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Social Media as a Living Laboratory for Researchers: The Relationship Between Linguistics and Online User Responses

Abstract

Purpose: Today, individuals use social media to express their opinions and feelings, which offers a living laboratory to researchers in various fields, such as management, innovation, technology development, environment, and marketing. It is therefore necessary to understand how the language used in user-generated content and the emotions conveyed by the content affect responses from other social media users.

Design/methodology/approach: In this study, almost 700,000 posts from Twitter (as well as Facebook, Instagram, and forums in the appendix) are used to test a conceptual model grounded in signaling theory to explain how the language of user-generated content on social media influences how other users respond to that communication.

Findings: Extending developments in linguistics, this study shows that users react negatively to content that uses self-inclusive language. We also show how emotional content characteristics moderate this relationship. The additional information provided indicates that while most of the findings are replicated, some results differ across social media platforms, which deserves users' attention.

Originality/value: We extend research on internet behavior and social media use by providing insights into how the relationship between self-inclusive language and emotions affects user responses to user-generated content. Furthermore, we provide actionable guidance for researchers interested in capturing phenomena through the social media landscape.

Keywords: social media venues, language, user-generated content, sentiment analysis, data sources, emotional positivity index

1. Introduction

An increasing number of users around the world are using social media to post comments and pictures, like and comment on others' content, or send private messages, contributing to the high growth rates of social media usage worldwide. Ten years ago, only 5% of American adults used at least one social media site; today, 72% of Americans use social media for multiple purposes (Pew Research Center, 2022). In 2023, the penetration of social media users in the U.S. was 90% percent as per Statista (Dixon, 2023), and this percentage is expected to increase to 94.4 by 2026.

As the popularity of social media increases, a growing body of scholarly work has examined the online behavior of social media users. The literature has largely investigated the role of content characteristics (Berger and Milkman, 2012), network structure (e.g., connectivity; Peng *et al.*, 2018), and characteristics of the transmitter—such as expertise (Stephen, 2016)—in social media content transmission (Stephen and Lehmann, 2016). Research has demonstrated how modality (i.e., speaking and writing; Shen and Sengupta, 2018), channels (e.g., desktop computers and smartphones; Grewal and Stephen, 2019; Melumad *et al.,* 2019), and audiences (e.g., close versus distant others; Dubois *et al.,* 2016) affect what people share. However, there has been less research on how the language used by users in their social media communication influences how other users respond to that communication. Language factors that determine the liking and sharing reactions of users are especially important in social media communication, which is by default asymmetric (Aleti *et al.,* 2019). Communication asymmetry arises from the original poster having full control and insight over the content posted and other users having limited insights. Thus, they have to interpret the language of the post as a signal needed (Berger and Milkman, 2012) to decide on their own reaction. Hence, research on the relationship between linguistics in communications in a social media context and the responses of users to these communications is important to gain insights about individuals' behavior online (Aleti *et al.,* 2019). The importance of this research increases when considering that subtle linguistic elements and their associated emotions have the power to guide conversation with other users and affect the perlocution (Aleti *et al.,* 2019; Van Laer *et al.,* 2019).

Language not only conveys information about its sender or transmitter but also wields influence over the consuming audience (Berger and Packard, 2021). For example, in marketing communications, language plays a pivotal role in shaping users' attitudes (Zhang and Schmitt, 2004). Previous studies have examined the effect of language choice (Packard and Berger, 2021), the phonetic processing of brand names (Schmitt *et al.,* 1994), and the use of rhetorical devices (e.g., metaphors and rhymes) on users' responses to marketing communications (Ottati *et al.,* 1999). With respect to the role of language in marketing communication, past research has shown that content that uses emotional (vs. informative) language is more likely to go viral (Akpinar and Berger, 2017). The same was confirmed for online reviews, for which Ludwig *et al*. (2013) proved that more affective content enhances sales and conversion rates.

We extend these developments in the area of user-generated content to examine users' responses to the language employed in such content (Berger and Packard, 2021). More specifically, we build on signaling theory to investigate how self-inclusive language (i.e., linguistic) used by a transmitter on a social media site is liked (i.e., consequence) by other users (i.e., receivers). We define self-inclusive language by the use of first-person singular pronouns—such as I, me—with high frequency of statements that explicitly include the speaker (Chen and Loftus, 2019). We further test how user-generated content characteristics (i.e., emotional positivity index) influence other users' responses to posts that use self-inclusive language. In the additional information provided in this research, we examine how these results hold or differ across four main social media venues: Twitter[1] (rebranded to X in July 2023), Facebook, Instagram, and forums.

The main findings of the study provide new contributions to the literature. By testing a theoretically sound conceptual model, we identify the negative effects of self-inclusive language on user responses to user-generated content. We further extend the literature on the expression of emotions in social media (Berger *et al.*, 2022) by identifying the role of the emotional content of posts in changing the responses of users to user-generated content that uses self-inclusive language. Finally, by describing the procedure used to collect data from social media (i.e., Twitter as well as Facebook, Instagram, and forums in the appendix) and by analyzing over 700,000 posts, we provide detailed insight into the data collection and analysis procedures that can be easily replicated in other domains of research. In doing so, we empirically demonstrate the power of social media data to test theory-driven research models beyond empirics-first perspective (Golder *et al.,* 2023).

2. Theoretical Background

2.1. Signaling Theory: Social media as a context of informational asymmetry

Social media is an environment characterized by information asymmetry (Javornik *et al.*, 2020), with users having varying degrees of access to information. This information asymmetry becomes particularly important in the context of user-generated content when users make decisions about how to respond to specific content created by other users. On one hand, certain users may possess information about brand quality derived from past experiences or non-publicly available sources. They leverage this information to determine

[1] At the time of data collection and analysis for this article, the social media platform now known as "X" was referred to as "Twitter." The rebranding and change of name occurred after the data-gathering process. As such, throughout the paper, the platform is consistently referred to by its name "Twitter" to accurately reflect the context and time frame during which the study was conducted. Any mention of the platform's new name, "X," is a retrospective consideration and does not pertain to the period covered by the research.

their responses to user-generated brand-related content, granting them an advantage in shaping their reactions to such content. On the other hand, most users will be in a situation of information asymmetry, where they lack complete information and therefore must rely on language signals to make inferences that allow them to form opinions and make decisions (Huber and McCann, 1982).

Signaling theory is primarily concerned with how information can be asymmetric and how information asymmetry between two parties is reduced (Spence, 2002). Signaling theory assumes that signaling serves as a means for parties to overcome information asymmetries about latent and unobservable quality attributes (Connelly *et al.,* 2011; Spence, 1978). Thus, in this study, we rely on signaling theory and consider user-generated content to be a mechanism for signaling. Following Spence (1978), we define signals as attributes of user-generated content that, by design or accident, alter the beliefs of or convey information to other individuals. This is in line with Chen *et al.* (2023) who draw on signaling theory to investigate the effects of language signals (i.e., length, sentiment, and use of first-person pronouns) on crowdfunding performance in medicine. According to signaling theory, the use of first-person pronouns in communications can influence how others respond to the narrative, impacting perceived emotionality (Packard *et al.,* 2018), credibility, and trustworthiness (Stern, 1991).

Indeed, social media platforms encourage new and innovative forms of signaling (Valsesia and Diehl, 2022), and what individuals do online can signal different aspects of themselves (Valsesia *et al.,* 2020), their opinions, their experiences, and their attitudes. These include the types of posts they make, the people they follow, the groups they belong to, and the language they use. In the context of our study, we focus on language used as a signal within user-generated content. More precisely, we distinguish between self-inclusive and non-self-inclusive language. In addition, we acknowledge the signaling role of emotions that, when expressed through user-generated content, contain information about the user's emotional state and intentions and thus can shape the reaction of other users (Lee *et al.,* 2019; Hennig-Thurau *et al.,* 2004).

2.2. Self-Inclusive Language

Prior studies have investigated the role of language in information processing and behavior (Kronrod *et al.*, 2012; Patrick and Hagtvedt, 2012). In this research, we focus on how self-inclusive language, (i.e., use of first-person singular pronouns), influences the responses of other users. To strengthen the contextualization of our research, we offer a synthesized summary of existing empirical studies published on self-inclusive language (Table I).

Insert Table I about here[2]

As per Table I, there is mixed evidence in the literature regarding the use of first-person singular pronouns in communications. On the one hand, first-person singular pronouns (e.g., "I") indicate identity and self-focus (Pennebaker *et al.*, 2003). The "I" pronoun is linked to a speaker's egotistical self-focus (Pennebaker, 2011) or self-interest (e.g., Ickes *et al.*, 1986). People rate their own and others' interpersonal relationships as of lower quality and distant when they are described using the pronoun "I" rather than "we" (Fitzsimons and Kay, 2004). On the other hand, personal pronouns help establish the roles and responsibilities of interaction participants. The "I" pronoun signals emotional and behavioral involvement with the needs of the receiver. "I" pronoun use has been linked to the speaker's personal concern about a situation (Scherwitz *et al.*, 1978) and attempts to understand an interaction partner (Ickes *et al.*, 1986).

[2]Table I includes studies that have high relevance or have been published in academic journals with a minimum rating of 3 in the Academic Journal Guide. This is to ensure that only publications meeting rigorous and high-quality standards are taken into account, as per Hiebl (2023).

Due to conflicting findings in the literature concerning the use of first-person pronouns in communications, it is unclear how users will respond to the use of self-inclusive language in user-generated content. It is possible that when individuals communicate on social media, they are more likely to use first-person singular pronouns to demonstrate an individuated identity. Moreover, when people experience a destabilizing situation, first-person singular pronouns are increasingly used (Pennebaker and Lay, 2002). Hence, users can view user-generated content that includes a first-person singular pronoun (i.e., self-inclusive) as more reflective of the experiences of that person. As such, content typically signals a speaker's self-focus (Pennebaker, 2011) or a speaker's self-interest (e.g., Ickes *et al.,* 1986). Thus, we predict that other users will respond more negatively to user-generated content that uses self-inclusive language.

2.3. Emotional content characteristics and user responses

Experiences (Liu *et al.,* 2017) and emotions are central components of user-generated content (Berger and Milkman, 2012; Hartmann *et al.,* 2019; Melumad *et al.*, 2019; Valsesia, *et al.*, 2020). These expressions range from positive to negative and, in some cases, neutral sentiments (Melumad *et al.,* 2019). In this research, we investigate whether emotional content plays a moderating role in how the use of self-inclusive language in user-generated content influences other users' responses. In addition, we calculate the emotional positivity index as the difference between positive and negative emotional content (Valsesia *et al.,* 2020). Next, we present the arguments related to self-inclusiveness and the latter constructs.

2.3.1. Positive emotional content

Individuals may respond differently to a communication that has positive emotional content (vs. a communication that does not). On the one hand, positive brand-related emotional content indicates that the content creator is loyal and is providing a positive recommendation (Chung *et al.,* 2022); thus, it positively influences information sharing

(Berger and Milkman, 2012), conversion rates (Ludwig *et al.,* 2013), and purchase decisions (Li and Zhan, 2011). On the other hand, user-generated content characterized by positive emotional content may be viewed as a pleasing and dishonest signal (Belkin *et al.*, 2013).

How, then, will users respond to user-generated content that uses self-inclusive language and is high in positive emotional content? We predict that positive emotional content written in self-inclusive language may signal self-focus. This means less explicitly conveying the experience and more explicitly conveying that the individual feels positive, which results in more negative responses from other users. However, do all types of positive emotional content result in fewer positive responses to user-generated content that uses self-inclusive language? Previous studies have shown that how individuals react to content shared online by others is often a function of the identifiable linguistic features of the content (Berger and Milkman, 2012). Hence, in addition to investigating the role of positive emotional content on the use of self-inclusive language in response to user-generated content, we investigate the roles of happiness, fun, and love, specifically.

Happiness is an emotion that is high in arousal, and high-arousal content increases attention (Mather, 2007). Happiness signals a greater focus on the outer world at the expense of the inner world; hence, it is associated with less self-focus (Green *et al.*, 2003). We predict that user-generated content that uses self-inclusive language and is high in happiness will be perceived as less self-focused and more about the experience described in the post, leading to fewer negative responses.

Fun signals self-focus (Uzieblo *et al.*, 2007). There is a positive correlation between fun-seeking and self-centered impulsivity (Miller and Lynam, 2012). Hence, we predict that user-generated content that uses self-inclusive language and is high in fun will be perceived as more self-focused and less about the experience described in the post, leading to more negative responses from other users.

Love is characterized by the human need to feel excited and inspired, signaling the high-arousal (Branden, 1980). Love signals selflessness (Whang *et al.*, 2004). Hence, we predict that user-generated content that uses self-inclusive language and is high in love will be perceived as less self-focused and more about the experience described in the post, leading to fewer negative responses.

2.3.2. Negative emotional content

Users may respond differently to a communication that has negative emotional content (vs. a communication that does not). On the one hand, users may avoid processing communication that has negative emotional content because they want to avoid negative information (Berger *et al.,* 2019). On the other hand, they may pay more attention to communication that is high in negative emotional content (Rozin and Royzman, 2001). User-generated content that has high negative emotional content may be considered a signal of an untrustworthy source (Przybyła and Soto, 2021).

How, then, will users respond to user-generated content that uses inclusive language and is high in negative emotional content? We predict that negative emotional content may signal that content that uses self-inclusive language is less self-focused and less reflective of self-interest, as the focus is more on the content and more explicitly conveys the experience, resulting in fewer negative responses. However, do all different types of negative emotional content result in fewer negative responses to user-generated content that uses self-inclusive language? Previous studies have shown that how individuals react to content shared online by others is often a function of the identifiable linguistic features of the content (Berger and Milkman, 2012). In particular, anxiety, sadness, and anger have been identified as text characteristics that result in content being shared more often (Valsesia *et al.,* 2020). Hence, in addition to investigating the role of negative emotional content on the use of self-inclusive language in users' responses to user-generated content, we investigate the roles of anxiety, anger, and sadness, specifically.

Anxiety is a high-arousal emotion. It is highly correlated with self-focus (Brockmeyer *et al.,* 2015), and it often attracts attention (Mather, 2007). We predict that user-generated content that uses self-inclusive language and is high in anxiety will be perceived as more self-focused and less about the experience presented in the content, leading to more negative responses from other users.

Sadness is an emotion that is low in arousal (Berger *et al.,* 2019). Previous research has associated sadness with a greater focus on the current (vs. future) self (Lerner *et al.,* 2012), a greater intimate connection with the self (Cryder *et al.*, 2008), and greater self-focus (Wood *et al.*, 1990). We predict that user-generated content that uses self-inclusive language and is high in sadness will be perceived as more self-focused, leading to more negative responses from other users.

Anger is an emotion that is high in arousal, and high-arousal content increases attention (Mather, 2007). Anger is associated with attributions of responsibility to another and hence less self-focus (Green and Sedikides, 1999). Therefore, we predict that user-generated content that uses self-inclusive language and is high in anger will be perceived as less self-focused and more about the experience presented in the post, leading to fewer negative responses from other users.

2.3.3. Emotional positivity index

Finally, users can communicate by involving different emotions, positive and negative, at the same time (Melumad *et al*., 2019). The emotional positivity index is the difference between the scores related to positive emotions and negative emotions, with higher scores indicating a more positive emotion (Berger and Milkman, 2012; Valsesia *et al.,* 2020). Similar to our prediction for user-generated content that uses self-inclusive language and is high in positive emotional content, we expect that user-generated content that uses self-inclusive language and is high in the emotional positivity index will be perceived as more self-focused and more self-interested, less explicitly conveying the experience described in the post but being more about the individual's positive feelings. Thus, it will result in more negative responses.

Figure 1 graphically represents the conceptual model of the relationship between the use of self-inclusive language in user-generated content and other users' responses with the inclusion of emotional content characteristics as possible moderators.

Insert Figure 1 about here

3. Materials and methods

3.1. Data

The Twitter data were collected through the Twitter application programming interface, which allowed tweets to be downloaded in real time. Initially, we collected all tweets that included the names of at least one of the top 100 brands from the 2016 Interbrand Global Brands list (e.g., Apple, Google, Coca-Cola, Microsoft, IBM, Toyota, Samsung, General Electric, McDonald's, Amazon, BMW, Mercedes, Disney, Intel, Cisco, Oracle, Nike, HP, Honda, and Louis Vuitton) over a 30-day period. In line with previous research (Valsesia *et al.,* 2020) and with our research aims, we removed all retweets because Twitter is the only social media venue that has the retweet option. This left us with 656,912 tweets produced by 124,433 users[3].

The dataset that we built included information on the number of likes that each post

[3] In the appendix, we also report the effects across 3 more media venues. Specifically, we collected data from Instagram, Facebook, and forums (e.g., Reddit) using the Pulsar platform (www.pulsarplatform.com). Based on our resources, we collected data on the top 10 Interbrand (2022) brands. Moreover, we specified that we wanted to focus only on posts in English to facilitate the textual analysis. We requested data on posts from the beginning of 2022 to February 07, 2022 (the date when we started analyzing the data). We used all the posts in our analyses ($N_{Instagram}$ = 34,883; $N_{Facebook}$ = 1,726; N_{Forums} = 73,862).

obtained. We used this as a proxy for other users' responses to user-generated content. The number of likes has previously been used as a proxy for the degree to which other users approve of a message posted online (Hartmann *et al.,* 2021; Herhausen *et al.,* 2019; Overgoor *et al*., 2021). We used this proxy with the assumption that a greater (vs. lower) number of likes is an indicator of more positive (vs. negative) responses from other users. Descriptive statistics on this and all other variables can be found in the appendix.

3.2. Independent variable: Self-inclusive language

In line with previous research (e.g., Hartmann *et al.,* 2021; Herhausen *et al.,* 2019; Valsesia *et al.,* 2020), we relied on the output of Linguistic Inquiry and Word Count (LIWC versions 2015 and 2022) software to identify the linguistic characteristics of the user-generated content in our dataset. LIWC is a computerized text analysis program and it has two main features that are central to its operations: a processing component and a series of dictionaries. The former focuses on comparing each word contained in a text—which may be text coming from essays, poems, blogs, novels, short messages, social media posts, etc.—with a set of dictionaries (Pennebaker *et al.*, 2015). If the word is present in any of the dictionaries, then it is recorded as such and the score for those dictionaries is incremented. Following the same procedure for every word in a text, LIWC then calculates the percentage of each LIWC category in the given text (i.e., the percentage of all the words in a text that belong to each of the LIWC categories). This way, it provides continuous scores of the percentages that we apply in research to estimate the extent to which texts belong to any particular category. This software uses an internal dictionary of approximately 6,400 words divided into categories based on topics. In linguistic research, LIWC has been considered "an efficient and effective method for studying the various emotional, cognitive, and structural components present in individuals' verbal and written speech samples" (Pennebaker *et al.*, 2015, p.2). Thus, we relied on LIWC default dictionary categories to proxy linguistic features of the content regarding self-inclusive language (Herhausen *et al.,* 2019; Valsesia *et al.,* 2020).

Specifically, we proxied self-inclusive language using data on the relative frequency of words in each post that included a first-person singular pronoun (e.g., I, me, mine; Pennebaker *et al.*, 2015). Sample posts that used a first-person singular pronoun (i.e., self-inclusive language) included “@LouisVuitton is me, me, me,” and “@gucci was talking about me.” This category of the LIWC dictionary has been previously used in research to quantify and proxy the extent to which online user-generated content is related to the self (Hartmann *et al.,* 2021).

3.3. Moderator: Emotional content characteristics

3.3.1. Negative emotional content measure

In line with previous research (e.g., Hartmann *et al.,* 2021), we relied on the output of LIWC (versions 2015 and 2022) software to identify the negative emotional content in our dataset together with anxiety, sadness, and anger. Specifically, the *negative emotion* category included words such as bad, hate, hurt, and tired (e.g., “My Google-fu is failing me. :(”). *Anger* includes words such as hate, mad, angry, and frustr* (e.g., “Been an Android guy from jump. I own a MacBook and an iPad. I might trade in my S21 and get an iPhone. This has me so pissed off. The pricing they are offering is ridiculous. I really hate Google”). *Sadness* includes words and emoticons such as :(, sad, disappoint*, and cry (e.g., “I was so depressed with my last Disney trip!??????”). *Anxiety* includes words such as worry, fear, afraid, and nervous (e.g., “Well now I'm worried about my new Samsung washer I got less than 6 months ago??”).

3.3.2. Positive emotional content measure

The *positive emotion* category includes words such as good, love, happy, and hope (e.g., “@Google I absolutely love my Pixel!”) and has been included in previous research on online content as a proxy for positive emotional content (Herhausen *et al.,* 2019; Valsesia *et al.,* 2020). Given that LIWC does not provide specific subcategories for positive emotions (i.e., happiness, love, or fun), we created three subcategories using the most recurrent themes among all the words included in the *positive emotion* category and then created our own dictionary for these emotions (Herhausen *et al.,* 2019). Specifically, we explored the most frequently recurring themes among all the words belonging to the positive emotion category. Thus, we listed all the words that could be used to describe or be associated with happiness, love, or fun separately. LIWC allows the generation of user dictionaries by feeding the software the list of words that describe a specific category. Hence, by inputting into LIWC a list of words belonging to the happiness, love, and fun dictionaries separately, we obtained three variables that we considered measures of the relative frequency of words pertaining to each of these emotions. These three user-generated LIWC dictionaries also allowed us to include in our analyses specific positive emotions from the three self-generated dictionaries from the list of words included in the category of positive emotions.

Happiness includes words such as cheer, cheerful, cheers, cheery, cherish*, enjoy*, glad, gladly, happier, happiness, happy, jolly, joy*, merr*, smil*, well, wellbeing, and wellness (e.g., “McDonald's was one of my grandpa's favorite places. It was always a treat when he'd take us. I remember happy meals and vanilla milkshakes with him”). *Fun* includes words such as adventur*, amaze*, amazing, amazingly, ecsta*, entertain*, enthus*, excitement, excited, excitedly, excitement, exciting, fantastic, fantastical, fantastically, fantasy, fun, funny, funner, funnies, funniest, funnily, funniness, giggl*, ha, hah, haha*, hoho*, humor*, humour*, hurra*, joke*, joking, kidding, laugh*, lmao*, lmfao*, lol, playful, playfully, playfulness, pleasur*, plays, playing, played, and thrill* (e.g., “McDonald's French fries are my guilty pleasure. I know they're Awful but omg”). *Love* includes words such as amor*, beloved, darlin*, dear, dearly, hugg*, hug, hugs, kiss*, like, likeab*, liked, likes, liking, love, loved, lovelier, loveliest, lovely, lover*, loves, loving*, nurtur*, warm, warmed, warmer, warmest, warming, warmly, warms, warmth, soulmate*, romanc*, and romantic* (e.g., "@Toyota—I love my Toyota").

3.3.3. Emotional positivity index

Prior research has defined the emotional positivity index as greater values indicating more emotionally positive content and lower values indicating more emotionally negative content (Valsesia *et al.,* 2020). Specifically, previous research has calculated the emotional positivity index as "…the difference between the scores (percentages) for positive and negative emotion words and is computed on a scale from 1 to 100" (Valsesia *et al.,* 2020, p.1157). Hence, we adopted this approach to calculate the emotional positivity index. Thus, for each post, we have subtracted the score of negative emotion from the score of positive emotion, to obtain a value for the emotional positivity index. For instance, for a text observation that scores 5 in the positive emotions index and 3 in the negative emotions index, the emotional positivity index would be equal to 2. This value can also be understood as a net emotional indicator, which takes into account both positive and negative emotions."

3.3.4. Controls

We included word count and netspeak as controls for all the models (Valsesia *et al.*, 2020). We also controlled for the number of followers and number of friends, as suggested in previous studies (Gerrath *et al.,* 2023).

4. Empirical testing

4.1. Procedure and results

Previous research has used negative binomial estimation to investigate relationships in which the dependent variable is the number of likes received by a post on social media (e.g., Valsesia *et al.,* 2020). Thus, we also conducted the analyses using negative binomial regression with the Twitter sample. In our analyses, we reported the estimations first without the inclusion of the controls and then with the inclusion of the controls (i.e., word count, netspeak, number of followers, and number of friends).

Self-inclusive language. The results suggested a main relation of self-inclusive language in user-generated content with the number of likes that the tweet received (b = -0.021, SE = 0.001, $p < 0.01$), as shown in Model 1a in Table II. This finding held when the controls were included (b = -0.005, SE = 0.001, $p < 0.01$), as shown in Model 1b in Table II.

Negative emotions. The results suggested a significant and positive interaction between the use of self-inclusive language in user-generated content and the negative emotion of the content on the number of likes that the tweet received (b = 0.004, SE = 0.001, $p < 0.01$), as shown in Model 2a in Table III. This finding held when the controls were included (b = 0.003, SE = 0.001, $p < 0.01$), as per Model 2b in Table III. These results suggested that the negative association between self-inclusive language and number of likes was attenuated for content characterized by negative emotions.

Anger. In support of the previous finding, the results suggested a significant and positive interaction between the use of self-inclusive language in user-generated content and a particular type of negative emotion—anger—in the content and the number of likes that the tweet received (b = 0.003, SE = 0.001, $p < 0.01$), as shown in Model 3a in Table III. This finding held when the controls were included (b = 0.002, SE = 0.001, $p < 0.01$), as per Model 3b in Table III. These results, once more, suggested that the negative association between self-inclusive language and number of likes was attenuated for content characterized by anger.

Sadness. We repeated our analyses using sadness as a particular case of negative emotion. Consistently, the results suggested a significant and positive interaction between the use of self-inclusive language in user-generated content and sadness in the content and the number of likes that the tweet received (b = 0.006, SE = 0.001, $p < 0.01$), as shown in Model

4a in Table III. In this case, while directional, the results did not hold when the controls were included (b = 0.002, SE = 0.001, p = 0.138), as per Model 4b in Table III. However, these results provided supporting evidence of the negative association between self-inclusive language and number of likes and how it is smoothened for content characterized by sadness.

Anxiety. When using anxiety as a type of negative emotion, we did not initially find a significant interaction effect between self-inclusive language in user-generated content and anxiety and the number of likes that the tweet received (b = 0.003, SE = 0.003, p = 0.144), as shown in Model 5a in Table III. However, this effect was positive and significant when the controls were included (b = 0.006, SE = 0.002, p < 0.01), as displayed in Model 5b in Table III, providing further support for the attenuating role of certain negative emotions, in this case, anxiety, on the association between self-inclusive language in user-generated content and the number of likes that the tweet received.

Positive emotional content. We regressed the number of likes on the extent of self-inclusive language in user-generated content, positive emotions, and their interaction term. In contrast to the findings regarding negative emotions, the results here suggested a negative and marginal interaction between the use of self-inclusive language in user-generated content and the positive emotion of the content and the number of likes that the tweet received (b = -0.001, SE = 0.001, p < 0.1), as shown in Model 6a in Table IV. This finding became completely significant when the controls were included (b = -0.001, SE = 0.001, p < 0.01), as displayed in Model 6b in Table IV. These results suggested that the negative association between self-inclusive language and the number of likes is aggravated by content characterized by positive emotions.

Happiness. We investigated the previous effect with specific positive emotions. Initially, we regressed the number of likes on the extent of self-inclusive language in user-generated content, happy emotions, and their interaction term. Surprisingly, the findings suggested a positive and significant interaction between the use of self-inclusive language in user-generated content and the happy emotion of the content and the number of likes that the tweet received ($b = 0.004$, SE = 0.001, $p < 0.01$), as shown in Model 7a in Table IV. This finding became marginal when the controls were included ($b = 0.002$, SE = 0.001, $p = 0.105$), as per Model 7b in Table IV. These results suggested that the negative association between self-inclusive language and the number of likes, while it was aggravated for positive emotions overall, was attenuated for content characterized by happiness.

Fun. When using fun as a type of positive emotion, we did not initially find a significant interaction effect between self-inclusive language in user-generated content and fun and the number of likes that the tweet received ($b < 0.001$, SE < 0.001, $p = 0.272$), as shown in Model 8a in Table IV. However, this effect was negative and significant when the controls were included ($b = -0.001$, SE < 0.001, $p < 0.01$), as per Model 8b in Table IV. This finding supported the aggravating role of some positive emotions, such as fun in this case, in the association between self-inclusive language in user-generated content and the number of likes that the tweet received.

Love. Findings were mixed when using love as a type of positive emotion. We initially found a significant and positive interaction effect between self-inclusive language in user-generated content and love and the number of likes that the tweet received ($b = 0.005$, SE = 0.001, $p < 0.01$), as shown in Model 9a. However, this effect became negative and significant when the controls were included ($b = -0.003$, SE = 0.001, $p < 0.01$, Model 9b), providing mixed support of the aggravating role of this type of positive emotion on the association between self-inclusive language in user-generated content and the number of likes that the tweet received. We believe this may be mostly due to the specific sample of observations used in this study, and we speculate that the results may hold if the sample were larger or were collected at another time or with another set of brands.

Emotional positivity index. Without including the control variables, we found a significant and positive interaction effect between self-inclusive language in user-generated content and emotional positivity index and the number of likes that the tweet received (b < 0.001, SE < 0.001, p < 0.05), as shown in Model 10a in Table V. However, this effect became negative and significant when the controls were included (b = -0.001, SE < 0.001, p < 0.01), as displayed in Model 10b in Table V.

4.2. Analysis Across Media Venues

In this section, we report the analysis on the role of social media venues as moderators of the main relationships in our conceptual mode, using the merged dataset. The merged dataset allows for comparisons across media venues, indicating how the relationship in each media venue stands in comparison to the other media venues. We regressed the number of likes on self-inclusive language, the categorical variable indicating the media venue with Twitter as the baseline condition, and interaction between self-inclusive language and the categorical variable indicating the media venue with Twitter.

Results of the interaction between self-inclusive language and media venue are displayed numerically in Table VI. Specifically, we compare each venue with the others. Overall, the results suggest that the relationship between self-inclusive language and number of likes differs across media venues: the relationship is the most negative on forums and the most positive on Facebook. Instagram and Twitter still seem to lead to a reinforcement of the effect between self-inclusive language and other user responses, with Twitter being slightly less detrimental than Instagram.

Insert Table VI about here

Focusing on the main emotional indicators (i.e., positive emotions, negative emotions, and emotional positivity index), we regressed the emotional score, each media venue—keeping Twitter as the baseline condition for comparison—self-inclusive language, the three-way interaction between these three variables, and the two-way combinations between each of them on number of likes, see Table VII. Results suggest that the interaction between negative emotions and self-inclusive language is significantly detrimental on Instagram (vs. Twitter, $b = -0.011$, SE = 0.003, $p < 0.01$), but there is no significant difference across Facebook and forums, when compared to Twitter. Regarding the interaction between positive emotions and self-inclusive language, we find that this is again—albeit marginally—worse on Instagram (vs. Twitter, $b = -0.004$, SE = 0.002, $p < 0.1$), but this relationship is attenuated on forums (vs. Twitter, $b = 0.012$, SE = 0.002, $p < 0.01$). Finally, the interaction between emotional positivity index and self-inclusive language across media venues was only significantly different when comparing forums to Twitter ($b = -0.007$, SE = 0.002, $p < 0.01$). Overall, results indicate to mainly avoid Instagram as a media venue when focusing on text with high emotional intensity and high self-inclusive language.

Insert Table VII about here

4.3. Robustness Analyses

As in previous research with social media data (e.g., Hartmann *et al.,* 2021), we performed robustness analyses. In the appendix, Tables SII to SIV, we report the results of the alternative model: Poisson estimation. The robustness check using a Poisson estimation is often used in studies with Twitter data, where the variable of interest—specifically likes in our case—is collected as count data. Furthermore, previous studies using count data from Twitter, including works by Akpinar and Berger (2017) and Hartmann *et al.* (2021), primarily consider negative binomial regressions and Poisson regressions. Given that we have reported the main findings using negative binomial, which is also the regression mostly used in past research focusing on likes (Hartmann *et al.,* 2021; Valsesia *et al.,* 2020), we provide the results using Poisson regression in the appendix for robustness.

In Table SV in the appendix, we contrast the results for each media venue using a Poisson estimation. In Tables SVI to SVIII in the appendix, we report the results with a Poisson estimation for each media venue.

Additionally, to investigate the robustness of the results with comparable sample sizes across media venues, we estimate the models with a randomly reduced sample of tweets. Please refer to the appendix for details on the analyses and findings. The results are mostly robust and were replicated across different models.

5. Discussion

Our findings, across robustness checks with Poisson, controlling for word count, netspeak, number of friends, and number of followers and with a randomly reduced number of tweets to balance the sample size across media venues, suggest a negative relationship between self-inclusive language and other users' responses. Across multiple analyses and data sources (Twitter, Instagram, Facebook, and forums), we consistently find that emotional content characteristics change this relationship.

Namely, the relationship is mostly attenuated for content characterized by negative emotions and mostly holds for specific negative emotions, such as anger, sadness, and anxiety. However, the negative relationship between the use of self-inclusive language in user-generated content and the response that it receives from other users online is trickier when it comes to content characterized by positive emotions. Overall, positive emotions can aggravate this relationship, but using happiness—and to some extent love—as an emotion can actually result in an attenuation of the negative relationship between the use of self-inclusive language in user-generated content and the response that it receives from other users online.

The results are mostly robust and were majorly replicated when estimated with Poisson regression and when conducted with a truncated sample, comparable in size across the different media venues. Moreover, findings suggest that the relationship between self-inclusive language and number of likes differs across media venues. Overall, the relationship is the most negative on forums and the most positive on Facebook. Instagram and Twitter still seem to lead to a reinforcement of the effect between self-inclusive language and other user responses, with Twitter being slightly less detrimental than Instagram. Moreover, regarding the relationship between self-inclusive language and emotional content, across media venues, results suggest avoiding Instagram as a media venue when focusing on text with high emotional intensity and high self-inclusive language.

5.1. Theoretical Contributions

The study's key findings make several novel contributions, adding to extant research in three main ways. First, the findings extend the research on marketing communication on social media (e.g., Aleti *et al.,* 2019; Berger and Milkman, 2012; Berger *et al.,* 2019; Hartmann *et al*., 2021; Hartmann *et al.,* 2019; Herhausen *et al*., 2019; Valsesia *et al*., 2020) to the domain of user-generated content. While prior research has focused mainly on communication styles of celebrities or brands on social media, we focus on a novel but important gap: that of the linguistic style and emotions embedded in user-generated content and their impact on the responses of other online users to said content. Specifically, by building on signaling theory, this study observes the self-inclusive language of user-generated content as a signal that has the power to affect other users' responses to this content, highlighting the importance of emotions as signals in this process. Thus, the theoretical contribution of the study is the application of signaling theory (Spence, 1978; Connelly *et al.*, 2011) to the context of user-generated content. In this study, we show that social media communication is an environment characterized by information asymmetry, and that signaling through self-inclusive language and emotions serves as a means to overcome information asymmetries in terms of latent and unobservable elements of user-generated content.

Second, we respond to the call for more empirical research on the temporal aspects of emotional expressions in social media (Chen *et al.,* 2023). We do so by pointing out that the emotionality of the content is also a signal that has the power to change the responses of other users to user-generated content that uses self-inclusive language. By doing so, we extend the literature on the expression of emotions in social media (Aleti *et al.,* 2019; Berger *et al.,* 2022; Valsesia *et al.,* 2020). We contribute, hence, to research that focuses on writing styles and linguistic aspects (Aleti *et al.,* 2019), but we add to it by focusing on user-generated content as an antecedent to other online user responses to it.

Finally, this study introduces the importance of observing more than one social media platform (Hartmann *et al.,* 2021) in studies that utilize data from social media. We do so by providing a post hoc analysis in the appendix, in which we identify the role of media venues (i.e., Twitter, Instagram, Facebook, and forums) in changing responses to user-generated content that uses self-inclusive language. We find that self-inclusive language generally has a negative effect on other users' responses across different media venues, as the results persist for Twitter, Instagram, Facebook, and forums (Table SV). The negative effect of self-inclusive language on other users' responses is attenuated if the content is posted on Facebook (vs. Twitter or vs. Instagram vs. forums) and aggravated if it is posted on forums (vs. Twitter, Instagram, or Facebook). These results suggest that Facebook may be the venue where the relationship between self-inclusive language in user-generated content and other users' responses is the least harmful and forums the venue where it is the most harmful.

Moreover, using different social media platforms, we support our empirical evidence through large-scale real data. Given the importance of research that utilizes social media to explain various phenomena and given the growing importance of textual data in contemporary research (Berger *et al.,* 2019), this paper also disentangles the process of using textual analysis of social media content.

5.2. Practical Implications

Understanding the relationship between linguistic features of user-generated content and user responses is important for many different stakeholders, from marketers, policy-makers, and data scientists to those interested in advocacy and lobbying. Marketers are constantly and increasingly interested in how consumers talk about their brands or how celebrities endorse their brands on online social media (Aleti *et al*., 2019; Berger and Milkman, 2012; Valsesia *et al.,* 2020). Thus, understanding the relationship between the linguistic characteristics of user-generated content when referring to brands and other user responses can aid marketers not only in predicting followers' behavior online but also in proactive preparation. In particular, we contend that our findings within a user-generated content context can be extrapolated to guide how brands and endorsers communicate online, aiming to influence responses from other online users. Our findings imply that social media managers should establish an early-warning system (e.g., AI-based) to monitor users employing self-inclusive language when discussing brands, aiming to nurture, incentivize and drive emotional content related to happiness and love. Interestingly, our findings suggest that empowering users to express even their negative emotions in the content they generate is not fully problematic, as it alleviates the negative relationship between self-inclusive language and other users' responses.

Companies and public institutions use a series of social media platforms to communicate with their audience. They often diffuse the same communication across different media venues. We challenge this assumption and suggest that user responses to linguistic elements and emotions evoked in online communications differ among online social media platforms. Specifically, the findings of our post hoc analysis that includes other social media platforms (Instagram, Facebook, and forums) suggest that the relationship between self-inclusive language and other users' responses differs across media venues. We find that the effect on the number of likes per post is the most negative on forums and the most positive on Facebook when user-generated content uses self-inclusive language. Thus, social media managers should favor and incentivize generating conversations about their brand on Facebook.

Finally, our study is of great importance to the business development managers of various social listening tools (such as Pulsar and Determ), as the results can serve as inspiration for new features to be integrated into social listening tools and offered to the market. In particular, this study clearly shows that algorithms based on a one-size-fits-all approach need to be revised when social listening tools are offered to monitor user-generated content on different media venues.

5.3. Limitations and Future Research Opportunities

This research has several limitations that open future research opportunities. First, textual analyses of online user-generated content in this research present limitations related to the LIWC categorization of emotional content (Berger *et al.,* 2022). The expression of positive or negative emotional content does not necessarily equate to a "good" or "bad" (Lerner and Keltner, 2000) attitude. For example, sentiment analysis may detect an increase in positive emotions in user-generated content with a hidden meaning expressed through irony. To correctly take advantage of this situation, further research could use more advanced methods, such as Machine Learning and Latent Dirichlet Allocation modeling, to capture underlying themes based on a full-text corpus rather than on particular words that are part of the dictionary.

Second, although we speculate that the relationship between self-inclusive language and other users' responses can be explained by self-inclusive language being more self-focused, we do not test for this and alternative mechanisms that underlie the relationship between self-inclusive language and other users' responses. Future research can empirically test for the role of self-focus and alternative explanations.

Finally, the empirical analyses of this research are based fully on textual analyses of data from four different social media venues, providing correlational support for the predictions. Future research can test the predictions using an experimental method to make the findings more robust by providing a cause-and-effect relationship between self-inclusive language in user-generated content and other users' responses.

6. Conclusion

Researchers in different fields are interested in how users talk and relate to each other online. Our study is thus a timely response to the growing interest of scholars in social media data and demonstrates that the use of self-inclusive language in user-generated content (e.g., using words such as I, my, and mine) is associated with a less positive response from other online users. However, we suggest that this relationship can be attenuated by negative emotions of the content or aggravated by positive emotions of the content. We view this research as a useful step toward exploring users' responses to user-generated content written in self-inclusive language. We hope that this research stimulates further work on textual analyses of user-generated content.

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Table I. Summary of the literature on the role of self-inclusivity on people's behavior

Study	**Aim**	**Independent variables**	**Outcome**	**Mediating variables**	**Moderating variables**
Adam-Troian *et al.* (2021)	Testing whether the use of first-person plural pronouns can predict real-life social mobilization in the US	Use of first-person plural pronouns (e.g., "we", "us") in search data from Google Trends	Real-life social mobilization, as indicated by the number of protests and the number of participants/protesters		
Aleti *et al.* (2019)	Understanding how linguistic styles in tweets affect consumer WOM	Linguistic styles: Narrative vs. analytical, Internal vs. external, Positive vs. negative emotion	Consumer WOM on Twitter (retweet)		
Belkin *et al.* (2013)	Investigating the role of affective tone in online negotiations, and how the expression of happiness and anger can signal dominance and influence the outcomes in a negotiation	Affective tone (angry versus happy affective displays)	Individual outcome (gains in negotiations)	Perceptions of partner's dominance: dominance and submissiveness.	Resource power assignment (high versus low resource power)
Berger and Milkman (2012)	Understanding how overall emotionality, emotional valence, and specific emotions affect the spreading of contents	Activation (high vs low) of positive (amusement) and negative emotions (anger)	Social transmission (sharing)	Arousal	Activating vs deactivating emotion: although without a formal moderation test, it is found that increasing deactivating emotion reduces the likelihood of sharing

Berger *et al.* (2022)	Investigating the difference between writing and speaking in emotional expression in consumer reviews and the subsequent consequences	Expression modality: writing vs. speaking	Word-of-mouth; Interest in target	Serial mediation: Emotionality Perceived emotionality Perceived liking	Opinion valence: positive vs. negative Deliberation vs. no deliberation
Berger *et al.* (2010)	Investigating how publicity influences sales of well-known and less known products	Publicity valence (positive vs. negative)	Purchase likelihood; Product evaluation	Product awareness	Product Awareness Time delay in reporting purchasing likelihood
Berger *et al.* (2019)	Investigating how content characteristics shape continued engagement, especially reading	Content characteristics: Emotionality, Specific emotion (anger, anxiety and sadness), Complexity	Continue engagement	Uncertainty Arousal	
Brewer and Gardner (1996)	Testing personal, relational, and collective levels of self-definition	Pronoun (we, they) vs. adjective priming; Type of judgment (similarity vs. dissimilarity)	Response latencies; Self-descriptions (interpersonal and collective)		Valence: Positive or negative Group size: small vs large
Brockmeyer *et al.* (2015)	Investigating the relationship between self-focused attention and depression and anxiety	Self-focused attention (measured by the usage of first-person singular pronouns)	Symptoms of depression and anxiety		
Burnkrant and Unnava (1995)	Exploring the effects of self-referencing on persuasion and message elaboration	Self-referencing (high vs. low)	Persuasion: Attitude toward the product, attitude toward the ad and message recall		Picture relevance (high vs low) Grammatical form (questions vs. statements)
Chau *et al.* (2020)	Developing a distress detection system that uses a mix of machine-learning classification and rule-based classification	Language patterns Self-referencing words Writing styles	Emotional distress in online social media		

Cryder *et al.* (2008)	Investigating whether the misery-is-not-miserly effect depends on one's level of self-focus and whether self-focus mediates the effect	Emotion condition (sadness vs neutral)	Buying price	Self-focus (measured by frequency of self-references in essays written by the participants)	Self-focus (as both mediator and moderator)
Escalas (2004)	Examining whether and how consumers develop meaningful connections with brands through narrative processing	Narrative processing (storytelling ad vs. vignette ad)	Brand attitudes/behavioral intentions	Self-brand connections (SBC)	
Escalas (2007)	Investigating how self-referencing and the strength of arguments in advertisements impact consumers' attitudes and behavior	Self-referencing (no SR vs. analytical SR vs. narrative SR) Argument strength (strong vs. weak)	Brand evaluations; Transportation (Narrative); Critical evaluation of the ad		
Fennis and Wiebenga (2017)	Investigating the effect of using first-person pronouns, such as "I" and "my", in brand names on brand judgment	Type of prefix (self-referencing vs. non-self-referencing) (Presence of personal pronouns in brand names)	Brand judgment (evaluation of the brand, willingness to buy, and willingness to pay)		Self-esteem; Self-view manipulation; Type of product (self-expressive vs. non-self-expressive)
Fitzsimons and Kay (2004)	Investigating how incidental language variations and pronoun usage can affect perceptions of interpersonal relationships	Pronoun usage (we vs. she and I) in relationship description	Perceived closeness Importance Intimacy	Unit perceptions (perceptions of similarity and common fate)	
Goldenberg *et al.* (2007)	Exploring the effects of individual and network-level negative word-of-mouth and examine how it affects the net present value of a firm	Negative word-of-mouth (Both individual and network-level)	Net Present Value of the firm	Number of rejecters Number of un-activated nets	

Green and Sedikides (1999)	Investigating how different affective states impact self-focused attention	Affect orientation (reflective affective states vs. social affective states)	Self-focused attention		
Gustafsson Sendén *et al.* (2014)	Understanding how language, especially personal pronouns, reflects biases in social evaluations	Pronoun used (self-inclusive vs. self-exclusive) (we vs. they); Level of inclusiveness (individual vs. collective) (I vs. we)	Evaluative Context: How positive or negative the context is in which the pronouns are used.		Communication contexts (individual vs. interpersonal vs. and intergroup)
Hartmann *et al.* (2021)	Examining the role of brand imagery in social media marketing	Brand-image type: brand selfie, consumer selfie, and packshot	Brand engagement User response	Net self-thoughts: the difference in self-reference between the brand and other-related words in the comments	
Ho-Dac *et al.* (2013)	Investigating the relationship between online customer reviews and sales, and how this relationship is moderated by brand equity	Cumulative positive and negative online user reviews	Sales		Brand Equity (Strong vs. weak)
Huang and Yeo (2018)	Investigating the social media messages of top executives and online user responses to them	CEOs' industry; background; content types of tweets; use of supplementary information; linguistic features of tweets	Retweetability of messages		

Labrecque *et al.* (2020)	Investigating how the use of pronouns in social media posts influences consumer engagement activities, with a focus on Interbrand's Top 100 Global Brands	First-person singular pronouns, first-person plural pronouns, second- person pronouns, third-person singular pronouns, and third-person plural pronouns	Consumer engagement actions on social media (likes, comments, and shares)		
Lerner *et al.* (2012)	Examining the causal role of sadness in influencing intertemporal decision-making and its implications for understanding irrational high discount rates	Emotional state: sadness, neutral and disgust	Impatience in intertemporal choices (preferences for immediate rewards over delayed rewards)		
Li and Zhan (2011)	Examining how language style, organizational structure, and other content features of online product reviews affect review adoption	Information valence Emotional strength	Perceived Helpfulness Source Expertise Source Trustworthiness	Argument quality Source credibility	Prior attitude Involvement
Ludwig *et al.* (2013)	Understanding how positive changes in affective content combined with increasing degrees of linguistic style matching influence conversion	Affective content and linguistic style match in online reviews	Purchase intention and perceived identification with the reviewers		
Meyers-Levy and Peracchio (1996)	Exploring the impact of self-reference on persuasion in advertising and investigate potential moderating factors	Level of self-reference in advertising manipulated at 3 levels: extremely low, moderate, and extremely high	Persuasion (evaluations of the advertised products)		Motivation to attend (low vs. high); Level of elaboration (low vs. high); Outcome favorableness (positive vs. negative)

Packard and Berger (2021)	Demonstrating that using more concrete and specific language can improve consumer attitudes and behaviors	Use of concrete language by customer servers	Customer satisfaction Willingness to purchase	Perceived listening	
Packard *et al.* (2018)	Understanding how the use of "I" pronouns instead of "we" pronouns affects customer perceptions of empathy and agency	Pronoun (I vs. we vs. you) used by firm agent during customer-firm interactions	Satisfaction Purchase intentions	Perceptions of agent empathy and agency	Empathy and agency cue: (no vs. yes)
Patrick and Hagtvedt (2012)	Investigating how using "I don't" vs. "I can't" can influence psychological empowerment and the ability to resist temptation	Framing of refusal: "I don't" vs. "I can't"	Goal-directed behavior	Empowerment index	
Rogers *et al.* (1977)	Determining whether encoding information in relation to oneself (self-referential processing) enhances memory performance compared to other types of encoding	Type of encoding task (self-reference vs. semantic judgments, phonemic judgments, and structural judgments)	Performance of recall tasks	Potential mediators: elaboration, organization, and emotional valence	Potential Moderators: self-esteem, cultural differences, and depression
Smith *et al.* (2012)	Comparing brand-related user-generated content across different social media platforms (YouTube, Facebook, and Twitter)	Type of social media platform (YouTube, Facebook, and Twitter)	Promotional self-presentation; Brand centrality Marketer-directed communication; Response to online marketer action Factual information about the brand		

Wang and Karimi (2019)	Determining how the use of first-person pronouns affects review helpfulness, and how this impact may be influenced by review attributes	Use of first-person singular pronouns	Perceived review helpfulness.		Valence review extremity Emotionality
Wood *et al.* (1990)	Investigating what type of affect drives self-focus attention in general, and how depressed people become self-focused	Affect (sad vs. neutral) (happy vs. neutral)	Self-focused attention		
Yin *et al.* (2022)	Investigating how the use of singular and plural pronouns in communication relates to abstract and concrete language and whether matching pronoun use with linguistic abstraction can enhance communication effectiveness	First-person pronouns (singular "I" and plural "we")	Liking Persuasiveness Writer's competence	Perception of fit	Communication: (abstract vs concrete)

Source: Author's own creation/work

Table II. Relationship between self-inclusive language and other users' responses

Variables	Model 1a	Model 1b
Self-inclusive language	-0.021***	-0.005***
	(0.001)	(0.001)
Word count		0.030***
		(0.001)
Netspeak		0.050***
		(0.001)
Number of friends (divided by 1000)		0.002***
		(0.001)
Number of followers (divided by 1000)		0.01***
		(0.0001)
Constant	0.654***	-0.681***
	(0.004)	(0.012)
Observations	656,910	656,910

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table III. Role of negative emotions in the relationship between self-inclusive language and other users' responses

Variables	Model 2a	Model 2b	Model 3a	Model 3b	Model 4a	Model 4b	Model 5a	Model 5b
Self-inclusive language	-0.014***	-0.008***	-0.020***	-0.005***	-0.020***	-0.005***	-0.021***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Negative emotions	0.065***	0.028***				-0.059***		
	(0.001)	(0.002)				(0.007)		
Self-inclusive language * Negative emotions	0.004***	0.003***				0.002		
	(0.001)	(0.001)				(0.001)		
Word count		0.030***		0.030***		0.0301***		0.030***
		(0.001)		(0.001)		(0.001)		(0.001)
Netspeak		0.031***		0.049***		0.050***		0.050***
		(0.001)		(0.001)		(0.001)		(0.001)
Number of friends (divided by 1000)		0.002***		0.002***		0.002***		0.002***
		(0.001)		(0.001)		(0.001)		(0.001)
Number of followers (divided by 1000)		0.010***		0.01***		0.010***		0.01***
		(0.000)		(0.000)		(0.000)		(0.000)
Anger			-0.136***	-0.085***				
			(0.006)	(0.006)				
Self-inclusive language * Anger			0.003***	0.002***				
			(0.001)	(0.001)				
Sadness					-0.102***	-0.059***		
					(0.008)	(0.007)		
Self-inclusive language * Sadness					0.006***	0.002		
					(0.001)	(0.001)		
Anxiety							-0.075***	-0.060***
							(0.010)	(0.010)
Self-inclusive language * Anxiety							0.003	0.006***
							(0.003)	(0.002)
Constant	0.327***	-0.708***	0.661***	-0.669***	0.657***	-0.677***	0.656***	-0.679***
	(0.008)	(0.012)	(0.004)	(0.012)	(0.004)	(0.012)	(0.004)	(0.012)
Observations	656,910	656,910	656,910	656,910	656,910	656,910	656,910	656,910

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table IV. Role of positive emotions in the relationship between self-inclusive language and other users' responses

Variables	Model 6a	Model 6b	Model 7a	Model 7b	Model 8a	Model 8b	Model 9a	Model 9b
Self-inclusive language	-0.022*** (0.001)	-0.006*** (0.001)	-0.021*** (0.001)	-0.006*** (0.001)	-0.020*** (0.001)	-0.006*** (0.001)	-0.023*** (0.001)	-0.005*** (0.001)
Positive emotions	0.031*** (0.002)	0.0301*** (0.002)						
Self-inclusive language * Positive emotions	-0.001* (0.001)	-0.001*** (0.001)						
Word count		0.030*** (0.001)		0.030*** (0.001)		0.031*** (0.001)		0.031*** (0.001)
Netspeak		0.051*** (0.001)		0.050*** (0.001)		0.050*** (0.001)		0.049*** (0.001)
Number of friends (divided by 1000)		0.002*** (0.001)		0.002*** (0.001)		0.002*** (0.001)		0.002*** (0.001)
Number of followers (divided by 1000)		0.010*** (0.000)		0.010*** (0.000)		0.010*** (0.000)		0.010*** (0.000)
Happiness			0.021*** (0.006)	0.049*** (0.005)				
Self-inclusive language * Happiness			0.004*** (0.001)	0.002 (0.001)				
Fun					-0.010*** (0.003)	0.032*** (0.003)		
Self-inclusive language * Fun					< 0.001 (< 0.001)	-0.001*** (< 0.001)		
Love							0.036*** (0.004)	0.061*** (0.003)
Self-inclusive language * Love							0.005*** (0.001)	-0.003*** (0.001)
Constant	0.634*** (0.005)	-0.704*** (0.012)	0.652*** (0.004)	-0.686*** (0.012)	0.657*** (0.004)	-0.696*** (0.012)	0.647*** (0.004)	-0.702*** (0.012)
Observations	656,910	656,910	656,910	656,910	656,910	656,910	656,910	656,910

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table V. Role of emotional positivity index on the relationship between self-inclusive language and other users' responses

Variables	Model 10a	Model 10b
Self-inclusive language	-0.011***	-0.006***
	(0.001)	(0.001)
Emotional positivity index	-0.030***	-0.001
	(0.001)	(0.001)
Self-inclusive language * Emotional positivity index	< 0.001**	-0.001***
	(< 0.001)	(< 0.001)
Word count		0.030***
		(0.001)
Netspeak		0.049***
		(0.001)
Number of friends (divided by 1000)		0.0002***
		(0.001)
Number of followers (divided by 1000)		0.001***
		(0.000)
Constant	0.524***	-0.677***
	(0.006)	(0.012)
Observations	656,910	656,910

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table VI. Relationship between self-inclusive language and other users' responses across media venues

Variables	Interaction of media venues vs. Twitter	Interaction of media venues vs. Instagram	Interaction of media venues vs. Facebook	Interaction of media venues vs. Forums
Self-inclusive language	-0.021***	-0.037***	0.148***	-0.422***
	(-0.001)	(-0.006)	(-0.026)	(-0.003)
Twitter (vs. media venue)		-4.041***	-2.397***	-2.335***
		(-0.019)	(-0.121)	(-0.016)
Instagram (vs. media venue)	4.041***		1.644***	1.706***
	(-0.019)		(-0.123)	(-0.023)
Facebook (vs. media venue)	2.397***	-1.644***		0.062
	(-0.121)	(-0.123)		(-0.122)
Forums (vs. media venue)	2.335***	-1.706***	-0.062	
	(-0.016)	(-0.023)	(-0.122)	
Self-inclusive language * Twitter (vs. media venue)		0.017***	-0.169***	0.402***
		(-0.006)	(-0.026)	(-0.003)
Self-inclusive language * Instagram (vs. media venue)	-0.017***		-0.186***	0.385***
	(-0.006)		(-0.027)	(-0.007)
Self-inclusive language * Facebook (vs. media venue)	0.169***	0.186***		0.571***
	(-0.026)	(-0.027)		(-0.026)
Self-inclusive language * Forums (vs. media venue)	-0.402***	-0.385***	-0.571***	
	(-0.003)	(-0.007)	(-0.026)	
Constant	0.654***	4.695***	3.051***	2.990***
	(-0.004)	(-0.018)	(-0.121)	(-0.015)
Observations	767,379	767,379	767,379	767,379

Robust standard errors in parentheses, ***p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

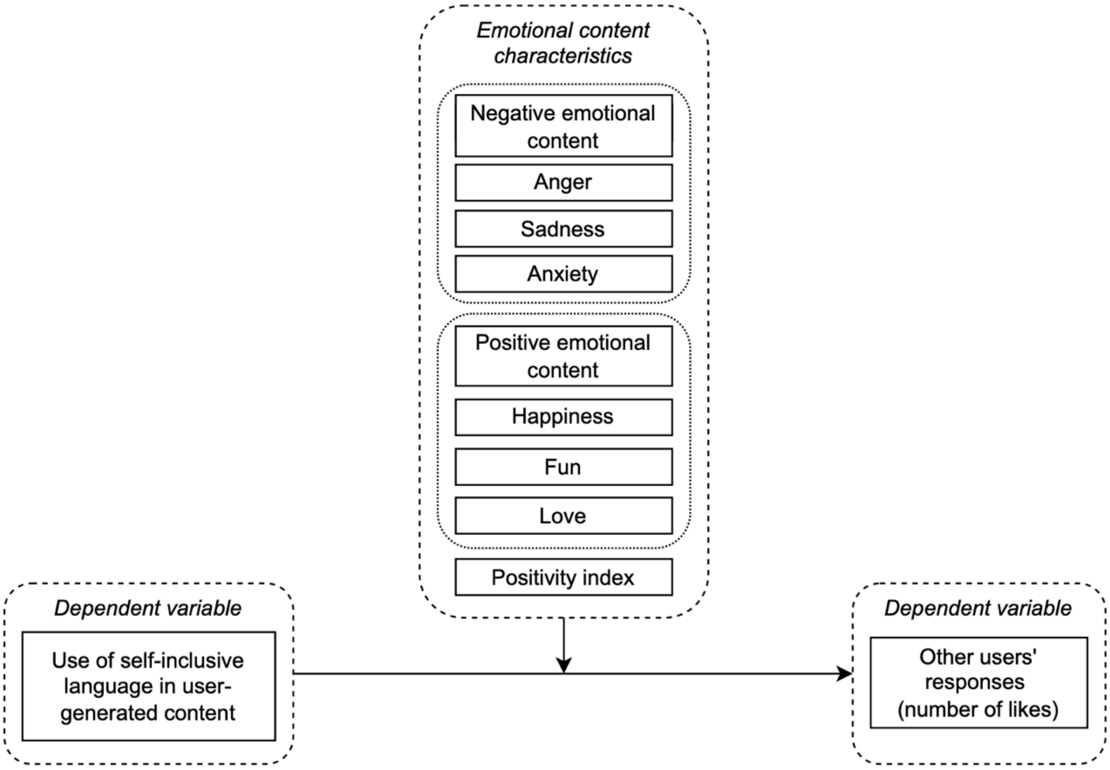
Table VII. Relationship between self-inclusive language and other users' responses comparing media venues

Variables	Model 1	Model 2	Model 3
Self-inclusive language	-0.014***	-0.022***	-0.011***
	(0.001)	(0.001)	(0.001)
Negative emotions	0.065***		
	(0.001)		
Self-inclusive language * Negative emotions	0.004***		
	(0.000)		
Instagram (vs. Twitter)	4.385***	4.071***	4.168***
	(0.020)	(0.020)	(0.020)
Facebook (vs. Twitter)	2.853***	2.379***	2.482***
	(0.134)	(0.137)	(0.121)
Forums (vs. Twitter)	2.774***	2.389***	2.476***
	(0.018)	(0.016)	(0.016)
Instagram (vs. Twitter) * Self-inclusive language	-0.022***	-0.009	-0.023***
	(0.006)	(0.007)	(0.007)
Facebook (vs. Twitter) * Self-inclusive language	0.141***	0.155***	0.159***
	(0.028)	(0.029)	(0.026)
Forums (vs. Twitter) * Self-inclusive language	-0.410***	-0.395***	-0.412***
	(0.003)	(0.003)	(0.003)
Instagram (vs. Twitter) * Negative emotions	-0.159***		
	(0.017)		
Facebook (vs. Twitter) * Negative emotions	-0.281***		
	(0.094)		
Forums (vs. Twitter) * Negative emotions	-0.293***		
	(0.008)		
Instagram (vs. Twitter) * Self-inclusive language * Negative emotions	-0.011***		
	(0.003)		
Facebook (vs. Twitter) * Self-inclusive language * Negative emotions	0.035		
	(0.025)		
Forums (vs. Twitter) * Self-inclusive language * Negative emotions	0.002		
	(0.002)		
Positive emotions		0.031***	
		(0.002)	
Self-inclusive language * Positive emotions		-0.001*	
		(0.000)	
Instagram (vs. Twitter) * Positive emotions		-0.039***	
		(0.008)	
Facebook (vs. Twitter) * Positive emotions		-0.024	
		(0.079)	
Forums (vs. Twitter) * Positive emotions		-0.282***	
		(0.008)	
Instagram (vs. Twitter) * Self-inclusive language * Positive emotions		-0.004*	
		(0.002)	
Facebook (vs. Twitter) * Self-inclusive language * Positive emotions		0.019	
		(0.021)	
Forums (vs. Twitter) * Self-inclusive language * Positive emotions		0.012***	
		(0.002)	
Emotional positivity index			-0.030***
			(0.001)
Self-inclusive language * Emotional positivity index			0.0003*
			(0.000)

Instagram (vs. Twitter) * Emotional positivity index			0.034***
			(0.008)
Facebook (vs. Twitter) * Emotional positivity index			0.124*
			(0.074)
Forums (vs. Twitter) * Emotional positivity index			0.074***
			(0.012)
Instagram (vs. Twitter) * Self-inclusive language * Emotional positivity index			-0.003
			(0.002)
Facebook (vs. Twitter) * Self-inclusive language * Emotional positivity index			-0.007
			(0.018)
Forums (vs. Twitter) * Self-inclusive language * Emotional positivity index			-0.007***
			(0.002)
Constant	0.327***	0.634***	0.524***
	(0.008)	(0.005)	(0.006)
Observations	767,379	767,379	767,379

Robust standard errors in parentheses, ***p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Figure 1. Conceptual model



Source: Author's own creation/work

Appendix

Table SI. Dataset description

	Source	Content	Language	Mean	SD	Min	Max	N
Twitter								
Inclusive language	Twitter API	UGC	N/A	1.591	3.981	0	50	656912
Number of likes	Twitter API	UGC	N/A	1.866	48.257	0	28844	656910
Negative emotions	LIWC	UGC	N/A	4.250	3.674	0	50	656912
Anger	LIWC	UGC	N/A	0.096	0.891	0	50	656912
Sadness	LIWC	UGC	N/A	0.052	0.643	0	33	656912
Anxiety	LIWC	UGC	N/A	0.026	0.439	0	33	656912
Positive emotions	LIWC	UGC	N/A	0.701	2.614	0	60	656912
Happiness	Calculated	UGC	N/A	0.094	0.888	0	33.33	656912
Fun	Calculated	UGC	N/A	0.344	1.735	0	60	656912
Love	Calculated	UGC	N/A	0.202	1.438	0	60	656912
Positivity index	Calculated	UGC	N/A	-3.549	4.712	-50	60	656912
Netspeak	LIWC	UGC	N/A	4.881	4.350	0	67	656912
Word count	LIWC	UGC	N/A	18.241	9.658	0	312	656912
Instagram								
Inclusive language	Pulsar	UCG	English	0.929	2.312	0	33	34882
Number of likes	Pulsar	UCG	English	106.168	1520.34	0	200118	34883
Negative emotions	LIWC	UGC	English	0.223	1.023	0	25	34882
Anger	LIWC	UGC	English	0.024	0.330	0	17	34882
Sadness	LIWC	UGC	English	0.029	0.398	0	20	34882
Anxiety	LIWC	UGC	English	0.030	0.394	0	18	34882
Positive emotions	LIWC	UGC	English	1.059	2.408	0	33	34882
Happiness	Calculated	UGC	English	0.258	1.222	0	33.33	34883
Fun	Calculated	UGC	English	0.608	1.722	0	40	34883
Love	Calculated	UGC	English	0.292	1.256	0	33.33	34883
Positivity index	Calculated	UGC	English	0.837	2.622	-25	33	34883
Netspeak	LIWC	UGC	English	0.901	2.414	0	75	34882
Word count	LIWC	UGC	English	42.090	36.457	1	367	34883
Facebook								
Inclusive language	Pulsar	UCG	English	3.596	3.778	0	25	1726
Number of likes	Pulsar	UCG	English	41.791	305.536	0	9410	1726
Negative emotions	LIWC	UGC	English	0.638	1.171	0	9	1726
Anger	LIWC	UGC	English	0.024	0.174	0	2	1726
Sadness	LIWC	UGC	English	0.041	0.314	0	8	1726
Anxiety	LIWC	UGC	English	0.059	0.391	0	8	1726
Positive emotions	LIWC	UGC	English	1.201	1.797	0	17	1726
Happiness	Calculated	UGC	English	0.325	0.759	0	11.11	1726
Fun	Calculated	UGC	English	0.491	0.995	0	9.64	1726
Love	Calculated	UGC	English	0.234	0.718	0	10	1726
Positivity index	Calculated	UGC	English	0.563	2.216	-9	17	1726
Netspeak	LIWC	UGC	English	0.665	1.313	0	14	1726
Word count	LIWC	UGC	English	123.581	97.783	4	430	1726
Forums								
Inclusive language	Pulsar	UCG	English	3.803	3.767	0	40	73861
Number of likes	Pulsar	UCG	English	12.232	1800.430	0	442200	73862
Negative emotions	LIWC	UGC	English	0.761	1.426	0	23	73861
Anger	LIWC	UGC	English	0.086	0.462	0	14	73861
Sadness	LIWC	UGC	English	0.048	0.352	0	20	73861
Anxiety	LIWC	UGC	English	0.068	0.437	0	17	73861
Positive emotions	LIWC	UGC	English	0.601	1.353	0	33	73861
Happiness	Calculated	UGC	English	0.184	0.651	0	25	73862
Fun	Calculated	UGC	English	0.495	1.168	0	33.33	73862
Love	Calculated	UGC	English	0.201	0.885	0	33.33	73862
Positivity index	Calculated	UGC	English	-0.160	1.989	-23	33	73862
Netspeak	LIWC	UGC	English	1.046	2.111	0	43	73861
Word count	LIWC	UGC	English	109.017	91.698	2	415	73862

Source: Author's own creation/work

Table SII. Role of negative emotions on the relationship between self-inclusive language and other users' responses on Twitter venue with Poisson estimation

Variables	Model S2a	Model S3a	Model S4a	Model S5a
Self-inclusive language	-0.174***	-0.096***	-0.096***	-0.096***
	(0.021)	(0.016)	(0.016)	(0.016)
Negative emotions	-0.340***			
	(0.028)			
Self-inclusive language*Negative emotions	0.017***			
	(0.001)			
Anger		-0.228***		
		(0.075)		
Self-inclusive language*Anger		0.003		
		(0.008)		
Sadness			-0.121**	
			(0.055)	
Self-inclusive language*Sadness			0.003	
			(0.006)	
Anxiety				0.062
				(0.066)
Self-inclusive language*Anxiety				-0.031**
				(0.014)
Constant	3.000***	2.168***	2.163***	2.157***
	(0.139)	(0.107)	(0.107)	(0.107)
Observations	767,379	767,379	767,379	767,379

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table SIII. Role of positive emotions on the relationship between self-inclusive language and other users' responses on Twitter venue with Poisson estimation

Variables	Model S6a	Model S7a	Model S8a	Model S9a
Self-inclusive language	-0.100***	-0.098***	-0.096***	-0.098***
	(0.017)	(0.016)	(0.017)	(0.016)
Positive emotions	0.018			
	(0.019)			
Self-inclusive language * Positive emotions	0.002			
	(0.001)			
Happiness		-0.004		
		(0.016)		
Self-inclusive language * Happiness		0.007***		
		(0.002)		
Fun			0.030	
			(0.024)	
Self-inclusive language * Fun			-0.003	
			(0.003)	
Love				0.001
				(0.012)
Self-inclusive language * Love				0.003***
				(0.001)
Constant	2.148***	2.160***	2.149***	2.159***
	(0.112)	(0.108)	(0.110)	(0.109)
Observations	767,379	767,379	767,379	767,379

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table SIV. Role of emotional positivity index on the relationship between self-inclusive language and other users' responses

Variables	Model S10a
Self-inclusive language	-0.118***
	(0.017)
Emotional positivity index	0.085***
	(0.002)
Self-inclusive language * Emotional positivity index	-0.002***
	(0.001)
Constant	2.358***
	(0.108)
Observations	767,379

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table SV. Relationship between self-inclusive language and other users' responses across media venues

Variables	Interaction of media venues vs. Twitter	Interaction of media venues vs. Instagram	Interaction of media venues vs. Facebook	Interaction of media venues vs. Forums
Self-inclusive language	-0.017***	-0.049**	0.113***	-1.365***
	(0.006)	(0.024)	(0.038)	(0.390)
Twitter (vs. media venue)		-4.056***	-2.551***	-3.150***
		(0.092)	(0.239)	(0.606)
Instagram (vs. media venue)	4.056***		1.505***	0.906
	(0.092)		(0.251)	(0.611)
Facebook (vs. media venue)	2.551***	-1.505***		-0.598
	(0.239)	(0.251)		(0.650)
Forums (vs. media venue)	3.150***	-0.906	0.598	
	(0.606)	(0.611)	(0.650)	
Self-inclusive language * Twitter (vs. media venue)		0.032	-0.130***	1.348***
		(0.025)	(0.039)	(0.390)
Self-inclusive language * Instagram (vs. media venue)	-0.032		-0.162***	1.316***
	(0.025)		(0.045)	(0.391)
Self-inclusive language * Facebook (vs. media venue)	0.130***	0.162***		1.478***
	(0.039)	(0.045)		(0.392)
Self-inclusive language * Forums (vs. media venue)	-1.348***	-1.316***	-1.478***	
	(0.390)	(0.391)	(0.392)	
Constant	0.649***	4.705***	3.200***	3.799***
	(0.034)	(0.085)	(0.236)	(0.605)
Observations	767,379	767,379	767,379	767,379

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table SVI. Effect of self-inclusive language and negative emotions on users' responses

Twitter (Observations: 656,910)				
Self-inclusive language	-0.009*	-0.016***	-0.017***	-0.017***
	(0.005)	(0.006)	(0.006)	(0.006)
Negative emotions	0.050***			
	(0.009)			
Self-inclusive language * Negative emotions	0.001			
	(0.001)			
Anger		-0.151***		
		(0.012)		
Self-inclusive language * Anger		0.002		
		(0.001)		
Sadness				-0.110***
				(0.024)
Self-inclusive language * Sadness				0.005***
				(0.002)
Anxiety			-0.078***	
			(0.028)	
Self-inclusive language * Anxiety			0.003	
			(0.003)	
Constant	0.405***	0.656***	0.650***	0.652***
	(0.035)	(0.035)	(0.035)	(0.035)
Instagram (Observations: 34,882)				
Self-inclusive language	-0.043*	-0.049**	-0.048*	-0.049**
	(0.025)	(0.025)	(0.024)	(0.025)
Negative emotions	-0.083*			
	(0.046)			
Self-inclusive language * Negative emotions	-0.028*			
	(0.015)			
Anger		0.020		
		(0.115)		
Self-inclusive language * Anger		-0.010		
		(0.022)		
Sadness				-0.022
				(0.066)
Self-inclusive language * Sadness				-0.003
				(0.023)
Anxiety			-0.077	
			(0.102)	
Self-inclusive language * Anxiety			-0.038	
			(0.032)	
Constant	4.719***	4.705***	4.707***	4.706***
	(0.087)	(0.086)	(0.086)	(0.085)
Facebook (Observations: 1,726)				
Self-inclusive language	0.106**	0.114***	0.113***	0.112***
	(0.043)	(0.038)	(0.038)	(0.039)
Negative emotions	-0.172			
	(0.174)			
Self-inclusive language * Negative emotions	0.025			
	(0.024)			

Anger		0.573		
		(0.398)		
Self-inclusive language * Anger		-0.111		
		(0.076)		
Sadness				-0.343
				(0.336)
Self-inclusive language * Sadness				0.112*
				(0.067)
Anxiety			-0.105	
			(0.164)	
Self-inclusive language * Anxiety			-0.007	
			(0.029)	
Constant	3.272***	3.193***	3.208***	3.194***
	(0.289)	(0.240)	(0.238)	(0.243)
Forums (Observations 73,861)				
Self-inclusive language	-1.378***	-1.356***	-1.355***	-1.355***
	(0.367)	(0.388)	(0.397)	(0.387)
Negative emotions	-0.586			
	(0.529)			
Self-inclusive language*Negative emotions	0.100***			
	(0.038)			
Anger		-2.547***		
		(0.585)		
Self-inclusive language*Anger		0.264***		
		(0.060)		
Sadness				-2.110***
				(0.585)
Self-inclusive language*Sadness				0.170***
				(0.042)
Anxiety			0.171	
			(0.111)	
Self-inclusive language*Anxiety			-0.088	
			(0.140)	
Constant	4.059***	3.834***	3.781***	3.814***
	(0.667)	(0.605)	(0.616)	(0.605)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table SVII. Effect of self-inclusive language and positive emotions on users' responses

Twitter (Observations: 656,910)				
Self-inclusive language	-0.018***	-0.017***	-0.017***	-0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
Positive emotions	0.017***			
	(0.005)			
Self-inclusive language * Positive emotions	0.000			
	(0.001)			
Happiness		0.016		
		(0.010)		
Self-inclusive language * Happiness		0.002		
		(0.001)		
Fun			-0.010	
			(0.014)	
Self-inclusive language*Fun			0.000	
			(0.001)	
Love				0.025***
				(0.008)
Self-inclusive language * Love				0.001*
				(0.000)
Constant	0.637***	0.647***	0.652***	0.644***
	(0.036)	(0.035)	(0.035)	(0.035)
Instagram (Observations: 34,882)				
Self-inclusive language	-0.042	-0.048*	-0.040	-0.048*
	(0.028)	(0.025)	(0.026)	(0.025)
Positive emotions	-0.007			
	(0.044)			
Self-inclusive language * Positive emotions	-0.004			
	(0.009)			
Happiness		-0.178***		
		(0.036)		
Self-inclusive language * Happiness		0.0120		
		(0.013)		
Fun			-0.041	
			(0.062)	
Self-inclusive language * Fun			-0.009	
			(0.012)	
Love				-0.050**
				(0.025)
Self-inclusive language * Love				0.001
				(0.006)
Constant	4.712***	4.732***	4.725***	4.717***
	(0.090)	(0.087)	(0.091)	(0.089)
Facebook (Observations: 1,726)				
Self-inclusive language	0.116***	0.116***	0.116***	0.115***
	(0.042)	(0.041)	(0.039)	(0.040)
Positive emotions	0.057			
	(0.080)			
Self-inclusive language * Positive emotions	0.000			
	(0.013)			
Happiness		0.164*		

		(0.096)		
Self-inclusive language * Happiness		0.017		
		(0.022)		
Fun			0.119	
			(0.162)	
Self-inclusive language * Fun			-0.013	
			(0.022)	
Love				0.206*
				(0.118)
Self-inclusive language * Love				-0.002
				(0.020)
Constant	3.111***	3.101***	3.159***	3.129***
	(0.276)	(0.236)	(0.236)	(0.251)
Forums (observations: 73,861)				
Self-inclusive language	-1.292***	-1.329***	-1.386***	-1.351***
	(0.366)	(0.376)	(0.410)	(0.384)
Positive emotions	-1.541***			
	(0.491)			
Self-inclusive language * Positive emotions	0.144***			
	(0.038)			
Happiness		-1.609		
		(1.063)		
Self-inclusive language * Happiness		0.146***		
		(0.054)		
Fun			-0.232	
			(0.500)	
Self-inclusive language * Fun			0.071	
			(0.145)	
Love				-1.985***
				(0.715)
Self-inclusive language*Love				0.132***
				(0.041)
Constant	3.955***	3.859***	3.874***	3.861***
	(0.609)	(0.610)	(0.665)	(0.608)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Table SVIII. Effect of self-inclusive language and emotions on users' responses for each media venue with Poisson estimation

Twitter (Observations: 656,910)		
Self-inclusive language	-0.017***	-0.010*
	(0.006)	(0.005)
Emotional positivity index		-0.029***
		(0.009)
Self-inclusive language * Emotional positivity index		-0.000
		(0.001)
Constant	0.649***	0.527***
	(0.034)	(0.031)
Instagram (Observations: 34,882)		
Self-inclusive language	-0.049**	-0.048*
	(0.024)	(0.025)
Emotional positivity index		0.003
		(0.034)
Self-inclusive language * Emotional positivity index		-0.001
		(0.005)
Constant	4.705***	4.702***
	(0.085)	(0.086)
Facebook (Observations: 1,726)		
Self-inclusive language	0.113***	0.115***
	(0.038)	(0.039)
Emotional positivity index		0.082
		(0.051)
Self-inclusive language * Emotional positivity index		-0.006
		(0.008)
Constant	3.200***	3.151***
	(0.236)	(0.241)
Forums (Observations: 73,861)		
Self-inclusive language	-1.365***	-1.364***
	(0.390)	(0.387)
Emotional positivity index		0.0393
		(0.032)
Self-inclusive language * Emotional positivity index		0.016
		(0.048)
Constant	3.799***	3.812***
	(0.605)	(0.608)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own creation/work

Robustness Analyses

Analyses with reduced random sample from Twitter. Given that the number of observations collected from Twitter is greater than those of the other media venues, we have repeated the analyses using a random selection of posts from the complete Twitter pool of observations (e.g., Jaidka, Guntuku, & Ungar, 2018). Specifically, we have asked Stata to generate a random pool of observations equal to 10% of the original one. We have repeated the analyses using this reduced random sample from Twitter (N = 65,691), again using a negative binomial regression.

The results support the main relationship between self-inclusive language and number of likes (b = -0.110, SE = 0.002, $p < 0.01$), the moderating effects of anger (b = 0.006, SE = 0.002, $p < 0.01$) and anxiety (b = -0.038, SE = 0.005, $p < 0.01$) and an effect of sadness (b = -0.013, SE = 0.006, $p < 0.01$). Moreover, the results support the moderating effects of positive emotional content (b = -0.002, SE = 0.001, $p < 0.01$), fun (b = -0.002, SE = 0.001, $p < 0.01$), and love (b = 0.012, SE = 0.001, $p < 0.01$). Emotional positivity index again has a negative moderating effect (b = -0.007, SE = 0.001, $p < 0.01$).

Finally, the findings support that using Facebook as a media venue—as opposed to Twitter (b = 0.15, SE = 0.025, $p < 0.01$), Instagram (b = 0.16, SE = 0.026, $p < 0.01$), or forums (b = 0.49, SE = 0.025, $p < 0.01$)—results in a more positive relationship between self-inclusive language and number of likes, and that forums—as opposed to Twitter (b = -0.33, SE = 0.005, $p < 0.01$), Instagram (b = -0.32, SE = 0.008, $p < 0.01$), or Facebook (b = -0.48, SE = 0.025, $p < 0.01$)—result in a more negative relationship between use of self-inclusive language in user-generated content and number of likes.