Do We Tweet Differently From Our Mobile Devices? A Study of Language Differences on Mobile and Web-Based Twitter Platforms

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Using Twitter as a case study, this article hypothesizes that social media content that is produced on mobile versus web platforms may be qualitatively different. As we increasingly tweet from our smartphones, we may be encouraged to “report” on our immediate thoughts, feelings, physical self, and surroundings. This article seeks to understand whether these presentations of self tend to be more egocentric, negative/positive, gendered, or communal depending on whether they were tweeted from mobile devices or web platforms. Using 6 weeks of Twitter data collected in 2013, we found evidence that users tweet differently from mobile devices and that mobile tweeting is informing new behaviors, attitudes, and linguistic styles online.

Keywords: Mobile, Desktop, Twitter, Gender, Egocentric, Communal, Social Media.

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Mobile penetration worldwide has increased exponentially in the last decade. The International Telecommunications Union (2015) reports that there are over 7.08 billion mobile phone subscriptions. In many ways, the smartphone has become ubiquitous (Niels, 2013). Smartphones allow their users to access a host of additional applications that go beyond traditional phone calls such as accessing the Internet, taking and uploading photographs, and providing GPS services. Indeed, 64% of American cell phone users own a smartphone (Smith, 2015). Given this pervasiveness, it is important to understand how the rise of mobile computing has changed (if at all) social media content.

Social researchers have found Twitter, the popular microblogging platform, extremely useful in understanding a multitude of complex social processes due to its easily accessible data, brief messages, and timeliness (Murthy, 2015; Sloan, Morgan, 2015).

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Burnap, & Williams, 2015). However, there remains a lack of understanding as to how mobile or web engagement of Twitter changes one’s use of the medium in current Twitter literature. Owing to their small data size, tweets can be easily sent out over mobile devices or via text messages in instances where web access is unavailable (Veinott, Cox, & Mueller, 2009). Indeed, Twitter was first conceived as an SMS-based service with a 140-character limit. Yet, we do not have a complete picture as to when mobile access to Twitter is more prevalent than web access. We increasingly document what we are doing “in the moment” such as what we are eating, watching, or who we are with via mobile-based Twitter apps (Naaman, Boase, & Lai, 2010). But, is the content of these mobile-originated tweets any different from those we produce on our desktop/laptop computers? This study seeks to directly answer this question by investigating the differences in content between mobile and web-based tweets as well as categorizing differences in content through the notion of social media “styles.” Specifically, tweets are considered to reflect gendered, communal, and egocentric styles.

However, the study of mobile Twitter usage can be particularly challenging. Because of the plethora of Twitter clients, the literature has generally singled out the most frequently used mobile and desktop platforms (Wohn & Na, 2011). Previously, studies of mobile Twitter usage had been oriented toward marketing or business intelligence, leaving a gap in the literature. Studying mobile usage of Twitter from an academic perspective is critically important to better understanding the context of social media content production. This article seeks to fill this gap by providing a detailed comparison of tweets originating from mobile and web-based platforms. Ultimately, we seek to understand whether our social media presentations of self tend to be more egocentric, negative/positive, gendered, or communal depending on whether they were tweeted from mobile devices or web platforms. We selected these specific categories based on previously established word lists in social psychology to investigate our research questions. Additionally, these categories covered a broad range of behaviors that represent the user population as a whole. Using 6 weeks of Twitter data, we found that we tweet differently from our mobile devices. Specifically, we found that mobile tweets do tend to use more egocentric language than web-based tweets. We also found that tweets tend to be gendered, employing masculine language, but this does not vary significantly by platform. Importantly, we found that negative language is used more frequently by mobile users, suggesting that our in the moment social media reporting of our lives may be skewed toward negative portrayals.

Studying mobile tweet content

Burrows and Savage (2014) argue that the use of unobtrusive research methods that leverage “trace” metadata can open up whole new ways of studying social life. For example, they argue that “Big Data’ digital tracing,” involving the study of metadata such as the reporting of location via smartphones, can give us a better picture of social life based on actual actions rather than “accounts of actions” (Burrows & Savage, 2014, p. 3). The rising popularity of social media contributes to this potential
of digital tracing. Because so much of our social life exists in social media, it is critical that we use a wide variety of interdisciplinary methods such as natural language processing to try and discern the extremely complex and nuanced social processes that are being performed, enacted, and articulated in these technosocial spaces. Though Burrows and Savage (2014) single out sociology, the social sciences have historically struggled to leverage the power of social Big Data. Fortunately, many social scientists are beginning to embrace it. For example, Tinati, Halford, Carr, and Pope (2014) studied tweets regarding the UK student fees protests to uniquely understand the flow of information and the emergence of social networks over time. They conclude that the broadening of experimental methodology with large social datasets such as Twitter allows for novel ways to study “detailed content as well as overall patterns” (Tinati et al., 2014, p. 678). Sloan et al. (2013) argue that the Twitter spritzer stream (1% of all tweets) is an important data source for social science. They argue that understanding the demographics of Twitter users via these data provides extremely large sample sizes for social scientific analytic methods. However, there remains much to uncover about user demographics as well as general sociolinguistic behavior on Twitter to get to Sloan et al.’s (2013) desired endpoint.

Though there is a general lack of scholarship on mobile Twitter use, studies of mobile Internet usage have found that mobile content production and consumption centers on activities such as watching TV and eating dinner and that mobile-web usage tends to peak late at night around 10 pm (Cui & Roto, 2008). Chae and Kim (2003) found that mobile-web usage was more intimate since most users do not share their cell phone. Page (2012, p. 7) argues that mobile technologies such as smartphones have led to an “untether[ing] from static computer terminals” and have facilitated interactions that are “interwoven increasingly with daily experience.” Though not specific to mobile tweets, Naaman et al. (2010) found that, on average, over 40% of a user’s messages consisted of emotional or physical status updates, a class of messages they term “me-now.” Tweets regarding what users are eating, for example, could help reveal important dietary choices and better contribute to the health of Twitter users (Hingle et al., 2013). While these choices reflect a user’s personal life, we also see instances of real-time Twitter use for professionals. Some surgeons live-tweet during surgeries and educators successfully used the medium to further engage with students outside the classroom (Junco, Heiberger, & Loken, 2011). This literature explores some aspects of mobile social media but generally does not specifically compare mobile- and web-based platforms.

**Categorizing tweets**

Previous work on gender and Twitter has concluded that it is difficult to sort tweets by categories such as gender (Mislove, Lehmann, Ahn, Onnela, & Rosenquist, 2011). Gender on Twitter is enacted and performed in nuanced ways. Bamman, Eisenstein, and Schnoebelen (2012), for example, examine the gendering of tweets by setting linguistic structure such as the use of emotion terms, pronouns, family terms, and
conjunctions. Gendered content, rather than the biological sex of a user, is important as a common unit of analysis for the content of tweets. However, sex has been an important variable for studying social media use. For example, Lasorsa (2012) found that female journalists tend to reveal more about themselves and their personal lives on Twitter than their male counterparts. Sloan et al. (2013) collected a large set of tweets using the Twitter API to investigate demographic characteristics of Twitter users. They found near gender parity among users in their sample. While the ratio of female to male users on Twitter is nearly equal, it is important to consider how the gendered content of language may or may not change across devices. Different devices may provide particular “affordances” (Treem & Leonardi, 2012) for certain types of tweeting (e.g., sharing professional content with colleagues versus sharing intimate content with family and friends), encouraging the use of more gendered language on a particular device over another. Others argue that context collapse in platforms such as Facebook and Twitter has led to some users taking great care to restrict what content (including biographical information) can be seen by the public or by less close ties (Page, 2013). While it is difficult to grasp a full picture of Twitter users by gender, there have been successful broader examinations of self-presentation within the medium (e.g., Marwick & boyd, 2011).

This self-presentation is often strongly me-centric or communal as discussed in the previous section. Following Bakan’s (1966) argument that human behavior can often be categorized into “agency” and “communion,” tweets could potentially be grouped into similar categories. For Bakan, agency includes behavior that focuses on achievement and success, while communion represents behavior aimed at improving social ties. Adjectives representing agentic ideas include those like “assertive,” “confident,” and “outspoken.” Conversely, adjectives considered to represent communal ideals include “affectionate,” “tactful,” and “caring” (Madera, Hebl, & Martin, 2009). Others have found that participants were more likely to describe themselves and others in communal ways (Abele & Bruckmüller, 2011). However, Leonard (1997) cautions against viewing agency and communion as opposite ends of a spectrum. She found that these traits can rise and fall in tandem. These traits are often mapped along gender lines with agentic traits often considered more masculine and communal traits more feminine (Rudman & Glick, 2001).

Temporal aspects are also important to studying tweets. Understanding how users exhibit a particular behavior throughout a specific, standardized time interval can shed more light on specific patterns in tweeting behavior. The social media literature has found that patterns in tweeting behavior are consistent with our daytime patterns as well as sleep patterns and overall circadian rhythm and that individuals tended to get up later on weekends (Golder & Macy, 2011). Lampos, Lansdall-Welfare, Araya, and Cristianini (2013) use geo-located Twitter data from the United Kingdom to examine changes in mood over a diurnal pattern. While they found no clear difference in patterns across seasons, they did find that emotions tend to peak around 9 a.m. and experience a moderate decline until 8 p.m., when emotions tend to experience another increase until midnight. To determine this, they sampled words
from the WordNet Affect database (Strapparava & Valitutti, 2004). Naaman, Zhang, Brody, and Lotan (2012), in their study of tweets from 29 major cities in the United States & United Kingdom, focused on the diurnal patterns associated with certain keywords. They found that certain words associated with repeated actions—like sleep and lunch—appeared consistently during certain times regardless of city, while others—like lol or funny—did not appear in similar patterns. This use of Twitter data has been important for discerning macrolevel trends.

The use of natural language processing techniques to study Twitter data has become established in the literature (Hachey & Osborne, 2010). For example, Grinberg, Naaman, Shaw, and Lotan (2013) study aggregate daily patterns of Foursquare check-ins and use Twitter data to extract similar patterns. Like the work of Golder and Macy (2011), their work is also diurnally focused. Grinberg et al. use bigrams and trigrams in order to analyze speech patterns of tweets during Hurricane Sandy. They use a hybrid approach to label the top 200 terms they extracted from Twitter and Foursquare data. They found the diurnal patterns in Foursquare—which are closely tied to face-to-face actions—are extremely similar to patterns on Twitter. Using analytic techniques from sociolinguistic scholarship, Zappavigna (2011) applied Systemic Functional Linguistics (SFL) to study sentiment toward the election of Barack Obama in the wake of the 2008 U.S. presidential election. She argues that tweet content provides affordances—especially through hashtags—that make it searchable (what she terms “searchable talk”) and, as such, conducive to the work of Internet linguistics (Zappavigna, 2012).

Research questions (RQs)

Research Question (RQ1): Are mobile tweets more egocentric than web tweets? As a result of the inherently personal nature of mobile devices, we hypothesize that tweets from mobile sources will contain more references to the self. This follows from Deuze’s (2012, p. 57) argument that mobile phones have facilitated “processes of personal transformation toward greater individualization.” On the other hand, the web may represent a source that results in more reflection and thus more references to others in addition to the self.

Research Question 2 (RQ2): Do mobile tweets employ more “feminine” language than web tweets? While the user population in Sloan et al.’s (2013) study represents near gender parity, women have been found to have different motivations for using social media (e.g., for keeping in touch with family and friends) compared to men (Smith, 2011). Mobile tweeting could be complementing these relationship maintenance behaviors. Additionally, different computer-mediated communication contexts have been found to have consequences for gendered language use (Huffaker & Calvert, 2005). Mobile platforms may encourage feminine language through a perceived social connectedness.

Research Question 3 (RQ3): Are mobile-based tweets more negative than web-based tweets? One strength of mobile devices is their ability to capture various happenings
and occurrences in the moment. Styles of tweeting from mobile devices are likely to be more in the moment partially due to ease of access. While this likely provides a more in-depth look into an active user’s life, the ease with which the user can tweet may be facilitating more sentiment in tweets. And a pull to negative sentiment could occur much like the “negativity bias” in online reviewing (Yin, Bond, & Zhang, 2014). In comparison, tweeting from the web may not have the same ease of access as mobile throughout the day. As a result, web tweets may encourage more careful reflections of the day’s events, leading to less sentiment-laden tweets.

Research Question 4 (RQ4): Are mobile tweets more agentic than web tweets? In Research Question 1, we predict that mobile tweets could be more egocentric than web-based tweets. Consequently, we hypothesize that mobile tweets would also center more on individualistic attributes of the self. These traits tend to reflect bold, outspoken, and frank personalities as well as reflection and censorship. As a result, web-based tweets may be more representative of communal characteristics. These traits emphasize behavior that contributes to the health of the group as opposed to the individual.

These four research questions seek to provide a more nuanced understanding of the similarities and differences between mobile and web usage of Twitter by exposing and evaluating possible tweeting behaviors and patterns in self-presentation found in tweets of each source. Each of these questions evaluates expressions of differences in time and space between mobile- and web-based tweets. More specifically, these questions address the level of egocentricity in tweets, gendered tweets, the level of positivity or negativity in tweets, and the nature of agentic and communal traits exhibited in tweets across mobile and web sources.

Methods

Within both sociology and psychology, the study of individual agency versus more communal formations has been a fundamental question. In sociology, rich methods have been developed to study these two ideas empirically. However, this work is usually not focused on individual words or sets of words. Because of the large volume of data we obtained, we sought to utilize methods that would be able to usefully understand various processes including agency and community as well as aspects of gender and egocentrism. We relied upon established word lists (examples of these lists are presented in this section) to compare to a series of n-grams observed within our Twitter data. The use of n-grams—a series of unbroken characters, in this case words—to evaluate online content has been successful. For example, Yarkoni (2010) relied on n-grams to characterize aggregated blogger content to determine personality. He found that personality does have an effect on the language bloggers used. Additionally, lexical work has found success in linguistics and computer science to discern macro patterns of discourse on Twitter (Williams & Katz, 2012). Drawing from these and other interdisciplinary methods, we explore whether tweets exhibit significant differences by mobile versus web sources.
**Data collection**

Twitter provides an Application Programming Interface (API) that allows for the collection of a stream of sampled tweets from the overall flow of all global tweets at any given time. Twitter delivers approximately 1% of all tweets via the free “Spritzer” stream. We used a Hadoop distributed file system (HDFS) to store the tweets and accompanying metadata and this data was queried using the Apache Hive distributed database system (Murthy & Bowman, 2014). In the summer of 2013, we collected over 235 million tweets at a rate of approximately 5 million tweets per day.

**Tweet classification and filtering methods**

In order to investigate differences between mobile and web Twitter usage, it is important to be able to identify individual tweets as having been published via web/desktop clients or from a mobile device. Information about tweet sources is recorded in the metadata delivered with each tweet. In a previous study of mobile versus non-mobile Twitter usage (Perreault & Ruths, 2011), a list of commonly used tweet sources was generated and coded as mobile, nonmobile, or mixed sources. Because of the large number of unique sources observed, only the top 215 were coded, accounting for about 90% of all sources observed. Our data indicate that in a typical day, more than 15,000 unique sources are observed, though only a few sources are popularly used. In fact, over 90% of all tweets can be sourced to just the top 20 Twitter sources. This aggregation of Twitter source diversity may be in part related to the fact that in recent years, Twitter has taken a greater interest in controlling the Twitter experience through limiting access of third-party Twitter clients (Gayomali, 2013; Valentino-DeVries, 2011). The specific classification of sources and their weights within the overall sample are reported in Table 1. We were able to select a set of eight official, Twitter-sanctioned sources and classify them as mobile or nonmobile in nature. In particular, the presence of a diversity of types for mobile sources reduces the potential for bias introduced by favoring one type over another. For example, a dataset containing only Twitter for iPhone may represent a population of users with inherent similarities. The presence of different types of mobile tweeting platforms in our dataset minimizes the possibility for such bias. The differences in percentage of users tweeting from these platforms also indicate that mobile tweets will proportionally represent behaviors corresponding to types of mobile devices. These eight sources (as detailed in Table 1) account for 81.2% of all tweets.

To better explore diurnal trends in tweeting behavior, we chose to focus our investigation of tweets to a particular range of time zones largely encompassing the American continents (UTC −5 to UTC −8). Further, we limited our analysis to English-language tweets. These tweets were obtained through a query selecting tweets with metadata fields matching the desired time zones and language. These data allowed for the comparison of diurnal behavior differences between time zones or to combine data from different time zones to serve as a relative proxy for Americas-centric diurnal tweeting patterns of tweets published in English. In these collected data, we found that 33% of tweets come from the selected time zones.
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Table 1  Sources used in Mobile/Nonmobile Tweet Sample and Percentage Usage Among All Tweets

<table>
<thead>
<tr>
<th>Nonmobile</th>
<th>Mobile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web</td>
<td>21.6%</td>
</tr>
<tr>
<td>TweetDeck&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.5%</td>
</tr>
<tr>
<td>TweetButton&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.7%</td>
</tr>
<tr>
<td>Twitter for iPhone</td>
<td>25.2%</td>
</tr>
<tr>
<td>Twitter for Android</td>
<td>19.2%</td>
</tr>
<tr>
<td>Twitter for BlackBerry</td>
<td>8.7%</td>
</tr>
<tr>
<td>Twitter for iPad</td>
<td>2.1%</td>
</tr>
<tr>
<td>Mobile Browser</td>
<td>2.2%</td>
</tr>
</tbody>
</table>

<sup>a</sup>Tweet Deck was previously a mixed platform since their purchase by Twitter in May 2011. They discontinued the mobile version and desktop client of TweetDeck as of May 2013.

<sup>b</sup>TweetButton is the officially sanctioned website-embeddable tweet button, typically employed to allow web users to easily share content from the web. Although not explicitly limited to nonmobile, it is limited to website interactions and mobile “tweet button” usage is rare.

regardless of language, while 34% of tweets regardless of time zone are English-language. The final dataset taking into consideration common sources, time zones, and languages of interest is comprised of roughly 24 million tweets, about 10% of the overall number of tweets collected over the same time period. This gives 500 K tweets per day and roughly 21 K tweets per hour on average.

Tweet n-gram analysis

To explore differences in the patterns of language usage between mobile and nonmobile tweets, we looked at the frequency of occurrences of various unigrams over time. Specifically, we determined and counted the top 2,500 for each of the three n-gram categories (tweet unigrams, bigrams, and trigrams) for each hour, source, and time zone tuple in the observation period, removing stop words such as “the.” To model mobile vs. nonmobile differences in tweet language, we aggregated unigram counts using the mobile/nonmobile classification scheme detailed in Table 1. We also aggregated all the time zones together into a single diurnal time series representing a single averaged proxy for English language tweeting behavior in the western hemisphere. Because in practice, each individual source/time zone pair has its own unique set of 2,500 n-grams, when combined, we actually have a larger number of n-grams per hour when aggregated into mobile and nonmobile categories. The exact number of unique n-grams per bin varies slightly per date-hour and source class. The average number of tweets per hour is around 21K but ranges from around 5–40K over the course of a day. In any given hour, we found that the count of the most frequently occurring n-grams does not typically exceed 50% of the total number of tweets per hour. This makes sense as we would not generally expect any individual word or phrase to occur in more than 50% of all tweets per hour. Thus the most frequently occurring n-grams per hour-source, usually “I,” “RT,” or “http,” are typically seen about 7 – 12K times per hour. The distribution of n-gram counts decays exponentially, typically falling to only double digit occurrences per n-gram beyond the top 10% of unique n-grams. Bigrams
and trigrams typically have lower max occurrences for the top n-gram in each category, but also decay at a slower rate. This follows as bigrams and trigrams project the finite word space, $W$ per hour, onto larger $W^2$ and $W^3$ spaces.

In order to model the various behaviors proposed in our research questions, we selected a set of words for each behavioral aspect category of the research questions. We grouped n-grams via a series of lookup tables created for each category, assigning specific n-grams to groups by date-hour, source, and aggregate frequency. This allowed us to track and compare these behaviors over time as well as between mobile and non-mobile Twitter usage. Each category underwent the same process. For certain categories, the set of chosen words are not all common n-grams; some may not even consistently occur among the top n-gram for any given hour. By grouping together collections of words, we sought to smooth the diurnal time series for each group and serve as a proxy for overall relative volumes of occurrences of n-grams which indicate the chosen categorical traits within the available tweet corpus.

In developing our groupings, we extended to Twitter data word lists developed by Greenwald and Farnham (2000) for use in Implicit Association Tests (IAT), an associative psychosocial personality test often used to test positive and negative associations with self and other. This test relies on presenting a series of words selected from four word lists representing two binary concepts. Users are asked to repeatedly classify words presented randomly from each list from one pole of each binary opposition together. The speed with which this can be accomplished represents the level to which the association is natural to the user. For instance if the binaries selected in the test are gendered words and self/other words, most women should be able to more easily associate the self-words with the feminine words and thus complete the test faster. Though the nature of our work is not about issues of implicit association, the word lists developed by Greenwald and Farnham provide good, simple lists of words associated with several of the behavioral patterns we seek to address in this article, specifically self concept, gender concept, and emotional concept. To investigate agency in the Twitter unigram corpus, we developed word lists based on Madera et al.’s (2009) work that seeks to categorize agentic versus communal language.

**Self style**

To test RQ1, we utilized Greenwald and Farnham’s (2000) set of words associated with the notion of “self.” A partial list of these words includes words such as I, me, my, mine, and self against they, them, their, it, and other. Applying these lists to the body of tweets we have collected serves as a good proxy for the overall egocentricity of tweets.

**Gender style**

To test RQ2, we used Greenwald and Farnham’s (2000) gendered language word list. This list includes words such as gentle, warm, and tender for feminine and competitive, forceful, and aggressive for masculine. The potential strength of this word list is that it mostly consists of concepts and adjectives traditionally associated with a particular
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gender, as opposed to common gendered nouns and pronouns. This was thought to be more accurate for discerning the gendered valence of tweet messages themselves as opposed to common gendered object of tweet messages.

**Emotional style**

To test RQ3, we used Greenwald and Farnham's (2000) positive and negative emotion word list that includes a set of words that represent both positive and negative emotions. This list incorporates words such as happy, smile, and joy for positive and pain, grief, and agony for negative. We used this list instead of traditional sentiment libraries, because these lists were developed to represent concepts generally accepted by most individuals as associated with the positive or negative. Additionally, traditional sentiment dictionaries are often challenged by tweet language and do face difficulties in terms of the classification of negation, sarcasm, etc. (Martínez-Cámara, Martín-Valdivia, Urena-López, & Montejo-Ráez, 2014). Though any list is bound to face these challenges, we hypothesized that a list of general words which focuses on negative or positive concepts as opposed to action words or adjectives would help us avoid some of these common sensitivities and gauge the level to which tweets contain positive and negative ideas.

**Agentic and communal style**

To test RQ4, we used Madera et al.'s (2009) agentic and communal word list. This list uses words such as assertive, confident, and ambitious for agentic and affectionate, helpful, and sympathetic for communal. This comprehensive list is particularly suited to investigating the level to which tweets display agentic or communal properties and allowed us to group tweet unigrams within our sample.

**Results**

The data we collected and the interdisciplinary methodological approaches we employed allowed us to reach conclusions regarding the ways in which language on Twitter operates in terms of whether that language is more individualistic (agentic) or more societally oriented (communal). We were also able to evaluate gendered patterns within tweets and whether language in tweets was considered more egocentric. Some of the key areas we explored were: the percentage difference between mobile and web sources for a particular research question, the time of peak tweet frequency for a particular research question, and the prevalence of one source over another across all research questions. These conclusions are similar to Naaman et al.’s (2010) study of the egocentric nature of mobile tweets but different than literature that correlates communal traits with gender (Rudman & Glick, 2001).

**RQ1: Egocentricity**

RQ1 states that tweets from mobile sources are more likely to contain egocentric content. Our data confirm this hypothesis. Figure 1 illustrates the frequencies of
mobile *self* and *other* unigrams versus nonmobile *self* and *other* unigrams across an average day. The results demonstrate that both mobile and web have consistently higher frequencies for *self* than their counterpart. While *self* continues to increase steadily into the night for both mobile and web, *other* exhibits a shallower slope or even a decreasing slope at the same hour.

While Figure 1 effectively illustrates the rise and fall of frequencies for *self* and *other* categories over mobile and web sources, it fails to demonstrate if one source is more egocentric than the others due to a lack of scaling. In order to see more clearly the relationship between the volume of *self* and *other* focused language, Figure 2 renders that relationship as the percent by which *self*-centered language dominates over *other*-centered language for each date-hour for mobile and nonmobile tweets respectively. We were able to observe that mobile tweets are consistently around 2.5% more egocentric than nonmobile users on average. All tweets are observed to be least egocentric in the late mornings (around 9 to 10 a.m.). From that point onward, mobile and nonmobile gradually rise into the evening and through to the next morning, peaking around 3–4 a.m. This, in part, helps to confirm RQ1 by demonstrating that mobile tweets contain a higher ratio of egocentric language at all times of the day. We found that regardless of tweet source, egocentricity is most tempered during the hours of the day when people are usually at work. This is despite the fact that overall tweet volume is known to steadily increase throughout the day. Though tweeting is not suppressed midday, our egocentricity is. When we are at work or school, we may focus more on activities that are communal or we may not have time to tweet. After school
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Figure 3 Self versus other for mobile- and web-based tweets across an average week (by percent).

and after work hours, the focus seems to shift back to a more egocentric presentation of self.

Self-unigrams are consistently used most regardless of day or source. However, we found no special relationship between the frequency of egocentric language produced in tweets and the days of the week. Each typical day was found to be more or less identical to the day before, aside from a small drop in typical frequencies on Fridays and Saturdays. This may be due to Twitter users not using their phones to tweet as frequently while going out on the weekend. This finding contradicts the general assumption that users provide a real-time rundown of their weekend tweet by tweet. This trend is not as pronounced for the web for either self or other unigrams. Sunday morning exhibits especially low frequencies for web-sourced egocentric language. This may speak to a slower pace of life on Sundays or visiting houses of worship, which results in lower frequencies of web-based tweets. As fewer total tweets are produced on those days, the production of egocentric and nongenocentric language is similarly blunted.

Figure 3 affirms the findings illustrated in Figure 2. By examining the percentage by which egocentric unigrams outnumber nongenocentric ones over time, mobile tweets are at least 2.5% more egocentric than nonmobile tweets on average. The drop-off in egocentricity is not as severe on Saturdays and Sundays as users are more likely to be free from work and school commitments on those days.

Another interesting finding is how the depression in daytime egocentricity is greater for web users than mobile ones. This could be because web users typically publish tweets from a personal computer or laptop. Many users may not have access to their nonmobile computing technologies during the day and those who do may be at work and have restrictions on personal mobile use. Despite this, many Twitter users have their phone with them and may still find times to tweet via mobile devices throughout the day. In some cultural contexts, this may also say something about class as more middle-class workers (e.g., in Anglo-American countries) are more likely to access mobile apps during the day than those in manual jobs. This is also congruent with our findings of a disproportionate number of iPhone-based tweets despite the device’s high cost and relatively low market share (Jones, 2014).
We also found that the daily egocentricity depression and mobile-web deficit increases toward the middle of the week, peaking with an 11% web deficit on Wednesdays. It may be that Wednesday is the day when people are most distant from their personal selves in what has been referred to popularly as “Hump Day” (Areni & Burger, 2008). Thursdays and Fridays bring the promise of the weekend and tweets are more connected with our personal selves, resulting in an increasing tendency to publish egocentric tweets. Once the weekend has passed, tweets again move away from the personal, confirming a relationship between tweeting patterns and free time.

**RQ2: Gender**

Research Question 2 posits that mobile tweets are gendered, specifically containing more feminine-associated words than web-based tweets. Our data negate this research question. Figure 4 illustrates that for mobile and web-based tweets, unigrams associated with masculinity clearly dominate in typical usage. For mobile and web, “masculine” unigrams not only rise in frequency earlier in the morning than “feminine” unigrams, but also experience a dramatic rise and a sharp fall after midnight (see Figure 4). Furthermore, masculine unigrams exhibit a rise or plateau into the late evening, whereas feminine-associated unigrams demonstrate a general decline across mobile and web.

Despite the general dominance of masculine unigrams at all times, we observed that web-based tweets typically contain 25% more feminine-associated unigrams. On the whole, both mobile and web tweets exhibit maximum levels of feminine-associated unigrams in the early morning, with a sharp drop-off in the later morning. Mobile hits a later peak in the evening for a maximum in feminine-associated unigrams than web, but both mobile and web experience a sharp decline in feminine-associated unigrams during the very early morning. Expanding our analysis to frequencies and ratios over a typical week did not reveal further differences. Figure 5 confirms that mobile usage in general is depressed on weekends. Using these data, web usage of masculine and feminine language was found to not be similarly depressed and was more consistent across all days. The low frequency counts in these data are due to the size of the word list for both feminine and masculine

![Figure 4](image_url)  
*Gendered n-gram use in tweets by day.*
words. Each list consists of only six words, which reduces the chances of finding a match in these data.

Data by week is noisy and does not actually reveal any clear daily pattern in either instance (see Figure 6). This noisy relation is likely the result that tweets do not consistently use particular words to signify gender. As we measured the gendered presence of n-grams which are typically associated as masculine or feminine, these data are not intended to indicate the relative number of male or female users of Twitter on various devices over time. Rather, it indicates that regardless of user gender, a more linguistically masculine discourse is dominant. Our results also indicate that time matters. For example, feminine-associated unigrams on mobile do not rise dramatically during school or work hours, whereas masculine-associated unigrams on mobile experience dramatic rises in frequency. Indeed, feminine-associated unigrams on mobile only rise sharply after 8 p.m.

RQ3: Positive/Negative
Research Question 3 posits that mobile-based Twitter users have a greater propensity for using more negative words in their tweets. Since mobile access allows for real-time updates to a user’s Twitter profile, this could encourage users to tweet experienced sentiment in real-time. And a tendency to tweet the negative potentially parallels “negativity bias” in online reviewing (Yin et al., 2014). Web users may be less inclined to share any sentiment at all as they may be more self-censored or because they tweet less spontaneously. However, tweeting in the moment via mobile may also not
necessarily imply negativity, but could simply result in an increase in sentiment—both negative and positive—as users may reflect minimally before tweeting. In contrast, the reflection of web users may be part of intentional self-presentation in positive terms, processes that have benefits for employment as well as our social lives.

Figure 7 illustrates that there are more occurrences of positive words than negative words for both mobile and web Twitter users. While the occurrence of positivity is higher than negativity, Figure 8 illustrates that we found a higher percent of negative tweets from mobile users over an average day in our sample. These data indicate that over an average week in our sample, there appears to be an unexpectedly large tendency toward negative tweets from both mobile and web sources on Saturday evening.

Figure 7 compares positive and negative unigrams over the course of an average day. Positive unigrams were found to have a slightly higher frequency for both sources. Mobile, negative unigrams tend to start rising in frequency later in the morning than positive unigrams. The same trend can be seen for the web data. Additionally, negative unigrams tend to decline earlier in the evening than positive unigrams.

Figure 8 illustrates the percent difference between mobile and web for positive and negative tweets. These data confirm the hypothesis that mobile tweets are more negative than web-based tweets. At any given point in the day, mobile tweets are at least 25% more negative than web-based tweets. Negativity is highest for both mobile and web sources in the late evening, but there is also a significant
amount of negativity early in the morning. The level of negativity experiences a steep drop-off in the late morning and steadily climbs until evening for both sources.

Figure 9 illustrates the frequencies of positive and negative unigrams for mobile and web sources across an average week. Again, frequencies are highest for positive unigrams across mobile and web sources. Moreover, these peaks experience significant drops in frequency during Friday and Saturday (with the exception of spikes in negative tweets attributed to discrete events such as the death of actor Cory Monteith). There is a level of tweet frequency that is constant (e.g., see Figure 3). However, the magnitude of some events can skew the expected frequency distribution of tweets. Web-based positive unigrams have similar frequency peaks in the morning and evening, whereas mobile evening peaks are significantly higher. In terms of mobile-based tweets, negative peaks appear to occur earlier in the day on Monday and Tuesday than the positive peaks.

By expanding our time frame from an average day to an average week, mobile tweets were found to continue to be more negative throughout the week. As Figure 10 indicates, the general trend for mobile indicates a higher level of negativity in the early morning, followed by a steep drop-off in the late morning. This is followed by a steady increase to a peak in the late evening early in the week. However, as the week progresses, the peak in the evening shifts to a peak in the early evening. This trend starts...
on Thursdays. Additionally, the moment where web users become more negative than mobile users is on Saturday during the late morning.

**RQ4: Agentic/Communal**

Research Question 4 posits that mobile tweets are more agentic than web-based tweets. This hypothesis was refuted as mobile-based tweets were not found to be more agentic than web-based tweets. Figure 11 illustrates the relative frequencies of agentic and communal unigrams across mobile and web sources. This figure indicates that communal n-grams are more prevalent than agentic for both mobile and web sources. However, there are some fundamental differences in mobile and web. For example, mobile has a steady increase into the late evening for both communal and agentic n-grams, whereas web has a decrease.

Figure 12 illustrates data that negate the hypothesis that mobile tweets are more agentic than web-based tweets. Web is slightly more agentic than mobile as indicated by the fact that the majority of the web curve is above the mobile curve in Figure 12. For both mobile and web, the peak of agentic tweeting occurs in the early morning and steadily declines until the late evening. Web-based tweets particularly experienced a severe drop in the evening, highlighting more agentic mobile tweets during the end of the day.

Figure 13 illustrates that over an average week, mobile-based tweets tend to exhibit communal traits at much higher rates than agentic. This trend is consistent across both mobile- and web-based. There is a significant rise of communal tweets on Monday.
night. Unusual spikes are likely occurring because of specific events associated with a particular word for a brief time during the observation period. When we account for unusual spikes, there is no significant difference in the use of communal and agentic unigrams on Twitter. These n-grams rise and fall in conjunction with the expected volume of tweets over the week.

When comparing the percent of agentic and communal tweets across source, we found that consistent patterns emerged, suggesting a greater number of communal tweets across both platforms. There is a considerable increase in these tweets from web sources on Monday evening. As before, this is likely due to particular events skewing the data.

**Conclusion**

This study developed from our belief that Twitter is an increasingly important space for social communication and that the medium—mobile or other—where tweeting occurs can shape that communication (Murthy, 2013). This is not to say that the medium is deterministic of the content. Rather, tweets constructed to echo a particular sentiment or tell a particular side of a story can and do appear on both mobile and web-based platforms. However, as McLuhan (1964) famously argued, the “nature of the medium” itself should be an important object of study for media scholars. Given the ubiquitous nature of smartphones and their push toward “greater individualization” (Deuze, 2012), mobile media was hypothesized to be influencing tweet styles.

Given that the influence of mobile technologies on tweeting patterns has been understudied, we sought to bridge this gap by examining whether tweets from mobile- and web-based sources differ significantly in their linguistic styles. We studied 6 weeks of Twitter spritzer stream data, containing 235 million tweets. We focused on the analysis of tweets by source—specifically mobile versus web-based sources by time of day. This involved evaluating several categories or subsets in which mobile sources may be similar to or different from web sources. We used word lists from social psychology to test for levels of egocentricity, gender style, emotional content, and agency in both mobile and web tweets.
Ultimately, we found that mobile tweets are not only more egocentric in language than any other group, but that the ratio of egocentric to nonegocentric tweets is consistently greater for mobile tweets than from nonmobile sources. We did not find that mobile tweets were particularly gendered. Regardless of platform, tweets tended to employ words traditionally associated as masculine. We did find that negative language is used more frequently by mobile users at any point in time, a finding that would benefit from further research. The ratio of negative to positive unigrams was also found to be consistently greater for mobile tweets than web tweets. Lastly, we did not find that mobile-based tweets are more agentic than web-based tweets. Rather, both platforms tended to employ language that was associated with communal behaviors.

These conclusions are important for several reasons. This is the first study to investigate tweets for the daily and weekly trends for various behaviors by mobile- and web-based platforms. This is significant because we did find significant differences between mobile- and web-based social media use. Our results provide evidence of linguistic styles that emerge based on the source of social media content. Some of the differences between mobile- and web-based platforms speak to the on-the-go nature of tweeting from a mobile device. We increasingly tweet while we move through our day (e.g., while we walk, travel, and eat). Our results also illustrate interesting patterns in terms of the diurnal rise and fall of tweet frequency for both mobile- and web-based sources. For example, egocentric spikes tend to occur in the early morning, whereas negative spikes tend to occur in the late evening for both mobile and web. Overall, we found that not all tweets are the same and the source of tweets does influence tweeting patterns. This article also underscores the point that social media research should investigate the source of social media content in addition to raw textual content.

Ultimately, a major argument this article makes is that the context of media production really matters. We have highlighted the value of keeping the question open as to whether the type of people who tweet from mobile devices are qualitatively different from those who tweet from web-based platforms. This question requires further study but is fundamentally important. This is particularly true because scholarship across the disciplines has been quick to study Twitter data but often with minimal effort in understanding differences in how these data are produced.

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