

Who is bragging more online? A large scale analysis of bragging in social media

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Abstract

Bragging is the act of uttering statements that are likely to be positively viewed by others and it is extensively employed in human communication with the aim to build a positive self-image of oneself. Social media is a natural platform for users to employ bragging in order to gain admiration, respect, attention and followers from their audiences. Yet, little is known about the scale of bragging online and its characteristics. This paper employs computational sociolinguistics methods to conduct the first large scale study of bragging behavior on Twitter (U.S.) by focusing on its overall prevalence, temporal dynamics and impact of demographic factors. Our study shows that the prevalence of bragging decreases over time within the same population of users. In addition, younger, more educated and popular users in the U.S. are more likely to brag. Finally, we conduct an extensive linguistics analysis to unveil specific bragging themes associated with different user traits.

Keywords: bragging, social media, computational sociolinguistics, computational linguistics

1. Introduction

Bragging (self-praise) is a speech act that involves disclosing positive content about oneself or their close network (Dayter, 2014, 2018) such as achievements, possessions or feelings (Scopelliti et al., 2015; Matley, 2018). It falls in the category of self-presentation strategies with the goal of building and establishing a positive social image of one self (Goffman et al., 1978; Jones et al., 1982; Jones, 1990; Bak et al., 2014). This desire for attaining a positive self-image is a key driver of human behavior (Baumeister, 1982; Leary and Kowalski, 1990; Sedikides, 1993; Tetlock, 2002), as it can bring benefits like admiration, respect, attention by other people and personal rewards (Gilmore and Ferris, 1989; Hogan, 1982; Schlenker, 1980). Bragging as a behavior was found to be related to user traits including personality and it can differ based on communication strategies favored by the participants to the bragging act (Miller et al., 1992; Van Damme et al., 2017; Sezer et al., 2018).

Social media presents a unique environment to study bragging (and self-presentation strategies more generally) as users' craft and control the information they expose to their audience. Further, due to the nature of online interactions, this information can represent a significant part of what most of the audience knows about a person. Thus, users on social media platforms pay great attention to building their online social image (Chou and Edge, 2012; Michikyan et al., 2015; Halpern et al., 2017) and studies have shown that online self-presentation is predominantly positive (Matley, 2018; Chou and Edge, 2012; Lee-Won et al., 2014). Moreover, so-

Type	Text
Bragging	<i>Just impressed myself with how much French I think I understood! One semester at KC FTW!</i>
Non-bragging	<i>Glad to hear that! Well done Jim!</i>

Table 1: Example of bragging and non-bragging tweets.

cial media platforms include functionality that rewards and promotes positive statements such as likes or positive reactions to users' posts (Reinecke and Trepte, 2014) which often are used to quantify impact on the platform (Lampos et al., 2014; Mu et al., 2024). Traditionally, bragging is considered a high risk act (Van Damme et al., 2017; Brown and Levinson, 1987; Holtgraves, 1990) and can lead to the opposite effect than intended, such as dislike or decreased perceived competence (Matley, 2018; Jones et al., 1982; Sezer et al., 2018). However, bragging is acceptable and even desired in certain online contexts (Dayter, 2018). According to Dayter (2018); Matley (2020); Ren and Guo (2020) self-promotion is pervasive on social media. Bragging in particular is more frequent on social media than face-to-face interactions (Ren and Guo, 2020). Table 1 shows examples of bragging and non-bragging tweets.

To date, bragging behavior was quantitatively studied in specific contexts through manual analyses of small data sets of hundreds of posts (Dayter, 2014, 2018; Matley, 2018; Tobback, 2019; Rüdiger and Dayter, 2020). This paper aims to provide the first large scale quantitative study on the prevalence

of online bragging using a longitudinal data set that includes over 1 million English tweets posted by a group of 2,685 Twitter users in the U.S. over ten years. We identify bragging through Natural Language Processing (NLP) methods, including using a state-of-the-art neural model (Jin et al., 2022) for identifying bragging in social media posts. Our main findings are as follows:

- Bragging steadily decreases over time in the past 10 years within the same group of users.
- Bragging is more prevalent among users who are female, generally younger, more educated, have a higher income and are more popular on Twitter.
- Male users and users with higher income brag more about leisure activities. Female users and users with lower education focus more on themselves when bragging. Bragging by older users and users who have higher education are more likely to involve others. Emojis are more frequently used by female and younger users while bragging.

2. Related Work

Bragging as a Social Behavior Bragging enhances one's positive social image and can trigger high-quality interactions with other users (Miller et al., 1992). Therefore, it is acceptable and even desirable on social media to some extent (Dayter, 2018). However, bragging is also widely considered as a face-threatening act for speakers according to the modesty maxim (Leech, 2016) and politeness theory as it threatens both positive and negative face (Brown and Levinson, 1987). As a result, it may damage user likability if it is negatively perceived by the audience (Matley, 2018). Thus, social psychology and linguistic studies have mostly focused on investigating the impact of self-promotion for identifying its pragmatic strategies (e.g., shifting focus to others who are closely related to them). These strategies help the speakers/users to mitigate the social risk and negative effects caused by bragging (Scopelliti et al., 2015; Tobback, 2019; Matley, 2020).

Analysis of Bragging The use of pragmatic strategies for bragging has been analyzed qualitatively by linguists and psychologists across languages such as Mandarin (Wu, 2011), English (Speer, 2012; Dayter, 2021), Spanish (Maíz-Arévalo, 2021), or Russian (Dayter, 2021). In social media, Dayter (2014) identified a series of overlapping strategies in a small ballet community on Twitter. Matley (2018) examined the pragmatic function of hashtags (e.g., #brag, #humblebrag) used

by Instagram users and Tobback (2019) studied the impact of bragging about professional skills on LinkedIn. Also, the frequency of different bragging strategies used by regular people (Ren and Guo, 2020) and celebrities (Guo and Ren, 2020) has been examined in Weibo (a Chinese social media platform). Furthermore, the emotional influence of bragging from the audience perspective was studied by Scopelliti et al. (2015). More recently, Jin et al. (2022) introduced the task of automatically identifying bragging and classifying its types on Twitter using computational methods.

Language Use and User Traits Previous work in computational sociolinguistics showed that user traits (e.g., age, gender and personality) and popularity correlate with language use and online behavior (Preotiuc-Pietro et al., 2015b; Nguyen et al., 2016; Preotiuc-Pietro et al., 2017; Preotiuc-Pietro and Ungar, 2018; Villegas et al., 2023). Schwartz et al. (2013) found significant variations in language on Facebook with age, gender and personality while Preotiuc-Pietro et al. (2015c) examined the correlations between user income and a variety of factors such as profile features, demographic and psychological traits.

Studies on differences in self-disclosure have focused on gender through different platforms (Valkenburg et al., 2011; Sheldon, 2013; Altenburger et al., 2017; Farinosi and Taipale, 2018; Wang et al., 2021), where most of them have suggested that women disclose more about themselves than men do. Also, racial background was investigated in self-disclosure behavior (Chen, 1995; Rui and Stefanone, 2013). Bak et al. (2012) investigated the relationship between self-disclosure and user relationship strength (e.g., strong and weak) on Twitter, while Moon et al. (2016) examined the relationship between narcissism (i.e., a personality trait reflecting a grandiose and inflated self-concept) and self-promoting on Instagram. To the best of our knowledge, no previous study has attempted to study the relationship between bragging and social factors.

3. Measuring Bragging Prevalence

3.1. Data for Model Training

We use a publicly available data set developed by Jin et al. (2022) to train a bragging classifier and it consists of 6,696 English tweets and each tweet is manually annotated as bragging or non-bragging. In total, there are 544 bragging tweets and 2,838 non-bragging tweets in the training set; 237 bragging tweets and 3,077 non-bragging tweets in the

Label	Training set	Dev/Test set	All
Bragging	544 (16.09%)	237 (7.15%)	781 (11.66%)
Non-bragging	2,838 (83.91%)	3,077 (92.85%)	5,915 (88.34%)
Total	3,382	3,314	6,696

Table 2: Statistics of the bragging data set.

development and test set (see Table 2).¹

3.2. Predictive Model

We re-implement the best performing predictive model proposed by (Jin et al., 2022) on identifying whether a tweet contains bragging or not (BERTweet-LIWC).² The BERTweet-LIWC model generates word embeddings using BERTweet (Nguyen et al., 2020) and combines it with Linguistic Inquiry and Word Count (LIWC; (Pennebaker et al., 2001)) features. The feature combination is performed through a fusion mechanism, which was originally introduced by Rahman et al. (2020), to control the influence of word representations and linguistic features. The joint representation of text and LIWC features is sent to the BERTweet encoder, followed by an output binary classification layer.

3.3. Bragging Prevalence Metrics

Our analyses rely on computing a user-level bragging prevalence score. We expect that the base rate of bragging will change over time. However, we aim to compare groups of users based on their traits and we want to ensure the bragging score is adjusted to the base rate in bragging over a certain time period. Thus, we normalize the score over several smaller time chunks.

Overall Bragging Prevalence First, we obtain the time series of total bragging tweets and total tweets posted by all users over each month, denoted as $P = \{p_1, \dots, p_n\}$ and $Q = \{q_1, \dots, q_n\}$ respectively where n is the number of months in the data set. We compute the distribution of average bragging percentage across all users for each month $A = \{a_1, \dots, a_n\}$ such that:

$$A = \frac{P}{Q} \quad (1)$$

¹This data set is also manually annotated according to six bragging types (i.e., *Achievement, Action, Feeling, Trait, Possession, Affiliation*). We only use the binary label because of the small number of examples in each bragging type which results in low performance on type prediction. This can introduce noise in our analysis.

²We achieve similar performance on the bragging test set (72.51 macro F1).

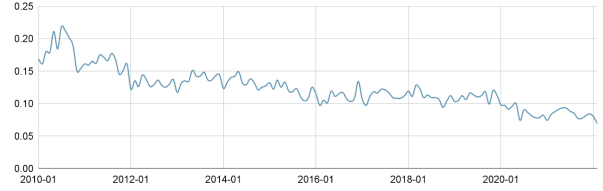


Figure 1: Bragging percentage by year and month.

User Bragging Prevalence To compute a bragging score of an individual user u , we first obtain the distributions of bragging tweets and total tweets over each month for u , which are denoted as $B_u = \{b_{u1}, \dots, b_{un}\}$ and $T_u = \{t_{u1}, \dots, t_{un}\}$ respectively. We obtain a time-normalized bragging distribution $D_u = \{d_{u1}, \dots, d_{un}\}$ for each user over months by dividing each data point from the user distribution by the overall bragging prevalence in each time window:

$$D_u = \frac{B_u}{T_u * A} \quad (2)$$

Finally, we average the normalized bragging distribution D_u for each user l :

$$l = \frac{\sum_{i=1}^n d_{ui}}{n} \quad (3)$$

The normalized bragging percent practically compares the bragging tendency of a single user to that of the population average in the same time range. We normalize with time to account for possible temporal shifts in bragging prevalence over time (see Figure 1).

4. Analysis Data

To analyze the social factors of bragging, we need a large set of Twitter users associated with socio-demographic characteristics. We combine three data sets that contain such information in the following papers as provided by the original authors on request: the first data set (developed by Preotiuc-Pietro et al. 2016) contains 863 users, the second data set (developed by Guntuku et al. 2017) contains 4,568 users and the third data set (developed by Jaidka et al. 2020) contains 938 users. All user information is obtained through self-reports on questionnaires. All users are mapped to their self-reported gender and age, while the users in the second data set also self-report their education degree and annual income range. In total, our combined data set contains 6,369 users, all from the U.S.. For details about user sampling, please refer to the original papers. Subsequently, we collect all historical tweets from these users resulting in more than 9.7 million tweets. We stop data collection at the end of 2021.

4.1. Filtering

For computing user bragging behavior, we need to only study content that is original and authored by the user. For this, we employ the following filtering steps:

- We filter out non-English content using the language code provided by Twitter, as our classifier is only trained to classify English content.
- We exclude replies and retweets through the parameters exposed through the Twitter API.
- We remove duplicate tweets from the same user by using the first five content tokens (excluding numbers, usernames and hashtags), because duplicate tweets are unlikely to be original content created by users.
- All tweets that are automatically generated from third parties are filtered out using source labels that indicate original authorship such as "Twitter Web Client" or "Twitter for Android". We found that tweets with source labels such as "The Sims 4 Game" and "Paradise Island 2" are likely to be generated automatically and would negatively impact our analysis (e.g., "*I played the Sandy Caps mini game in Paradise Island 2, and my score was: 68 #Paradiselsland2 #GameInsight*").
- Finally, we remove all users that have posted fewer than 20 tweets, as computing an average bragging ratio across a very small number of tweets results in unreliable estimates.

In total, our analysis data contains 2,685 users with 1,031,276 tweets, with each user having 384 posts on average.

4.2. Text Processing

We pre-process the collected tweets by lower-casing and tokenizing using TweetTokenizer from NLTK Toolkit (Bird et al., 2009). We also replace all URLs and username mentions with a single word token <URL> and <USER> respectively.

4.3. Computing Bragging Ratio

We use the bragging predictive model to identify the category (bragging or non-bragging) of all 1,031,276 individual tweets in our analysis data set. Then we compute the normalized bragging ratio for each user using Equation 2 and Equation 3.

To investigate the performance of the model on the analysis data, we manually evaluated a batch of 100 tweets across different users and years and found that the model achieved 78.55 macro F1, which was a higher absolute performance number on the test data set than the one reported in Jin et al.

(2022) (72.51 macro F1). Also, we notice that it is easier for the model to misclassify non-bragging tweets as bragging in the analysis data set due to positive sentiment or gratitude expressions in the text (e.g., "*Just installed box.net iOS app and signed up for a FREE 50gb lifetime cloud space account. Thx <USER>! #gaetc #gaetcsmackdown #freeapp*"); while bragging tweets are misclassified as non-bragging are mostly due to indirect expressions (e.g., "*#MyBestFriendsKnow that I am that one friend <URL>*"). This is in line with the error analysis in Jin et al. (2022). In general, mispredicted tweets are evenly distributed over the entire data coverage period except for the years 2012 and 2018. Among these error cases, 40% of tweets are posted by males and 60% of these are posted by females; while 55% of them are generated by users born before 1988 and 45% of them are generated by those born after 1988.

4.4. User Demographic Traits

To examine the relationship between bragging behavior online and the following user demographic traits, we use the following attributes.

- **Gender.** There are 859 self-identified males (33.81%) and 1,678 self-identified females (66.19%). Self-identified non-binary users represented a very small number of the total participants, hence were removed from the analysis.
- **Age.** Reported as the year of birth. The age reported throughout the paper refers to user age as of the end of 2021.
- **Education.** It contains six categories: (1) users who have not completed high school; (2) high school or equivalent; (3) associate's degree or equivalent; (4) bachelor's degree or equivalent; (5) master's degree or equivalent; and (6) doctoral degree or equivalent.
- **Income.** The annual yearly income of a user in U.S. dollars is divided into eight categories: (1) below 10K; (2) 10-25K; (3) 25-40K; (4) 40-60K; (5) 60-75K; (6) 75-100K; (7) 100-200K; and (8) above 200K.

4.5. User Popularity Traits

Popularity reflects other people's interest in users' accounts or posts. We quantify this using the following metrics: (1) the number of followers (the higher, the more popular); (2) the ratio between friends or users being followed and followers (the lower, the more popular) and (3) the number of times a user was listed (the higher, the more popular). Note that, for computing the correlation between popularity metrics and bragging, we log scale the values such

Trait	Mean	Median
Demographic Traits		
Age	35.99	33
User Impact		
No. Followers	22,951.06	186
No. Friends/No. Followers	2.62	1.58
No. Listings	47.72	2.0

Table 3: Statistics of user socio-demographic traits and popularity.

that their distribution are closer to a Gaussian distribution. We collect the popularity user information at the end of 2021, consistent with the cut-off date for the data collection.

Table 3 shows statistics of the demographic and popularity traits in our data. The trait distributions in the data set are presented in Figure 2.

5. Results and Discussion

5.1. Bragging Prevalence over Time

We first look at the frequency of bragging on Twitter through our data set and its dynamics over time. The mean bragging ratio is 0.1114 and the median bragging ratio is 0.0968 (0.0020 and 0.0013 after normalization) for all users. This shows that bragging is a common occurrence in original tweets from U.S. users, with users bragging on average in 1 out of 9 of their tweets. Next, we study the temporal dynamics of bragging. Figure 1 shows the bragging percentage over time across the ten years of the data set. This shows that overall the bragging percentage is slowly decreasing with time. The decline in bragging behavior on Twitter during the study period may be attributed to various factors such as a shift in focus to other social media platforms. Thus, it would be challenging to ascertain the exact reasons based solely on our Twitter data. Additionally, this finding highlights the need for temporal normalization of the bragging ratio, as users who published more recently could be skewed to having a lower overall bragging ratio.

5.2. When to Brag and How

Next, we investigate the time (e.g., day of the week, time of the day) of bragging and the linguistic patterns around these times. Overall, we do not find any significant correlations between bragging rate and either the time of day, when split into ranges, or the day of the week (e.g., weekday vs. weekend $\rho = 0.02$).

However, even if the bragging rate is similar, we also explore if the expressions of bragging across days of the week and times of the day vary using

Weekday vs. Weekend			
Unigram	r	Unigram	r
class	.050	sunday	.034
professor	.028	night	.029
semester	.028	friday	.028
job	.026	church	.028
campus	.024	<user>	.026
classes	.023	#livepd	.025
#tbt	.023	weekend	.025
thursday	.021	we	.024
interview	.021	state	.024
exam	.021	watching	.020
office	.020	bar	.020
bio	.020	game	.020
monday	.020	won	.019
killed	.019	football	.019
grow	.019	drinking	.019
vote	.019	rewards	.018
internship	.018	afternoon	.018
ago	.018	party	.018
teeth	.017	racing	.018
gym	.017	jam	.017

Table 4: Unigram feature correlations with bragging between weekday and weekend, sorted by Pearson correlation (r). All correlations are significant at $p < .001$, two-tailed t-test.

a linguistic analysis. For this, we use a unigram (i.e., token) feature analysis to identify words and themes associated with bragging by computing the correlations between the distribution of each unigram across posts and the label of the post (i.e., bragging or not bragging). Then, we use univariate Pearson correlation to rank the unigrams similar to (Schwartz et al., 2013).

Day of the Week Table 4 presents the top-20 unigram features correlated with bragging in weekdays vs. weekends. For this analysis, we normalize the creation time of each post to the local time by using the timezone difference which was inferred from the zip code that users have provided.

To demonstrate the face validity of the analysis, we first observe that bragging statements from both weekdays and weekends involve words related to time (e.g., *thursday*, *sunday*, *night*, *weekend*, *afternoon*). Secondly, we observe that users mostly brag about their school life or work on weekdays (e.g., *class*, *professor*, *interview*, *office*, *internship*). For example, a user mentions his/her professor when bragging.

T1: "My professor for accounting saw what I

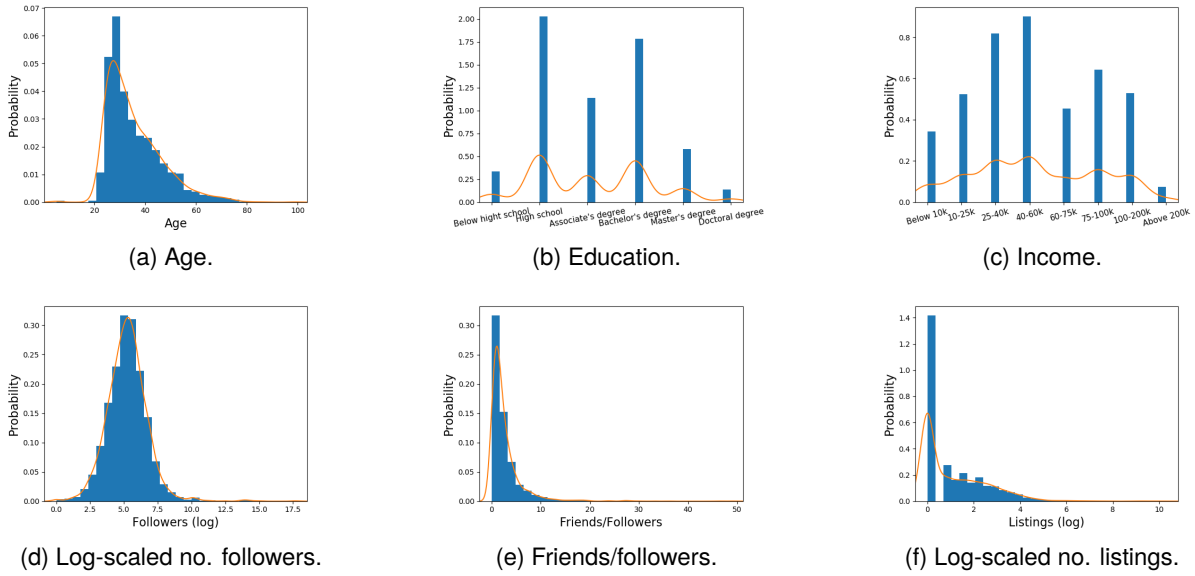


Figure 2: Histograms of user socio-demographic traits and popularity.

carry all day and said I must have great upper body strength lol”.

Another popular bragging topic on weekdays is about going to the *gym*. Bragging on weekends usually focuses on certain entertainment, recreation and worship activities (e.g., *church, watching, bar, football, drinking, party*) or church attendance (*church*) (see example T2).

T2: “Yay, I’m picking up my cute new glasses tomorrow. Now I can rock them at Mom’s party tomorrow”.

In addition, this could also involve activities that are done as part of a group, as exemplified by the first person plural pronoun *we*.

Time of Day Table 5 shows the unigrams associated with bragging at different times in a day. Similar to the day of the week analysis, our findings demonstrate face validity since the top correlated tokens are related to the time of bragging (e.g., *morning, yesterday, tonight, 2:30*).

Next, we observe that bragging about eating or sharing food such as *coffee, lunch, pizza* and *beer* is popular at all times except at night (see example T3).

T3: “Just made some lamb burgers with home-made tzatziki sauce. Starting to feel confident about my cooking skills.”.

Also, bragging in the morning is usually about things that happened the previous day (e.g., *yesterday, sleep*) or study/work (e.g., *school, class, “Secured a B in my principles of marketing class this semester!!!”*) while bragging in the afternoon or evening involves a wide variety of recreational

activities (e.g., *shopping, fitness, #music, “Finally, newest member of planet fitness!”*). Finally, many users tend to brag about their upcoming activities in the evening (e.g., *tomorrow, morning*).

5.3. Bragging Prevalence and Demographic Factors

Next, we explore the relationship between bragging rate and user demographic traits. To understand what types of users brag more than others in U.S. Twitter, we perform a correlation analysis by computing the Pearson correlation coefficient between user traits and the user-level bragging metric described in Equation 2 and Equation 3. The results are summarized in the top part of Table 6.

We first analyze gender and age. According to our analysis, gender and age are strongly associated with the bragging percentage ($p < .001$). Note that correlations around 0.1 with such a large sample size ($N=2,685$) are highly significant and in terms of magnitude in line with correlations between other well known linguistic variables and traits (Carey et al., 2015; Holgate et al., 2018).

Thus, we examine the rest of the demographic traits by controlling for gender and age using partial correlation (Preoȃuc-Pietro et al., 2015a), where education level and annual income are represented in the ordinal scale described in Section 4.4. The main findings are:

- Gender is significantly correlated with bragging in the sense that female users brag more than male users ($r = 0.10, p < .001$). This is consistent with the findings of previous studies related to self-presentation (Sheldon, 2013; Wang et al., 2021) and it can be explained

06:00-09:00		09:00-12:00		12:00-15:00		15:00-18:00		18:00-21:00		21:00-00:00		00:00-03:00		03:00-6:00	
Unigram	r	Unigram	r	Unigram	r	Unigram	r	Unigram	r	Unigram	r	Unigram	r	Unigram	r
morning	.131	morning	.042	lunch	.053	dinner	.040	dinner	.042	tomorrow	.049	i	.055	sleep	.069
last	.055	coffee	.040	just	.029	<url>	.025	#piano	.031	tonight	.047	night	.044	awake	.069
breakfast	.055	class	.037	afternoon	.023	store	.022	#music	.026	bed	.040	sleep	.043	morning	.069
today	.051	last	.031	shopping	.020	pizza	.021	tonight	.024	i	.038	midnight	.041	early	.058
day	.048	today	.029	basically	.020	came	.021	beer	.022	night	.029	bed	.032	up	.057
up	.046	lunch	.028	outside	.020	bags	.020	tomorrow	.020	#livepd	.026	😭	.032	4am	.051
sleep	.044	yesterday	.028	shop	.020	fitness	.018	#musicmonday	.020	midnight	.026	2:30	.031	5:30	.047
coffee	.044	woke	.028	break	.020	mail	.018	pizza	.021	win	.025	drunk	.031	6:30	.042
school	.044	breakfast	.027	cleaning	.019	published	.018	#classicalmusic	.021	life	.025	tonight	.030	covet	.041
yesterday	.043	classes	.025	food	.019	rain	.017	wine	.021	absolutely	.023	friends	.030	singles	.039

Table 5: Unigram feature correlations with bragging between different time periods in a day, sorted by Pearson correlation (r). All correlations are significant at $p < .001$, two-tailed t-test.

Trait	r	p_{unc}	p_{corr}
User Demographics			
Gender (♀-1, ♂-0)	0.10	<.001	<.001
Age	-0.16	<.001	<.001
Education	0.14	<.001	<.001
Income	0.07	<.003	<.002
User Popularity			
No. Followers	0.12	<.001	<.001
No. Friends/Followers	-0.10	<.001	<.001
No. Listings	0.09	<.001	<.001

Table 6: Pearson correlations between user-level traits and their bragging metric. p_{unc} and p_{corr} refer to uncorrected and corrected (Bonferroni correction) p-values.

by the fact that women show more interest in developing friendships online (Holmes, 2013), which can be accomplished by positive self-presentation.

- There is a significant association between age and bragging, with younger users bragging more than older ones ($r = -0.16$, $p < .001$). This might result from younger people’s desire to increase their status among peers and peer approval (MacIsaac et al., 2018). Social comparison was found to occur more frequently in younger age groups than in older ones (McAndrew and Jeong, 2012), which explains why younger users tend to create positive self-presentations online (Yau and Reich, 2019).
- Users with higher education levels tend to brag more ($r = 0.14$, $p < .001$). This might be explained by the fact that users with a higher educational level tend to express more joy which could include self-disclosure statements (Volkova and Bachrach, 2015).
- Users with higher income significantly brag more frequently online ($r = 0.07$, $p < .003$).

.003) than users with lower incomes. Users with higher income were found to be more likely to produce positive tweets (Volkova and Bachrach, 2015). Previous work also suggested that rich people are characterized by a self-focused and narcissistic personality (Leckelt et al., 2019). This causes them to produce more content that is related to self-promotion in social media (Buffardi and Campbell, 2008; Moon et al., 2016).

- Higher income and education are positively correlated with older age (income: $r = 0.16$, $p < .001$; education: $r = 0.30$, $p < .001$). Older age however has an inverse relationship to bragging than income and education. This highlights a divergence along these traits, where users who are either highly educated or young are likely to brag more.

We further explore the relationship between language use and bragging behavior across different demographic characteristics.

Gender Table 7 (left column) shows the top-25 unigrams correlated with gender. We observe that male users mostly brag about their partners (e.g., *wife*), but also mention other users (e.g., *<user>*). As illustrated in example T4, popular bragging topics for males are entertainment achievements such as games (e.g., *#dnd*, *#league*, *#twitch*, *playing*) and sports (e.g., *tournament*, *win*, *football*, *championship*, *teams*).

T4: “I’m so genuinely happy I witnessed that. #NationalChampionship”.

On the other hand, female users prefer to brag with first person pronouns (e.g., *my*, *me*, *i*). They also brag about personal traits (e.g., *hair*), feelings (e.g., *love*, *happy*) and their partners (e.g., *boyfriend*). For example, a female user mentions her haircut appointment in example T5.

T5: “HOORAY!! I finally got a haircut appointment!! It’ll be 64 days since my last cut (I normally go every 5 weeks so this’ll be close to

Male vs. Female				Born after 1988 vs. before 1988			
Unigram	r	Unigram	r	Unigram	r	Unigram	r
<url>	.073	my	.083	i	.099	<url>	.141
<user>	.071	so	.063	my	.069	<user>	.079
game	.061	😊	.060	😊	.069	!	.077
team	.047	:)	.059	me	.057	join	.036
games	.040	:p	.058	so	.050	#livepd	.033
#dnd	.036	❤	.048	😂	.050	local	.032
#league	.036	hair	.048	m	.049	kids	.031
wife	.034	mom	.043	😂	.047	our	.031
tournament	.034	😂	.042	😂	.041	we	.031
podcast	.033	😂	.041	class	.040	wife	.031
win	.033	bed	.041	exam	.039	daughter	.030
#livepd	.033	love	.040	college	.038	via	.029
football	.033	😂	.040	semester	.038	w	.029
#twitch	.033	😂	.040	lol	.037	play	.028
fantasy	.033	me	.039	myself	.036	#dnd	.028
great	.032	😂	.037	life	.036	pe	.028
stream	.032	♀	.036	😂	.036	inboxdollars	.028
aw_prints	.031	👤	.035	ve	.035	app	.028
inboxdollars	.031	😂	.034	best	.035	challenge	.027
championship	.030	😂	.034	😂	.035	covet	.026
playing	.030	🏠	.033	😂	.035	show	.026
teams	.030	because	.033	😂	.035	awesome	.025
congratulations	.029	i	.033	😂	.035	#positive	.025
app	.029	happy	.033	like	.034	photo	.025
bout	.029	boyfriend	.033	mom	.034	#_am	.024

Table 7: Unigram feature correlations with bragging between gender and age, sorted by Pearson correlation (r). All correlations are significant at $p < .001$, two-tailed t-test.

double my normal tim, and yeah, it feels like I have about twice as much hair to cut!!”.

According to [McAndrew and Jeong \(2012\)](#), women spend more energy than men in presenting themselves for impression management. Furthermore, bragging by females usually contains female-related terms (e.g., ♀) or positive emoticons (e.g., :), :p) and emojis (e.g., 😂, ❤) to strengthen the meaning of their posts. This corroborates findings that positive emojis are used more frequently in positive contexts ([Derks et al., 2008](#)). Results are also consistent with the observation that female users communicate using more emotional exchanges ([Gefen and Ridings, 2005](#)). They also use emojis more often than men ([Chen et al., 2017](#); [Prada et al., 2018](#)).

Age In terms of age, we split the users into two age groups (born before 1988 and after 1988) using the population median. Table 7 (right column) shows the top-15 unigram features correlated with age. We notice that younger users (born after 1988) brag more about themselves (e.g., *i*, *my*, *me*, *myself*) and school life (e.g., *class*, *exam*, *college*, *semester*). Example (T12) indicates how a younger user brags about his/her exam result.

T12: “Also somehow got a 90 on my soils exam... how...”.

Also, they use more emojis in their bragging posts, which is consistent with the fact that in general

Higher vs. Lower Education				Higher vs. Lower Income			
Unigram	r	Unigram	r	Unigram	r	Unigram	r
<user>	.062	i	.074	<user>	.061	:)	.043
students	.040	lol	.059	<url>	.051	my	.030
<url>	.039	my	.055	aw_prints	.032	lol	.030
our	.030	😊	.043	*congrats	.030	got	.026
*congrats	.029	m	.038	#iteachk	.029	#livepd	.023
pe	.025	👉	.035	pe	.029	work	.023
ss	.025	look	.033	#piano	.029	cory	.022
season	.025	😂	.032	*#hc	.027	covet	.022
zak	.025	got	.032	students	.026	renee	.021
conference	.024	😂	.031	#music	.024	makes	.021
beer	.024	😂	.030	team	.024	boyfriend	.021
#piano	.023	*#10bw	.028	golf	.024	yay	.021
their	.023	😂	.027	win	.024	m	.020
delicious	.023	baby	.027	❤	.023	then	.019
student	.021	😂	.026	bet	.023	kiss	.019

Table 8: Unigram feature correlations with bragging between higher and lower education level annual income, sorted by Pearson correlation (r). All correlations are significant at $p < .001$, two-tailed t-test. *congrats, *#10bw, *#hc is congratulations, #10billionwives, #happyclassrooms.

younger users tend to use more emojis than older ones do in social media ([Prada et al., 2018](#)).

The group of users above median age brag more about collective activities (e.g., *our*, *we*) and their affiliation such as family members (e.g., *kids*, *wife*, *daughter*), which suggests older people are more family-focused and engage more with family activities ([McAndrew and Jeong, 2012](#)). In example (T13), a user in this group mentions his/her daughter while bragging.

T13: “My daughter is hands down the coolest person I know!”.

Education & Income: Table 8 (left column) presents the top 15 unigrams in bragging posts correlated with higher and lower education. We observe that people with higher levels of education use a smaller number of emojis. As illustrated in example (T14), they brag more about their jobs (e.g., *student*, *conference*) and activities involving food (e.g., *beer*, *delicious*).

T14: “Glad I’ve been working on my Adobe Suite skills this year. I’m going to be making a very special obituary poster for my uncle’s celebration of life to highlight testimonials from friends and family ❤”.

Furthermore, people with higher education mention others (e.g., *<user>*, *our*, *their*) when bragging. As illustrated in example (T15), This is in contrast with lower educated users who focus on their personal traits, possessions or activities (e.g., *i*, *my*, *look*, *got*).

T15: “I look cute as hell in this hoodie”.

Similar income and education levels share a similar language (e.g. *<user>*, *students*, *congratulations* in higher education and higher income, *my*,

lol, baby, boyfriend in lower education and lower income) (see Table 8 right column for the top 15 unigrams in bragging posts correlated with higher and lower income). In addition, bragging expressions from higher income users are more related to entertainment events such as *#music, golf* compared with higher education (see example (T16)).

T16: “Great golf lesson with <USER> at the PAGA! Already see the results. Now-practice to see them more often. #GonnaBreak80”.

5.4. Bragging Prevalence and User Popularity

Finally, we investigate whether bragging prevalence is related to user popularity on Twitter. Table 6 shows that users who are more popular on Twitter are likely to brag more across all three popularity metrics (r between 0.09 and 0.12, $p < .001$), when controlled for gender and age.

It is possible that users with many followers (e.g., micro- or macro-influencers) tend to interact with and try to maintain followers or obtain more followers (Guo and Ren, 2020) by establishing a positive social image through bragging. It is expected that users with higher follower counts are less likely to have an audience that knows them personally and thus they aim to shape their perception through self-presentation strategies. This is in contrast with the users who have fewer friends and followers and who do not feel the need to use self-presentation strategies such as bragging to their close network. Past research showed that users are more willing to share content with positive sentiment with people that share a weak relationship (e.g., online followers) than with actual real-life friends (Bak et al., 2012).

The linguistic feature analysis did not result in any clear patterns or meaningful insights into the expression of bragging in terms of user popularity.

6. Conclusion

We have presented the first large-scale quantitative study of bragging on social media, focusing on understanding the prevalence, temporal dynamics and user factors impacting bragging prevalence. Our analysis of more than 1 million English Twitter posts from users in the U.S. showed that bragging slowly becomes less prevalent with time, it is more prevalent during the weekends and daytime and that females, younger users, users with higher education, income and popularity tend to brag more. Furthermore, we uncovered using linguistic methods the prevalent topics distinctive of each user group.

For future work, we plan to compare how bragging is perceived towards building a positive self-image, reactions to bragging and cultural differences in bragging behavior across locations and languages.

7. Ethics Statement

Our work has received approval from the Ethics Committee of our institution and complies with the Twitter data policy for research.³

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³<https://developer.twitter.com/en/developer-terms/agreement-and-policy>

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