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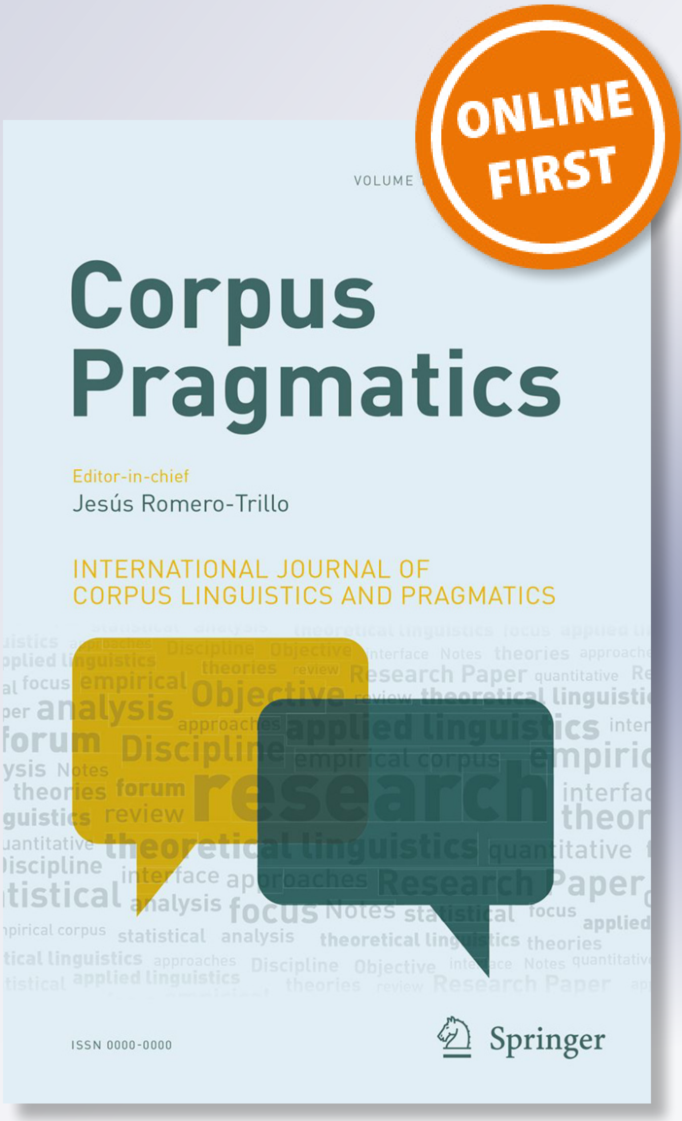
Martin Schweinberger

Corpus Pragmatics
International Journal of Corpus Linguistics and Pragmatics

ISSN 2509-9507

Corpus Pragmatics
DOI 10.1007/s41701-019-00062-z



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https://doi.org/10.1007/s41701-019-00062-z

ORIGINAL PAPER

A Sociolinguistic Analysis of Emotives

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Received: 4 March 2019 / Accepted: 17 September 2019

Abstract

This study details a replicable method for annotating emotionality of natural language that can be used in sociopragmatic, corpus-based analyses of discourse. A case study uses a type of sentiment analysis based on the crowd-sourced *Word-Emotion Association Lexicon* to investigate the social stratification of emotives, i.e. words associated with one of eight core emotions (ANGER, ANTICIPATION, FEAR, DISGUST, JOY, SADNESS; SURPRISE, and TRUST). The sentiment analysis is applied to dialogue data taken from the Irish component of the *International Corpus of English* and emotion scores provided by the sentiment analysis are correlated with the age and gender of speakers, the audience size, conversation type (same- vs. mixed gender conversation), dialogue setting (private vs. public), and part-of speech. The results of mixed-effects binomial regression models show that speakers use FEAR emotives significantly more frequently in public settings while JOY, DISGUST, and SURPRISE emotives are used more in private settings. In addition, men are significantly more likely to use ANGER and FEAR emotives, while women show higher rates of JOY emotives. Speakers aged 33 and older are more likely to use TRUST emotives compared with younger speakers. The results challenge common gendered social stereotypes according to which emotional language is associated with young women in particular. In contrast, the study shows that the genders exhibit emotion-specific preferences. In addition, the finding that negative emotions are more frequent in public discourse may indicate a general tendency even in apolitical conversation. However, the socio-political context in which the data were gathered has to be taken into account. It is highly likely that the linguistic expression of emotion was substantially affected by the communal tensions during the Northern Ireland conflict and findings should thus be treated with care not be naively generalized.

Keywords Sentiment analysis · Emotion language · Sociolinguistics · Gender differences · Emotives

✉ Martin Schweinberger
m.schweinberger@uq.edu.au

1 School of Languages and Cultures, The University of Queensland, Gordon Greenwood Building, St Lucia, QLD 4072, Australia

Published online: 04 October 2019

Introduction

One of the core functions of language consists of communicating one's emotional state to others. Yet, there exists relatively little corpus-based sociopragmatic research on how speakers convey their emotions to others. One reason for this lack of sociopragmatic investigations of emotional language consists in problems relating to the replicable and intersubjective annotation of emotionality. It is still common practice to annotate emotionality based on single raters or only a few individual raters. The present study addresses this issue by exemplifying an application of a type of sentiment analysis[1] that allows a replicable and intersubjective coding of emotional language. The sentiment analysis used in the present study is based on a crowd-sourced *Word-Emotion Association Lexicon* (Mohammad and Turney 2013) to code for emotional language use. This is innovative in at least two aspects:

(i) While being frequently used and common in consumer behavior analyses or analyses of either social media (e.g. Pak and Paroubek 2010; Weller et al. 2014), consumer behavior (e.g. Kennedy and Inkpen 2006; Dave et al. 2003) and political discourse (Bakliwal et al. 2013; Hoffmann 2018), or register variation, sentiment analyses have only recently begun to be used to investigate sociolinguistic stratification;
(ii) The vast majority of sentiment analyses only differentiate between positive and negative polarity (cf. Stine 2019) while the sentiment analysis applied here additionally provides association scores between words and eight specific core emotions (ANGER, ANTICIPATION, FEAR, DISGUST, JOY, SADNESS; SURPRISE, and TRUST).

Thereby, the sentiment analysis exemplified here allows us to conduct more fine-grained qualitative analyses of the linguistic expression of emotion that can be utilized in research on the pragmatics of emotional language. Although sentiment analyses suffer from various deficiencies such as their restriction to the lexical domain, their inability to incorporate contextual factors and formulaic expressions, and their inability to account for negation, they are intriguing as they allow to code emotionality in a replicable and time-efficient manner.

In addition to exemplifying the use of a sentiment analysis to produce reliable coding of emotionality that can be utilized in more detailed pragmatic or conversational research, the aim of the present study is to evaluate the validity of culturally accepted stereotypes according to which women are more emotional than men (Aldrich and Tenenbaum 2006: 776, cf. also Coates 2015; Holmes 1997; Lakoff 1973) and younger speakers over-proportionately use emotional language compared to their older peers. Empirical studies based on linguistic resources have partially added support to these stereotypes showing that women talk more about emotions

[1] It should be noted that the name of the procedure, sentiment analysis, is used as this is the common reference term. However, from a functional perspective it would be more accurate to refer to the type of sentiment analysis presented here as emotion analysis.

(Goldschmidt and Weller 2000) and report being more emotionally expressive (Bronstein et al. 1996) than men do. Furthermore, there is supportive evidence showing that emotions are at least partially gender specific with women being and expressing sadness more than men (Grossman and Wood 1993) and girls and female adolescents report "sadness" more frequently compared to their male peers (Brody 1984; Stapley and Haviland 1989). In contrast, boys have been found to express anger more readily than girls (Brody et al. 2016).

The body of research that has emerged from investigating the verbalization of emotion has typically focused on issues relating to subjectivity (Langacker 1985; Lyons 1981), the expression of stance (cf. e.g. Goodwin et al. 2012), or it has taken a cognitive approach based in conceptual metaphor theory to analyze metaphoric construals of emotion (cf. e.g. Köveces 2000; Meier and Robinson 2005). Theoretical approaches to emotion language have focused mainly on componential analysis of word meaning following Wierzbicka's (1972, 1992) theory of semantic primitives. Early corpus-based research on emotion language did not use conversational data but relied on a self-compiled corpus of words associated with five core emotions (see Johnson-Laird and Oatley 1989). The reason for using word-lists rather than conversational data was motivated by aiming at providing a theoretical model for emotion language rather than an assessment of its real-world usage. Contrasting with these approaches, the present study was designed to investigate systematic differences in emotional language by taking a corpus-based quantitative approach to emotion language which focuses on frequency differences of words (emotives) that are associated with one of eight emotional states (anger, anticipation, disgust, fear, joy, sadness, surprise, trust) (cf. Ekman 1992; Plutchik 1980). The current analysis utilizes the frequencies of emotives by correlating them with extra-linguistic factors (age and gender of speakers, private vs. public setting, same vs. mixed gender conversation, and audience size) in order to investigate which factors correlate with more emotionally expressive language. While the focus on quantitative aspects implies that the present study cannot provide fine-grained analysis of conversation that are the hallmark of pragmatic research, it is important to keep in mind that the present study merely serves as a a show case of how sentiment analysis may be utilized to inform future research that takes a more qualitative approach.

Various studies have called the accuracy of these stereotypes into question. To elaborate, studies which have specifically focused on the verbal expression of emotions did not find significant gender differences (Shimanoff 1985) and additional research has shown that, even if gender differences exist, the effect of other factors such as the conversational topic is substantially larger than that of a speaker's gender (Anderson and Leaper 1998). Furthermore, in a study of the verbal expression of the gender-stereotyped emotions anger, sadness, and frustration among adolescents and in parent–child interactions, Aldrich and Tenenbaum (2006) found that boys but not girls used higher frequencies of words associated with sadness, while girls were more likely to use words associated with frustration compared to boys. Interestingly, Aldrich and Tenenbaum (2006) did not find significant differences in the verbal expression of anger, sadness, and frustration among adults.

The following section introduces the data and the methodology used in the present study while "Visualizations and Results" section visualizes the data and displays the results of the statistical analysis. "Discussion" section discusses the results of the analysis and "Outlook" section provides an outlook for future research and elaborates on the application of sentiment analyses to sociopragmatic issues more broadly.

Data and Methodology

One problem that is common when investigating emotional language or emotionality in discourse from a corpus-based pragmatic perspective relates to the reliability of the coding of emotionality especially because, in pragmatic research, the coding of emotionality is required to be more detailed than mere polarity categorization. The study avoids subjective judgements of associations between lexical elements and emotional states by applying a sentiment analysis (cf. Crossley et al. 2016 for a detailed description of sentiment analysis and its application) in R (R Development Core Team 2008) using the syuzhet package version 1.0.0 (Jockers 2017). Sentiment analysis is a cover term for approaches which extract information on emotion or opinion from natural language (cf. Crossley et al. 2016; Hutto and Gilbert 2014; Liu 2012; Pang and Lee 2008). Sentiment analyses have been successfully applied to analysis of language data in a wide range of disciplines such as psychology, economics, education, as well as political and social sciences (cf. Hutto and Gilbert 2014). Commonly sentiment analyses are used to determine the stance of a larger group of speakers towards a given phenomenon such as political candidates or parties, product lines or situations. Crucially, sentiment analyses are employed in these domains because they have advantages compared to alternative methods investigating the verbal expression of emotion. One advantage of sentiment analyses is that the emotion coding of sentiment analysis is fully replicable. Replicability is achieved by using a large, crowd-sourced term-emotion data bases whereas subjective coding, as it is commonly used, relies on subjective evaluations by either single raters or a limited number of raters. The most substantive advantage of the sentiment analysis used in the present paper (cf. Jockers 2017) is that it allows the investigation of overall emotionality as well as distinct emotions. This is relevant as most other types of sentiment analyses employ a simple positive–negative polarity to classify emotions. In contrast to such relatively simplistic classification methods, the more fine-grained approach taken here is made possible as the sentiment analysis performed for the current study uses the *Word-Emotion Association Lexicon* (Mohammad and Turney 2013), which comprises 10,170 terms, in which lexical elements are assigned scores based on ratings gathered through the crowd-sourced *Amazon Mechanical Turk service*. For the *Word-Emotion Association Lexicon* raters were asked whether a given word was associated with one of eight emotions according to their judgement. The resulting associations between terms and emotions are based on 38,726 ratings from 2216 raters who answered a sequence of questions for each word which were then fed into the emotion association rating (cf. Mohammad and Turney 2013). Each term was rated 5 times. For 85 percent of words, at least 4 raters provided identical ratings. For instance, the word *cry* or *tragedy* are more readily associated with SADNESS while words such as *happy* or *beautiful* are indicative of JOY and words like *fit* or *burst* may indicate ANGER. This means that the sentiment analysis here allows us to investigate the expression of certain core emotions rather than merely classifying statements along the lines of a crude positive–negative distinction (cf. e.g. the various sentiment classifiers discussed in Stine 2019). It is this more detailed output of the type of sentiment analysis implemented here that creates the potential for sentiment analysis to guide and inform corpus-based pragmatic studies of emotional language in the future.

One major shortcoming of the analysis exemplified in the present paper is that it is exclusively lexical in nature and assumes that certain words are associated with emotional states while other words lack such associations. For instance, the lexical items *happy*, *love*, and *good* are associated with the basic emotion JOY, while *hit*, *whip*, and *death* are associated with the emotion ANGER. In addition, lexical items can be associated with more than one emotion. The word *death*, for example, is associated with both ANGER and SADNESS. The concept of emotion in the present study rests on Ekman (1992), who argues for the existence of six basic emotions, i.e. joy, sadness, anger, fear, disgust, and surprise, and Plutchik (1980, 1994) who proposes eight basic emotions by adding trust and anticipation to Ekman's basic emotions. The association between words and emotions is of course not fixed as words often vary in meaning depending of the given context. Nonetheless, if many speakers rate a given word coherently as associated with a certain emotional state it seems likely that a word is prototypically used in contexts in which it is associated with a given emotion. Also, the reliance on lexical elements is a noteworthy limitation of this method as it implies that the mere occurrence of a word forms the basis for assigning emotionality scores regardless of whether the word occurs in fixed-expressions. For instance, if *good* is used in a fixed expression such as "good morning", it is treated on par with its use in utterances such as "That's a very good idea". Other shortcomings relate to the disregard of context and semantic ambiguity as well as the underlying assumption that the meaning of a lexical item is fixed, context-independent, and remains relatively stable over time. These are serious shortcomings of automated sentiment analysis and they are discussed more thoroughly in the discussion section of this paper.

The analysis is based on data from the Irish component of the *International Corpus of English* (ICE Ireland 1.2.2; cf. Kirk and Kallen 2008), which comprises data collected between 1990 and 2005. The Irish ICE component is particularly interesting for present purpose because it is accompanied by a wealth of metainformation not only about the conversational setting but also about the social and cultural background of speakers (cf. Kirk and Kallen 2008). The coding of the (self-reported) age and gender of speakers as well as the setting of the conversations is based the metadata provided by the compilers of ICE Ireland (cf. Kirk and Kallen 2008). Other variables, for instance audience size and conversation type, have been derived from the corpus data and the metadata as they were not explicitly provided in the metadata. The wealth of metainformation that accompanies the Irish ICE data is a major advantage of the Irish data over other ICE components and represent one motivating factor for the present analysis. Thus, focusing on linguistic expression of emotions in Irish English was made possible only because of the provision of the extensive metadata that accompanies the Irish ICE component. In addition, using the Irish ICE data, in particular, is motivated by the political context that was present during the time of data collection. In this regard, the study aims to evaluate if corpus-linguistic methods are able to unearth linguistic expressions of emotion that may be associated with the political context in Ireland during the 1990s such as the Troubles psyche, the peace process, and cross-community issues. To elaborate, the socio-historical context during which the corpus data was compiled has to be taken into account when interpreting the findings. The linguistic behavior that is reflected in the data mirrors the social and cultural circumstances of the speakers during times of civil unrest and traumatizing tensions especially within Northern Irish communities.

The current study uses informal spoken language to tap into unmonitored naturally occurring speech. More specifically, the data comprises private dialogues which consist of transcribed face-to-face and telephone conversations, as well as unscripted public dialogues consisting e.g. of classroom lessons and broadcast discussions. The corpus data represents almost exclusively native speakers of Irish English above an age of 18. Non-native speakers of Irish English, for instance speakers of other varieties of English, were tagged and their output was removed from the analysis. The ICE over-represents educated speakers as the intention of the compilers was to create a corpus that represents the national standard language. In addition, female speakers are over-represented in the data as the compilers relied heavily on students studying English and females are over-proportionately represented in this student body.

During the data processing, the corpus data is split into individual words and aligned with the speakers' biodata (age, gender, etc.). Stop words, i.e. function words which have little semantic content, were removed and the ratings provided by the sentiment analysis were added to the data so that the resulting table contained one word per row, the values of the demographic variables as well as the emotion category ratings. As Wang and Hsieh (2007) found that women preferred adjectives and verbs to express emotions while men exhibited a preference for nouns (2007: 89, 92–93) the present study added part-of-speech annotation to each word using the openNLP package in R (Hornik 2016). Due to the low emotion scores of word class other than adjectives, common nouns, and verbs, all other word classes were removed from the analysis (including proper nouns). In addition, whether a given conversation took place between same gender interlocutors or whether the conversation had mixed gender interlocutors was assessed in order to determine whether or not the gender of the interlocutor affected the use of emotives and whether the effect was potentially gender specific, i.e. the gender of the interlocutor could have an effect on men but not women or vice versa. In a similar vein, the audience size was coded to determine whether the likelihood to utter emotives changes in the presence of different numbers of interlocutors. Furthermore, it was determined for each word whether it occurred in a private dialogue (e.g. meal time conversations or telephone calls) or in a public dialogue (lectures or discussions broadcasted on TV). The reason for coding the setting was that speakers may differ in their use of emotives based on the formality or intimacy of a given speech situation.

The independent and dependent variables of the present analysis as well as their operationalization are shown in Table 1 below.

Table 1 Overview of the independent and dependent variables in the final data set of the Irish ICE data with scales, levels and short description

Variable	Scale	Levels	Description
Independent variables (predictors)			
Random intercepts			
Speaker	Categorical	S1A-001$A : S1B-080$P	Individual speaker
POS	Categorical	Adjective; Noun; Verb	Part-of-speech
Fixed effects			
Age	Categorical	19–25; 26–33; 34–49; 50+	Age of speaker
Gender	Nominal	Men; Women	Self reported gender of speaker
POS	Categorical	Adjective; Noun; Verb	Part-of-speech
Setting	Nominal	Private; Public	Conversation has taken place in a private setting or with a public audience (coding reflects the categorization provided by the ICE compilers)
ConversationType	Nominal	SameGender; MixedGender	Same or mixed gender conversation
AudienceSize	Categorical	Dyad, Small (3–5), Large (6+)	Number of interlocutors
Dependent variables			
EMOTIONALITY	Nominal	0;1	Word is associated with any emotion
ANGER	Nominal	0;1	Word is associated with ANGER
ANTICIPATION	Nominal	0;1	Word is associated with ANTICIPA-TION
DISGUST	Nominal	0;1	Word is associated with DISGUST
FEAR	Nominal	0;1	Word is associated with FEAR
JOY	Nominal	0;1	Word is associated with JOY
SADNESS	Nominal	0;1	Word is associated with SADNESS
SURPRISE	Nominal	0;1	Word is associated with SURPRISE
TRUST	Nominal	0;1	Word is associated with TRUST

The final data set consists of educated standard Irish English dialogues encompassing speech of 537 speakers uttering 77,107 non-stop words. An overview of frequency of emotives per variable level in the final data set is provided in Table 2.

To gain a better understanding of the relationship of emotive use by variable level, Table 3 provides the mean percentages of emotives per variable level (see below).

We will now turn to the specifics of the statistical methods used in the present paper. The statistical analysis uses a correspondence analysis (Greenacre 1984, 2017) using the FactoMineR (Le et al. 2008) and factoextra packages (Kassambara and Mundt 2017) in R to investigate which words are associated with which emotion. In addition, mixed-effects binomial regression models (Bates et al. 2018) are applied to test the overall correlations between the independent variables (and two-way interactions between them) and the use of emotives. The random effect structure of the model contains random intercepts for (a) part-of-speech to control the effect of differences caused

Table 2 Frequency of speakers, words, emotives and non-emotional words by variable levels in the final data set of Irish ICE data

Variable	Levels	Speakers	Words	EMOTIONALITY	ANGER	ANTICIPATION	DISGUST	FEAR	SADNESS	SURPRISE	TRUST	NON-EMOTIONAL
Age	19–25	209	27,602	3701	684	1455	525	773	899	666	1475	23,901
	26–33	87	12,248	1784	337	682	238	437	423	258	683	10,464
	34–49	120	17,149	2828	421	900	265	707	573	363	1243	14,321
	50 +	121	20,108	3025	517	1156	308	688	676	481	1260	17,083
Gender	Men	216	31,748	5064	910	1685	516	1311	1139	676	2075	26,684
	Women	321	45,359	6274	1049	2508	820	1294	1432	1092	2586	39,085
POS	Adjective	507	11,503	2954	551	1202	581	628	866	815	1363	8549
	Noun	529	34,189	5756	991	1806	496	1448	1124	615	2505	28,433
	Verb	529	31,415	2628	417	1185	259	529	581	338	793	28,787
Setting	Private	299	46,244	6331	1129	2666	879	1272	1484	1169	2534	39,913
	Public	238	30,863	5007	830	1527	457	1333	1087	599	2127	25,856
Conversation-Type	MixedGender	294	35,565	5260	902	1892	587	1255	1152	806	2109	30,305
	SameGender	243	41,542	6078	1057	2301	749	1350	1419	962	2552	35,464
AudienceSize	Dyad	67	17,747	2507	417	943	319	559	597	378	1057	15,240
	Small	148	12,611	1826	302	573	185	442	403	213	729	10,785
	Large	322	46,749	7005	1240	2677	832	1604	1571	1177	2875	39,744
Total		537	77,107	11,338	1959	4193	1336	2605	2571	1768	4661	65,769

Table 3 Percentage values of emotives by variable levels in the final data set of Irish ICE data

Variable	Level	EMOTIONALITY	ANGER	ANTICIPATION	DISGUST	FEAR	SADNESS	SURPRISE	TRUST	NON-EMOTIONAL
Age	19–25	13.4	2.5	5.3	1.9	2.8	3.3	2.4	5.3	86.6
	26–33	14.6	2.8	5.6	1.9	3.6	3.5	2.1	5.6	85.4
	34–49	16.5	2.5	5.2	1.5	4.1	3.3	2.1	7.2	83.5
	50+	15.0	2.6	5.7	1.5	3.4	3.4	2.4	6.3	85.0
Gender	Men	16.0	2.9	5.3	1.6	4.1	3.6	2.1	6.5	84.0
	Women	13.8	2.3	5.5	1.8	2.9	3.2	2.4	5.7	86.2
POS	Adjective	25.7	4.8	10.4	5.1	5.5	7.5	7.1	11.8	74.3
	Noun	16.8	2.9	5.3	1.5	4.2	3.3	1.8	7.3	83.2
	Verb	8.4	1.3	3.8	0.8	1.7	1.8	1.1	2.5	91.6
Setting	Private	13.7	2.4	5.8	1.9	2.8	3.2	2.5	5.5	86.3
	Public	16.2	2.7	4.9	1.5	4.3	3.5	1.9	6.9	83.8
ConversationType	MixedGender	14.8	2.5	5.3	1.7	3.5	3.2	2.3	5.9	85.2
	SameGender	14.6	2.5	5.5	1.8	3.2	3.4	2.3	6.1	85.4
AudienceSize	Dyad	14.1	2.3	5.3	1.8	3.1	3.4	2.1	6.0	85.9
	Small	15.0	2.7	5.7	1.8	3.4	3.4	2.5	6.1	85.0
	Large	14.5	2.4	4.5	1.5	3.5	3.2	1.7	5.8	85.5
Total		14.7	2.5	5.4	1.7	3.4	3.3	2.3	6.0	85.3

Fig. 1 Results of the correspondence analysis

by word class rather than other predictors and for (b) speaker to avoid assigning an effect caused by idiosyncratic preferences to any of the tested predictors. The dependent variable is in all cases nominal and it denotes whether or not a given word is emotional (EMOTIONALITY) or associated with any of the eight core emotions. In all cases, a step-wise step-up procedure was applied during which predictors are added consecutively. During this procedure a model without a given variable was compared to a model with that variable. If the difference between models was significant (reported as χ^2-statistics) the variable was retained in the model. If a predictor was included but the model comparison did not report a significant increase in model fit, then the variable was dropped. If including a predictor caused values of variance inflations factors (VIFs) to exceed a value of three, the predictor was also removed despite being reported significant as models with high VIFs are uninterpretable and provide unreliable results (Field et al. 2012: 276; Zuur et al. 2010). The variables that were tested are shown in Table 1. In addition to testing the effect of variables, the statistical analyses assessed all secondary or two-way interactions between variables. Interactions were not included in cases where this would have led to complete separation, cases of incomplete information (cf. Field et al. 2012: 322–323), or if their inclusion caused VIF-values to exceed a value of three.

Visualizations and Results

This section provides visual summaries of the emotives and the predictors that were reported as significantly correlating with the predictors by the statistical analyses. Figure 1 shows the results of the correspondence analysis which evaluates which words are particularly associated with which emotion.

Figure 1 shows that there are two clusters of emotions along the first dimension which corresponds to the polarity dimension (positive–negative). The negative emotion cluster (ANGER, DISGUST, FEAR, and SADNESS) are grouped very closely together while the positive cluster members (ANTICIPATION, JOY, SURPRISE, and TRUST) are spread out along the second dimension. Among the words that are most strongly associated with emotives, *kind* and *friend* are associated with TRUST, while *start*, *long*, *time*, *thought*, *coming*, and *public* are associated with ANTICIPATION. The most frequent adjective, *good*, clearly associates with the positive cluster but does not align with any of the positive core emotions in particular. The words *mad*, *bad*, *hate*, *awful*, *terrible*, and *bloody* are associated with DISGUST and ANGER while *problem*, *case*, and *government* are more associated with FEAR and SADNESS.

The figures to follow focus exclusively on variables that have been determined to significantly correlate with the respective emotion by the statistical analyses. Each figure provides the percentage values of emotives in a given cohort.

Emotionality

We now turn to overall emotionality. Figure 2 displays the overall percentage values of emotives among non-stop words in educated standard Irish English across parts-of-speech (left panel), conversation setting (center panel), and age (right panel).

The left panel of Fig. 2 shows that adjectives exhibit the highest rates of emotives, while nouns and verbs have substantially lower rates of emotives. Emotives are significantly more likely to occur in public compared to private settings. In contrast to what would be expected given socially accepted stereotypes, the use of emotives increases with age as speakers older than 25 consistently exhibit higher percentages of emotives compared with the youngest cohort.

The mixed-effects binomial regression model reports part-of-speech as well as speaker as significant random effects and confirmed part-of-speech (χ^2: 2046.4, *DF*: 2, $p<.001$***), conversational setting (χ^2: 5.89, *DF*: 1, $p<.001$***), and age (χ^2: 9.87, *DF*: 3, $p<.01$**) as significant predictors (cf. Table 8 in the Appendix). With respect to differences between age groups, the regression model shows that only speakers between the ages of 34 and 49 differ significantly from the youngest speakers in the data (aged between 19 and 25) which serve as the reference category. Neither other main effects nor interactions between predictors significantly correlate with frequency of emotives in the data.

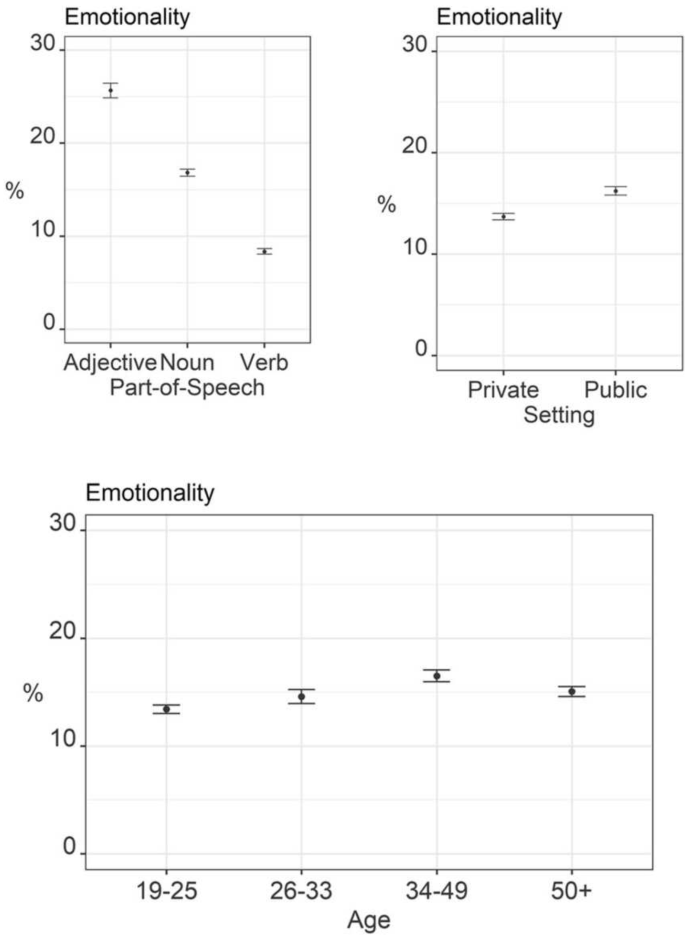


Fig. 2 Distribution of emotives in the Irish ICE data across parts-of-speech (top left panel), conversation setting (top right panel), and age (lower panel)

After inspecting the overall measure of emotionality, the following subsections display the distributions of specific emotives and provide the results of the statistical analyses.

Anger

Figure 3 shows the percentage of ANGER emotives among non-stop words in educated standard Irish English across parts-of-speech (left panel), and gender (right panel).

The mixed-effects model regressions confirm the visual displays in Fig. 2 in that nouns and verbs have significantly lower rates of emotives compared to adjectives (reference category) (χ^2: 407.3, *DF*: 2, $p < .001$***). Furthermore, the regression

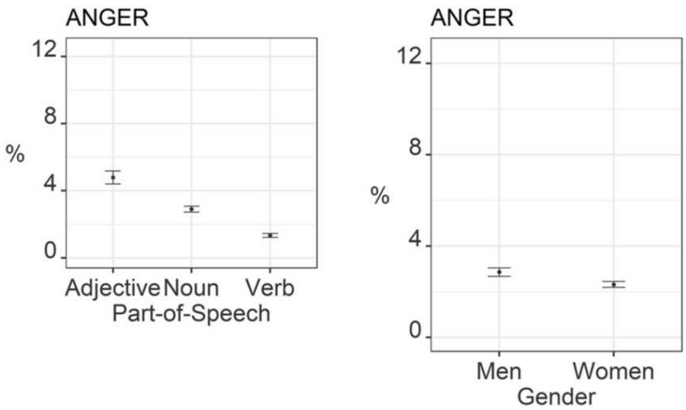


Fig. 3 Distribution of ANGER emotives in the Irish ICE data across parts-of-speech (left panel), and gender (right panel)

confirms that women are 0.83 times less likely to use ANGER emotives compared with men (χ^2: 6.66, *DF*: 1, $p < .001$***). Neither other main effects nor interactions between predictors significantly correlate with the frequency of ANGER emotives in the Irish ICE data.

Anticipation

Figure 4 shows the percentage of ANTICIPATION emotives among non-stop words in the Irish ICE data across parts-of-speech, conversation setting and with respect to the audience size.

According to the regression analysis (cf. Table 10 in the Appendix), adjectives exhibit the highest rates of emotives while nouns and verbs show substantially lower rates of ANTICIPATION emotives. In addition, speakers are significantly more likely to utter ANTICIPATION emotives in private compared with public settings (χ^2: 11.97, *DF*: 1, $p < .001$***). The finding for AudienceSize is somewhat unusual, as none of the variable levels differ significantly but including AudienceSize still significantly improved model fit (χ^2: 8.15, *DF*: 2, $p = .017$*). Therefore, AudienceSize was retained in the final model, although the model does not report any significant trend with respect to audience size and its effect on the use of ANTICIPATION emotives. Neither other main effects nor interactions between predictors significantly correlate with frequency of ANTICIPATION emotives in the data.

Disgust

Figure 5 shows the percentage of DISGUST emotives among non-stop words in Irish English across parts-of-speech (left panel) and setting (right panel).

The mixed-effects regression model reports parts-of-speech (χ^2: 784.37, *DF*: 2, $p < .001$***) and the conversation setting (χ^2: 18.58, *DF*: 1, $p < .001$***) as

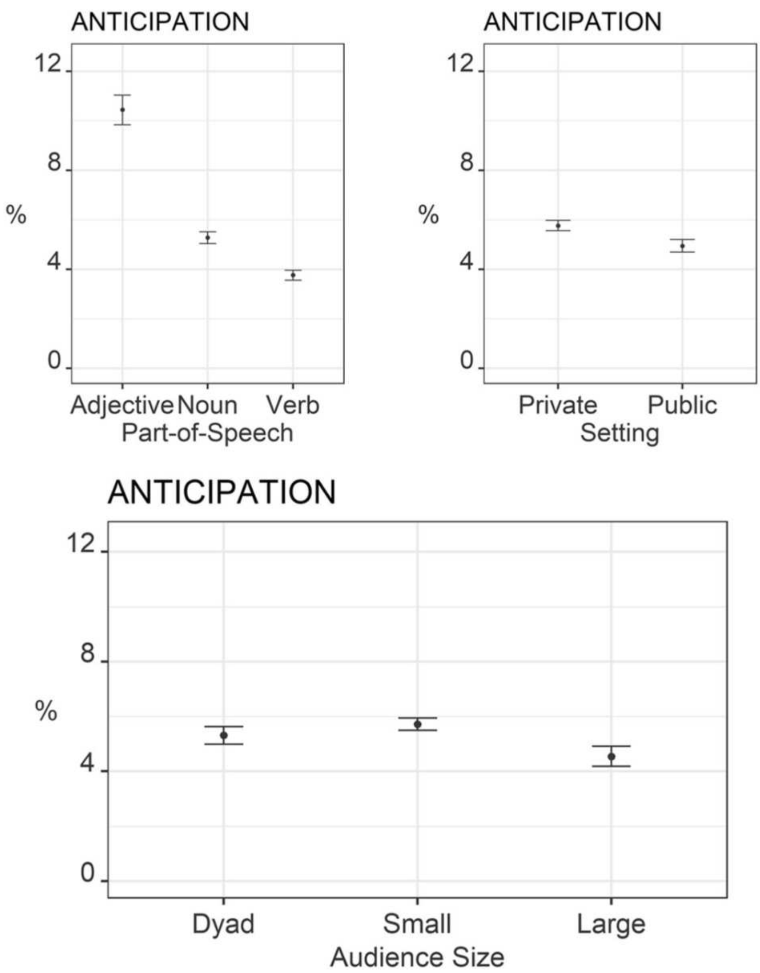


Fig. 4 Distribution of ANTICIPATION emotives in the Irish ICE data across parts-of-speech (top left panel), conversation setting (top right panel), and audience size (lower panel)

significant predictors. According to the regression analysis (cf. Table 11 in the Appendix), adjectives (reference category) exhibit significantly higher rates of DISGUST emotives compared to nouns and verbs. The odds ratios of POS:Noun and POS:Verb confirm a hierarchy of DISGUST emotives across parts-of-speech from adjective over nouns to verbs. Furthermore, speakers are more likely to utter DISGUST emotives in private settings compared with public settings (χ^2: 18.58, *DF*: 1, $p < .001$***). Neither other main effects nor interactions between predictors significantly correlate with frequency of DISGUST emotives in the data.

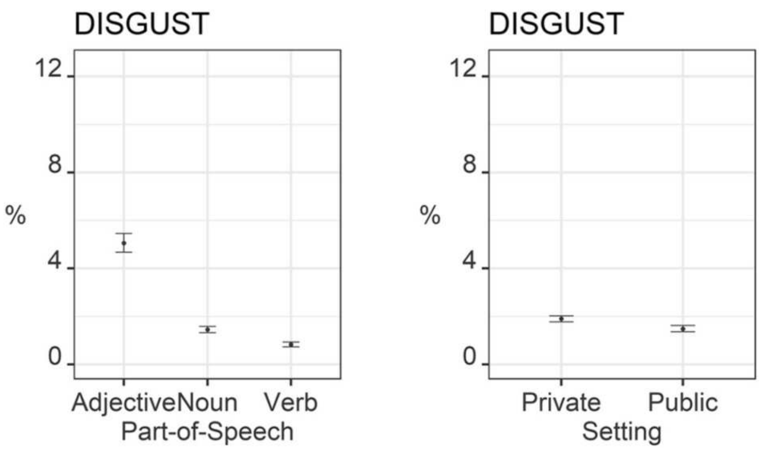


Fig. 5 Distribution of DISGUST emotives in the Irish ICE data across parts-of-speech (left panel) and conversation setting (right panel)

Fear

Figure 6 shows the percentage of FEAR emotives among non-stop words in the Irish ICE data across parts-of-speech (left panel), gender (center panel), conversation setting (right panel).

The regression model confirms that parts-of-speech ($\chi^2=434.15$, $DF=2$, $p<.001$***), gender ($\chi^2=6.32$, $DF=1$, $p=.011$*), and the conversation setting ($\chi^2=13.63$, $DF=1$, $p<.001$***) significantly affect the use of FEAR emotives. Again, adjectives exhibit the highest rate of FEAR emotives compared with nouns and verbs (cf. Table 12 in the Appendix). Furthermore, FEAR emotives are used significantly more frequently by men compared with women as the OddsRatio of Gender:Women is lower than 1. To elaborate, women are 0.81 times less likely to use FEAR emotives compared with men. Also, speakers are significantly more likely to use words associated with FEAR in public settings compared with private settings. Neither other main effects nor interactions between predictors significantly correlate with frequency of FEAR emotives in the Irish ICE data.

Joy

Figure 7 shows the percentage of JOY emotives among non-stop words in the Irish ICE data across parts-of-speech (left upper panel), gender (upper right panel), conversation setting (lower left panel), and audience size (right panel).

The regression model shows that part-of-speech ($\chi^2=1460.06$, $DF=2$, $p<.001$***), gender ($\chi^2=12.23$, $DF=1$, $p<.001$***), the conversation setting ($\chi^2=23.33$, $DF=1$, $p<.001$***), and the audience size ($\chi^2=19.28$, $DF=1$, $p<.001$***) significantly affect the use of JOY emotives. As before, adjectives exhibit the highest rates of JOY emotives while nouns and verbs show substantially lower rates (cf. Table 13 in the Appendix). In contrast to ANGER and

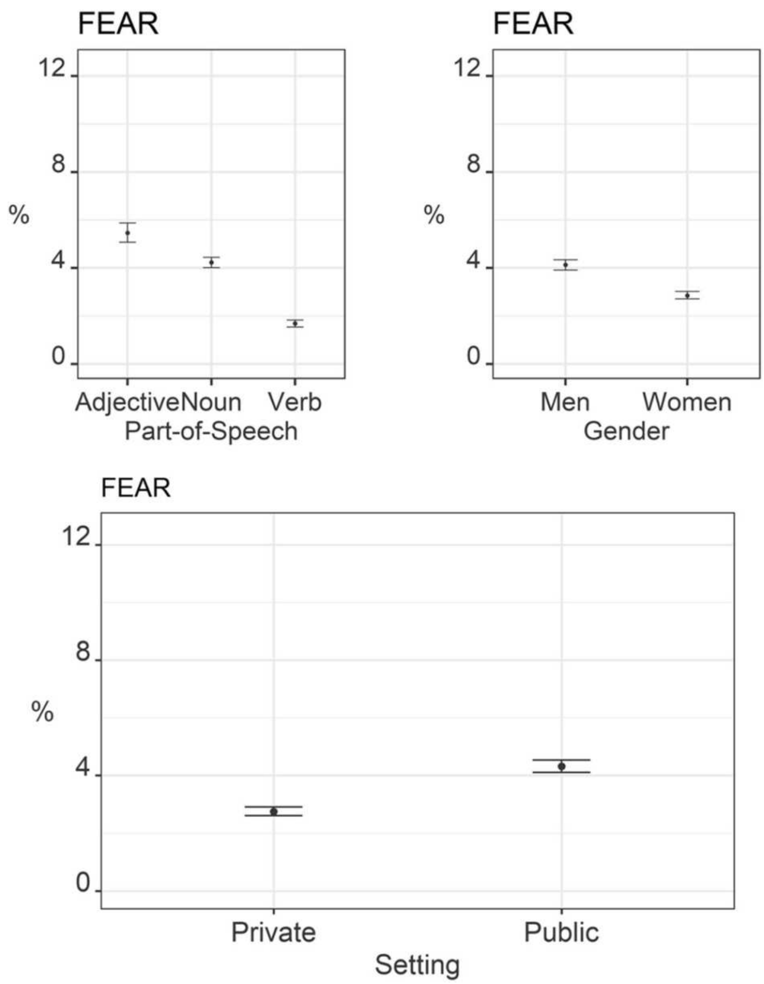


Fig. 6 Distribution of FEAR emotives in the Irish ICE data across parts-of-speech (top left panel), gender (top right panel), and conversation setting (lower panel)

FEAR emotives that showed higher rates among men, JOY emotives are used more by women compared with men. Also, speakers are more likely to utter JOY emotives in private compared to public settings. Finally, speaker use significantly fewer JOY emotives when there are many interlocutors compared with situations when there are only two participants in a conversation. Neither other main effects nor interactions between predictors significantly correlate with frequency of JOY emotives in the data.

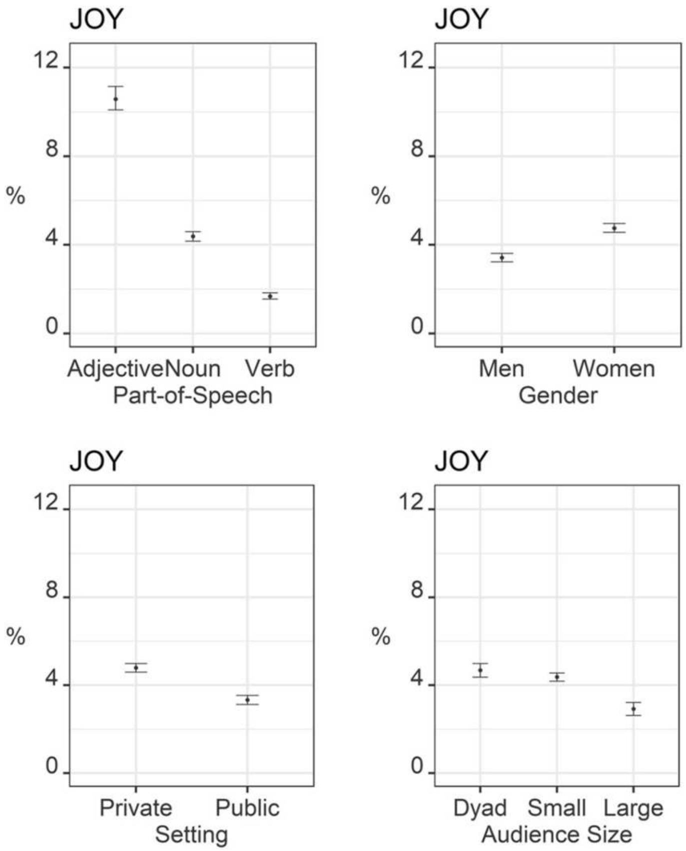
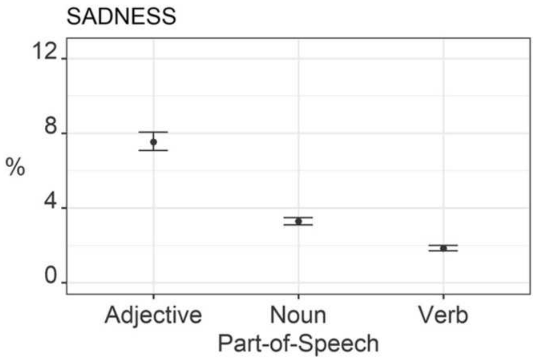


Fig. 7 Distribution of JOY emotives in the Irish ICE data across parts-of-speech (upper left panel), gender (upper right panel), conversation setting (lower left panel), and audience size (lower right panel)

Fig. 8 Distribution of SADNESS emotives in the Irish ICE data across parts-of-speech



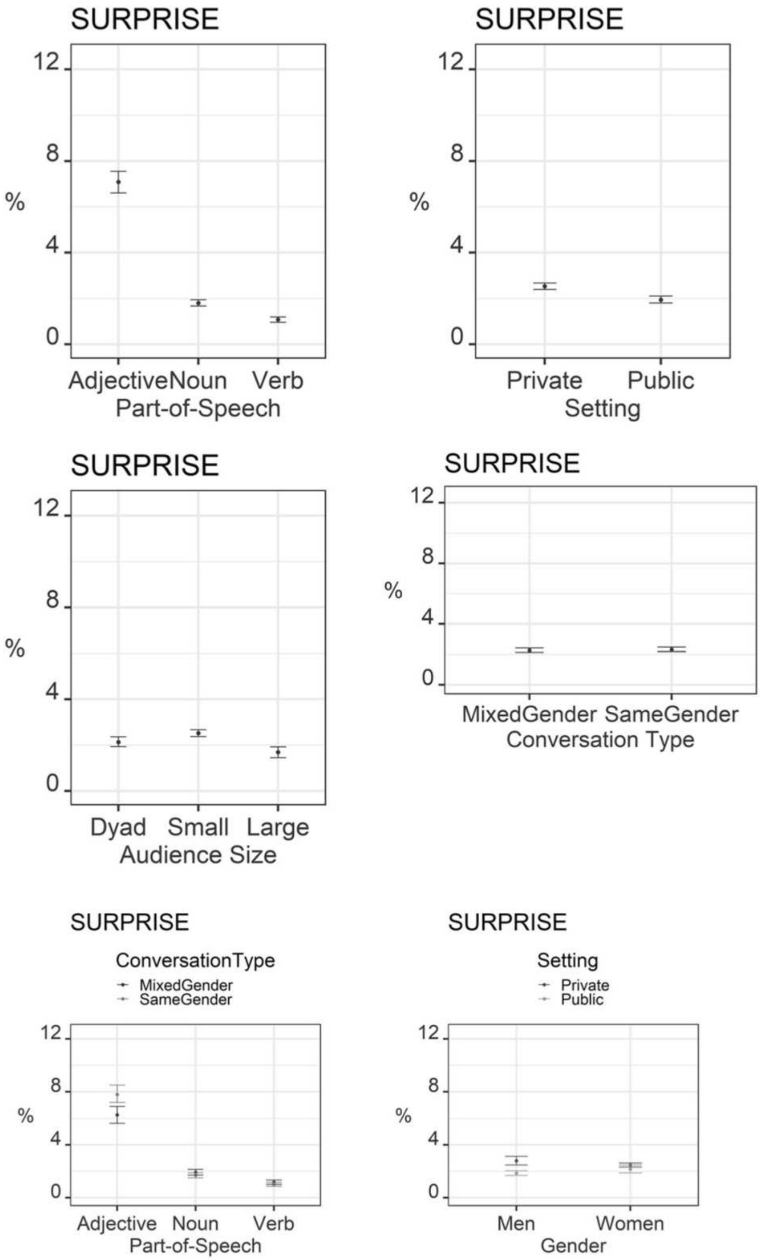


Fig. 9 Distribution of SURPRISE emotives in the Irish ICE data across parts-of-speech (upper left panel), conversation setting (upper right panel), audience size (center left panel), conversation setting (center right panel), conversation type by part-of-speech (lower left panel), and gender by conversation setting (lower right panel)

Sadness

Figure 8 shows the percentage of SADNESS emotives among non-stop words in the Irish ICE data.

The only significant predictor detected by the regression analysis is part-of-speech ($\chi^2 = 753.81$, $DF = 2$, $p < .001$***). According to both Fig. 8 and Table 14, adjectives exhibit the highest rates of SADNESS emotives while nouns and verbs show significantly lower rates (cf. Table 14 in the Appendix). Neither other main effects nor interactions between predictors significantly correlate with frequency of SADNESS emotives in the data.

Surprise

Figure 9 shows the percentage of SURPRISE emotives among non-stop words in the Irish ICE data across parts-of-speech (upper left panel), conversation setting (upper right panel), audience size (center left panel), conversation type (center right panel), conversation type by part-of-speech (lower left panel), and gender by conversation setting (lower right panel).

The regression model confirms that part-of-speech ($\chi^2 = 411.84$, $DF = 2$, $p < .001$***), the conversation setting ($\chi^2 = 16.25$, $DF = 1$, $p < .001$***), the audience size ($\chi^2 = 14.44$, $DF = 1$, $p < .001$***), the conversation type ($\chi^2 = 5.72$, $DF = 1$, $p = .0167$*), an interaction between part-of-speech and conversation type ($\chi^2 = 12.83$, $DF = 2$, $p = .0016$**) as well as an interaction between gender and conversation setting ($\chi^2 = 4.40$, $DF = 1$, $p = .0360$*) significantly affect the use of SURPRISE emotives (cf. Table 15 in the Appendix). According to both the upper left panel in Fig. 9 and Table 15, adjectives exhibit the highest rates of SURPRISE emotives while nouns and verbs show significantly lower rates. Again, the typical hierarchy adjectives > nouns > verbs emerges. The declining odds ratios confirm a hierarchy of SURPRISE emotives from adjective over nouns to verbs. Also, the regression model confirms that speakers are more likely to use SURPRISE emotives in private compared to public settings. In addition, speakers are more likely to use SURPRISE emotives in small groups (3 to 5 interlocutors) compared to conversations with only two interlocutors (the reference category). However, the regression analysis does not show a significant difference between the use of SURPRISE emotives in dialogues compared to conversations among more than six interlocutors.

In addition to these main effects, the regression model confirms two significant interactions. In conversations among interlocutors of the same gender, speakers are more likely to use adjectives expressing SURPRISE compared with mixed-gender conversations. However, this difference is restricted to adjectives and does not emerge among nouns or verbs (cf. the lower left panel in Fig. 9 and Table 15). Furthermore, men are more likely to use SURPRISE emotives in private settings compared with public settings while the setting does not affect women (cf. the lower right panel in Fig. 9 and Table 15). No other effects significantly correlate with frequency of SURPRISE emotives in the data.

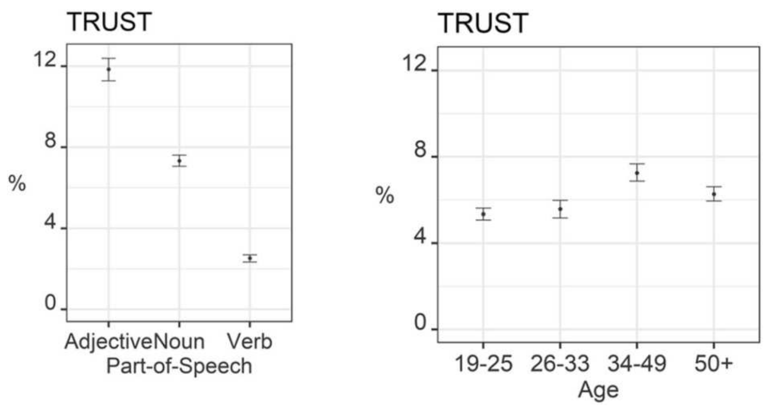


Fig. 10 Distribution of TRUST emotives in the Irish ICE data across parts-of-speech (left panel), and age (right panel)

Table 4 Overview of significant predictors

	EMOTIONALITY	ANGER	ANTICIPATION	DISGUST	FEAR	JOY	SADNESS	SURPRISE	TRUST
Predictor									
POS	√	√	√	√	√	√	√	√	√
Setting	√	–	√	√	√	√	–	√	–
Gender	–	√	–	–	√	√	–	–	–
AudienceSize	–	–	√	–	–	√	–	√	–
Age	√	–	–	–	√	–	–	–	√
Conversation-Type	–	–	–	–	–	–	–	√	–
Interactions									
Gender:Setting	–	–	–	–	–	–	–	√	–
POS:Conv.Type	–	–	–	–	–	–	–	√	–

Trust

Figure 10 shows the percentage of TRUST emotives among non-stop words in Irish English across parts-of-speech (left upper panel), conversation setting (upper right panel), age (lower left panel), and conversation type (lower right panel).

According to the regression analysis, part-of-speech ($\chi^2=1281.06$, $DF=2$, $p<.001$***) and the age of speakers ($\chi^2=28.14$, $DF=1$, $p<.001$***) significantly affect the use of TRUST emotives. As in all previous cases, adjectives exhibit the highest rates of TRUST emotives while nouns and verbs show substantially lower rates. Also, the patterning shows a near-linear decline in the rate of TRUST emotives from adjectives over nouns to verbs. This trend is additionally confirmed by the OddsRatios for POS:Noun and POS:Verb in Table 16 (cf. "Appendix"). Speakers older than 33 are significantly more likely to utter TRUST emotives compared to speakers between the ages of 19 and 25 (reference category). Neither other main effects nor interactions between predictors significantly correlate with frequency of TRUST emotives in the data.

Before turning to a discussion of the results, Table 4 provides an overview of the results of the statistical analyses.

Table 4 shows that part-of-speech is the most consistent predictor as adjectives, nouns, and verbs differ systematically with respect to their association with core emotions and overall emotionality. Surprisingly, only two interactions were confirmed as being significantly correlated with the rates of emotives (SURPRISE emotives). The conversation setting affected the use of emotives in six cases, gender and audience size in three cases, the age of speakers in two and the conversation type only in regards to SURPRISE emotives. The following section summarizes and discusses the results as well as weaknesses of the present analysis. Finally, a conclusion and an outlook are provided.

Discussion

The present study represents one of the first applications of sentiment analysis to an investigation of stratification of linguistic phenomena from a corpus-based sociopragmatic perspective. The most substantive advantage of the type of sentiment analysis employed in the current study lies in the fact that it does not merely provide scores for positive or negative polarity but allows the quantification of associations between lexical items and distinct core emotions. This more fine-grained output constitutes an advantage over other types of sentiment analyses and render the type of sentiment analysis implemented here particularly relevant for more detailed analyses of the pragmatics of emotional language. Furthermore, the present study has exemplified how sentiment analysis can be utilized in sociopragmatic research and serves as a starting point for research into the qualitative aspects of the pragmatics that underly verbalizations of emotion. This is made possible, on the one hand, by the substantive size of the *Word-Emotion Association Lexicon* (Mohammad and Turney 2013) that underlies the type of sentiment analysis employed in the present analysis. On the other, the advantage of the current analysis builds on the reliability of that lexicon which has been achieved by tapping onto the crowed-sourced *Amazon Mechanical Turk service*. The resulting associations between terms and emotions are based on 38,726 ratings from 2216 raters (cf. Mohammad and Turney 2013) and at least four raters provided identical ratings for 85 percent of words. The aim of the current study was to exemplify the utility of this type of sentiment analysis for sociolinguistic research that relies on replicable coding of emotional language.

The most consistent finding of the present case study is that the expression of emotionality correlates with part-of-speech as speakers rely predominantly on adjectives to convey emotionality. Part-of-speech is the only predictor that correlates with emotive use across all core emotions and overall emotionality or emotive use. This result was confirmed both by significant random as well as fixed effects for part-of-speech. Accordingly, inspection of the visualizations as well as the results of the

Table 5 Preference in conversation setting by emotive type

Preference	EMOTION-ALITY	ANTICIPA-TION	DISGUST	FEAR	JOY	SURPRISE
Setting						
Private	–	√	√	–	√	√
Public	√	–	–	√	–	–

statistical analyses confirmed that adjectives are most prone to convey emotionality compared to other parts-of-speech. The odds ratios shown in the regression result tables (cf. Tables 8, 9, 10, 11, 12, 13, 14, 15 and 16) as well as the visualizations suggest a hierarchy of emotionality in the sense that typically adjectives have higher rates of emotives than nouns that have higher emotive rates compared with verbs—the hierarchy can be described as adjectives > nouns > verbs. The finding that parts-of-speech is a meaningful predictor is, however, not surprising and quite expected and thus substantiates previous research which has shown that speakers convey attitudes and emotionality via adjectives (cf. e.g. Mestre-Mestre 2016; Rocklage and Fazio 2015 among others).

The relationship between conversation setting (private vs. public conversations) and emotive use is more complex as emotives differ with respect to their preference. Overall, emotives are more likely to be used in public settings but this general trend overshadows emotion-specific distributions. It is interesting to note that negative emotions (FEAR) are significantly more likely to be uttered in public settings, while positive emotions occur significantly more often in private settings (cf. Table 5). This finding is particularly intriguing as the dialogue data focuses on private family- or leisure-related topics rather than discussing political issues (based on closer readings of the corpus data). The tendency to talk publicly about negative emotions such as fear is thus not confined to political discourse but may represent a more general discursive behavior. However, a more cautious interpretation and also a more likely explanation of this finding relates to the historical and sociopolitical context in which the data were gathered.

Indeed, the interpretations of how social factors, in particular conversation setting, gender, and age and, to a lesser degree, also audience size, affect the linguistic expression of emotion must be framed in the context of the Norther Irish conflict. The Troubles, a phase of ethno-nationalist conflict in Northern Ireland during the latter half of the twentieth century, have doubtlessly had a substantial effect on the speakers represented in the data. As such, the tendency to express negative emotions (FEAR) publicly rather than privately is likely to result of the highly politized atmosphere and the continuing cross-community issues that accompanied the peace process and have continued to affect Northern Irish communities. Also, the gender differences in the expression of emotion can only be understood in terms of this social and cultural context. While the Troubles affected both Northern Ireland and the Republic, women and men, young and old, the data suggests that men were more likely to express negative emotions (FEAR). This is relevant here because women were not confined to supportive roles as both men and women served as prominent

Table 6 Gender preference by emotive type

Preference	ANGER	FEAR	JOY
Gender			
Men	√	√	–
Women	–	–	√

spokes persons during the Troubles. Bernadette Devlin, for instance, was not only the leader of the People's Democracy (PD) organization but also the foremost figure in the civil-rights movement.

The finding that DISGUST emotives, as a more negative emotion, are more common in private settings is somewhat at odds with this trend. However, for DISGUST to be part of private rather than public discourse is likely an effect of the social information value of that discourse. Issues triggering DISGUST as an affective response are thus deemed to posses a lower information value for topics that are discussed on a public level—and could even be regarded as counterproductive at a point in time in which community building and coming together after decades of civil unrest.

The finding for gender-specific expressions are also intriguing in that they call gendered stereotypes about emotional language into question. Contrary to socially accepted stereotypes as well as findings from previous research on the verbal expression of emotion among children and adolescents (e.g. Aldrich and Tenenbaum 2006), men exhibit relatively higher frequencies of emotives. This result is also at odds with previous research according to which women are more emotionally expressive than men (Bronstein et al. 1996) and with studies which did not find significant gender differences in verbalized emotion among adults (Aldrich and Tenenbaum 2006). However, one should be careful not to overgeneralize this gender difference given the afore mentioned socio-political context in which the data was collected and compiled (Table 6).

Nonetheless, the fact remains that studies investigating the expression of individual emotions which have shown that women and girls are more likely to verbalize sadness (Grossman and Wood 1993) could not be substantiated here as SADNESS emotives did not correlate significantly with either gender in the present data. Also, contrary to various studies showing no gender differences in the expression of anger (Anderson and Leaper 1998; Shimanoff 1985), the present analysis lends support to claims stating that boys more readily express anger than girls. This finding thus ties in with the notion that anger as an emotion is associated with masculine rather than

Table 7 Overview of which variable level of AudienceSize has the highest rates of emotives (√) and which other levels differ from that level significantly (*)

Preference	ANTICIPATION	JOY	SURPRISE
Audience size			
Dyad	ns	√	*
SmallAudience (3–5)	ns	ns	√
LargeAudience (6+)	ns	***	ns

feminine stereotypes (cf. Galasinski 2004; Shields 1984). The higher frequencies of ANGER emotives produced by men may thus be seen to substantiate the notion that men more readily express anger as a masculine stereotypical emotion compared to neutral or feminine stereotypical emotions such as joy. Overall, it appears as if males more readily express negatively attributed emotions (ANGER, FEAR) while women are more likely to express positively stereotyped emotions (JOY).

While these gender differences are likely also linked to differences in the involvement in and being affected by the socio-historical conflicts of the time, an alternative and more generalizable explanation for the findings summarized above could be seen in an adaptation of Labov's gender paradox (Labov 2001: 261–293). According to Labov's gender paradox, women are less likely to produce stigmatized variants despite showing strong tendencies for variants that carry prestige, are neutral, and/or are operating below the level of consciousness. To elaborate, in accordance with Labov's gender paradox, men would be more likely to exhibit (verbal) behavior that is stigmatized or socially discouraged while women would be more like to express emotions that are not. While, according to Labov (2001), the gender paradox is restricted to cases where the communal or individual grammar is unstable—i.e. in cases of ongoing language change—the present study might suggest that this mechanism may also be applicable to stable linguistic conditions. As such, the results of the study presented here can be taken to substantiate an interpretation of Labov which is in line with social cognitive theory (Bandura 1997) which poses that social norms and values, i.e. underpinnings of cultural stereotypes, are endorsed and manifested in social and communicative interactions, which in turn, feed into culturally accepted gender roles and stereotypes. It is crucial to note, however, that this alternative explanation has to be treated carefully given the socio-historical context in which the data were collected. In order to get a more nuanced understanding of the gender difference in emotive use, studies investigating data that reflect other varieties of English and that were collected in different social contexts would be necessary.

In addition to the effects of gender described above, the study has revealed significant age differences between the youngest cohort (19 to 25 year-olds which served as the base-line category) and older speakers (speakers aged 34 and older) with respect to the expression of TRUST. To date, there appears to be no systematic empirical research on the effect of age on the verbal expression of emotion. The finding that older speakers are more likely to use TRUST emotives compared with younger speakers is thus in itself an interesting starting point for further research. A possible explanation for the results could be that the social networks of speakers above a certain age are more stable and that speakers with relatively stable social networks are more willing to express their emotional state compared to speakers who are in the process of tapping into and building stable social bonds. However, this explanation falls short of detailing why there are no age differences for emotive other than TRUST emotives. Alternatively, the higher frequencies of TRUST emotives produced by older speakers may show the positive contributions of older members of society in cases where communities need healing. In other words, older people might be more forgiving.

Given the present data, the audience size appears to have only a minor effect on the expression of emotionality as the only significant correlations are reported for JOY and SURPRISE emotives (the correlation between individual levels of audience size and ANTICIPATION emotives did not breach the .05 alpha level but audience size was included into the model as the inclusion of all levels of audience size simultaneously did significantly increase model fit).

In the case of JOY and SURPRISE emotives, a smaller audience size made it more likely for these emotives to be used (cf. Table 7). This is interpreted to indicate that speakers feel more comfortable to express JOY and SURPRISE in conversations with few interlocutors—maybe to avoid conveying emotionality and thereby avoiding face loss in larger groups.

Another notable finding is the absence of significant correlations between conversation type (same-gender conversations vs. mixed-gender conversations) and the use of emotives other than SURPRISE where speakers were more likely to use SURPRISE emotives in same-gender conversations compared with mixed-gender conversations. This finding indicates that the gender of the interlocutors as well as group identity may have only a minor effect on the expression of emotionality although further and more fine-grained analyses are required as sexual attraction is a potential factor in this respect that was not considered here.

The fact that interactions were only reported as being significant with respect to the use of SURPRISE emotives is startling. There are at least two likely causes for this. On the one hand, the lack of significant interactions is a result of careful statistical modelling during which interactions which caused exceedingly high variance inflation factors were disregarded. If these interactions had been included, this would have led to unacceptable levels of multicollinearity and consequently to unreliable results. On the other hand, the lack of significant interactions is a result of the relatively moderate size of the available data. Unfortunately, the current data is unfit for allowing a closer analysis of interactions between predictors and their emotive use. Possibly, a larger and more balanced data set could remedy this issue.

Another potential deficiency of the present study relates to the use of sentiment analyses based on word emotion dictionaries. While lexicon-based sentiment analyses render the classification of emotionality more objective in that the scores are replicable, the method still suffers from shortcomings such as the neglect of negation, coercion or the use of fixed expressions. Hence, although this study has unearthed significant social stratification in emotive use, it must be kept in mind that this study has limitations in that the analysis focuses exclusively on lexical items (non-function words) and neglects contextual factors such as fixed expressions. In other words, the use of *good* and *well* in fixed expressions such as “good morning”, “sleep well”, etc. is treated on par with their uses in utterances such as “That’s a very good idea” or “You have done extremely well!”. This means that the mere occurrence of a given lexical element was the determining factor of assigning emotionality scores. Furthermore, the study has not investigated whether significant correlations were caused by an overuse of an individual word type by a given social cohort. Changes in meaning or semantic ambiguity were equally not considered in the analysis, as was the social proximity of interlocutors—which would have been highly interesting as it would have allowed for a more fine-grained analysis of the effects of social networks on emotional language—as this information was not recoverable from the data. However, and despite the shortcomings of the sentiment analysis employed in the present study, the results indicate that sentiment analysis can be a valuable tool in determining the emotionality of both individual words and utterances. This is not trivial as emotionality is a crucial factor in analyses of various phenomena, e.g. in analyses of intensification of adjective in grammaticalization as well as studies on semantic and lexical change. The current study is thus a case study which exemplifies the implementation of an intersubjective and fully replicable method for operationalizing and coding the emotionality of linguistic elements.

In conclusion, the present analysis substantiates previous research which has shown that emotionality is expressed predominantly by adjectives. However, the findings presented here also call into question the validity of social stereotypes about gendered linguistic behavior according to which young female speakers are more likely to use emotional language compared to other societal cohorts. In fact, according to the finding presented here men—regardless of age—are more likely to produce lexical elements associated with core emotional states (emotives) compared to women. Furthermore, men produce significantly more ANGER and FEAR emotives compared to women who are significantly more likely to use JOY emotives. Also, the present study found that positive emotions, such as JOY, are verbalized more often in private settings while negative emotions (FEAR) are more readily expressed publicly even in apolitical discourse. Finally, this study has shown that sentiment analyses represent a computational tool for sociolinguistic research as they allow an intersubjective operationalization and coding of emotionality.

Outlook

The case study presented here represents an exemplification of a practical solution to the reliable and relative fine-grained annotation of emotionality of naturally occurring language. There exists a wealth of phenomena in linguistics that require a method for reliably annotating emotionality of linguistic elements. For instance, changes in the intensifier domain have been linked to the emotionality of adjectives (cf. e.g. Lorenz 2002; Murphy 2010: 119–220; Peters 1994; Tagliamonte and Roberts 2005: 289). Furthermore, the type of sentiment analysis implemented here can be utilized to investigate pragmatic differences between highly emotional and rather non-emotional texts or it could be used to inform fine-grained qualitative analysis of the pragmatics of emotional language that would complement the quantitative approach taken here. The presented study serves as an example for how sociopragmatic research can operationalize emotionality in a reproducible and automated manner.

The results shed doubt on the validity of social stereotypes about the linguistic expression of emotion and pose the question whether or not the trends detected in educated standard Irish English could potentially be more general in nature. It would be interesting to know if the tendencies unearthed here were indeed consistent and can be replicated in other varieties and registers. If they were consistent, then this would raise issues with regard to the relationship between social stereotypes about emotional language and linguistic behavior more broadly. In addition, the finding that JOY emotives are overrepresented in private discourse while FEAR emotives are overrepresented in public discourse could indicate a more general phenomenon. If true, then this tendency to convey negative emotions publicly more readily than positive emotions underlies rather than mirrors trends in contemporary political discourse. In addition, this tendency to express negativity publicly highlights that such trends do not emerge ex nihilo but exist covertly. However, as stated above, this trend is more likely to reflect effects of the socio-historical contexts in which the data were gathered rather than generalizable gender differences. Further research using data from varied social contexts would be necessary to determine the causes of the differences and tendencies described above. It would therefore be intriguing to see the application of sentiment analyses to the analyses of historical political discourse to investigate whether trends, which appear to have entered the public consciousness only recently, represent trajectories that have more historical depth than commonly assumed. Indeed, such analyses could greatly contribute to the way in which we think and understand current heated political debates.

Compliance with Ethical Standards

Conflict of interest The author declares that there are no conflicts of interest.

Appendix

See Tables 8, 9, 10, 11, 12, 13, 14, 15 and 16.

Table 8 Results of the mixed-effects binomial logistic regression model for all emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.06	0.24	2464.3	2	$p<.001$***
	POS					$p<.001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	− 1.18		0.31	0.03	− 35.5	$p<.001$***
POS:Noun	− 0.54	1.6	0.58	0.03	− 20.9	$p<.001$***
POS:Verb	− 1.33	1.6	0.26	0.03	− 44.6	$p<.001$***
ConversationContext: Public	0.1	1.5	1.10	0.04	2.43	$p<.05$*
Age: 26–33	0.04	1.2	1.04	0.05	0.78	$p=.438$
Age: 34–49	0.16	1.7	1.17	0.05	3.13	$p<.01$**
Age: 50+	0.08	1.5	1.08	0.05	1.72	$p=.085$+
Model statistics						Value
Number of groups						537
Observed misses						65,769
Observed successes						11,338
Residual deviance						61,870.9
R^2 (Nagelkerke)						0.07
C						0.67
Somers' D_{xy}						0.33
AIC (BIC)						61,888.9 (61,972.1)
Prediction accuracy						85.3%
Model LL ratio test				L.R. χ^2: 2520.3	*DF*: 8	$p<.001$***

$^+$.1 > *p* >= .05 is marginally significant; **p* < .05 is significant; ***p* < .01 is very significant; ****p* < .001 is highly significant

Table 9 Results of the mixed-effects binomial logistic regression model for ANGER emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.28	0.53	617.7	2	$p<.001$***
	POS					$p<.001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	− 3.00		0.05	0.07	− 44.0	$p<.001$***
POS:Noun	− 0.53	1.4	0.57	0.05	− 9.81	$p<.001$***
POS:Verb	− 1.32	1.4	0.27	0.07	− 20.2	$p<.001$***
Gender:Women	− 0.19	1.0	0.83	0.07	− 2.58	$p<.01$**
Model statistics						Value
Number of groups						537
Observed misses						75,148
Observed successes						1959
Residual deviance						17,613.0

Table 9 (continued)

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
R^2 (Nagelkerke)						0.071
C						0.721
Somers' D_{xy}						0.442
AIC (BIC)						17,625.0 (17,680.5)
Prediction accuracy						97.5%
Model LL ratio test				L.R. χ^2: 644.7	*DF*: 5	$p<.001$***

+.1 > *p* >= .05 is marginally significant; **p* < .05 is significant; ***p* < .01 is very significant; ****p* < .001 is highly significant

Table 10 Results of the mixed-effects binomial logistic regression model for ANTICIPATION emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.09	0.30	750.46	2	$p<.001$***
	POS					$p<.001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−2.14		0.12	0.06	−36.31	$p<.001$***
POS:Noun	−0.74	1.46	0.48	0.04	−18.98	$p<.001$***
POS:Verb	−1.12	1.47	0.33	0.04	−26.12	$p<.001$***
Setting:Public	−0.17	1.04	0.85	0.05	−3.46	$p<.001$***
AudienceSize:Small	0.08	1.52	1.08	0.06	1.33	$p=.1852$
AudienceSize:Large	−0.10	1.57	0.90	0.08	−1.28	$p=.1999$
Model statistics						Value
Number of groups						537
Observed misses						72,914
Observed successes						4193
Residual deviance						31,779.0
R^2 (Nagelkerke)						0.045
C						0.655
Somers' D_{xy}						0.310
AIC (BIC)						31,795.0 (31,869.0)
Prediction accuracy						94.56%
Model LL ratio test				L.R. χ^2: 792.96	*DF*: 7	$p<.001$***

+.1 > *p* >= .05 is marginally significant; **p* < .05 is significant; ***p* < .01 is very significant; ****p* < .001 is highly significant

Table 11 Results of the mixed-effects binomial logistic regression model for DISGUST emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.35	0.59	851.04	2	$p<.001$***
	POS					$p<.001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−2.95		0.05	0.06	−46.26	$p<.001$***
POS:Noun	−1.30	1.18	0.27	0.06	−21.02	$p<.001$***
POS:Verb	−1.90	1.18	0.15	0.08	−25.26	$p<.001$***
Setting:Public	−0.39	1.00	0.68	0.09	−4.31	$p<.001$***
Model statistics						Value
Number of groups						537
Observed misses						75,771
Observed successes						1336
Residual deviance						12,593.0
R^2 (Nagelkerke)						0.108
C						0.77
Somers' D_{xy}						0.539
AIC (BIC)						12,605.0 (12,660.5)
Prediction accuracy						98.27%
Model LL ratio test				L.R. χ^2: 892.05	*DF*: 5	$p<.001$***

$^+$.1 > *p* >= .05 is marginally significant; **p* < .05 is significant; ***p* < .01 is very significant; ****p* < .001 is highly significant

Table 12 Results of the mixed-effects binomial logistic regression model for FEAR emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.32	0.57	980.52	2	$p<.001$***
	POS					$p<.001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−3.02		0.05	0.09	−34.02	$p<.001$***
POS:Noun	−0.27	1.49	0.76	0.05	−5.60	$p<.001$***
POS:Verb	−1.18	1.49	0.31	0.06	−19.66	$p<.001$***
Gender:Women	−0.21	1.34	0.81	0.08	−2.51	$p=.0119$*
Setting:Public	0.31	1.34	1.37	0.08	3.69	$p<.001$***
Model statistics						Value
Number of groups						537
Observed misses						74,502
Observed successes						2,605
Residual deviance						21,728.35
R^2 (Nagelkerke)						0.084
C						0.726
Somers' D_{xy}						0.452
AIC (BIC)						21,747.3 (21,812.1)
Prediction accuracy						96.62%
Model LL ratio test				L.R. χ^2: 1037.9	*DF*: 9	$p<.001$***

$^+$.1 > *p* >= .05 is marginally significant; **p* < .05 is significant; ***p* < .01 is very significant; ****p* < .001 is highly significant

Table 13 Results of the mixed-effects binomial logistic regression model for JOY emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.15	0.39	1742.71	2	$p < .001$***
	POS					$p < .001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−2.12		0.12	0.09	−23.86	$p < .001$***
POS:nnp	−0.95	1.23	0.39	0.04	−23.56	$p < .001$***
POS:vbf	−2.00	1.23	0.14	0.05	−37.32	$p < .001$***
Gender:Men	0.23	1.32	1.26	0.07	3.50	$p < .001$***
Setting:Public	−0.33	1.35	0.72	0.07	−4.83	$p < .001$***
AudienceSize:Small	−0.07	1.47	0.93	0.07	−1.01	$p = .3144$
AudienceSize:Large	−0.40	1.51	0.67	0.10	−4.10	$p < .001$***
Model statistics						Value
Number of groups						537
Observed misses						73,865
Observed successes						3242
Residual deviance						25,032.95
R^2 (Nagelkerke)						0.101
C						0.734
Somers' D_{xy}						0.469
AIC (BIC)						25,051.0 (25,134.2)
Prediction accuracy						95.8%
Model LL ratio test				L.R. χ^2: 1860.6	*DF*: 8	$p < .001$***

$^+$.1 > p >= .05 is marginally significant; *p < .05 is significant; **p < .01 is very significant; ***p < .001 is highly significant

Table 14 Results of the mixed-effects binomial logistic regression model for SADNESS emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.23	0.48	955.65	2	$p < .001$***
	POS					$p < .001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−2.62		0.07	0.04	−58.53	$p < .001$***
POS:Noun	−0.88	1.32	0.42	0.05	−18.84	$p < .001$***
POS:Verb	−1.46	1.32	0.23	0.05	−26.66	$p < .001$***
Model statistics						Value
Number of groups						537
Observed misses						74,536
Observed successes						2571
Residual deviance						21,565.9
R^2 (Nagelkerke)						0.076
C						0.716
Somers' D_{xy}						0.432
AIC (BIC)						21,575.9 (21,622.2)
Prediction accuracy						96.67%
Model LL ratio test				L.R. χ^2: 976.8	*DF*: 4	$p < .001$***

$^+$.1 > p >= .05 is marginally significant; *p < .05 is significant; **p < .01 is very significant; ***p < .001 is highly significant

Table 15 Results of the mixed-effects binomial logistic regression model for SURPRISE emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.13	0.36	1131.09	2	$p < .001$***
	POS					$p < .001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−2.65		0.07	0.12	−22.4	$p < .001$***
POS:Noun	−1.24	2.53	0.29	0.08	−15.4	$p < .001$***
POS:Verb	−1.79	2.54	0.17	0.10	−18.4	$p < .001$***
Gender:Women	−0.10	2.59	0.91	0.10	−0.94	$p = .3488$
Setting:Public	−0.46	2.90	0.63	0.11	−4.03	$p < .001$***
AudienceSize:Small	0.18	1.49	1.20	0.08	−2.26	$p = .0239$*
AudienceSize:Large	−0.15	1.73	0.86	0.12	1.25	$p = .2104$
ConversationType:SameGender	0.22	2.19	1.25	0.09	2.39	$p = .0167$*
Gender:Women::Setting:Public	0.34	2.39	1.41	0.16	2.10	$p = .0360$*
POS:Noun::Conv.Type:SameGender	−0.35	2.77	0.70	0.11	−3.21	$p = .0013$**
POS:Verb::Conv.Type:SameGender	0.36	2.62	0.70	0.13	−2.69	$p = .0071$**
Model statistics						Value
Number of groups						537
Observed misses						75,339
Observed successes						1768
Residual deviance						15,634.3
R^2 (Nagelkerke)						0.099
C						0.741
Somers' D_{xy}						0.482
AIC (BIC)						15,660.3 (15,780.6)
Prediction accuracy						97.7%
Model LL ratio test				L.R. χ^2: 1210.47	*DF*: 12	$p < .001$***

$^+$.1 > p >= .05 is marginally significant; *p < .05 is significant; **p < .01 is very significant; ***p < .001 is highly significant

Table 16 Results of the mixed-effects binomial logistic regression model for TRUST emotives among non-stop words in the Irish ICE data

	Group(s)	Variance	SD	L.R. χ^2	*DF*	Significance
Random effects	Speaker	0.08	0.29	1596.5	2	$p<.001$***
	POS					$p<.001$***
Fixed effect(s)	Estimate	VIF	OddsRatio	SE	z	Significance
(Intercept)	−2.14		0.12	0.04	−48.35	$p<.001$***
POS:Noun	−0.54	1.35	0.58	0.04	−15.09	$p<.001$***
POS:Verb	−1.65	1.35	0.19	0.05	−35.62	$p<.001$***
Age: 26–33	−0.01	1.20	0.99	0.07	0.20	$p=.8382$
Age: 34–49	0.28	1.26	1.32	0.06	4.84	$p<.001$***
Age: 50+	0.13	1.27	1.14	0.06	2.34	$p=.0191$*
Model statistics						Value
Number of groups						537
Observed misses						72,446
Observed successes						4661
Residual deviance						33,545.6
R^2 (Nagelkerke)						0.072
C						0.697
Somers' D_{xy}						0.394
AIC (BIC)						33,561.6 (33,635.6)
Prediction accuracy						93.96%
Model LL ratio test				L.R. χ^2: 1646.0	*DF*: 7	$p<.001$***

$^+$.1 > *p* >= .05 is marginally significant; **p* < .05 is significant; ***p* < .01 is very significant; ****p* < .001 is highly significant

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