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#MeToo as an 'angry mob', or, in search of meaning: Using linguistic markers to assess the accuracy of the negative stereotype.

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Abstract

The #MeToo movement on Twitter has been characterized as an angry mob, out for revenge. This study used Linguistic Inquiry Word Count to assess the accuracy of this stereotype by examining #MeToo tweets collected at four different events. Several mixed measures ANOVAs, comparing word usage at the original October 15, 2017 event to subsequent events, were conducted. There were more cognitive than anger words used at all events. Power words were accompanied by more first-person singular pronouns than first-person plural pronouns at all events. Finally, the initial event used a first-person perspective, whereas subsequent events used a third-person perspective. These results suggested that #MeToo language did not reflect the angry mob stereotype, but rather, a focus on personal empowerment and meaning-making. We conclude that examining the language of social media movements can help to understand whether criticisms of these movements are justified.

Since its 2017 incarnation on social media, the #MeToo movement on Twitter has been stereotyped as "mob justice". Headlines such as, "MeToo and Trial by Mob" (Hernroth-Rothstein, 2017) and "#Metoo has become a vicious hate mob …" (Walden, 2017) depict the movement as one marked by rage, out for power and revenge. This characterization of the movement has even evolved into a way to refer to a man being accused of sexual harassment: "Op-Ed: My Ex was just #MeTooed…" (Davidson, 2018); "Being wrongly #MeToo'd has ruined my life" (Tunison, 2020). This phrase is pervasive enough in public discourse to be defined in Urban Dictionary: "Reasons of someone (mostly female) to posting serious claims of rape and/or sexual assault or abuse on social media are often for attention, clout and most importantly for revenge…".

These stereotypes of the #MeToo movement may not be surprising given how large groups are traditionally depicted. As any introductory social psychology text implies, group presence is depicted as causing bad decision making: when a group is present, bad things like conformity, obedience, and groupthink occur. Moreover, as Drury and colleagues have argued (Drury, 2002; Drury, 2018; Stott & Drury, 2017) the behaviour of larger politicized groups has historically been characterized as emotional and violent, hence derogatory terms such as 'mob rule' and 'riot'. Although the #MeToo movement that occurred on Twitter was not a physical group, it can be conceived of as a digital protest group participating in a form of online activism (Foster, 2019; Foster, Hennessey, Blankenship & Stewart, 2019; Mendes, Ringrose & Keller, 2018), referred to as "information activism" (Halupka, 2016) or "persuasive actions" (Postmes & Brunsting, 2002) whereby participants attempt to gather and spread information, provide solidarity to protestors and influence opinion. As an online activism group, #MeToo appears to be subject to the same negative stereotypes as physical protest groups.

However, Drury's (2018) review of crowd events shows that the negative behaviours (e.g., panic, violence) attributed to groups are rarely seen, and instead, positive responses such as helping, are actually more common. One explanation for the attribution of negative stereotypes to large groups is that it benefits hierarchical systems to demean disadvantaged groups in these ways so that the movement's political concerns become delegitimized. As such, systems do not feel obligated to take responsibility for change (Drury, 2002; Stott & Drury, 2017). For example, in a discursive analysis of an anti-pedophile crowd event, Drury (2002) showed that while media referred to the event with demeaning language such as 'panic' and 'hysteria', the discourse of the participants themselves suggested their motives were rational and conventional (e.g., the name of the protestor group was "the Peaceful Protestors of Paulsgrove). Thus, it is unclear whether the Twitter #MeToo movement was actually functioning as a 'hate mob' (Walden, 2017) as the stereotype suggests, or whether it could have been subject to the same discrediting discourse that often surrounds other in-person protests.

Alternatively, the #MeToo movement may have been functioning as a means of healing trauma through meaning making, whereby survivors try to understand their experience ('why did this happen to me?') and ultimately come to incorporate the experience into new ways of seeing themselves and the world (Janoff-Bulman, 1992; Park, 2010; Tedeschi, Park & Calhoun, 1998). For example, the more cancer survivors positively reframe the illness, attributing it to the reason they have better relationships or increased spirituality, the more well-being they experience (e.g., Park, Edmondson, Fenster & Blank, 2008).

There is indeed precedent for a social movement to have developed out of a need to find meaning in negative experiences. The grassroots consciousness-raising groups that gained popularity in the 1970s began with discussions of women's history and how the historical status of women had influenced individual women's present-day experiences of economic inequities, rape and abuse (Bowles & Duelli Klein, 1983; Kimmel, 1989; Lerner, 1986; Stanley & Wise, 1983). The goal was to encourage a re-framing of their belief system--that their personal experiences of discrimination were not due to their own personal inadequacies, but due to a bigger picture of the systemic discrimination that most women experienced. By connecting the individual experience to the larger group's experience, women gained new meaning for their personal difficulties -- the personal became political. In today's digital activism era, where the purpose of a hashtag is to link people with common experiences (Zappavigna, 2011), #MeToo's slogan similarly connected the individual to the group experience. Moreover, there is growing evidence that across a variety of contexts (see Muldoon, Haslam, Haslam, Cruwys, Kearns & Jetten, 2019 for a review), group connections enhance post-traumatic growth, namely the positive outcome of a search for meaning (Tedeschi et al., 1998). For example, Muldoon, Acharya, Jay, Adhikari, Pettigrew and Lowe (2017) showed that after the 2015 Nepal earthquake, greater identification with community predicted greater post-traumatic growth. As such, it is feasible that connecting to the group of other women who had experienced harassment and assault via #MeToo also encouraged meaning-making.

However, the empirical evidence to support whether meaning making was a focus for #MeToo, is sparse. One study (Strauss Swanson & Szymanski, 2020) has examined whether large anti-violence movements were linked to meaning-making, by interviewing 16 adults who were survivors of sexual assaults and participants in sexual assault activism. One of the most common themes among participants was that they reported developing a greater understanding of their experience (i.e., meaning-making). Because the types of activism in which participants were engaged were not reported, it is unknown whether these participants were in #MeToo, or in other forms of activism. Studies that have specifically examined #MeToo via Twitter have focused on alternative hypotheses, such as how the movement affected activism discourse, (Suk, Abhishek, Zhang, Ahn, Correa, Garlough, & Sha., 2019) or classifying themes such as advocacy and support (Bogen, Bleiweiss, Leach & Orchowski, 2019; Hosterman, Johnson, Stouffer, Herring, 2018).

The Current Study

The goal of the current study therefore was to assess the accuracy of the negative stereotypes attached to #MeToo, (that it was a rage-based, power-grab mob seeking revenge), or whether it was based on a desire to make meaning of negative experiences. To do so, the language of #MeToo tweets were analyzed using Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth, Boyd, & Francis, 2015), a text analysis computer program that calculates the percentage of the total number of words for particular word categories. Language, by definition, conveys meaning. As such, the words individuals choose to convey their meanings can provide valuable information about their focus, feelings and prominent psychological processes (Pennebaker & Chung, 2007; Tausczik & Pennebaker, 2010). A particular benefit of using language to measure psychological constructs is that it is considered a more unobtrusive means of examination compared to other forms of measurement (Salicru, 2018; Wolf, Sedway, Bulik & Kordy, 2007). For example, one of its strengths over other forms of content analysis is that it relies less on the researcher's idiosyncratic perspective to examine content themes, and/or on the subjective opinions of judges to rate those themes. One of its strengths over surveys is that it is less subject to demand characteristics and biases such as social desirability. Moreover, there is extensive research supporting the use of linguistic markers to predict a variety of psychological constructs such as personality traits (Yarconi, 2010), health and well-being (Frattaroli, 2006; Schwartz et al., 2016), and experiences such as childhood sexual abuse (Stanton, Meston & Boyd 2017).

Much of the #MeToo discourse suggests that the goal of the movement shifted over time; for example, headlines like '#MeToo *has become* a vicious mob' or articles debating whether #MeToo has "gone too far" (Smith, 2018; Yoffe, 2019) imply it functioned as something else before it was a vicious mob. If so, different language patterns would be expected at subsequent #MeToo events as compared to the original day. To assess this, tweets were collected at four different time points, corresponding to significant events: October 15, 2017, when Alyssa Milano sent the first tweet following the Harvey Weinstein accusations of sexual assault; September 27, 2018, when Dr. Christine Blasey Ford testified against Brett Kavanaugh at the Senate Judiciary hearings regarding his alleged assault; October 6, 2018, when Brett Kavanaugh was confirmed to the U. S. Supreme Court; and February 24, 2020 when Harvey Weinstein was convicted of sexual assault.

To examine the language of #MeToo at those four time points, word categories that have been previously validated were tested. These are described below.

Emotion and cognitive words. Emotion words in LIWC include both positive and negative affect and are indicators of emotional states; people induced to feel positively or negatively use more positive and negative emotion words, respectively (Edwards, Shivaji, Micek & Wupperman, 2020; Kahn, Tobin, Massey & Anderson, 2007). Within the negative emotions, LIWC provides a category for anger; given the stereotype of #MeToo as a 'vicious mob', anger was the negative emotion category that was tested. People induced to express anger report more anger words, and anger words are correlated with self-report anger measures (Burns, Holly, Quartana, Wolff, Gray & Bruehl, 2008; Matsumoto et al., 2016).

Cognitive words in LIWC include words reflecting causation (e.g., because, hence), insight (e.g., think, know, understand) and discrepancy words (e.g., should, could), reflecting many of the cognitive processes necessary in meaning-making, namely trying to link events to understand why the trauma occurred and how to accommodate the discrepant pre- and post-trauma world views (Park, 2010). Cognitive words are higher when participants are describing a stressful event compared to non-stressful events (Boals & Klein, 2005; Boals & Stern Perez, 2009; Cohn, Mehl, & Pennebaker, 2004), indicating people are attempting to understand a stressful event. Moreover, cognitive words are related to other measures indicative of two types of meaning-making. Park (2010) distinguishes between the *process* of meaning-making, whereby individuals are actively searching for meaning, and the *outcome* of meaning-making, whereby meaning is made. Cognitive words are related to measures of both types of meaning-making, such as positive reframing (Boals, Banks, Hathaway & Schuettler, 2011) as well as measures indicative of meaning-made, such as posttraumatic growth (Abe, 2015; Ullrich & Lutgendorf, 2002). To understand the language of #MeToo, cognitive words, anger words and positive emotions words were compared across the four events.

Hypothesis 1: If #MeToo reflected meaning-making, there should be more cognitive than emotion words (anger and positive emotions), at each event. Alternatively, if the negative stereotypes of #MeToo as a 'vicious mob' were accurate, there should be more anger words than either cognitive words or positive emotion words at each event.

Hypothesis 1a: If the #MeToo movement morphed into a 'vicious mob' or 'went too far', then anger words should be higher and positive emotions should be lower in the subsequent events than during the original Weinstein accusation event.

First-person singular vs First-person plural and power

A second way to assess if the negative stereotype of #MeToo as a vengeful mob is accurate, is to examine language that reflects a desire for power. The LIWC category for power includes words that reflect an orientation towards status and the desire for influence over others (e.g., ambition, dominant); tracking power words provides an understanding of the degree to which individuals are focused on these needs (Jordan & Pennebaker, 2015). Power words in LIWC have been found at higher frequencies in the texts of terrorists compared with a random sample of blog texts (Cohen, Kaati & Shrestha, 2014). In addition, the more company CEO's use power words in their communications, the higher is the company's net income (Pike, 2019).

However, in the case of #MeToo, the intention underlying power words may be unclear; power word usage could reflect a desire for power over others (consistent with the stereotype), or, a desire for victims to re-acquire their own power that was removed by assault, (i.e., personal empowerment). For example, the word 'threat' could be used by someone wanting to threaten someone else (as would be expected if the #MeToo movement was a power-grab seeking revenge) or by an individual feeling threatened by someone else (as would be expected if a victim is recounting a sexual assault experience).

As such, to assess whether power language reflects a focus on *attaining power over*, or *attaining personal empowerment*, the pattern of first-person pronouns was examined. First-person singular words (I, me, mine) indicate self-focus whereas first-person plural words (we, us) indicate a focus on the self, but one in relation to others (Zimmermann, Wolf, Bock, Peham & Benecke, 2013). First-person singular pronouns are consistently related to depression (e.g., Edwards & Holtzman, 2017; Pennebaker & Lay, 2002; Rude, Gortner & Pennebaker, 2004; Tackman et al., 2019), a state marked by avoidance (Ferster, 1973; Folkman & Lazarus, 1986), rather than the approach-based behaviours of someone looking to acquire power over others (Keltner, Gruenfeld, & Anderson, 2000). Moreover, those in low status conditions (natural and experimental) use more first-person singular words, whereas those in high status conditions use more first-person plural words (Chung & Pennebaker, 2007; Dino, Reysen & Branscombe, 2009; Foster, et al., 2019; Reysen, Lloyd, Katzarska-Miller, Lemker & Foss, 2010; Kacewicz, Pennebaker, Davis, Jeon & Graesser, 2014). As such, if power words are accompanied by more first-person singular words (indicating depression and low status) than first-person plural words, this may suggest the power on which participants are focused is about personal empowerment rather than power over others.

Hypothesis 2: If power words are accompanied by more first-person plural (we-words) than first-person singular (I) words, then #MeToo power language likely reflects a 'royal we' expression of power, focused on power over others. In contrast, if power language is accompanied by more first-person singular than plural pronouns, power language more likely reflects a focus on personal empowerment.

Hypothesis 2a: If #MeToo language fits the stereotype of having gone 'too far' (Yoffe, 2019), then different pronoun patterns across different events would be expected. If #MeToo started off seeking personal empowerment, but then morphed into a 'power-grab', more first-person singular than plural pronouns would be expected during the original event, but the opposite pattern would expected at subsequent events.

First-person vs. third-person pronouns: Because cognitive words accompany both the active search for meaning (meaning-making) as well as the outcome (meaning-made), (Abe, 2015; Boals et al., 2011; Ullrich & Lutgendorf, 2002), it can be difficult to discern which type of meaning-making the cognitive language is reflecting (Boals, 2012; Boals et al., 2011). Understanding the difference between these two concepts is also a way to test the accuracy of the 'angry mob' stereotype because research shows that when people are in the midst of the process of meaning making, there is more negative affect. The 'why me' is still fresh, and negative emotions are high because people are struggling with trying to reconcile previous worldviews (e.g., people get what they deserve) with why something so bad happened to them (Park, 2010; Park et al., 2008). Once meaning has been made however, those discrepancies are reduced and greater well-being ensues. Thus, even if the #MeToo stereotype of 'angry mob' is accurately reflected in its language, it could be because those tweeting were in the process of meaning-making. In contrast, if the language of #MeToo reflects meaning-made, anger would be less likely to be reflected in the language.

Boals et al., 2011 have argued that one way to distinguish between the two types of meaning-making is that meaning-made will be most evident in 'closed' versus 'open' events (i.e., a memory in which there has been psychological closure, or none, respectively). They showed that cognitive words were associated with measures of meaning-making (positive reframing) only for open memories, but not for closed memories. This suggests that cognitive words may reflect the process of meaning-making for events in which people are still immersed. In contrast, meaning-made is more likely once someone feels more distant from the event (Kross & Ayduk, 2008; Kross & Ayduk, 2011; Kross, Ayduk, & Mischel, 2005; Park, Ayduk & Kross, 2015). For example, Kross et al., (2005) showed that when participants who were distanced from an event describe their experience, their insight and closure statements also involve less emotional reactivity than participants who are immersed in an event. Given negative affect decreases once meaning has been made (e.g., Park, 2010), this suggests that cognitive words used when detached from an event reflect meaning-made.

Whether someone is immersed in, or detached from a negative event has been examined using pronouns; there is extensive research on how pronoun use provides information about attentional focus, that is, an individual's primary concern (e.g., Pennebaker, 2011; see Tausczik & Pennebaker, 2010 for a review). Both sets of first-person pronouns (I, we) suggest an internal, or first-person perspective, whether that focus is on ourselves as unique (I-words), or ourselves as a part of others (we-words) (Zimmermann et al., 2013). In contrast, third-person pronouns (she, he, they) suggest an external focus, or third-person perspective (Abe, 2015; Kacewicz, et al., 2014). For example, Abe (2015) has shown that cognitive words and more self-distancing words (i.e., third-person pronouns) were related higher scores on meaning-made measures (post-traumatic growth), whereas more first-person pronouns were related to lower meaning-made. This suggests that when third-person pronouns accompany cognitive words, the cognitive words reflect meaning-made. Thus, to further understand the nature of the cognitive language in #MeToo, first and third-person pronouns were also compared.

Hypothesis 3: If #MeToo tweets reflect the meaning-making process, more first than third-person pronouns should accompany the cognitive words. In contrast, if the #MeToo language reflects meaning-made, more third- than first-person pronouns would be expected.

Hypothesis 3a: Given meaning-making precedes meaning-made (Park, 2010), then different pronoun patterns would be expected at the original event compared to subsequent events. Specifically, more first than third-person pronouns would be expected for the original Weinstein accusation event, and the opposite pattern would be expected for subsequent events.

Method

Participants and Procedure

In order to collect tweets, a Twitter premium API search script was developed by the second author. The script was created in RStudio to collect tweets from Twitter's full database with specific hashtags from past dates, and download them into an Excel file for ease of analysis in LIWC.

Tweets were collected if they included the #MeToo hashtag and were tweeted within 24 hours of each event: Weinstein's accusation (October 15, 2017); Kavanaugh's accusation (September 27, 2018); Kavanaugh's confirmation (October 6, 2018); Weinstein's conviction

(February 24, 2020). Because no explicit guidelines regarding sample size collection for online data exist (Jones, Wojcik, Sweeting, & Cohen Silver, 2016), we attempted to achieve a balance between choosing too few versus too many tweets. On the one hand, a benefit of big data is that the ease of accessing large numbers allows for greater generalizability to the population. Indeed, #MeToo was tweeted 19 million times in one year (Pew Research Center, 2018), and therefore, collecting enough tweets to achieve external validity is a goal. On the other hand, collecting too much data could make any conclusion susceptible to the *p*-value problem, whereby increasingly larger sample sizes result in progressively smaller *p*-values (e.g., Lin, Lucas & Shmueli, 2013). To attempt to achieve a balance between collecting too few and too many tweets, 2000 tweets were requested for each date, in an effort to isolate 1000 unique tweets for each event. Once tweets were saved in an Excel file, all identifying information was removed. Consistent with other studies, all duplicate, non-English, and irrelevant tweets were deleted (Bogen et al., 2019; Hosterman et al., 2018). This resulted in 3683 unique tweets: 1178 for the original October 15 date; 969 for the Kavanaugh accusation date; 895 for the Kavanaugh confirmation date; 641 for the Weinstein conviction date. Then, a random subsample of 300 tweets/event were selected; Lin et al., 2013 suggest that one way to address the *p*-value problem is to test the robustness of effects on a subsample by choosing sample size that will not reduce the *p*-value beyond values that are traditionally consistent with the topic/discipline. As such, 300 was chosen based on Lin's Significance Threshold Chart for $p = .01$; beyond n = 300, power is increased and the *p*-value is driven down beyond $p = .01$.

Because this study only accessed publicly available tweets, deleted any identifiers and given the researchers were not signed into Twitter when the data was being collected, it was considered exempt from the Research Ethics Board review (Tri- Council Policy Statement, 2018).

Results

All analyses were run on both the full sample and subsample and were the same, except where otherwise noted. To be conservative, the subsample results appear below. Overall correlations and distribution statistics appear in Table 1. Means, standard deviations by event are presented in Table 2.

Hypothesis 1, 1a: Cognitive versus emotion words

To compare cognitive and emotion words, a 3(language; cognitive, anger, positive emotion) X 4(event; Weinstein Accused; Kavanaugh Accused; Kavanaugh Confirmed; Weinstein Guilty) mixed measures ANOVA was conducted, with language as the within-subjects variable and event as the between-groups variable. Mauchly's test of sphericity was violated, $\mathcal{X}^2$ (2) = 319.92, p < .0001, as such, Greenhouse-Geisser corrected tests are reported ($\in\ = .81$). There were significant main effects for both language, $F(1.62, 1937.03) = 775.00$, $p < .0001$, $\eta^2 = .39$, and event, $F(3,1196) = 8.64$, $p < .0001$, $\eta^2 = .02$ that were qualified by a significant interaction, $F(4.86, 1937.03) = 6.96$, $p < .0001$, $\eta^2 = .02$. To further understand the nature of the interaction, the simple effects of language were examined and were significant for each event, $F_{WeinsteinAccused}(2,2392) = 284.16$, $p < .0001$, $\eta^2 = .19$, $F_{KavanaughAccused}(2,2392) = 201.93$, $p < .0001$, $\eta^2 = .15$, $F_{KavanaughConfirmed}(2,2392) = 192.70$, $p < .0001$, $\eta^2 = .14$, $F_{WeinsteinConvicted}(2,2392) = 117.08$, $p < .0001$, $\eta^2 = .09$. To assess hypothesis 1 (if #MeToo language reflected meaning-meaning, cognitive words should be greater than emotion words, but the opposite should occur if it reflected an emotional mob), planned orthogonal contrasts (Helmert) were performed to explore the differences within each event. The first contrast (cognitive words versus both emotion words) was significant in each event, $F_{WeinsteinAccused}(1,299) = 251.55$, $p < .0001$, $\eta^2 = .46$, $F_{KavanaughAccused}(1,299) = 386.28$, $p < .0001$, $\eta^2 = .56$, $F_{KavanaughConfirmed}(1,299) = 241.96$ $p < .0001$, $\eta^2 = .45$, $F_{WeinsteinConvicted}(1,299) = 219.06$, $p < .0001$, $\eta^2 = .42$ indicating, in contrast to the negative stereotype, that tweeters used more cognitive than both emotion words at each event. The second contrast (anger versus positive emotion) was significant for Kavanaugh's accusation $F(1,299) = 11.64$, $p = .001$, $\eta^2 = .04$ and for Weinstein's conviction, $F(1,299) = 3.94$, $p = .05$, $\eta^2 = .01$, such that tweeters used slightly more positive emotion words than anger words during each event. However, anger and positive emotion words were not significantly different for the other two events, $F_{WeinsteinAccused}(1,299) = .83$, $p = .36$, $\eta^2 = .00$, $F_{KavanaughConfirmed}(1,299) = 2.83$, $p = .09$, $\eta^2 = .01$.[1] Thus, inconsistent with the 'angry mob' stereotype, #MeToo language included either more positive emotion words or the same amount compared to anger words.

Hypothesis 1a (if #MeToo had morphed into an angry mob, then more anger words would be observed in later events than the original) was further assessed by first examining the simple effect of event within each word category. The events differed in their frequency of cognitive words, $F(3, 1196) = 9.99$, $p < .0001$, $\eta^2 = .04$ and anger words, $F(3,1196) = 3.44$, $p =.02$, $\eta^2 = .01$ but not in positive words, $F(3,1196) = .89$, $p = .45$, $\eta^2 = .00$. A planned contrast comparing the original October 15 date to the subsequent dates (-3 1 1 1) was used to test event differences for cognitive and anger words. In contrast to the negative stereotype that #MeToo 'went too far', more cognitive, $F(1, 1196) = 18.76$, $p < .0001$, $\eta^2 = .02$ and anger words,

$F(1, 1196) = 8.07$, $p = .005$, $\eta^2 = .01$ were used during the initial Weinstein accusation event than subsequent events.

Hypotheses 2, 2a: First-person singular, First-person plural pronouns and Power

To assess first-person singular pronoun use, a new category was first custom created to remove the word, "me" from the first-person singular category. This was done to ensure this category was not overestimated, given tweets were collected on the basis of the hashtag #MeToo. A 3(language; first-person singular, first-person plural, power) X 4(event; Weinstein Accused; Kavanaugh Accused; Kavanaugh Confirmed; Weinstein Guilty) mixed measures ANOVA was conducted, with language as the within-subjects variable and event as the between-groups variable. Mauchly's test of sphericity was violated, $\mathcal{X}^2$ (2) = 39.01, p < .0001, as such, Greenhouse-Geisser corrected tests are reported ($\in = .97$). There were significant main effects for both language, $F(1.94, 2317.56) = 139.24$, $p < .0001$, $\eta^2 = .10$, and event, $F(3,1196) = 3.84$, p = .001, $\eta^2 = .01$ that were qualified by a significant interaction, $F(5.81, 2317.56) = 11.42$, $p < .0001$, $\eta^2 = .03$. To understand the interaction, the simple effects of language were examined and each was significant, $F_{WeinsteinAccused}(2,2392) = 427.97$, p < .0001, $\eta^2 = .03$, $F_{KavanaughAccused}(2,2392) = 45.46$, $p < .0001$, $\eta^2 = .04$, $F_{KavanaughConfirmed}(2,2392) = 35.26$, $p < .0001$, $\eta^2 = .03$, $F_{WeinsteinConvicted}(2,2392) = 55.49$, $p < .0001$, $\eta^2 = .04$.

To test hypothesis 2 (if the negative stereotype of #MeToo as vengeful was accurate, then more first-person plural than singular pronouns would accompany power language, but the opposite would be the case if #MeToo's power language reflected personal empowerment), planned contrasts between the first-person singular and plural pronouns were examined at each event. For three of the four events, significantly more first-person singular than plural pronouns were used: $F_{WeinsteinAccused}(1,299) = 42.31$, $p < .0001$, $\eta^2 = .12$, $F_{KavanaughAccused}(1,299) = 34.46$, $p < .0001$, $\eta^2 = .10$, $F_{WeinsteinConvicted}(1,299) = 38.14$, $p < .0001$, $\eta^2 = .11$. Although the means were in the hypothesized direction, there were no significant differences in the subsample between the pronouns during the Kavanaugh confirmation, $F\ (1,299) = 1.32$, $p = .25$, $\eta^2 = .00$.[2] Thus, in contrast to the stereotype of #MeToo having 'gone too far', the movement's focus did not appear to morph into a power-grab, as would be expected if the pronoun pattern differed at subsequent events compared to the original.

To further explore the nature of the interaction, the simple effects of event at each word category were conducted and all were significant: $F_{first\text{-}person\ singular}(3,1196) = 16.46$, $p < .0001$, $\eta^2 = .04$, $F_{first\text{-}person\ plural}(3,1196) = 4.82$, $p = .002$, $\eta^2 = .01$, $F_{power}(3,1196) = 3.09$, $p =.03$, $\eta^2 = .01$. A planned contrast comparing the original Weinstein accusation event to the subsequent dates (-3 1 1 1) was again used to examine the differences within each word category. At the initial Weinstein accusation event, there were more first-person-singular pronouns, $F(1,1196) = 41.86$, $p < .001$, $\eta^2 = .03$, and fewer power words, $F(1, 1196) = 9.20$, $p = .002$, $\eta^2 = .01$ than at subsequent events. There were no differences in the first person plural words across the events, $F(1,1196) = 2.41$, $p = .12$, $\eta^2 = .00$.[2]

Hypothesis 3, 3a: First versus third person pronouns

To assess whether the cognitive words reflected meaning-*making*, or meaning-*made*, both sets of first-person pronouns were compared to third-person pronouns. Two composite scores were created (Abe, 2012, 2015). First-person pronouns were computed by adding the Z-scores of the first-person singular (again, without the word 'me') and first-person plural pronouns. Third-person pronouns were computed by adding the Z-scores of third-person singular (he/she) and third-person plural pronouns (they). A2(language; first-person pronouns, third-person pronouns) X 4(event; Weinstein Accused; Kavanaugh Accused; Kavanaugh Confirmed; Weinstein Guilty) mixed measures ANOVA was conducted, with language as the within-subjects variable and event as the between-groups measure. The main effect of language was not significant, $F(1, 1196) = .00$, $p = 1.00$. The main effect of event was significant, $F(1,1196) = 3.62$, $p = .01$, $\eta^2 = .01$ but was qualified by a significant interaction, $F(3,1196) = 16.85$, $p < .0001$, $\eta^2 = .04$. To test hypothesis 3 (if #MeToo language represented meaning-making, then cognitive words would be accompanied by more first than third person pronouns, but the opposite should occur if the language reflected meaning-made), the simple effects of language at each event were conducted. In support of hypothesis 3, there were more first-person than third-person pronouns, $F(1,1196) = 37.43$, $p < .0001$, $\eta^2 = .03$ at the original Weinstein accusation event, suggesting a focus on meaning-making. The opposite pattern of means was marginally significant for the Kavanaugh accusation event and $F(1,1196) = 3.39$, $p = .07$, $\eta^2 = .00$, and non-significant during the Kavanaugh confirmation, $F(1,1196) = 2.54$, $p = .03$, $\eta^2 = .00$.[3] By the final Weinstein conviction event, there were more third than first person pronouns, $F(1,1196) = 7.20$, $p = .007$, $\eta^2 = .01$. Thus, consistent with hypothesis 3a, the pronoun pattern (first-person perspective) at the original event reflected meaning-making, but at subsequent events (third-person perspective) reflected meaning-made.

The interaction was further probed by conducting the simple effects of event at each word category and these were significant for both first-person pronouns, $F(3,1196) = 14.65$, $p < .0001$, $\eta^2 = .04$ and third-person pronouns, $F(3,1196) = 6.35$, $p < .0001$, $\eta^2 = .02$. A planned comparison was used to compare the initial Weinstein accused event to the subsequent events.

Consistent with the hypothesis that meaning-making would be evident earlier whereas meaning-made would be evident later, language in the initial Weinstein accusation contained more first-person pronouns, $F(1,1196) = 35.57$, $p < .0001$, $\eta^2 = .03$ and fewer third-person pronouns, $F(1,1196) = 16.58$, $p < .0001$, $\eta^2 = .01$, than subsequent events.

Discussion

This study examined the linguistic basis for the stereotype of the #MeToo movement as a 'vicious hate mob' versus a social movement attempting to find meaning for past traumatic experiences. Overall, there was little linguistic evidence that #MeToo was functioning as hate mob. Had the #MeToo movement been functioning as a hate mob, then their language would likely have included more emotion words, especially anger, than cognitive words. However, at each #MeToo event, not only did tweets contain more cognitive than emotion words (suggesting they were more thought-focused than emotional), but anger words were either used less often, or the same amount as positive emotion words, suggesting tweets were not focused on anger. Nor did the movement get angrier with later events, as would be expected if the movement had morphed into something that had 'gone too far'. Instead, anger words were lower in subsequent events than in the initial event, which is consistent with research showing that expressive writing can reduce emotional reactivity over time (Park et al., 2015).

Second, although #MeToo tweets at subsequent events used more power words than the initial event, possibly suggesting that the movement had morphed into a power-grab, the pattern of pronoun use counters that negative stereotype. Specifically, at each event, power words were accompanied by more I-words than we-words (albeit one event did not reach significance in the subsample, but did so in the full sample). Given first-person singular pronouns (I, mine) are related to depression (e.g., Tackman et al., 2019) and are used in low status situations (e.g., Kacewicz et al., 2014), this suggests that any focus on power was less likely a vicious mob out for revenge, but rather, more likely individuals focused on re-establishing their personal sense of empowerment. Moreover, there no differences in first-person plural pronouns across events, suggesting that the we-words people use when in high-power situations (e.g., Kacewicz et al., 2014) did not increase with subsequent events, as would be expected if the movement had progressed into a power-grab.

Instead of #MeToo representing a hate mob, the use of more cognitive than emotion words, and the fact that cognitive words were highest at the initial Weinstein accusation event, more strongly supports the hypothesis that the movement was focused on meaning-making rather than anger or a power-grab. This is consistent with past work showing that cognitive words increase right after a stressor, and then decrease after time, suggesting that the most immediate response is to try to understand the stressor (e.g. Cohn et al., 2004). However, whether #MeToo tweets reflected the *process* or the *outcome* of meaning making seems to have shifted as the movement continued. The original Weinstein accusation event appears to have been focused on the process of meaning-making as evidenced by the cognitive words being accompanied by more first than third-person pronouns, and by the fact that more first-person pronouns were used than at subsequent events. Research has shown that the use of cognitive words reflects meaning-making when events are fresher in people's minds (Boals et al, 2011) and when people are adopting a first-person perspective versus a third-person perspective (Abe, 2012, 2015; Kross et al., 2005; Kross & Ayduk, 2011). This could also explain the greater anger words occurring at the original event compared to subsequent events, given that the process of meaning making is marked by distress as individuals try to understand, "why me" (e.g., Park, 2010). Thus, the first-person perspective accompanying the cognitive words at the original #MeToo events suggests that meaning-making was occurring.

In contrast, the pattern of pronouns shifted with subsequent events. Although this trend was non-significant in the subsample during the middle two events (but was significant in the full sample), by the final Weinstein conviction event, there were significantly more third- than first-person pronouns being used. Moreover, later events used more third-person pronouns than the original event suggesting that focus had shifted to a third-person/self-detached perspective. This is consistent with research showing that cognitive words are related to meaning-made measures (e.g., post-traumatic growth) when a third-person perspective is taken (e.g., Abe, 2015; Ullrick & Lutgendorf, 2002; Kross & Ayduk 2008). Moreover, given anger was lower in subsequent events than the initial event, meaning may have been made; past research also shows that once individuals are detached from a stressful event, third-person pronouns predict adaptive functioning measures such as gratitude and happiness (Abe, 2012; 2015; Kross et al., 2005; Kross & Ayduk, 2008).

Overall then, the language of #MeToo over several years does not accurately reflect a 'mob mentality', marked by anger and revenge. There was more thought than anger across the events assessed, and any focus on power that did exist was more in line with language focused on personal empowerment than attaining power over others. By the later events, #MeToo was marked by fewer cognitive words, less anger, and a greater third-person perspective than the original event, suggesting the search for meaning had been attained.

Limitations

Collecting big data from Twitter offers the opportunity to collect data, globally and naturalistically. However, it is not without its limitations. First, only public data is accessed, thus the sample includes only those comfortable with self-disclosure. It may be that those who had something to say about #MeToo but chose not to tweet, felt more negatively than those who chose to tweet. For example, past work that has experimentally manipulated public versus private tweeting behavior showed that private tweeters reported more negative emotion and lower well-being than public tweeters (Foster, 2015), suggesting that perhaps had private tweets been accessible, the angry mob stereotype could have been more supported. This may be unlikely however, given the act of expressive writing itself (even when not publicized) leads to higher well-being (e.g. Baikie & Wilhem, 2005; Frattaroli, 2006; Pennebaker & Chung, 2007) than not writing at all. Nevertheless, future research would benefit from additional controlled studies able to compare public and private social media accounts to assess how the samples differ.

Second, although there were several very strong effect sizes, there were also several very small effect sizes; they ranged from .01 to .56. While collecting naturalistic responses is a benefit of big data, doing so may also reduce the detectable effect sizes as field research tends to yield smaller effect sizes than lab studies with control (see Vanhove & Harms, 2015 for a review). Additionally, Twitter limits the text samples to 280 characters, and, in fact, was limited to 140 for tweets before November 17, 2017 (i.e., for the initial Weinstein accusation). As Okdie and Rempala (2019) point out, LIWC cautions against using small text size samples to make conclusions about people's behaviour. In the same way a one-item scale is a less valid indicator of behaviour than a multi-item scale, small text samples may be less accurate assessments of people's psychological processes. As such, substantial effect sizes may be harder to detect using small text samples. Finally, effect sizes are reduced by skewed data (Fritz, Morris & Richler, 2012), and LIWC data often has word categories with values of zero because people do not use certain words. Indeed, all the word categories in this study feature skewed distributions whereby the skewness was more than twice the standard errors (e.g., Coolican, 2009). Thus, although all the effect sizes in the subsample were replicated in the full sample, future research will need to replicate these effects to ascertain whether the small effect sizes are indeed an artifact of the type of data.

Despite limitations, this study suggests #MeToo was less about anger and revenge, and more about a focus on personal empowerment and meaning-making. Although using social media for information activism has often been criticized as 'slacktivism' (Gladwell, 2010), accumulating research is showing it can indeed impact other forms of activism (e.g., Fatkin & Lansdown, 2015; Foster et al., 2019; Lee & Hsieh, 2013), and this study suggests it may be able to promote personal healing as well. Given the relationship between activism and well-being (e.g., Foster, 2015, 2019; Klar & Kasser, 2009), social media activism, as a form of expressive writing, should continue to be examined for its social and personal benefits. Indeed, we are currently in the midst of other political movements making their voices heard on social media (e.g., #BlackLivesMatter); therefore, examining their focus via language will help to better understand whether criticisms of these movements are evidence-based, or as Drury (2002) argues, an attempt to pathologize those voices.

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Footnotes

[1] In the full sample, positive emotion was anger than anger at every event, and these differences were significant.

[2] In the full sample, there were more we-words used at the initial event compared with the subsequent events combined.

[3] These comparisons were significant in the full sample.

Table 1

Overall intercorrelations between language categories and overall distribution statistics

	1	2	3	4	5	6	7	8
<u>Word Category</u>								
1.Cognitive	-	.04	.08**	.11**	.10**	-.01	.15**	.13**
2. Anger		-	-.10**	-.00	-.01	.25**	-.01	.07*
3. Positive Emotion			-	.00	.08**	.06*	.06*	.03
4. First-person singular				-	-.12**	.03	.66**	.00
5. First-person plural					-	-.01	.66**	-.05
6. Power						-	.02	.02
7. First-person pronouns							-	-.04
8. Third-person pronouns								-
<u>Distribution statistic</u>								
M	8.47	1.98	2.24	2.23	.96	3.26	.00	.00
SE	.19	.09	.09	.11	.07	.11	.04	.04
Skew	.75	1.75	1.69	2.16	3.36	1.59	1.70	2.15

Note. First- and third-person pronouns were computed by summing the Z-scores for first-person singular and plural pronouns, and third-person singular and plural pronouns.
** *p* < .01, * *p* < .05.

Table 2

Means and standard deviations of word usage by event

	Weinstein Accused		Kavanaugh Accused		Kavanaugh Confirmed		Weinstein Convicted	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Word category								
Cognitive	9.89	8.30	8.49	5.60	8.53	6.58	6.94	5.57
Anger	2.40	3.69	1.67	2.61	2.03	2.92	1.82	2.49
Positive emotion	2.12	3.67	2.50	3.10	2.46	3.08	2.30	3.14
First-person singular	3.50	4.95	2.36	3.90	1.57	3.24	1.70	2.53
First-person plural	1.15	2.98	.82	1.87	1.27	2.70	.61	2.39
Power	2.70	3.94	3.45	3.42	3.41	3.99	3.50	3.62
First-person pronouns	.39	1.61	-.04	1.21	-.06	1.34	-.30	.98
Third-person pronouns	-.27	1.19	.16	1.44	.11	1.48	-.01	1.25

Note. Numbers are the percentage of the total number of words for each word category. First- and third-person pronouns were computed by summing the Z-scores for first-person singular and plural pronouns, and third-person singular and plural pronouns.