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Attentional Capture Helps Explain Why Moral and Emotional Content Go Viral

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Our social media newsfeeds are filled with a variety of content all battling for our limited attention. Across 3 studies, we investigated whether moral and emotional content captures our attention more than other content and if this may help explain why this content is more likely to go viral online. Using a combination of controlled lab experiments and nearly 50,000 political tweets, we found that moral and emotional content are prioritized in early visual attention more than neutral content, and that such attentional capture is associated with increased retweets during political conversations online. Furthermore, we found that the differences in attentional capture among moral and emotional stimuli could not be fully explained by differences in arousal. These studies suggest that attentional capture is 1 basic psychological process that helps explain the increased diffusion of moral and emotional content during political discourse on social media, and shed light on ways in which political leaders, disinformation profiteers, marketers, and activist organizations can spread moralized content by capitalizing on natural tendencies of our perceptual systems.

Keywords: morality, emotion, attention, social networks, social media

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There are now over 3 billion social media users around the globe (Williams, 2017). These online social media environments are often described as an "attention economy" (Williams, 2018), as content must break through an immense stream of noise in order to be noticed. Our social media newsfeeds are filled with $15 billion worth of advertisements bought annually by U.S. companies (Statistica, 2015), news and disinformation, passionate political debates, viral memes, and personal updates from our social network—all battling for our limited attention. Because noticing content is a necessary precursor to engagement (e.g., sharing, commenting, liking), attention serves as a bottleneck partially determining which content draws user engagement online. In short, the ability for content to capture attention may be a necessary prerequisite to reach a large audience (i.e., go viral) and exert social influence in domains such as morality and politics (Jost et al., 2018).

Several recent studies have found that social media communications containing expressions of morality and emotion are consistently associated with increased virality in the context of moral and political discourse (Brady, Wills, Jost, Tucker, & Van Bavel, 2017; Stieglitz & Dang-Xuan, 2013; Valenzuela, Piña, & Ramírez, 2017) and campaigns for social change (Van Der Linden, 2017). However, the psychological processes that explain why moral and emotional content tend to go viral currently remains untested. If attention is a bottleneck for user engagement on social media, then the ability for moral and emotional content to break through and capture our attention may play an important role in their subsequent diffusion. By "attentional capture" we mean prioritized selective processing where 'prioritized' means shifting of cognitive resources to the attended stimuli over others (e.g., Öhman & Mineka, 2001). This article examines the extent to which moral and emotional content—associated with greater diffusion on social media—captures more attention than neutral content, and link experimental data from laboratory measures of attention to real-world social media sharing behavior.

Moral and emotional content have a high potential to capture attention because both emotional and moral stimuli are motiva-

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tionally relevant (Brosch & Van Bavel, 2012; Gantman & Van Bavel, 2015). A stimulus is motivationally relevant if it can affect attainment of a goal. Stimuli that affect goal attainment tend to be prioritized in visual attention (Dijksterhuis & Aarts, 2010). Moral stimuli are motivationally relevant because morality fulfils numerous goals, including the need to belong in social groups (Haidt, 2012) and the need to believe in a "just" world (Lerner & Miller, 1978), and there is evidence that moral stimuli capture attention more than nonmoral stimuli (Gantman & Van Bavel, 2015). For example, people are more likely to identify a moral word than a matched nonmoral word when both were flashed briefly on screen near the threshold of conscious perception. Further, when people had their need for justice activated, justice-related words captured attention more than nonjustice related words (Baumert, Gollwitzer, Staubach, & Schmitt, 2011), and moral words (e.g., *obey*, *duty*, *law*) were more likely to "pop out" in conscious perception than neutral words (Gantman & Van Bavel, 2016). More broadly, when forming impressions about people and groups, moral character is one of the primary dimensions to which people attend (Brambilla & Leach, 2014; Goodwin, 2015). For example, studies that experimentally manipulate the moral goodness of a target have found that participants form more positive impressions of the person when they learn the person is morally good, even if other dimensions (e.g., warmth) are also manipulated (Goodwin, Piazza, & Rozin, 2014). Thus, moral content captures our attention because it fulfills our goals and help us learn about our social world (Gantman & Van Bavel, 2016).

Emotional stimuli tend to be highly motivationally relevant because they are associated with various goals (Todd, Cunningham, Anderson, & Thompson, 2012), including survival goals (e.g., detecting a snake; Ohman, Flykt, & Esteves, 2001) and social goals (e.g., understanding social behavior; Campos, Mumme, Kermoian, & Campos, 1994). Indeed, there is a large body of evidence suggesting that emotional stimuli are also prioritized in visual attention. For instance, emotional words are more easily identified compared to neutral words—especially under conditions of limited attentional resources (Anderson & Phelps, 2001; Anderson, 2005; Keil & Ihssen, 2004; Milders, Sahraie, Logan, & Donnellon, 2006). Furthermore, emotional stimuli can drive attentional capture in an automatic, stimulus-driven fashion (Arnell, Killman, & Fijavz, 2007; Ciesielski, Armstrong, Zald, & Olatunji, 2010; Most, Smith, Cooter, Levy, & Zald, 2007; Most & Wang, 2011). Thus, emotional stimuli can shape perceptual experience through decreased thresholds for attentional capture (see Phelps, Ling, & Carrasco, 2006), leading people to notice emotional content.

Current Research

The aim of the current research was to test whether attentional capture can help explain the advantage that moral and emotional content has over other content in spreading on social media. We further explored whether basic psychological characteristics such as arousal underlie attentional capture of moral and emotional stimuli. This research is also one of the first attempts to tie basic cognitive psychology methods to real social media behavior. The following studies use the classic attentional blink (AB) paradigm (Raymond, Shapiro, & Arnell, 1992) to assess the difference in attentional capture between moral and nonmoral emotion content compared to neutral content (Studies 1 and 2). To simulate the ecology of real social media use, we also created a modified version of the AB paradigm that uses complete Twitter messages as stimuli similar to the way people scroll through their social media feeds (Study 2). Finally, we measured the extent to which individual words capture attention in the lab is associated with sharing behavior (i.e., retweeting) in a large data set of 50,000 political messages on Twitter (Study 3). These studies provide a key test of the cognitive factors that underlie sharing of moralized content on social media.

Study 1: How Moral and Emotional Content Captures Attention

Study 1 examined whether moral and emotional content captures more attention than neutral content by testing specific words associated with morality and emotion in the AB paradigm (Raymond et al., 1992). The AB task simulates the experience of many users on social media as they rapidly scroll through posts and messages in their news feed. This task allowed us to conduct a precise experimental test of the capacity for different types of language to capture attention.

Method

In the AB paradigm, identification of a first target (T1) during rapid serial presentation of stimuli impairs the ability for identification of a second target (T2). The period when people are typically unable to identify T2 is known as the attentional blink and lasts between 200 and 500 ms (Raymond et al., 1992). We adapted a modified version of the AB paradigm in which we manipulated the moral and emotional content of words that appeared as T2 (e.g., Anderson & Phelps, 2001; see Figure 1). This allowed us to replicate prior work on emotional attention, while extending these processes to morality (and providing a database of attentional capture we could link to real behavior on Twitter). To the extent that moral or emotional words reduce the AB effect (as assessed by T2 accuracy), it can be inferred that those words capture greater attention than words that show less of a reduction. In other words, we examined whether moral and emotional words were less likely to exhibit an attention blink.

Participants. Fifty-one undergraduate students at New York University (46 females; M_{age} = 19.66, SD_{age} = 1.37) participated for partial course credit. We intended to collect 50 participants based on an a priori power analysis using *G*Power 3.1.9.2* to determine the sample size required to detect a small-to-medium (f = .15) main effect of word type with 80% power based on the following assumptions: (a) a within-subjects design with six repeated measures (see below) and (b) a correlation among repeated measures of at least .5. This power analysis was conservative because it assumed we averaged across trials and performed a repeated-measures ANOVA, but in actuality we used a larger amount of data by analyzing data at the trial and stimulus level using a mixed model (see "Results"). Seven participants were removed from the data set due to mean accuracy in early phase trials (see below) under 25%, leaving a final sample size of 44. However, the reported results are consistent when these participants remain in the data set (see online supplemental material, Section 1).

Procedure. Participants were told that the experiment was about word recognition and vision. The concepts of morality and

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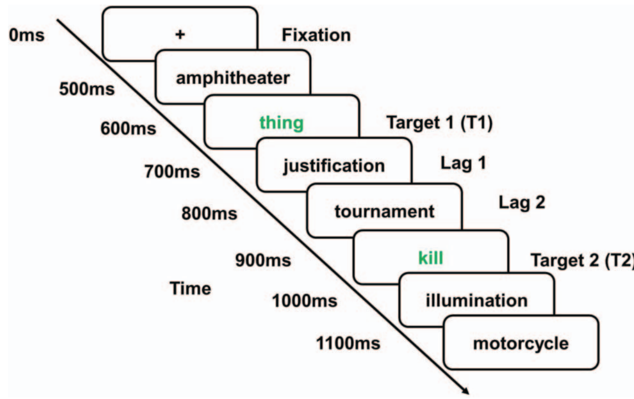

Figure 1. Participants viewed rapidly presented words in 100-ms intervals. Their task was to identify two target words that appeared in green. The first target (T1) appeared after fixation at a jittered position after 1–4 distractor words. The second target (T2) appeared one to seven words after T1, represented as the "lag" position (e.g., Lag 1). This figure depicts a trial where T2 appears at Lag 3. For each trial, T2 was a word from one of four categories: distinctly moral, distinctly emotional, moral-emotional, and neutral. Images are not shown to scale. See the online article for the color version of this figure.

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emotion were not mentioned in the instructions. The task was performed in DirectRT software on a Dell Optiplex 760 with a 60 hz refresh rate. Participants completed the study in a dimly lit room and sat approximately 20 in from the screen. All stimuli were presented in 24 pt, Times New Roman font at the center of the screen. The background was white, and all nontarget words were black. Participants were instructed to identify two target words that would appear in green, and at the end of each trial they were prompted to type the two green words they saw, in any order.

Each trial consisted of 15 words (13 distractors and two targets) displayed for 100 ms at a time. Distractors were neutral words of longer length than the target words to serve as a visual mask for following stimuli (Anderson & Phelps, 2001). T1 appeared after fixation at a jittered position after 1–4 distractor words to avoid anticipation. T2 appeared between 1 to 7 positions, or "lags" after T1 (Raymond et al., 1992; see Figure 1). Participants completed 224 total trials consisting of 56 trials for each of four possible T2 word types: distinctly moral, distinctly emotional, moral-emotional, and neutral words. Within the 56 trials of each word type, there were two trials per lag phase (1–7), such that each word type was presented an equal number of times in each lag phase. Within each type, words were assigned to each lag phase randomly, and trials were presented in randomized order. Participants were offered an optional 1-min break halfway through the experiment. All together, the experiment is a 4 (word type: moral, emotional, moral-emotional, and neutral) $\times$ 2 (early vs. late lag) within subjects design.

Stimuli. Twenty-eight words per category were determined based on an random selection of words from previously validated lexicon-based measures of morality and emotion in language (Brady et al., 2017). This approach distinguishes between distinctly moral words (e.g., *church*, *holy*, *pure*), distinctly emotional words (e.g., *weep*, *sad*, *afraid*), and moral-emotional words (e.g., *hate*, *shame*, *ruin*). Neutral words were chosen that were not classified as any of the other word types and to avoid confounds that could be related to attention, all word categories were matched for (a) length, (b) frequency in the English language, (c) number of orthographic neighbors, and (d) number of phonological neighbors (see online supplemental material, Section 1). All words, organized by category, are presented in online supplemental material, Table S1 and materials freely available to researchers at https://osf.io/z6evq/.

Results

Data preprocessing. All trials for which participants did not correctly identify T1 were dropped, as these trials represent those where an AB effect cannot be assessed (Anderson & Phelps, 2001; Keil & Ihssen, 2004). Lag phase was collapsed to a binary variable where lags 1–3 were coded as "early lag" and lags 4–7 were coded as "late lag" (Anderson & Phelps, 2001), but results did not change when modeling lag continuously (see online supplemental material, Section 1). Word type was treated as a categorical variable with 4 levels (distinctly moral, distinctly emotional, moral-emotional, neutral) and therefore was entered into the regression model as 3 dummy-coded variables where the reference level was not entered. T2 accuracy was treated as a binary variable where 1 = correct word identification and 0 = incorrect word identification.

Main analyses. In order to test whether the AB was reduced as a function of the T2 word type, we regressed T2 accuracy on word category, lag phase, and their interaction using each trial as an observation. To account for correlation in variance among stimuli and participants, we formed a multilevel model with trials nested within stimuli, and stimuli nested within participants using generalized estimating equations (GEE; Hardin, 2005) with robust standard error estimation and an exchangeable correlation structure (all analysis scripts are available at https://osf.io/z6evq/).

As expected, there was a significant main effect of lag, odds ratio (OR) = 2.90, $p < .001$, 95% CI [2.42, 3.46], such that participants were 2.9x more accurate in late lags compared to early lags. We then examined whether moral and emotional words reduced the AB relative to neutral control words. Critically, there were significant effects of all T2 word types compared to neutral

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words. Participants were 1.43× more likely to correctly identify a distinctly moral T2 word compared to a neutral T2 word, *OR* = 1.43, $p < .001$, 95% CI [1.18, 1.73], 1.80× more likely to correctly identity a distinctly emotional T2 word compare to a neutral T2 word, *OR* = 1.80, $p < .001$, 95% CI [1.49, 2.18], and were 1.58× more likely to identify a moral-emotional T2 word compared to a neutral T2 word, *OR* = 1.58, $p < .001$, 95% CI [1.31, 1.91]. See online supplemental material, Table S3 for model details. These differences in T2 accuracy between the moral/emotional words and neutral words were significant in both the early and late lag phases (see online supplemental material, Section 1). Modeling lag phase continuously did not change any statistical conclusions. Distinctly moral (*OR* = 1.28, $p = .001$, 95% CI [1.12, 1.48]), distinctly emotional (*OR* = 1.74, $p < .001$, 95% CI [1.51, 2.00]), and moral-emotional (*OR* = 1.34, $p < .001$, 95% CI [1.17, 1.55]) words all showed a significantly reduced AB effect compared to the neutral T2 category when adjusting for the continuous lag variable and its interactions with T2 category, demonstrating greater attentional capture (for model details, see online supplemental material, Table S7). These findings suggest that words related to either morality or emotion were prioritized in visual attention to a greater extent than neutral words as they were identified with greater accuracy under conditions of limited cognitive resources (see Figure 2).

Next, we directly compared T2 accuracies among distinctly moral, distinctly emotional, and moral-emotional T2 words. We found no significant differences between moral-emotional words and emotional T2 word accuracy, *OR* = 0.88, $p = .189$, 95% CI [0.72, 1.07], or moral-emotional versus distinctly moral T2 accuracy, *OR* = 0.90, $p = .297$, 95% CI [0.74, 1.09], but we found that distinctly moral T2 words attracted less attention than distinctly emotional words, *OR* = 0.79, $p = .018$, 95% CI [0.65, 0.96]. Thus, although moral language draws more attention than neutral content (see also Gantman & Van Bavel, 2014), it may garner even more attentional capture when emotional language is involved. Furthermore, it does not appear that moral language and emotional language produce additive increases in attentional capture.

Exploratory arousal analysis. Emotional expression with or without moral expression appeared to exhibit similar abilities to capture attention, raising the possibility that some other process could explain attentional capture of the words besides our theoretically derived categories. For example, *valence* and *arousal* are fundamental dimensions on which different emotions can be categorized (Russell & Barrett, 1999). Previous studies have found that the extent to which emotional words are arousing, rather than their valence, explains variation in attentional capture (Anderson, 2005). Thus, we tested the extent to which words are arousing could explain variance in T2 accuracy across our word categories.

To this end, we pulled human-coded arousal ratings for the T2 words used in our study from a database of 13,915 word ratings (the "extended ANEW" set; Warriner, Kuperman, & Brysbaert, 2013). Using this method, we obtained normative arousal ratings for 107 of our 112 T2 words (see online supplemental material, Section 1). We then ran a similar multilevel model from our main analysis above but replaced word type with arousal rating (see online supplemental material, Table S9 for model details). Results revealed a small but significant main effect of arousal across all word categories on T2 accuracy, *OR* = 1.06, $p = .020$, 95% CI [1.01, 1.12]. However, when word type and arousal were modeled together the effect of arousal was not statistically significant, *OR* = 0.97, $p = .201$, 95% CI [0.92, 1.02], whereas the effects of word type remained significant for distinctly moral (*OR* = 1.38, $p < .001$, 95% CI [1.19, 1.60]), distinctly emotional (*OR* = 1.96, $p < .001$, 95% CI [1.66, 2.32]) and moral-emotional (*OR* = 1.61, $p < .001$, 95% CI [1.37, 1.89]) words (see online supplemental material, Table S10 for model details). Model comparison tests also revealed that this model, which statistically adjusted for the effects of word type, was a significantly better fit of the data than the model with arousal as the sole predictor (see online supple-

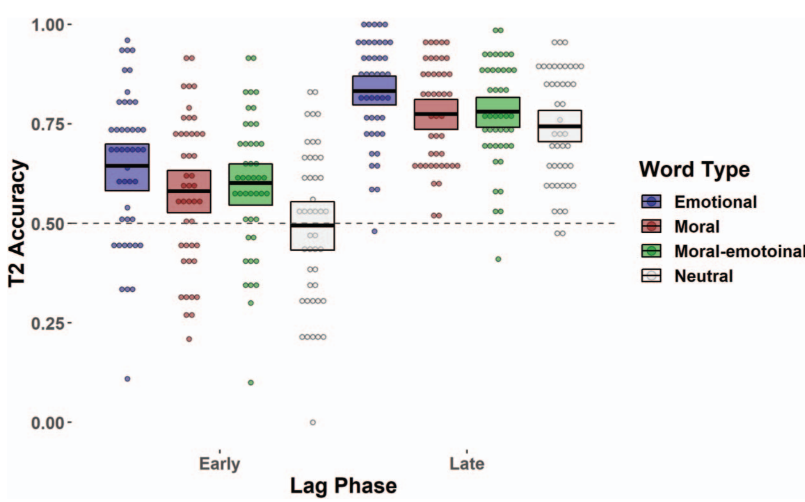

Figure 2. Target 2 (T2) accuracy as a function of lag and word type. Distinctly moral, distinctly emotional and moral-emotional word categories showed a significant reduction in the attention blink compared to neutral words, suggesting that they capture attention to a greater extent than neutral words. For visualization, the graph displays mean accuracies for each T2 word category for each participant, however data were analyzed with each trial as an observation. The horizontal dotted line represents mean accuracy of 50% which represents incorrect word identification on half of the trials. See the online article for the color version of this figure.

mental material, Section 1 for details). These results suggest that our theoretically derived word category distinctions explain unique variance in attentional capture beyond the arousal-level of each word.

Study 2: Attentional Capture in an Ecologically Valid Blink Task

We sought to replicate our finding that moral and emotional words capture more attention than neutral words in a more ecologically valid context. Although the AB task has some striking similarities to the way people engage with social media (e.g., it presents a sequence of verbal content) it is nevertheless a modest substitute for real social media environments where users perceive words embedded in full messages (e.g., in the form of a Tweet or a status update as they scroll through their feed). In Study 2 we created a novel version of the AB paradigm that more accurately simulates the experience of using social media. We presented people with a sequence of Tweets to simulate the experience of scrolling through their Twitter feed—an experience that over 335 million people engage in every month (Statistica, 2018). Including full tweets also tested whether the attentional capture effects from Study 1 generalize to full messages.

Method

Participants. Fifty-six undergraduate students at New York University (38 females; $M_{\text{age}} = 19.54$, $SD_{\text{age}} = 1.57$) participated for course credit. We intended to collect 50 participants based on the power analysis used in Study 1 but continued collecting data until the end of the semester anticipating the need to drop participants due to floor accuracy as in Study 1. This collection decision ultimately resulted in 56 participants. Three participants were removed from the data set due to mean accuracy under 25% in the early lag phase, leaving a final sample size of 53. However, the reported results are consistent when these participants remain in the data set (see online supplemental material, Section 2).

Procedure. We used the same procedure as in Study 1, with the exception that the stimuli and presentation timing were altered. Rather than presenting individual words, each trial consisted of 15 different fictitious Twitter messages that expressed pro gun control attitudes (13 distractors and two targets) were displayed for 110 ms at a time. The stimulus presentation time was increased slightly from Study 1 since the stimuli were full messages. Pilot testing revealed accuracies under 25% when the stimuli were presented at 100 ms, and the 10-ms adjustment raised mean accuracies (across all T2 categories) to levels near Study 1. We choose to present messages with traditionally liberal attitudes since the large majority of NYU undergraduate students are liberal, especially with regards to gun control.

Stimuli. Each short message consisted of two lines of text (nine total words) expressing a pro gun control attitude, and ended with one #hashtag word (e.g., #kill) alone on a third line. Distractor stimuli were messages with neutral hashtags that were black in color. T1 and T2 messages consisted of a blue-colored hashtag designed to mimic the hue of Twitter's hashtag designation (see Figure 3). T2 hashtags were manipulated to contain one of four word types (distinctly moral, distinctly emotional, moral-emotional, and neutral). The same T2 words from Study 1 were used for each word type. We selected a combination of neutral words from Study 1 and new neutral words that were matched on confounding dimensions as in Study 1 to ensure that the effects found in Study 1 were not an artifact of specific neutral words since its category is relatively large.

The position in which T1 appeared was again jittered to avoid anticipation, and T2 appeared between one to seven "lags" after T1 (see Figure 3). Participants completed 224 trials consisting of 56 trials for each of four possible T2 word categories. Within the 56 trials of each word type, there were two trials per lag phase (one to seven). Within each category, words were assigned to each lag phase randomly, and trials were presented in randomized order. Participants were offered an optional 1-min break halfway through the experiment. Example stimuli are presented in Figure 3. All stimuli are available at https://osf.io/z6evq/.

Results

Data preprocessing. As in Study 1, all trials for which participants did not correctly identify T1 were dropped. Lag phase was again collapsed to a binary variable where Lags 1–3 were

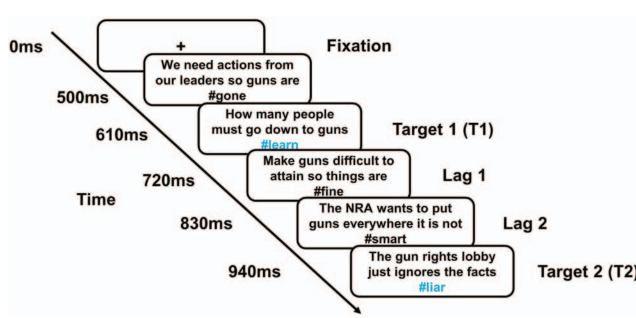

Figure 3. Social media attentional blink paradigm. Participants viewed rapidly presented words in 110-ms intervals. Their task was to identify two target words that appeared as a hashtag in blue. The first target (T1) appeared at a jittered position 500–830 ms after fixation. The second target (T2) appeared one to seven words after T1, represented as the "lag" position (e.g., Lag 1). This figure depicts a trial where T2 appears at Lag 3. For each trial, the T2 hashtag was a word from one of four types: distinctly moral, distinctly emotional, moral-emotional, and neutral. Images are not shown to scale. See the online article for the color version of this figure.

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coded as "early lag" and Lags 4–7 were coded as "late lag" (Anderson & Phelps, 2001), but results remained consistent when lag phase was modeled continuously (see online supplemental material, Section 2). Word category was treated as a categorical variable with four levels (distinctly moral, distinctly emotional, moral-emotional, neutral) and therefore was entered into the regression model as three dummy-coded variables where the reference level was not entered. T2 accuracy was treated as a binary variable where 1 = correct word identification and 0 = incorrect word identification.

Main analyses. To test whether the AB was reduced as a function of the word type of T2, we regressed T2 accuracy on word type, lag phase, and their interaction using each trial as an observation. To account for correlation in variance among stimuli and participants, we again used a multilevel model with trials nested within stimuli, and stimuli nested within participants using GEE (Hardin, 2005) with robust standard error estimation and an exchangeable correlation structure.

Replicating the results of Study 1, there was a significant main effect of lag, *OR* = 2.62, $p < .001$, 95% CI [2.22, 3.09], such that participants were 2.56× more accurate in late lags compared to early lags. Replicating Study 1, there were significant effects of all T2 word types compared to neutral words. Participants were 1.64× more likely to correctly identify a distinctly moral T2 word compared to a neutral T2 word, *OR* = 1.64, $p < .001$, 95% CI [1.37, 1.96], 1.93× more likely to correctly identify a distinctly emotional T2 word compare to a neutral T2 word, *OR* = 1.85, $p < .001$, 95% CI [1.61, 2.32], and 1.66× more likely to identify a moral-emotional T2 word compared to a neutral T2 word, *OR* = 1.66, $p < .001$, 95% CI [1.39, 1.99]. These differences in T2 accuracy between the moral/emotional words and neutral words did not vary as a function of lag phase (see online supplemental material, Section 2 for details). Modeling lag phase continuously did not change any statistical conclusions. Distinctly moral (*OR* = 1.47, $p < .001$, 95% CI [1.23, 1.68]), distinctly emotional (*OR* = 1.91, $p < .001$, 95% CI [1.66, 2.20]), and moral-emotional (*OR* = 1.65, $p < .001$, 95% CI [1.44, 1.89]) words all showed a significant reduced AB effect compared to the neutral T2 category when adjusting for continuous lag phase, demonstrating greater attentional capture (for model details see online supplemental material, Table S15). These findings replicate those of Study 1 and suggest that messages that include words related to both morality and emotion are prioritized in visual attention to a greater extent than messages with neutral words (See Figure 4).

We found one statistical trend but no significant differences when comparing any of the other categories to each other: distinctly emotional versus distinctly moral, *OR* = 1.18, $p = .087$, 95% CI [0.98, 1.42], distinctly emotional versus moral-emotional, *OR* = 1.16, $p = .113$, 95% CI [0.97, 1.40], nor moral-emotional versus distinctly moral, *OR* = 1.01, $p = .898$, 95% CI [0.84, 1.22]. Similar to Study 1, moral-emotional and emotional words did not show significantly different T2 accuracies, and the distinctly emotional words did show greater T2 accuracies than distinctly moral words (but it was only marginally significant in this study). These data suggest that both moral and emotional content draw more attention than neutral content, but likely do so with similar efficacy relative to one another.

Exploratory arousal analysis. As in Study 1, we explored whether the extent to which words are arousing could explain variance in T2 accuracy even across word types (see online supplemental material, Section 1). Replicating Study 1, results revealed a significant main effect of arousal across all word categories on T2 accuracy, *OR* = 1.07, $p = .009$, 95% CI [1.02, 1.14], but once again this effect did not remain significant when statistically adjusting for the effect of word category, *OR* = 0.97, $p = .311$, 95% CI [0.91, 1.03]. In this model, the effects of distinctly moral (*OR* = 1.37, $p < .001$, 95% CI [1.18, 1.58]), distinctly emotional (*OR* = 1.94, $p <$

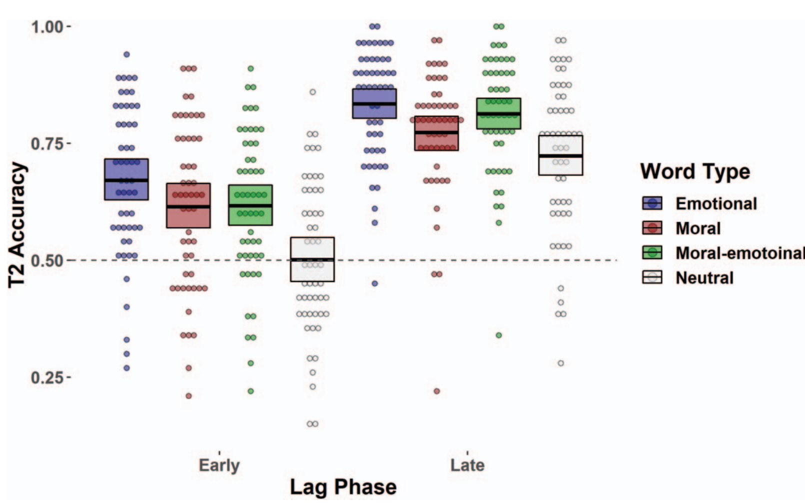

Figure 4. Target 2 (T2) accuracy as a function of lag and word type. Distinctly moral, distinctly emotional, and moral-emotional word categories showed a significant reduction in the attention blink compared to neutral words, suggesting that they capture attention to a greater extent than neutral words. For visualization, the graph displays mean accuracies for each T2 word category for each participant, however data were analyzed with each trial as an observation. The horizontal dotted line represents mean accuracy of 50% which represents incorrect word identification on half of the trials. See the online article for the color version of this figure.

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.001, 95% CI [1.65, 2.27]), and moral-emotional ($OR = 1.61$, $p <$ .001, 95% CI [1.36, 1.91]) words all remained statistically significant (see online supplemental material, Tables S16–17 for model details). Thus, again arousal could not fully account for the differences in attentional capture among moral and emotional word categories. In sum, Study 2 replicated the key results of Study 1 using stimuli that better simulated real social media experience. Furthermore, attentional capture differences among moral and emotional language cannot be fully explained by arousal.

Study 3: Attentional Capture Is Associated With Online Sharing

Studies 1 and 2 used tightly controlled experiments with increasing ecological validity, and we observed clear evidence that moral and emotional language alone and together capture attention to a greater extent than neutral language—even for a measure of attention designed to better mimic social media environments. The purpose of Study 3 was to evaluate whether there is a measurable connection between attention to moral and emotional words in the lab and retweet behavior during real moral and political social media communications. To our knowledge, this study is the first attempt to connect data from the AB paradigm in the lab to behavior in online social networks. Social media is a particularly important context to study moral and emotional messages since recent work suggests that social media is now the primary source of moral outrage for most people (Crockett, 2017) and there is reason to believe that such content can have aversive consequences under certain circumstances (Brady & Crockett, 2018).

Method

We analyzed a large dataset containing Twitter conversations about contentious political topics of gun control, same-sex marriage and climate change ($N = 563{,}312$; Brady et al., 2017). We explored whether attentional capture of individual words measured in a controlled lab setting lab would correlate with real sharing behavior (i.e., retweeting) of these Twitter messages. Insofar as attentional capture plays a role in the increased engagement garnered by moral and emotional content, and in social media engagement more generally, we expected that there would be a positive relationship between T2 accuracies for a given word and the extent to which messages containing those words are retweeted.

To determine each word's attentional capture score based on lab data, we first computed the mean of a word's accuracy across trials within a participant, defined as the number of correct identifications out of the total trials the word appeared (including all lag phases). Scores could therefore range from 0% to 100% accuracy. Using this score for each word and each participant, we then computed the mean across all participants. Thus, every T2 word in our study was assigned a mean accuracy score that represented the mean accuracy level for a word across participants in the study. The mean accuracies for each word from Study 1 and Study 2 were averaged for words that appeared in both studies (neutral words were varied in Study 2 and thus could not be averaged across both studies).

To associate mean T2 word accuracies with Twitter data, we used all topic data sets from Brady et al. (2017), which contains 563,312 combined original tweets and retweets about contentious political topics including gun control, same-sex marriage, and climate change. We searched for the presence of the 120 words from each word type category appearing as T2 in Studies 1 and 2 in the database of tweets. To do so, each tweet was tokenized and words used as T2 in Studies 1 and 2 were matched using the *R* package *tidytext* v. 0.1.8 (Silge & Robinson, 2016), thus assigning an attention capture value from the lab to any of the T2 words present in tweets. Because we only had attentional capture values for the 120 words appearing in our lab studies, we trimmed the dataset so it only contained tweets that had at least one of the 120 words in it, leaving a final sample of 47,552 original tweets.

Each tweet was then assigned one "attentional capture index" that represented the sum of the mean attention capture values for every word of the 120 that could have appeared in it. For instance, consider the following tweet: "Shame on President Trump for his abuse of power." This tweet contains two T2 words from our study: "shame" and "abuse." If the mean attentional capture score from the lab for "shame" was .80 and for "abuse" was .70, then the tweet would be assigned an attentional capture index value of 1.5. For cross-validation purposes, we also tested a model that formed an attentional capture index value by taking the mean attentional capture score of T2 words in a tweet rather than the sum. Results reported below remained consistent regardless of which specific formulation of the attentional capture index was used (see online supplemental material, Section 3 for more details). The *R* script for the method described above is available at https://osf.io/z6evq/.

Results

We examined the relationship between attentional capture of words as measured in the lab and retweet counts for those same words within messages on social media. We regressed the retweet count (the primary method of sharing on Twitter) of each tweet on the attentional capture index of each tweet using a negative binomial model (Hilbe, 2011) to account for overdispersion present for the retweet count variable. We confirmed the suitability of modeling the retweet counts using a negative binomial model by examining the distribution and formally testing differences in model fit compared to other count models (e.g., Poisson; see R script for Study 3, line 58, available at https://osf.io/z6evq/). This model revealed a positive, significant effect of attentional capture index on retweet count, incident rate ratio (IRR) = 1.38, $p < .001$, 95% CI [1.26, 1.52] (see Figure 5). In other words, tweets with a greater attention capture value (as assessed by specific words in the tweet) were associated with greater expected retweet counts. We explored whether a quadratic trend was also present in the relationship between attentional capture and retweeting, but this effect was not significant, IRR = 0.87, $p = .073$, 95% CI [0.75, 1.01]. In this model the linear effect still remained significant, IRR = 1.54, $p < .001$, 95% CI [1.32, 1.80]. Details for the model testing a quadratic effect are presented in Supplemental Table S19 in the online supplemental material. The results of our analyses provide novel evidence that attentional capture helps explain the increased ability for moral and emotional content to go viral on social media.

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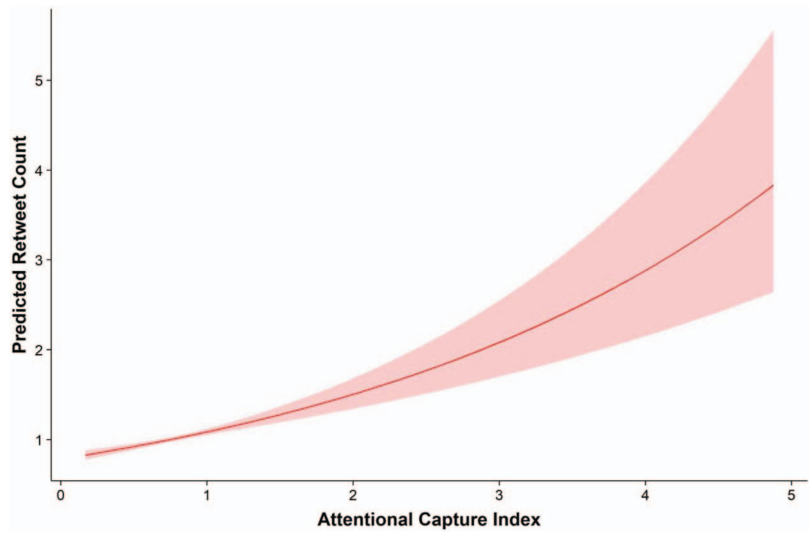

Figure 5. Retweet count as a function of attentional capture index. Tweets with greater attention capture value of as assessed by specific words in the tweet were associated with greater expected retweet counts. Attentional capture index was calculated based on the mean attentional capture data from our lab study for each Target 2 (T2) word present in a tweet. See the online article for the color version of this figure.

General Discussion

Overall, we find that moral and emotional language capture attention to a greater extent than neutral language, and that this may partly explain why messages using this language are more likely to be shared on social media. Two lab experiments using both traditional and novel methods provided strong evidence that moral and emotional language captures attention to a greater extent than neutral language. This conceptually replicates previous work demonstrating prioritized visual processing for emotional (Anderson & Phelps, 2001; Anderson, 2005; Keil & Ihssen, 2004), as well as moral stimuli (Gantman & Van Bavel, 2014). We also provided one of the first attempts to link attention capture as measured in the lab to real behavior on Twitter and found evidence that attentional capture is associated with retweet behavior in the context of online moral and political discourse. Our findings suggest that attentional capture may in part explain the advantage that moral and emotional content have over neutral content in drawing engagement on social media (Brady et al., 2017; Stieglitz & Dang-Xuan, 2013; Valenzuela et al., 2017).

This work also provided one of the first direct tests of whether moral versus emotional content is prioritized in rapid visual processing. Our results suggest that moral and emotional content are both prioritized and are prioritized somewhat equally in comparison (if anything, emotional content may have a slight advantage). There may be a general threshold for an attentional advantage that can be surpassed by any motivationally relevant content that is moral, emotional, or both. However, the decision to share content in the context of political communications does not appear to be fully explained by attentional capture. For instance, although moral-emotional content was more consistently associated with increased engagement than distinctly moral and emotional content (Brady, Wills, Burkart, Jost, & Van Bavel, 2018; Brady et al., 2017), we found no evidence that moral-emotional content generates an attentional advantage over purely moral or emotional content. Future research should investigate other basic cognitive and social processes that could explain the specific engagement advantage enjoyed by moral-emotional content including enhanced memory for moral and emotional content (Phelps, 2004), top-down effects of morality on perception (Gantman & Van Bavel, 2015; Van Bavel, FeldmanHall, & Mende-Siedlecki, 2015), or other social psychological processes such as the importance of moral identity (Aquino & Reed, 2002), and social identity concerns more broadly (Tajfel & Turner, 1986). Furthermore, moral and emotional language might be perceived by others as more diagnostic of their opinions, rendering a point more persuasive, or more urgent than other content, and this may also lead to greater retweet rates. There are undoubtedly multiple factors that go into a decision to retweet, and our results suggest that attentional capture is one such factor (see also Brady, Crockett, & Van Bavel, 2019).

Although Studies 1 and 2 demonstrate that the morality and emotionality of words appear to play a causal role increasing attentional capture, Study 3 was only able to establish a correlation between attentional capture and online sharing. This study makes a direct connection between carefully controlled laboratory experiments and ecologically rich behavior online. Nevertheless, because we did not manipulate the content on Twitter, this raises the possibility for an alternative explanation of Study 3's results: increased sharing might increase the attentional capture potential of moral and emotional content. This explanation is indirectly supported by studies suggesting that people engage with content more once they observe it is popular (i.e., when other people have already engaged with it; Salganik, Dodds, & Watts, 2006). Most likely, attention and online sharing affect one another to produce a relationship that resembles a feedback loop, such that more attention leads to more sharing, and more sharing leads to more attention. Future work that either manipulates attention to Twitter messages in the lab or directly on Twitter is required in order to

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fully clarify the precise causal relationship between attentional capture and online sharing. For instance, previous work has shown moral decisions can be influenced when attention to possible choices is manipulated (Pärnamets et al., 2015). We reiterate that sharing behavior online is a multiply determined process, and attentional capture is one of many factors that might play an important role. Future work can confirm the conditions under which attention is important, and conditions under which other factors, like those listed above, elicits online sharing behavior.

The results presented here also have implications for impression formation as it unfolds on social media. Particularly in the realm of political conversations, our data suggest that communication highlighting moral and emotional content can increase attentional capture and possibly lead to greater engagement. If impression formation is dominated by perceptions of moral character (Brambilla & Leach, 2014; Goodwin, 2015), political leaders and partisans can use morally framed conversations on social media to drive attention to their "good" character and make it salient over and above other information about them (see Brady et al., 2019). Future research should examine the conditions under which social media facilitates or creates barriers to judgment of people's moral character (e.g., the extent to which social cues are limited; Tanis & Postmes, 2003).

We also found that the arousal level of a word could not fully explain our findings. This raises the possibility that another psychological process explains variance in attentional prioritization between moral and nonmoral emotional stimuli. The explanation may lie in social psychological explanations of the theoretical and functional differentiation of moral versus nonmoral emotions (Haidt, 2003; Hutcherson & Gross, 2011; Scherer, 2001). For example, even though moral and nonmoral emotional stimuli may be similarly arousing, they could have differential effects regarding attentional capture in specific contexts that differ in terms of motivational relevance. For example, in contexts where one observes specific norm violations, moral-emotional stimuli such as outrage expression are especially relevant (see, e.g., Fiske & Tetlock, 1997; Salerno & Peter-Hagene, 2013), and may be prioritized in attention compared to nonmoral emotional stimuli. Although arousal may generally increase sharing of content such as news articles online (Berger & Milkman, 2012), our work suggests that the role of attentional capture in the sharing of moral and emotional content online cannot be explained exclusively by the extent to which the content is arousing.

Although we used a relatively large set of stimuli, this is merely a sample of the large range of possible moral and emotional stimuli that people encounter in their daily lives. Thus, the present results are limited to the relatively small selection of words that were used for maximal control in our studies. We also compared undergraduate students' attentional capture performance to sharing behavior of active Twitter users, which may have consequences for estimation of our effects. For example, this likely led us to underestimate how large the effect of attention capture is on sharing behavior: Twitter users who engage in political discussion may be more ideologically extreme than the average undergraduate student, and therefore moral and emotional content may be even more motivationally relevant for them compared to undergraduates. Future research should investigate a larger, more representative sample of words and sample a wider of range of demographics to better determine how well our results generalize to all moral and emotional content and all demographics. Furthermore, future research could measure attention and sharing behavior within a single context to draw a more direct test of the relationship between attentional capture and sharing behavior. Finally, our social media AB task in Study 2 used political messages that were liberal-learning due to our sample of university students. Future work should test whether results generalize to content expressing political views of both ideologies and from participants with varying ideologies, especially given that there is evidence of conservative-liberal asymmetry in the spread of moralized content online (Brady et al., 2018).

Conclusion

In three studies using tightly controlled lab experiments with increasing ecological validity and linking these data to real Twitter communications, we found that (a) moral and emotional language both capture attention to a greater extent than neutral language, and (b) such attentional capture potential in words is associated with real-world patterns of retweeting on Twitter. These data shed light on the cognitive underpinnings of the spread of moralized content online, which can help explain how political leaders, disinformation profiteers, marketers, and online activist organizations can spread content by capitalizing on natural tendencies of our perceptual systems.

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