A Dataset of Offensive German Language Tweets
Annotated for Speech Acts

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Abstract
We present a dataset consisting of German offensive and non-offensive tweets, annotated for speech acts. These 600 tweets are a subset of the dataset by (Strüß et al., 2019) and comprises three levels of annotation, i. e., six coarse-grained speech acts, 23 fine-grained speech acts and 14 different sentence types. Furthermore, we provide an evaluation in both qualitative and quantitative terms. The dataset is made publicly available under a CC-BY-4.0 license.

Keywords: Speech acts, hate speech detection, offensive language, annotation, corpus annotation

1 Introduction
In recent years, research has invested a considerable amount of effort in offensive language and other phenomena related to online communication. Hate speech not only affects individuals or minority groups but it might also threaten social cohesion (Weber et al., 2019). Thus, the automatic detection of hate speech and offensive language\textsuperscript{1} continues to be an important and very relevant research topic. While there is a large body of research in this area, approaches often merely classify text using binary labels (Burnap and Williams, 2016; Risch et al., 2021). Hate speech classification is in itself a complex task because it is highly subjective what constitutes hate speech. In addition, it is even more difficult to detect hate speech if it is expressed implicitly rather than explicitly (Palmer et al., 2020; Strüß et al., 2019). Surprisingly little research exists on the pragmatic characteristics of offensive language. Pragmatics is “the study of how utterances have meanings in situations” (Leech, 1983, p. x). To address this gap and contribute to the improvement of hate speech detection, we analysed the pragmatic characteristics of offensive language. We conducted a speech act analysis of a dataset of German tweets that contain offensive language. We use a subset of the 2019 GermEval Shared Task on the Identification of Offensive Language dataset (Strüß et al., 2019). Similar studies exist in which speech act theory (Austin, 1962; Searle, 1969) is applied to data (Jurafsky, 1997; Zhang et al., 2011; Compagno et al., 2018; Vosoughi and Roy, 2016; Weisser, 2018). However, many of these concentrate on spoken language, often confined to restricted discourse scenarios such as the SPAADIA Trainline Corpus (Leech and Weisser, 2013) which consists of phone conversations between call-centre agents and customers concerning bookings of train tickets. Other approaches apply speech act theory to data from Twitter (Zhang et al., 2011; Vosoughi and Roy, 2016) or Reddit (Compagno et al., 2018). Nevertheless, to our knowledge, only Dhayef and Ali (2020) investigate the distribution of speech acts in a hate speech dataset. Consequently, there appears to be a need for more research in this area. Our study aims to contribute to automated hate speech detection by providing a pragmatic analysis of offensive language and it also attempts to contribute to speech act theory by testing its applicability on real life data and sharing findings on frequency, syntactical realisation and common sequences of speech acts. We hypothesise the following: (i) there are more directives in offensive than in non-offensive language (excluding address); (ii) there are more expressives of type complain in offensive than in non-offensive language; (iii) speech acts of type assert occur less frequently in offensive than in non-offensive language; (iv) declarative sentences are the most dominant sentence types overall. Hypothesis (i) is based on Dhayef and Ali (2020); hypothesis (ii) is motivated due to the assumption that uttering a hateful comment corresponds to the speaker having a negative attitude towards the targeted person or group (Dhayef and Ali, 2020). Hypothesis (iii) is assumed because of the hypotheses (i) and (ii). If there are more expressives and directives in offensive language, then they might displace a number of assert speech acts. Moreover, hypothesis (iv) is expected because we regard declaratives to be the default sentence type (Weisser, 2018).

2 Related Work
Starting out with the publication of the first hate speech dataset (Spertus, 1997), a considerable body of research has been carried out in this field of research.
(Poletto et al., 2020), including a number of survey papers (Schmidt and Wiegand, 2017; Fortuna and Nunes, 2018; Mishra et al., 2020; Poletto et al., 2020). While English is the dominant language in current research, datasets in and for other languages also exist, including German (Ross et al., 2017; Wiegand et al., 2018; Struß et al., 2019). With regard to the annotation schemes, we can distinguish three main approaches (Poletto et al., 2020), i.e., binary classification (Risch et al., 2021; Burnap and Williams, 2016), non-binary classification consisting of more than two labels (Kumar et al., 2018; Struß et al., 2019) and more complex schemes that consist of multiple levels (Zampieri et al., 2019). Several authors examine hate speech for specific linguistic phenomena. Neutral adjectives, for example, can acquire a pejorative meaning if they are nominalized (Palmer et al., 2017; Palmer et al., 2020), using the definite plural instead of the bare plural can be used to indicate non-membership (Palmer et al., 2020) and the use of both including and excluding pronouns may contribute to construct a dichotomy between the in- and the out-group, i.e., distancing or othering (Palmer et al., 2020). Those findings have contributed to the development of more complex annotation schemes. In addition, Palmer et al. (2020) create an annotation scheme based on four questions which include the presence or absence of offensiveness, slurs, adjectival nominalization and distancing to establish a dataset. Regarding speech act theory, nowadays, various studies attempt to classify speech acts automatically. To enable automatic classification, they build speech act taxonomies which are often based on Austin (1962) and Searle (1979). Compagno et al. (2018), for example, develop a taxonomy based on Searle’s five speech act classes (assertives, directives, expressives, commissives, declarations) which they validate on a Reddit corpus with threads on autoimmune diseases. They also provide sub-classes, resulting in 17 speech acts in total. Similar approaches with taxonomies based on Searle’s classes include Zhang et al. (2011) and Vosoughi and Roy (2016). Weisser (2018) introduce a more complex scheme with the Dialogue Annotation and Research Tool (DART). The current version (version 3.03) of DART classifies dialogue by syntactic categories (ten in total) and speech acts (162 classes), among others.

### 3 Dataset

The annotation scheme was applied to a subset of the dataset created for task two of the 2019 GermEval Shared Task on the Identification of Offensive Language (Struß et al., 2019). It consists of offensive and non-offensive German language tweets that do not include any surrounding context in the form of other tweets. Evidently, this is not ideal for the application of speech act theory which highly depends on context. This is why we established the category *unsure*. Task two of the GermEval shared task included three subtasks. The first subtask uses binary classification (offense, other) and the second subtask uses a more fine-grained classification (profanity, insult, abuse, other). Tweets labeled as profanity only contain profane words such as swearwords but do not contain insults or abusive language. If they do, they are labeled as insult or abuse. The category abuse differs from insult insofar as in abusive language, the target functions as a representative of a group and “is ascribed negative qualities that are taken to be universal, omnipresent and unchangeable characteristics of the group” (Struß et al., 2019, p. 356) while tweets labeled insult are only targeted at individuals without being associated with a group. In addition, tweets containing instances of dehumanization are labeled as abuse as well. The third subtask uses binary classification by distinguishing between implicit and explicit offensive language. According to Struß et al. (2019), offensive language counts as being implicit when the reader needs to infer that the tweet is offensive, as the offense is only implied. Moreover, implicit offensive language also entails using figurative language (e.g., sarcasm or irony). The first and second subtask are based on the 2019 data which includes 7,025 tweets while the third subtask is based on the 2018 data only including tweets categorised as abuse or insult. The data for the third subtask consists of 8,541 tweets of which 2,888 are categorised as offensive (393 of these are instances of implicit offensive language) (Struß et al., 2019). The class profanity was excluded from the data used in subtask three as the authors argue that it is “by definition explicit offensive language” (Struß et al., 2019, p. 358). In both the 2018 and 2019 data, tweets were excluded if they did not exclusively contain German language, were retweets, contained less than five tokens or contained a URL (Wiegand et al., 2018; Struß et al., 2019). For our analysis we selected 600 tweets from this dataset. From each of the six classes (implicit, explicit, profanity, insult, abuse, other), 100 tweets were picked randomly. For the classes implicit and explicit, we used the 2019 gold standard files of the test data of subtask 3 (Struß et al., 2019b) and for the other four classes, we used the 2019 gold standard files of the test data from subtask 1 and 2 (Struß et al., 2019a). We randomly shuffled both test datasets using Python and for each class, the first 100 occurrences were selected; every tweet was saved as a text file. For the annotation proper we used the open source tool INCEpTION (Klie et al., 2018). The tool supports span annotations as well as the creation of new tagsets and annotation layers. The annotator first segmented the tweet (Section 4.1) and then decided on the speech act and sentence type labels. If uncertain which label to choose, the issue with the tweet was documented.
4 Annotation Scheme

Our annotation scheme is mainly inspired by Searle (1979) and Compagno et al. (2018). Additionally, building upon Weisser (2018), it includes two levels: the syntactical level describes the sentence type of each speech act and the speech act level (consisting of a coarse-grained and a fine-grained level) encodes the type of speech act.

4.1 Tweet Segmentation

Annotation guidelines have been established to help annotators in their decisions. Tweets were segmented according to the following rules (square brackets indicate segmentation boundaries):

- If two adjacent main clauses are connected using a comma or without a conjunction, they are split into two sentences. Exceptions are enumerations and sentences where one main clause has the V2 form due to colloquial language use but should actually be a subordinate clause (Vfin) as in example b) (Fahrer ist Fluchthelfer).

  Ex. a) Wir brauchen #Gelbwesten in der ganzen #EU. [LBR] Die Völker müssen zeigen das sie diese Scheiß Armutspolitik nicht mehr mit machen. weg mit #Macron weg mit #Merkel 2.0 #AKK\(^5\)
  \(\rightarrow\) [Wir brauchen #Gelbwesten in der ganzen #EU.] [LBR] Die Völker müssen zeigen das sie diese Scheiß Armutspolitik nicht mehr mit machen.] [weg mit #Macron] [weg mit #Merkel und Merkel 2.0 #AKK]

  Ex. b) Wenn das bislang nicht gefunden wurde, kann man zunächst davon ausgehen, Fahrer ist Fluchthelfer\(^6\).
  \(\rightarrow\) [Wenn das bislang nicht gefunden wurde, kann man zunächst davon ausgehen, Fahrer ist Fluchthelfer.]

- If unsure where to draw the line between two adjacent fragments, take punctuation into account. If there is none, treat the fragments as one unit.

  Ex. c) Deutschland das Land der drei Geschlechter der Duckmäusers und ja Sager der Toleranz Fanatiker. Das Land der Verblödung.\(^2\)
  \(\rightarrow\) [Deutschland das Land der drei Geschlechter der Duckmäusers und ja Sager der Toleranz Fanatiker.] [Das Land der Verblödung.]

- Sentence-ending punctuation (‘.’, ‘?’ ‘!’) is given priority. Exceptions are cases where main clauses have been split for stylistic reasons (ex. d)\(^8\).

  Ex. d) Ein Egomane. Nutzt jede Gelegenheit, um im Mittelpunkt zu stehen.\(^9\)
  \(\rightarrow\) [Ein Egomane. Nutzt jede Gelegenheit, um im Mittelpunkt zu stehen.]

4.2 Syntactical Level

The main clause of a sentence determines the sentence type (Dudenredaktion, 2016, p. 899). We adapted and slightly modified the annotation scheme of the Georgetown University Multilayer Corpus (GUM) (Zeldes, 2017)\(^10\) for the annotation of sentence types. GUM uses a total of 11 sentence types based on Leech et al. (2003), which explains the similarity between the sentence types used by Zeldes (2017) and Weisser (2018). Table 1 describes the 14 sentence types we use. Our public repository contains additional examples.\(^11\)

4.3 Speech Act Level

For the speech act annotation, we modify the taxonomy by Compagno et al. (2018). Our hierarchically structured scheme consists of 23 fine-grained and six coarse-grained speech acts. The six coarse-grained classes are: assertives, expressives, directives, commissives, unsure and other. Table 2 shows the 23 fine-grained speech acts. Examples can be found in our repository.\(^12\)

4.4 Examples

Figure 1 shows an example tweet from the dataset that was labeled as non-offensive and includes an expressive of the type complain that has the syntactical form of a fragment. Figure 2 shows a tweet labeled as abusive and contains a directive of the type require in the syntactical form of an imperative.

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\(^{5}\)Transl.: ‘We need #yellowvests in the whole #EU. | LBR The people have to show that they won’t take this crappy poverty policy any longer away with #Macron away with #Merkel and Merkel 2.0 #AKK.’

\(^{6}\)Transl.: ‘If that hasn’t been found yet, one can assume that the driver is a getaway driver.’

\(^{2}\)Transl.: ‘Germany, the land of three sexes, of cowards and yes-men, the land of tolerance fanatics. The land of stupidity.’

\(^{8}\)This example is disputable.

\(^{9}\)Transl.: ‘An egomaniac uses every opportunity to be the center of attention’

\(^{10}\)https://corpling.uis.georgetown.edu/wiki/doku.php?id=gum:tokenization\_segmentation

\(^{11}\)https://github.com/MelinaPl/speech-act-analysis#sentence-types

\(^{12}\)https://github.com/MelinaPl/speech-act-analysis#speech-acts
5 Results and Discussion

Section 5.1 presents our quantitative results, generated using Python. A qualitative evaluation follows in Section 5.2. Section 5.3 discusses our main findings.

5.1 Quantitative Evaluation

Tables 1, 2 and 3 show the results of the statistical analysis of the dataset. Table 1 presents the absolute frequencies of sentence types (Section 4.2) for each offensive language category. Table 2, illustrates the frequencies of coarse-grained and fine-grained speech acts (Section 4.3), for each offensive language category including binary categorization (offensive/other). Table 3 shows the frequencies of sentence types for each offensive language category, again including binary categorization. Additional details regarding the syntactical form of fine-grained speech act types are shown in Table 6 in the Appendix.

Table 2 demonstrates that there are 16.4% directives in offensive and 16.9% directives in non-offensive tweets (excluding the class address). Therefore, hypothesis (i) is refuted. Moreover, there are 14.6% of the class complain in offensive tweets while there are 5.2% in non-offensive tweets, confirming hypothesis (ii). Furthermore, assert occurs with a frequency of 28.9% in offensive tweets and with a frequency of 34.5% in non-offensive tweets, thus confirming hypothesis (iii).

With regard to the overall sentence type distribution, Table 3 shows that declarative sentences are the most frequently occurring sentence type by far, followed by mentions (19.4%), fragments (17.1%), which probably entail many declarative sentences as well that contain an ellipsis, and exclamatives (7.4%). The types that occur the least are alternative questions (0.3%), interjections (0.4%) and multiple (0.5%). Thus, the numbers show evidence in favor of hypothesis (iv). There is also a higher number of exclamatives in offensive tweets (8.3%) compared to non-offensive tweets (3.0%). The biggest difference can be viewed when comparing the number of exclamatives in tweets containing explicit language (16.5%) with tweets containing implicit offensive language (5.8%).

5.2 Qualitative Evaluation

The annotation process has raised a number of challenges regarding the decision which label to choose. One issue encountered during the annotation phase was the distinction between assert and rejoice or complain speech acts. Insults, for example, could be viewed as expressing a negative attitude towards someone and therefore could be annotated as complain speech acts. Nevertheless, if someone were to say “He is a devious man” or “He is not the brightest man” and these statements were actually true, could they still be considered as insults? Or do they rather describe reality, therefore fitting more into the speech act class assert? There are various cases where both speech acts occur simultaneously, leading to the difficult task of deciding on the most dominant speech act. Taking a closer look at the data, a rather unexpected finding was the frequent use of rejoice speech acts in tweets classified as containing explicit offensive language. After examination of these tweets, this can be explained with two ways in which rejoice speech acts have been used in general. The first use can be seen in example e). Here, “Hahaha!” has been annotated as an instance of rejoice, expressed through an interjection. In this example, the author uses an apparently joyful expression to comment on the previous question for the purpose of ridiculing it.

- Ex. e) @ObenausThomas @Jung_Us_Koelle @anna_Jima Der syrische Sozialtourist und eine Haftpflichtversicherung? Hahaha!\(^{15}\)

\(^{13}\)Due to class imbalance and the limited size of the dataset, no classification experiments have been carried out yet.

\(^{14}\)We assign one speech act class per segment only.

\(^{15}\)Transl.: ‘The Syrian social tourist and a liability insur-
Table 1: Frequency of sentence types in coarse-grained speech acts

| Sentence Types | Assertive | Commissive | Expressive | Directive | Unsure | Other | Total |
|----------------|-----------|------------|------------|-----------|--------|-------|-------|
| Alt-f          | 0         | 0          | 0          | 5         | 0      | 0     | 5     |
| Decl           | 359       | 6          | 110        | 13        | 36     | 0     | 524   |
| Excl           | 56        | 2          | 59         | 11        | 15     | 0     | 143   |
| F              | 2         | 0          | 0          | 80        | 0      | 0     | 82    |
| Frag           | 152       | 10         | 76         | 12        | 78     | 1     | 329   |
| Hashtag        | 1         | 0          | 5          | 3         | 0      | 62    | 71    |
| Imp            | 0         | 1          | 2          | 47        | 1      | 0     | 51    |
| Intj           | 1         | 0          | 5          | 0         | 1      | 0     | 7     |
| Kon            | 29        | 0          | 6          | 6         | 4      | 0     | 45    |
| Ment           | 0         | 0          | 1          | 372       | 0      | 0     | 373   |
| Mult           | 5         | 0          | 2          | 1         | 1      | 0     | 9     |
| Non-txt        | 0         | 0          | 105        | 1         | 0      | 0     | 106   |
| Other          | 59        | 1          | 21         | 9         | 13     | 5     | 108   |
| W-f            | 0         | 0          | 0          | 70        | 1      | 0     | 71    |
| **Total**      | 664       | 20         | 392        | 630       | 150    | 68    | 1924  |

Alt-f: alternative question; Decl: declarative; Excl: exclamative; F: yes-/ no-question; Frag: fragment; Imp: imperative; Intj: interjection; Kon: conjunctive; Ment: mention; Mult: multiple; Non-txt: non-textual; W-f: w-question

The second use of rejoice speech acts is illustrated in example f). Here, rejoice speech acts are used to express a positive attitude over something that can be viewed as offensive, thereby praising it. The segment “Das einzig Gute an #Jamaika @HeikoMaas ist endlich weg!” has been annotated as an instance of a rejoice speech act expressed through an exclamative sentence. The author of this tweet is expressing his positive attitude towards the assertion that “@HeikoMaas ist endlich weg!”, an utterance which can be regarded as being rather offensive.

* Ex. f) @Beatrix_vStorch @HeikoMaas @RegSprecher @BMJV_Bund Das einzig Gute an #Jamaika @HeikoMaas ist endlich weg!16

5.3 Discussion

With respect to the results on the frequency of speech acts in the data, it is striking that some of the fine-grained speech acts do not occur at all or only very rarely. This concerns the class accept (no occurrences) and the classes greet (0.1%), apologize (0.1%), refuse (0.1%), threat (0.3%), disagree (0.3%) and thank (0.4%). In general, commissives are very rare in the data (1.0%). The rare occurrence of greet is probably

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16 Transl.: ‘The only good thing about #Jamaika, @HeikoMaas is finally gone!’
partly owed to the type of dataset (single tweets without any context) and partly owed to the way how tweets were segmented. As Compagno et al. (2018) show in their annotation scheme, it is in the nature of accept and refuse speech acts that they depend on previous utterances. With the lack of conversational context, it is sometimes impossible to either distinguish accept and refuse from agree and disagree or to be entirely certain that the labels accept or refuse are the correct ones.

Hence, for an updated version of the annotation scheme that deals with the same type of dataset, rarely occurring categories should be excluded or subsumed by the class other; we could also reconsider the segmentation approach and foresee smaller segments that we assign speech acts to, as to reduce the possibility of multiple speech acts occurring simultaneously in one sentence. This approach, however, could lead to a demand for more speech act categories and, hence, annotations.
Another finding is that tweets with implicitly offensive language seem to be more made up of statements (consisting of 41.2% assertives) and containing less expressives overall (meaning rejoice and complain). This seems reasonable, as the author does not appear to express their feelings or attitudes in an obvious, explicit way. A further discovery that supports this explanation is that the category expressEmoji was used least frequently in tweets with implicit offensive language. It should be noted that the distinction between expressives and assertives (excluding the category expressEmoji) was the most prominent issue faced during annotation. It seems that tweets with implicit offensive language contained more speech acts that were phrased more like statements than expressives so that, when in doubt, the annotator chose the assert label instead of complain or rejoice.

Finally, the findings concerning the most common syntactic realisation of each speech act type (Table 6) correspond to the view in the literature regarding sentence types and their most frequently used speech acts. König and Siemund (2007) state that declaratives are used most frequently for speech acts such as asserting something, interrogatives are usually used for requests and imperatives are commonly used for orders. The observation that exclamatives mostly realize complain speech acts in this data seems logical as the definition in the Duden states that exclamatives are sentences that are uttered with emphasis (Dudenredaktion, 2016) and expressives such as complain probably transmit a lot of strong emotions that are best expressed by using an exclamative sentence.

6 Conclusions and Future Work

The results show that offensive language mainly differs from non-offensive language in the respect that offensive language contains more expressives and less assertives than non-offensive language. The biggest difference is most prominent when we compare tweets with implicit offensive language tweets with explicit offensive language. Tweets with implicit offensive language seem to lack the tendency to overtly express emotions, hence they have the lowest frequency of expressives (excluding non-offensive tweets) and the highest frequency of assertives. In contrast, tweets with explicit offensive language show the opposite: they have the lowest frequency of assertives and the highest frequency of expressives.

Our results suggest that differences exist with regard to the distribution of speech acts in offensive language and non-offensive language. It remains to be seen if an accurate speech act classifier can be developed as one additional component in larger hate speech detection systems. Also in terms of future work, we plan to annotate part of the dataset with two more annotators so that we can further improve our annotation approach and also to assess the quality of the dataset and annotations with regard to inter-annotator agreement.

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## Appendix

Table 4: Absolute frequencies of fine-grained speech acts in sentence types

| Speech Act     | Alt-f | Decl | Excl | F | Frag | Hashtag | Imp | Intj | Kon | Ment | Mult | Non-txt | Other | W-f | Total |
|----------------|-------|------|------|---|------|---------|-----|------|-----|------|------|---------|-------|-----|-------|
| Accept         | 0     | 0    | 0    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 0     |
| Address        | 0     | 0    | 1    | 0 | 0    | 0       | 0   | 0    | 371 | 0    | 0    | 1       | 0     | 2   | 375   |
| Agree          | 0     | 4    | 3    | 0 | 5    | 0       | 1   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 13    |
| Apologize      | 0     | 0    | 0    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 1       | 0     | 1   | 1     |
| Assert         | 0     | 305  | 43   | 0 | 140  | 1       | 0   | 0    | 24  | 0    | 0    | 4       | 58    | 0   | 575   |
| Complain       | 0     | 100  | 55   | 0 | 65   | 5       | 2   | 3    | 4   | 0    | 2    | 0       | 13    | 0   | 249   |
| Disagree       | 0     | 6    | 0    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 6     |
| Engage         | 0     | 3    | 0    | 10| 0    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 13    |
| Greet          | 0     | 0    | 0    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 1       | 0     | 1   | 1     |
| Guess          | 0     | 11   | 1    | 2 | 6    | 0       | 0   | 0    | 5   | 0    | 1    | 0       | 0     | 26  | 29    |
| Other          | 0     | 0    | 0    | 1 | 62   | 0       | 0   | 0    | 0   | 0    | 0    | 5       | 0     | 68  | 73    |
| Predict        | 0     | 24   | 7    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 1       | 0     | 32  | 33    |
| Refuse         | 0     | 0    | 0    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 1     |
| Rejoice        | 0     | 7    | 2    | 0 | 5    | 0       | 0   | 2    | 0   | 0    | 0    | 0       | 0     | 0   | 17    |
| Request        | 5     | 2    | 2    | 79| 1    | 0       | 2   | 0    | 2   | 1    | 0    | 0       | 1     | 68  | 163   |
| Require        | 0     | 7    | 7    | 1 | 6    | 3       | 45  | 0    | 1   | 0    | 0    | 0       | 6     | 0   | 76    |
| Suggest        | 0     | 4    | 1    | 0 | 5    | 0       | 0   | 0    | 3   | 0    | 1    | 0       | 1     | 0   | 15    |
| Sustain        | 0     | 9    | 2    | 0 | 1    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 12    |
| Thank          | 0     | 1    | 1    | 0 | 2    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 8     |
| Threat         | 0     | 3    | 2    | 0 | 0    | 0       | 0   | 0    | 0   | 0    | 0    | 0       | 0     | 0   | 6     |
| Unsure         | 0     | 36   | 15   | 0 | 78   | 0       | 1   | 1    | 4   | 0    | 1    | 0       | 13    | 1   | 150   |
| Wish           | 0     | 2    | 1    | 0 | 4    | 0       | 0   | 0    | 2   | 0    | 0    | 0       | 0     | 2   | 11    |
| expressEmoji   | 0     | 0    | 0    | 0 | 0    | 0       | 0   | 0    | 1   | 0    | 0    | 105     | 0     | 0   | 106   |
| Total          | 5     | 524  | 143  | 82| 329  | 71      | 51  | 7    | 45  | 373  | 9    | 106     | 108   | 71  | 1924  |

Alt-f: alternative question; Decl: declarative; Excl: exclamative; F: yes/no-question; Frag: fragment; Imp: imperative; Intj: interjection; Kon: conjunctive; Ment: mention; Mult: multiple; Non-txt: non-textual; W-f: w-question