order to find the examples of polite, neutral and impolite utterances. Then they are sorted according to a scenario, first for every emotion class and second for every dialogue act class.

---

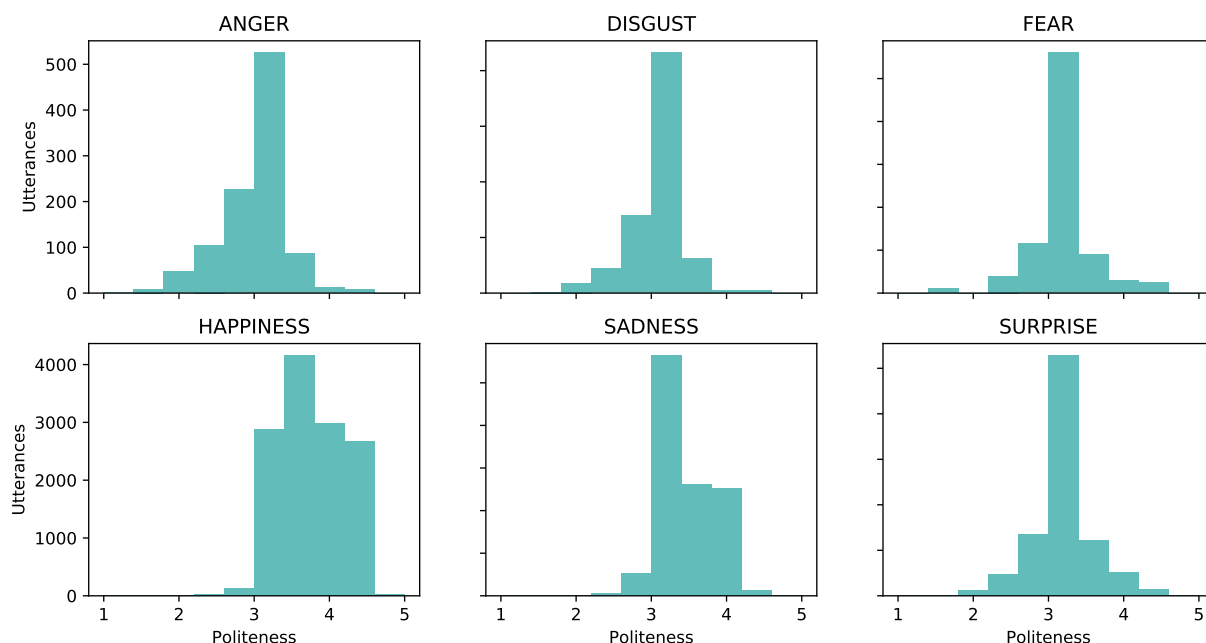[2]https://github.com/wujunjie1998/
Politenessr/

Figure 3: Politeness histograms for the emotion categories in the DailyDialog dataset

All the utterances are arranged in decreasing order, and Table 2 presents top polite, neutral and impolite utterances from the DailyDialog dataset annotated with the politeness analyzer. Five examples are presented from the top 10 in each extreme value range (only 5 examples are shown out of the top 10 to eliminate similar or repeated utterances). The value ranges are chosen as follows: all the utterances are arranged in decreasing order of the politeness values, and then 10 utterances are selected having two extreme values (top very polite and very impolite) and middle three ranges (very polite to centre, centre, and very impolite to centre). We find that most of the utterances in the first block with Happiness and 'thank you' phrases are recognized with a significantly higher degree of politeness. In contrast, most of the utterances in the last block with the Anger and Disgust emotion classes containing rude words like 'fool', 'idiot', or 'jerk' are recognized with a significantly lower degree of politeness. Furthermore, we can see that the second block contains comparatively less polite utterances than the first block. Similarly, the third block contains comparatively more polite utterances than the last block. On the other hand, the middle block contains relatively neutral utterances, at least reasonably neutral compared to other blocks. With these examples, we assure that the politeness analyzer annotates the utterances with significantly well degrees of politeness.

In the next phase, we sort all the utterances for the six emotion classes in the dataset. Then we plot histograms of the politeness values of the utterances against each emotion category, which is shown in Figure 3. As we can notice in these histograms, utterances in the emo-

tion classes Anger and Disgust are neutral and impolite on the politeness scale. On the other hand, many utterances in the Happiness and Sadness emotion classes are polite. Fear and Surprise emotion classes are mostly neutral on the politeness scale compared to other emotion classes. This analysis gives an exceptional insight into the relationship between emotional states and politeness strategies used in dialogues.

Finally, we sort the utterances for their respective dialogue acts according to the politeness values and plot
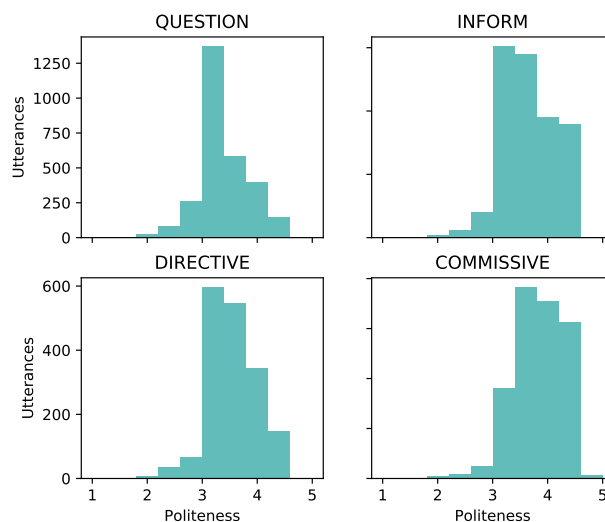


Figure 4: Politeness histograms for the dialogue acts in the DailyDialog dataset shows that the utterances in Question and Directive are mostly neutral whereas in Inform and Commissive are mostly polite

## Conversation 1: Surprise associated with neutral but impolite

I'm getting a tattoo tomorrow.
no_emotion
DialogAct: Inform

Impolite — Polite
0 — 5

Impolite — Polite
0 — 5

Are you nuts?
Emotion: Surprise
DialogAct: Question

## Conversation 2: Sadness associated with Polite utterances

I'm sorry I'm so late. I had a really bad day.
Emotion: Sadness
DialogAct: Inform

Impolite — Polite
0 — 5

Impolite — Polite
0 — 5

It's ten after six. We're late. But dinner is at six thirty.
no_emotion
DialogAct: Inform

I know. I know. I'm really sorry. I lost my bag.
Emotion: Sadness
DialogAct: Inform

Impolite — Polite
0 — 5

Impolite — Polite
0 — 5

I'll call the lost and found office.
no_emotion
DialogAct: Directive

I didn't think of it. Thank you. I do apologize for being late.
Emotion: Sadness
DialogAct: Commissive

Impolite — Polite
0 — 5

Figure 5: Polite Emotional Dialogue Act labels from the DailyDialog dataset focused on Surprise and Sadness emotion utterances, the utterance with the emotion Surprise shows an immediate reaction which becomes impolite, interestingly most of the utterances with the emotion Sadness are polite

the histograms as shown in Figure 4. We can notice that most of the utterances are neutral or polite on the politeness scale for all the dialogue acts. However, we observe that the Inform and Commissive dialogue act classes contain many polite utterances compared to Question and Directive dialogue acts. Interestingly, we discover that speakers in the dataset often tend to use polite utterances when answering, thanking, and agreeing (and the utterances that come under Inform and Commissive), whereas while asking, guiding, directing, ordering (under Question and Directive), most of the utterances are primarily neutral and polite.

Figure 5 provides two conversation examples containing Surprise and Sadness emotion utterances. We notice that the utterances with the emotion Sadness are primarily polite, which can be elicited from Figure 3. We also notice that most of the utterances with the Inform and Commissive dialogue acts are polite, as elicited in Figure 4. These analytical graphs provide an insightful discovery and statistical adherence of the social cues relatedness. It also confirms the hypothesis of natural selection of politeness strategies in various emotional states and dialogue acts.

## 5. Conclusion

Recognizing politeness in conversation is an essential aspect of conversational analysis, and we discover how politeness functions in a dialogue with respect to emotional states and dialogue acts. Moreover, sociolinguistic feature relatedness provides an additional dimension for the behavioural analysis of conversation partners and their use in the virtual assistant and human-robot interaction fields. This paper discovers how politeness is associated with emotions and dialogue acts in the given dataset. Specifically, we found that the utterances are mostly polite in Happiness and Sadness emotion classes and Inform and Commissive dialogue acts. Similarly, the utterances are primarily neutral and impolite for the Anger and Disgust emotion classes. We also observed that the utterances in the Question and Directive dialogue acts are mostly neutral; however, many are also polite. We also presented examples of utterances from the data demonstrating the discovered phenomenon and made the annotated politeness data available for the research community.

A continuation of the experiment is planned to extend to other dialogue datasets to demonstrate the discovered phenomenon. The politeness analyzer used in this experiment provided linguistically appropriate annotations for the degree of politeness. However, in the next step, more than one analyzer could be used for a more robust detection of politeness or annotate the utterances manually. Future work could extend to learning the social behaviours using analyzed socio-linguistic cues with the help of deep learning techniques. Moreover, the majority of the utterances in the explored dataset contain no emotion class; thus, using multimodal data could improve analytical insight.

## 6. Acknowledgements

## 7. Bibliographical References

Aubakirova, M. and Bansal, M. (2016). Interpreting Neural Networks to Improve Politeness Comprehension. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2035–2041. ACL.

Bao, J., Wu, J., Zhang, Y., Chandrasekharan, E., and Jurgens, D. (2021). Conversations Gone Alright: Quantifying and Predicting Prosocial Outcomes in Online Conversations. In *The Web Conference 2021 - Proceedings of the World Wide Web Conference, WWW 2021*, pages 1134–1145. Association for Computing Machinery, Inc.

Barros, P., Jirak, D., Weber, C., and Wermter, S. (2015). Multimodal emotional state recognition using sequence-dependent deep hierarchical features. *Neural Networks*, 72:140–151. Neurobiologically Inspired Robotics: Enhanced Autonomy through Neuromorphic Cognition.

Bothe, C., Garcia, F., Cruz-Maya, A., Pandey, A. K., and Wermter, S. (2018a). Towards Dialogue-based Navigation with Multivariate Adaptation driven by Intention and Politeness for Social Robots. In *Proceedings of the International Conference on Social Robotics*, pages 230–240. Springer.

Bothe, C., Magg, S., Weber, C., and Wermter, S. (2018b). Conversational Analysis using Utterance-level Attention-based Bidirectional Recurrent Neural Networks. In *Proceedings of the International Conference INTERSPEECH 2018*, pages 996–1000. International Speech Communication Association (ISCA).

Bothe, C., Magg, S., Weber, C., and Wermter, S. (2018c). Discourse-Wizard: Discovering Deep Discourse Structure in your Conversation with RNNs. *Computation and Language*.

Bothe, C., Weber, C., Magg, S., and Wermter, S. (2020). EDA: Enriching Emotional Dialogue Acts using an Ensemble of Neural Annotators. In *Proceedings of The 12th Language Resources and Evaluation Conference, LREC 2020*, pages 620–627. European Language Resources Association (ELRA).

Bothe, C. (2020). *Conversational Language Learning for Human-Robot Interaction*. Ph.D. thesis, Staats- und Universitätsbibliothek Hamburg Carl von Ossietzky, University of Hamburg.

Brown, P. and Levinson, S. C. (1987). *Politeness: Some Universals in Language Usage*, volume 4. Cambridge University Press.

Castro-González, Á., Castillo, J. C., Alonso-Martín, F., Olortegui-Ortega, O. V., González-Pacheco, V., Malfaz, M., and Salichs, M. A. (2016). The Effects of an Impolite vs. a Polite Robot Playing Rock-Paper-Scissors. In *Proceedings of the International Conference on Social Robotics*, pages 306–316. Springer.

Culpeper, J. and Tantucci, V. (2021). The Principle of (Im)politeness Reciprocity. *Journal of Pragmatics*, 175:146–164.

Culpeper, J. (2011). "It's not what you said, it's how you said it!": Prosody and impoliteness. In *Discursive Approaches to Politeness*, pages 57–84. De Gruyter Mouton.

Danescu-Niculescu-Mizil, C., Sudhof, M., Jurafsky, D., Leskovec, J., and Potts, C. (2013). A Computational Approach to Politeness with Application to Social Factors. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 250–259. ACL.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1*, pages 4171–4186. ACL.

Holmes, J. and Stubbe, M. (2015). *Power and Politeness in the Workplace: A Sociolinguistic Analysis of Talk at Work*. Routledge.

Kasper, G. (1990). Linguistic Politeness: Current Research Issues. *Journal of Pragmatics*, 14(2):193–218.

Kumar, S., Itzhak, E., Olatunji, S., Sarne-Fleischmann, V., Tractinsky, N., Nimrod, G., and Edan, Y. (2021). Exploratory evaluation of politeness in human-robot interaction. *arXiv:2103.08441*.

Lakomkin, E., Bothe, C., and Wermter, S. (2017). GradAscent at EmoInt-2017: Character and Word Level Recurrent Neural Network Models for Tweet Emotion Intensity Detection. In *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis at the Conference EMNLP 2017*, pages 169–174. ACL.

Langlotz, A. and Locher, M. A. (2017). (Im)politeness and Emotion. In *The Palgrave Handbook of Linguistic (Im)politeness*, pages 287–322, London. Palgrave Macmillan UK.

Li, Y., Su, H., Shen, X., Li, W., Cao, Z., and Niu, S. (2017). DailyDialog: A manually labelled multi-turn dialogue dataset. In *Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 986–995, Taipei, Taiwan. Asian Federation of Natural Language Processing.

Renner, B. (2020). *(In) directness as an (im) politeness strategy in the contact between german and Brazilian portuguese as additional languages*. Ph.D. thesis, Universidade de Brasília, Brasília.

Russell, J. A. and Barrett, L. F. (1999). Core Affect, Prototypical Emotional Episodes, and Other Things Called Emotion: Dissecting the Elephant. *Journal of Personality and Social Psychology*, 76(5):805.

Salem, M., Ziadee, M., and Sakr, M. (2014). Marhaba, how may I help you?: Effects of Politeness and Culture on Robot Acceptance and Anthropomorphization. In *Proceedings of the International Conference on Human-robot Interaction*, pages 74–81.

Srinivasan, V. and Takayama, L. (2016). Help Me Please: Robot Politeness Strategies for Soliciting Help From People. In *Proceedings of the Conference on Human Factors in Computing Systems*, pages 4945–4955. ACM.

Steinfeld, A., Fong, T., Kaber, D., Lewis, M., Scholtz, J., Schultz, A., and Goodrich, M. (2006). Common Metrics for Human-Robot Interaction. In *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-robot Interaction*, pages 33–40. ACM.

Wang, Z. and Jurgens, D. (2018). It's going to be okay: Measuring Access to Support in Online Communities. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 33–45, Brussels, Belgium. ACL.