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Self-Expression on Social Media: Do Tweets Present Accurate and Positive Portraits of Impulsivity, Self-Esteem, and Attachment Style?

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Abstract

Self-expression values are at an all-time high, and people are increasingly relying upon social media platforms to express themselves positively and accurately. We examined whether self-expression on the social media platform Twitter elicits positive and accurate social perceptions. Eleven perceivers rated 128 individuals (targets; total dyadic impressions = 1,408) on their impulsivity, self-esteem, and attachment style, based solely on the information provided in targets' 10 most recent tweets. Targets were on average perceived normatively and with distinctive self-other agreement, indicating both positive and accurate social perceptions. There were also individual differences in how positively and accurately targets were perceived, which exploratory analyses indicated may be partially driven by differential word usage, such as the use of positive emotion words and self- versus other-focus. This study demonstrates that self-expression on social media can elicit both positive and accurate perceptions and begins to shed light on how to curate such perceptions.

Keywords

self-expression, first impressions, accuracy, positivity, social media, Twitter

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Self-expression values have increased substantially in the last four decades, especially among younger cohorts (Inglehart, 2008; Inglehart & Oyserman, 2004). Self-expression is defined as "assertion of one's individual traits" (Self-Expression, n.d.) and individuals have dual motivations to have their traits be seen both positively and accurately (Goffman, 1959; McKenna & Bargh, 1999; Swann, 1983). Importantly, as self-expression values are increasing, the mediums for self-expression are changing, with a rise in the use of social media platforms. This raises the critical question of whether people are able to effectively express themselves in such contexts. The present research investigates whether the information provided on the widely used social media site Twitter enables individuals to elicit positive and accurate perceptions from unacquainted others regarding important characteristics, including self-views, relationship orientations, and behavioral tendencies.

Over 288 million active users are on Twitter, who collectively tweet an average of 500 million messages per day. In the United States, 23% of adult Internet users and 19% of the adult population use Twitter. In recent years, the percentage of users has increased, particularly among individuals aged 18 to 29, with 37% of this cohort using the platform (Duggan, Ellison, Lampe, Lenhart, & Madden, 2014). Although researchers have identified personality correlates of behavior on Twitter (Golbeck, Robles, Edmondson, & Turner, 2011; Quercia, Kosinski, Stillwell, & Crowcroft, 2011), research has not examined whether perceivers are able to detect Twitter users' personality. Given the self-expression attempts of such a large swatch of users, we investigated whether Twitter users are able to elicit positive and accurate perceptions from those who read their tweets.

We define accuracy in the current study as distinctive self-other agreement—the extent to which perceivers' impressions of an individual's (target's) personality (specifically, impulsivity, self-esteem, and attachment style) correspond to the target's own self-reported traits, controlling for the normative profile of responses on these traits. This form of tracking accuracy (Fletcher & Kerr, 2010) assesses the extent to which perceivers are able to accurately discern a target's unique patterning of traits (e.g., is the target higher in self-esteem than

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impulsivity?), relative to the average person or, equivalently, to determine a target's level on a given item relative to other targets' self-reported levels (e.g., is the target higher in self-esteem and impulsivity than other targets? Biesanz, 2010; Biesanz & Human, 2010; Kenny & Winquist, 2001).

Of note, by examining the extent to which perceivers' impressions of the target correspond to the normative profile (in addition to their distinctive self-reported profile), we also obtain an indicator of the positivity of impressions. This is because of the normative-desirability confound (Wood & Furr, 2016): the tendency for the normative profile to be highly positive and socially desirable (Borkenau & Zaltauskas, 2009). Thus, viewing a target more normatively implies viewing that target more positively (e.g., as higher in self-esteem than impulsivity). Note that accuracy and positivity in interpersonal perceptions can be independent of one another (e.g., Funder & Colvin, 1997; Gagné & Lydon, 2004), including when positivity is indexed as normativity (Human & Biesanz, 2012). Thus, this approach enables us to test whether tweets can simultaneously elicit both accurate impressions (distinctive self-other agreement) and positive impressions (normative agreement).

Is it likely that people are able to accurately distill the person behind the messages on Twitter? On one hand, this seems difficult: Tweets are limited to 140 characters and remove many forms of non-verbal communication present in more dynamic impression formation contexts. On the other hand, research on thin slices has found that people are able to accurately judge personality based on minimal information, such as very brief video clips (Ambady & Rosenthal, 1992). When examining perceptions based on social media, a similar picture has emerged. For example, perceivers are able to accurately perceive others' personality traits after viewing their Facebook profiles (Back et al., 2010) and personal webpages (Vazire & Gosling, 2004). Furthermore, personality traits can also be accurately detected based on textual information alone, including creative writing (Küfner, Back, Nestler, & Egloff, 2010) and autobiographical essays (Borkenau, Mosch, Tandler, & Wolf, 2016).

In addition, tweets may in some ways facilitate accurate self-expression. People self-disclose on the internet without strong privacy concerns (Tufekci, 2008), and self-expression on the Internet may provide an opportunity for individuals to share aspects of themselves with less fear of rejection or disapproval than face-to-face interactions with their close social network (Bargh, McKenna, & Fitzsimons, 2002). Furthermore, communicating to a large and diverse set of viewers limits a person's ability to tailor their message to specific audience members (Marwick & Boyd, 2011), which may increase the expression of stable personality traits rather than aspects of the self that vary across interaction partners. On social media platforms, users generate content themselves, which allows for self-expression both explicitly through self-disclosure and implicitly through word usage (VanLear, Sheehan, Withers, & Walker, 2005). Overall, then, it is likely that individuals will be perceived with some accuracy on Twitter.

In addition to being perceived accurately, is it likely that individuals will be seen positively on Twitter? Given that first impressions generally tend to involve quite high levels of normative agreement (e.g., Human & Biesanz, 2011), it seems plausible that impressions based on social media would similarly elicit normative and positive impressions. Indeed, Twitter may be an ideal platform for curating positive perceptions, as it enables individuals to have high control in managing how they present themselves and such control of self-presentation has been found to foster more positive impressions (Human, Biesanz, Parisotto, & Dunn, 2012). We therefore predict that individuals will also be seen positively on the basis of their tweets, although it is possible that positivity may not be quite as high as impressions based on more dynamic information (Schroeder & Epley, 2015).

In addition to predicting that individuals on average will be able to express themselves both positively and accurately using social media, we also expect that there will be individual variability in the tendency to do so. Indeed, in face-to-face interactions, individuals substantially vary in how accurately and normatively they are perceived (Human & Biesanz, 2013). Thus, extending prior research on personality perceptions on social media, we examine not only *whether* impressions are accurate and positive but also *how much* people vary in how accurately and positively they are viewed. This study will also take a preliminary, exploratory look at how it is that individuals may come to elicit positive and accurate perceptions from others through social media by examining the content of tweets, particularly word usage. The types of words people use can reveal individuals' personality traits and other internal experiences (e.g., Küfner et al., 2010; Mehl, Gosling, & Pennebaker, 2006; Rude, Gortner, & Pennebaker, 2004), including in tweets (De Choudhury, Gamon, Counts, & Horvitz, 2013), suggesting that word usage may be one way personality is detected and evaluated on Twitter.

Addressing these questions could have important implications for understanding self-expression values, communication via social media, and for psychological and social well-being. Indeed, being perceived accurately and positively can have positive social outcomes in first impressions contexts, promoting relationship development (Human, Sandstrom, Biesanz, & Dunn, 2013), and in close relationships, promoting relationship quality and longevity (Murray, Holmes, & Griffin, 1996; Neff & Karney, 2005). Being accurately perceived in first impressions is also associated with better psychological well-being (Human & Biesanz, 2011, 2013; Human, Biesanz, Finseth, Pierce, & Le, 2014). Knowing whether and how Twitter can be used as an effective medium for positive and accurate self-expression would therefore be informative with respect to whether the investment in self-expressing on this platform is beneficial for targets, and whether basing personality perceptions on such information is warranted for perceivers.

Method

Overview

In the present study, 128 undergraduate Twitter users (targets) completed a 105-item battery of personality items and provided their last 10 tweets. We chose trait measures designed to tap targets' behavioral tendencies, views of the self, and perspectives on interpersonal relationships. Specifically, we included items from scales assessing impulsivity, self-esteem, and attachment styles. Preliminary evidence suggests that tweets are likely to contain content related to self-esteem and belonging motives (Selim, Long, & Vignoles, 2014), suggesting that these are relevant domains in which to test personality perception accuracy. Eleven perceivers read the provided set of 10 tweets from a target and rated that target on the same 105 items. No other identifying information, such as gender or Twitter handle, was provided.

Targets

A total of 128 undergraduate students (targets) completed measures of their personality traits.[1] This set of targets (37 male, 91 female) ranged in age from 18 to 22 (M = 18.5; SD = .73). On average, this sample had been using Twitter for 2 years (SD = 1.21 years) and had an average of 218 Twitter followers (SD = 167).

Materials and Procedure

Targets first completed scales assessing their impulsivity, self-esteem, and attachment style.[2] They then entered their 10 most recent tweets, with instructions to remove the name of specific people (i.e., a friend they were describing) by replacing the person's name with "[Name]." Targets were instructed to report all their tweets and not to skip any. They were instructed to only include tweets they composed themselves, not retweets. No targets were excluded from data analysis.

Impulsivity. Targets completed the UPPS Impulsive Behavior Scale (Whiteside & Lynam, 2001), which is a 45-item scale with subscales assessing negative urgency (e.g., " When I am upset I often act without thinking"), premeditation (e.g., "My thinking is usually careful and purposeful"), sensation seeking (e.g., "I generally seek new and exciting experiences and sensations"), and perseverance ("I generally like to see things through to the end"). In addition, targets completed the positive urgency measure (Cyders et al., 2007), which contains 14 items (e.g., "I tend to lose control when I am in a great mood"). All impulsivity items included response options ranging from 1 (*strongly disagree*) to 5 (*strongly disagree*). On average, across domains, targets endorsed low-moderate levels of impulsivity (M = 2.75; SD = .39).

Self-esteem. Targets completed the Rosenberg Self-Esteem Scale (Rosenberg, 1965). This scale contains 10 items with response options ranging from 1 (*strongly disagree*) to 4 (*strongly agree).* Targets on average reported high levels of self-esteem (M = 3.04; SD = .51).

Attachment style. Targets completed the Experiences in Close Relationships–Revised (ECR-R; Fraley, Waller, & Brennan, 2000) scale. This scale contains 36 items, 18 of which tap a dimension of anxious attachment (e.g., "I'm afraid that I will lose my partner's love") and 18 of which tap a dimension of avoidant attachment (e.g., "I prefer not to show a partner how I feel deep down"). Targets were instructed: "We are interested in how you *generally* experience relationships, not just in what is happening in a current relationship." Response options ranged from 1 (*strongly disagree*) to 7 (*strongly agree*). Targets on average reported low levels of anxious (M = 3.43; SD = 1.10) and avoidant (M = 3.11; SD = 1.04) attachment.

Perceiver ratings. A set of 11 perceivers, all Twitter users who were undergraduates at the same university as the targets, were presented with the set of 10 tweets from each target, one at a time. They then rated the personality of the target using the same set of items the targets self-reported. The tweets remained on the computer screen while the perceivers made their judgments; perceivers completed all items for a single target before moving on to a new target. Raters were instructed not to judge participants if they thought they recognized the targets. No rater reported recognition of any target.

Analytical Approach

Accuracy and positivity were estimated with a multilevel model utilizing R's *lme4* package (Bates, Mächler, Bolker, & Walker, 2015; R Development Core Team, 2016), following the social accuracy modeling (SAM) procedures (Biesanz, 2010; Human & Biesanz, 2011). Specifically, in the within-perceiver part of the model (Level 1) perceivers' ratings of each target on each trait item were regressed on (a) the target's self-report on that item after subtracting the normative mean for that item (assessing distinctive accuracy) and (b) the normative mean for that item (assessing normativity/positivity). Each perceptual tendency was allowed to vary randomly across perceivers and targets as follows:

$$Y_{ijk} = \beta_{0ij} + \beta_{1ij}\mathrm{TSelf}_{jk} + \beta_{2ij}\mathrm{Mean}_k + \varepsilon_{ijk}. \quad (1.1)$$

$$\begin{aligned}\beta_{0ij} &= \beta_{00} + \beta_{01}\mathrm{Word}_j + u_{0i} + u_{0j} + u_{0(ij)}\\ \beta_{1ij} &= \beta_{10} + \beta_{11}\mathrm{Word}_j + u_{1i} + u_{1j} + u_{1(ij)}\\ \beta_{2ij} &= \beta_{20} + \beta_{21}\mathrm{Word}_j + u_{2i} + u_{2j} + u_{2(ij)}.\end{aligned} \quad (1.2)$$

Here Y_{ijk} is perceiver i's rating of target j on item k, and TSelf_{jk} is target j's self-report on item k after partialling out

$Mean_k$, the mean self-report on item k across all targets. The regression coefficient β_{1ij} thus represents the level of distinctive accuracy for perceiver i rating target j, or the extent to which perceiver i's ratings of target j correspond to target j's unique self-reported personality profile. The regression coefficient β_{2ij} reflects normativity/positivity, or the extent perceiver i's ratings of target j correspond to the mean self-reported personality profile. The fixed effects β_{00}, β_{10}, and β_{20} (Equation 1.2) represent the average intercept, distinctive accuracy, and normativity slope, respectively, across both perceivers and targets.

Items were not reverse coded prior to analysis. We estimated models for the full set of items to examine accuracy overall across all traits, maximizing power, as well as for each characteristic separately (impulsivity, self-esteem, and anxious and avoidant attachment style) to examine specificity. Note that because different constructs were assessed on different rating scales, items were standardized within-scale prior to analyses.

Importantly, SAM also allows for the assessment of the degree of individual differences in target distinctive accuracy and normativity on average across perceivers (see Biesanz, 2010). As outlined in Equation 1.2, this approach separates true latent variability into perceiver, u_i, and target, u_j, main effects and the residual dyadic components, $u_{(ij)}$, which reflect unique effects plus measurement error. Specifically, the us represent the random (latent) effects in terms of deviations from the grand mean (fixed effects). For example, u_{1j}, is target j's unique distinctive accuracy slope averaged across the 11 perceivers, u_{1i} is perceiver i's unique distinctive accuracy slope averaged across all 128 targets, and $u_{1(ij)}$ is the dyadic plus residual (error) component for perceiver i and target j. The variance of u_{1j} across targets is estimated to provide an indicator of the degree of reliable variance in distinctive accuracy due to targets and tested with a nested chi-square difference test comparing the models with versus without distinctive accuracy varying randomly as a function of targets. The same was approach was taken to assess variability around targets' unique normativity slopes, u_{2j}, to examine individual differences in how normatively or positively targets were viewed.

Equation 1.2 also demonstrates how we conducted our exploratory analyses of how word usage, such as the amount and type of words (e.g., affect, social, cognitive), might come to elicit accurate and positive perceptions. This was examined by including word categories ($Word_j$) as moderators of the distinctive accuracy and normativity slopes at Level 2 (see Equation 1.2). A positive relationship between a moderator variable (e.g., word count) and the distinctive accuracy (β_{11}) or normativity (β_{21}) slopes would indicate that using more words is associated with being viewed more in line with one's distinctive traits or as more normative, respectively. We report effect size estimates, ds, for all interaction effects, calculated as the change in standard deviations in the dependent variable for a two standard deviation change in the independent variable, to make these effect size estimates comparable with effect sizes for binary independent variables (e.g., Cohen's d; see Gelman, 2008).

Table 1. Levels of and Variability in Accuracy and Positivity.

	Mean levels		Target individual differences
Model parameters	b (SE)	z	SD
Overall			
Distinctive accuracy	$.05^{**}$ (.013)	3.66	$.13^{**}$
Normativity	$.30^{**}$ (.039)	7.57	$.12^{**}$
Impulsivity			
Distinctive accuracy	$.11^{**}$ (.024)	4.80	$.11^{**}$
Normativity	$.17^{*}$ (.029)	5.72	$.29^{**}$
Self-esteem			
Distinctive accuracy	$.03^{\dagger}$ (.016)	1.74	$.12^{**}$
Normativity	$.62^{**}$ (.058)	10.69	$.16^{**}$
Anxious attachment			
Distinctive accuracy	.02 (.018)	0.96	$.16^{**}$
Normativity	$.17^{**}$ (.036)	4.85	$.07^{**}$
Avoidant attachment			
Distinctive accuracy	.01 (.015)	0.45	$.09^{**}$
Normativity	$.28^{**}$ (.075)	3.77	$.25^{**}$

Note. Mean levels are the fixed effects slopes (unstandardized). Target individual differences were assessed as the variance (estimated SDs) around targets' unique distinctive accuracy, u_{1j}, and normativity, u_{2j}, main effects.
$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .001$.

Results

Primary Analyses

First, after viewing 10 tweets, did perceivers view targets normatively and therefore positively on average? Perceivers viewed targets with significant levels of normativity overall, $b = .30$, $z = 7.57$, $p < .001$, and on impulsivity, $b = .17$, $z = 5.72$, $p < .001$, self-esteem, $b = .62$, $z = 10.69$, $p < .001$, and anxious, $b = .17$, $z = 4.85$, $p < .001$, and avoidant, $b = .28$, $z = 3.77$ $p < .001$, attachment style (see Table 1). Because on average targets' self-reported traits were relatively positive, including high levels of self-esteem and lower levels of impulsivity, anxious attachment, and avoidant attachment (see Methods), being viewed in line with the average target self-report on these traits suggests that targets were on average also viewed relatively positively on these traits. These levels of normativity were generally lower than typically seen in perceptions of the Big Five after brief face-to-face interactions (e.g., $b = .93$; Human & Biesanz, 2011) and based on video perceptions (e.g., $b = .50$; Human et al., 2014). This may be due in part to the less dynamic impression formation context but is also likely in part a function of the differences in scaling, as our items were standardized prior to analyses, whereas prior research used original item metrics. Indeed, when normativity was assessed within trait

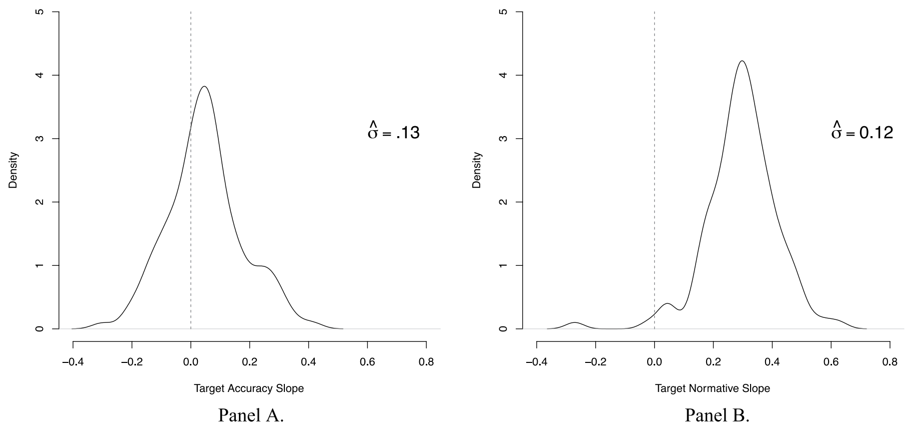

Figure 1. The degree of individual differences in how accurately (Panel A) and normatively (Panel B) targets were viewed are displayed with a kernel density plot of the distribution of the random effects (n = 128). The sigma-hat is the estimated standard deviation across unique target distinctive accuracy, u_{1j}, and normativity, u_{2j}, slopes.

with items in their original metric, levels were closer to that seen in video perceptions contexts but still lower than face to face impressions.

Were targets' distinctive traits also viewed accurately? On average, targets were viewed with significant levels of distinctive accuracy overall across traits, b = .05, z = 3.66, p < .001, and on impulsivity, b = .03, z = 2.06, p < .04, and with marginally significant levels of accuracy on self-esteem, b = .03, z = 1.74, p = .08 (see Table 1). However, targets were not viewed with significant levels of accuracy on either anxious, b = .02, z = 0.96, p = .34, or avoidant, b = .01, z = 0.45, p = .65, attachment style. These levels of distinctive accuracy are lower than what is typically observed in first impressions based on face-to-face interactions and video-based perceptions of the Big Five (e.g., b = .08; Human & Biesanz, 2011; Human et al., 2014), both when standardized and when left in their original metrics. Thus, the overall patterning of traits across all characteristics, and within impulsivity and self-esteem, were somewhat detectable based on tweets, but attachment style was harder to discern.[3]

Importantly, however, there was also significant variability in target distinctive accuracy and normativity, indicating that there were reliable individual differences in how accurately and positively targets were perceived based on tweets (see Table 1). Figure 1 provides the distributions of targets' distinctive accuracy and normativity slopes (i.e., how accurately and positively each target was seen on average across perceivers, respectively). Panel A demonstrates that there was substantial variability in how accurately targets were viewed, with some being viewed with high levels of accuracy (Max b = .39) and others being viewed with very inaccurately (Min b = −.28). Similarly, Panel B demonstrates the substantial variability in how positively targets were viewed, with some being viewed with high levels of normativity (Max b = .61), and others being viewed with much less normatively (Min b = −.24).

Exploratory Analyses

The aim of our exploratory analyses was to test whether word usage predicted how accurately and positively targets were viewed. According the realistic accuracy model (RAM; Funder, 1995), for a target to be perceived accurately, cues to the targets' personality must be both *available* and *relevant*. Thus, the quantity and quality of information provided in tweets may increase the cue availability and relevance stages of RAM, respectively, enabling accurate perceptions. Furthermore, both the quantity and type of information provided could influence how positively targets are viewed. To code word quantity and quality/type, we utilized the Linguistic Inquiry and Word Count program (LIWC2015; Pennebaker, Booth, Boyd, & Francis, 2015), which provides indicators of the amount of information (e.g., total word count, dictionary words) as well as a variety of information types, many of which could convey both diagnostic and evaluative information, including words that involve affect, other- versus self-focus, cognitive processes, drives, and personal concerns.

We examined whether each of the 93 LIWC categories were related to the accuracy and positivity in perceptions on average across all traits and for each trait separately. Given that this resulted in a very large number of analyses and therefore high potential for spurious findings, we focus on presenting cues that were a significant predictor of accuracy or positivity in the analyses that included all trait categories, as these may be more reliable effects (see Table 2 for key results and Table 3 for examples). Nevertheless, we emphasize that these analyses are highly exploratory, included to provide preliminary insights and suggest avenues for future research.

Predictors of normative perceptions. What aspects of tweets predicted being viewed in a more normative, positive manner? First, providing more information in the form of more

Table 2. Associations Between Accuracy and Positivity and Linguistic Characteristics of Tweets.

		Accuracy		Normativity	
Word category	*M* (*SD*)	*d*	*z*	*d*	*z*
Information quantity					
Word count	111.10 (33.88)	−0.11	−0.59	0.37*	1.99
Information quality					
Affect					
Tone	52.99 (36.54)	0.13	0.67	0.67***	3.74
Positive emotion	4.35 (2.54)	−0.04	−0.22	0.47*	2.52
Negative emotion	2.77 (2.00)	−0.31	−1.55	−0.56**	−2.83
Anger	0.98 (1.26)	−0.12	−0.59	−0.29	−1.43
Sad	0.68 (0.89)	−0.23	−1.23	−0.35†	−1.94
Anxiety	0.38 (0.71)	−0.42*	−2.37	−0.09	−0.50
Swear	0.70 (1.20)	−0.14	−0.60	−0.49*	−2.15
Sexual	0.26 (0.60)	−0.26	−1.30	−0.46*	−2.34
Negations	1.90 (1.36)	0.18	0.93	−0.42*	−2.32
Certainty	1.69 (1.39)	−0.03	−0.15	0.38*	2.12
Clout	52.57 (26.42)	0.42*	2.24	0.46*	2.50
All punctuation	28.52 (18.43)	0.34†	1.84	0.47**	2.59
Quotations	1.04 (2.01)	−0.16	−0.88	0.43*	2.35
Periods	5.95 (4.21)	0.43*	2.31	0.27	1.46
Self/other focus					
Personal pronouns	10.05 (3.37)	−0.39*	1.98	−0.10	−0.53
I-talk	6.84 (3.13)	−0.56**	−3.06	−0.17	−0.92
Male referents	0.71 (1.01)	0.55*	2.47	0.36	1.62
Experiential					
Feeling	0.60 (0.90)	0.38*	2.07	0.06	0.35
Time	6.78 (3.00)	0.43*	2.34	0.17	0.91

Note. Means represent mean total (word count, tone, clout, punctuation) or percentage across all 10 tweets.
†$p \leq .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 3. Example Tweets for Word Categories Associated With High and Low Levels of Accuracy and Positivity.

Perception	Linguistic category	Example
Accuracy		
Low	Anxiety	Prob failed bio . . . time to **stress** out about planning for the next 3 hrs
	I-talk	Every time **I** cyberstalk **I** end up with a pit in **my** belly because of how **I** feel toward what **I** view, you'd think **I**'d stop, right?
High	Male referents	It all started here just last year. So many memories with these **guys**!
	Feeling/time	It was **freezing**! Showered in the waterfall! I am **back**!!!
Positivity		
Low	Negative emotion/swear	Sometimes I really **fucking hate** going to class
	Sad	I knew this day would come but it's sort of **sad** reminiscing
High	Positive emotion	So **excited** for Christmas! Family **fun:)**))))
	Certainty	That was hands down the best match **ever**, great game **everyone**!
Accuracy and positivity		
High	Punctuation	When your little sister asks what **"marijuana"** is . . .

Note. These example tweets were constructed to resemble actual participant tweets that fit into these categories. The actual tweets were changed to protect participant confidentiality. Bolded words fall within the corresponding linguistic category.

total words overall was associated being perceived more positively (see Table 2). Furthermore, more affectively positive versus negative tweets were quite consistently associated with being viewed more positively (see Table 3 for examples).

This can be seen in the summary affective tone variable, which is an index of the ratio of positive to negative words, as well as the individual positive and negative emotion variables. Examining the negative emotion subscales indicates that this association was strongest for sadness-related words, although the association was marginally significant.

Using more swear and sexuality-related words were also associated with being perceived less positively. This may be due in part to the overlap in content between both of these word categories and negative emotion words (see Table 3 for an example). Furthermore, using more negations in speech (e.g., couldn't, don't, won't) was also associated with being viewed less positively, which may also be because such word use conveys greater negativity.

In contrast, tweets that involved more certainty words (e.g., always, every) were associated with being viewed more positively (see Table 3 for example). A similar pattern emerged for tweets higher in "clout," a summary indicator of confidence or leadership indicated by using fewer first person singular pronouns or I-talk (e.g., I, me) and more first person plural pronouns (e.g., we, us; Kacewicz, Pennebaker, Davis, Jeon, & Graesser, 2014). Finally, the use of more punctuation and quotations in particular were also associated with being viewed more positively. Although LIWC is not able to code for humor, an informal qualitative look at tweets higher in punctuation and quotations suggests they may have elicited more positive perceptions because they were often used as comic devices (see Table 3 for example). Thus, words that convey more positivity, confidence, and humor, and less negativity, may promote being viewed more positively.

Predictors of accurate perceptions. What aspects of tweets were associated with being viewed more accurately? Greater information quantity was not significantly associated with the accuracy of perceptions and only one affect word was significantly associated with accuracy: The use of more anxiety-related words was associated with being viewed less accurately (see Table 2). Using more personal pronouns (e.g., *I'm*, *we*) and, in particular, I-talk, was also associated with being viewed less accurately. This indicates that more self-focused tweets that expressed insecurity may have hindered accurate perceptions (see Table 3 for examples).

In contrast, using more male referents (e.g., boyfriend, brother), exhibiting greater clout (i.e., less I-talk), and using more punctuation, in particular periods, was associated with being viewed more accurately. Using more feeling (e.g., warm, cold, felt) and time (e.g., today, wait, back) words, potentially indicative of a more experiential, action-oriented focus, was also associated with being viewed more accurately. Taken together, these findings suggest that tweets that were more other-focused, confident, potentially humorous, and experiential in nature may have facilitated more accurate perceptions (see Table 3 for examples).

Discussion

Social media outlets such as Twitter represent widely used platforms for self-expression. Self-expression is a strongly held value in modern culture (Inglehart, 2008; Inglehart & Oyserman, 2004) that involves the dual motivations to be seen both positively and accurately (Goffman, 1959; McKenna & Bargh, 1999; Swann, 1983). In turn, being perceived positively and accurately in first impression settings predicts positive social consequences (Human et al., 2013) and is associated with better psychological functioning (Human & Biesanz, 2011; Human et al., 2014), suggesting that being perceived in such a manner on Twitter could benefit individuals. Thus, it is important to understand whether attempts at self-expression on social media platforms produce both veridical and positive perceptions of targets.

The present study provides evidence that individuals can be seen accurately on Twitter, or at least in line with their distinctive self-views, extending previous research examining other social media platforms, including Facebook (Back et al., 2010) and personal webpages (Vazire & Gosling, 2004). These findings also extend prior research, which has primarily focused on the Big Five personality traits, by examining other important dimensions of personality: impulsivity, self-esteem, and attachment style. In particular, this study indicates that it is possible to detect impulsivity and self-esteem on the basis of tweets, but that attachment style is more difficult to perceive. However, even the accuracy of perceptions of impulsivity and self-esteem tended to be lower than accuracy for the Big Five based on face-to-face interactions (Human & Biesanz, 2011) and video clips (Human et al., 2014), suggesting that, although possible, conveying a distinctively accurate impression on Twitter can be a difficult task and perceivers should be cautious about inferring too much from tweets alone.

We also examined how positively targets' personalities were perceived by examining the degree of normativity in perceptions (Wood & Furr, 2016), finding that impressions based on Twitter did tend to be quite positive. Interestingly, on average, targets were viewed with similar levels of normativity to those being rated on the Big Five after exposure to brief video clips (Human et al., 2014), but perceptions were less normative than those based on face-to-face impressions (Human & Biesanz, 2011). This suggests that dynamic, interactive social contexts may foster more positive impressions than more passive ones (see also Schroeder & Epley, 2015). However, research is needed that directly compares impressions based on Twitter and other social media contexts with impressions based on more dynamic and interactive social contexts.

Importantly, this study also extends previous research by demonstrating that there were significant individual differences in how accurately and positively targets were perceived on Twitter. Indeed, even though on average levels of accuracy were quite low, some individuals were viewed with much higher levels of distinctive accuracy, well above the average levels seen in face-to-face interactions. Similarly, even though impressions tended to be relatively normative, some individuals were viewed with quite low levels of normativity and therefore positivity. This variability suggests that there may be ways that individuals can actively attempt to elicit more (or less) accurate and positive perceptions on Twitter. To try to gain initial insight into why some individuals were perceived more accurately and positively than others, we explored what characteristics of tweets, such as their information quantity and quality, might contribute to this variability.

Interestingly, greater information quantity in tweets in the form of a greater number of words predicted being perceived more positively. This may be because more information in tweets may imply greater self-disclosure (Collins & Miller, 1994) and enhance familiarity (Reis, Maniaci, Caprariello, Eastwick, & Finkel, 2011), thereby increasing liking. Furthermore, just as a lower volume of tweets can indicate depression (De Choudhury et al., 2013), shorter tweets may similarly reflect and convey a less positive internal state, eliciting less positive perceptions.

Several other types of linguistic information were also associated with the positivity of perceptions. In particular, positive emotion words and indicators of greater confidence, such as more certainty words and lower self-focus, elicited more desirable perceptions. In contrast, expressing greater negative emotion, particularly sadness, using more negations, and swearing more elicited less desirable impressions. Greater use of negative emotion words have also been linked to greater depression, both in tweets (De Choudhury et al., 2013) and other written communications such as essays (Rude et al., 2004); thus, it is not surprising that such linguistic patterns would elicit less positive perceptions from perceivers. More surprisingly, greater use of punctuation, especially quotations, was also associated with more positive perceptions. This may have been due to their use as comical devices, but this speculation requires further examination. Thus, to be seen positively on traits such as impulsivity, self-esteem, and attachment style, individuals may wish to aim for positive, confident, and humorous tweets.

In contrast, even though greater information quantity has been linked to more accurate impressions (e.g., Blackman & Funder, 1998), information quantity as indexed here was not significantly associated with greater accuracy. This may be because the upper limit of 140 characters may have limited how much greater information could actually increase accuracy. Indeed, the benefits of greater information have been demonstrated when comparing larger differences in quantity, such as 5- to 10-min versus 25- to 30-min video clips (Blackman & Funder, 1998) or months versus years of acquaintanceship (Biesanz, West, & Millevoi, 2007). Thus, a difference of several words may not be sufficient enough to influence cue availability and in turn accuracy.

Although the amount of information in tweets did not significantly increase accuracy, other types of linguistic cues in tweets were linked to accuracy. In particular, more other-focused tweets, indicated by greater use of male referents and less I-talk, were associated with being perceived with greater accuracy, as were tweets that may have involved more experiential information. It is possible that tweets that focus more on others and actions, relative to the self, convey more relevant, diagnostic information about an individual than tweets that are more self-focused. Alternatively, self-focused tweets may not necessarily decrease cue relevance themselves, but may instead be a marker of worse psychological adjustment, which has been linked to the provision of less personality-relevant cues and lower accuracy in other social contexts (e.g., Human et al., 2014). Indeed, more self-focused language has been linked to negative psychological states and outcomes, including depression (De Choudhury et al., 2013; Rude et al., 2004) and suicidal tendencies (Stirman & Pennebaker, 2001). In line with this, the use of more anxiety-related words in tweets, which could be a market of maladjustment, was also associated with being viewed less accurately. Whether such linguistic patterns directly contribute to less accurate perceptions, or are an indicator of broader psychological functioning that influences accuracy, is a critical question for future research.

Of course, given the exploratory nature of these analyses, these effects must be interpreted cautiously and will ideally be replicated in future research with larger samples and in different social contexts. For example, although strangers may not respond very positively to more negative tweets, those within an individual's online social networks may view such self-disclosures more sympathetically (e.g., Forest & Wood, 2012). In addition, the sample involved college students who may use Twitter differently from other samples and age groups. Indeed, more generally, our data are limited because we examined undergraduate Twitter users who were rated by other undergraduates. Future research should investigate whether similar patterns are found for other types of users and raters, including older individuals, celebrities, and politicians. Furthermore, the sample was predominantly female, and although some gender differences emerged (see Footnote 3), more gender-balanced samples are needed to explore these effects.

More generally, the present results call for additional research and suggest avenues for future research on how personality is perceived and expressed on social media. One major question concerns the potential generalizability versus specificity of the findings. Twitter is now populated by more than 288 million active users who tweet about 500 million messages per day, making it a particularly important domain to investigate self-expression. If the present results are limited to Twitter and do not extend to other platforms, then such a finding would itself be interesting, and would call for research to investigate the critical differences across platforms. However, there is reason to believe the results will generalize to other social media platforms, as research investigating self-expression on Facebook (Back et al., 2010) and personal webpages (Vazire & Gosling, 2004) similarly demonstrate that accuracy can be achieved. However, different traits were examined in those contexts and different approaches were used; thus more research is needed on (a) which personality traits are accurately perceived on social media, (b) which social media platforms facilitate more versus less accuracy, and (c) whether specific platforms are more effective than others at communicating specific traits. It would also be interesting to examine whether these results generalize to other contexts in which brief text serves as the communication mode, such as text messages.

One potential limitation of these studies is the use of self-reports as the accuracy criterion. Although self-reports are a common and valid accuracy criterion (Funder & Colvin, 1997), using additional realistic accuracy criteria (Funder, 1995) to validate perceptions, such as close-other reports or behavioral indicators, would further strengthen conclusions about whether personality can be perceived accurately on Twitter. Indeed, it is possible that the apparently less accurate perceptions of those who use more I-talk are due to a lack of self-knowledge on the part of targets rather than inaccuracy on the part of the perceiver. This is especially possible given the evaluative nature of these traits, which the self may not always have accurate insight into (Vazire, 2010). On the contrary, the less observable nature of many of the traits examined in the present study does suggest that reliance on self-reports is valid, as the self tends to have unique insight into such traits, relative to outside observers (Vazire, 2010). Moreover, given that being viewed in line with one's self-views, even when negative, is in itself an important and often positive experience, socially, psychologically, and physiologically (e.g., Ayduk, Gyurak, Akinola, & Mendes, 2013; Swann, 1983), self-reports remain an important comparison with outside observers' perceptions.

Conclusion

Overall, these results contribute to research demonstrating that social media platforms can be an effective outlet for accurate and positive self-expression of personality traits, extending such findings to the widely used platform of Twitter and to previously unexplored personality traits, such as impulsivity, self-esteem, and attachment style. Indeed, just 10 tweets from a person provided enough information for perceivers to accurately distill the person behind the message, particularly for impulsivity and self-esteem, while also eliciting generally normative and therefore positive perceptions. There was also, however, significant variation in how accurately and positively individuals were perceived on Twitter, with some individuals being relatively open and enjoyable books, and others being more difficult and less enjoyable to read. Exploratory analyses suggest that word usage in tweets contributed to these individual differences, with affective content and degree of other- versus self-focus appearing to play particularly important roles. Ideally, future work will continue to examine what characteristics are accurately and positively perceived on social media, through what cues and processes, and whether such perceptions are in turn consequential for both targets and perceivers.

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Supplemental Material

The online supplemental material is available at http://pspb.sagepub.com/supplemental.

Notes

1. We recruited 150 targets. Twenty-two potential participants did not have Twitter accounts and therefore completed an unrelated study.
2. Targets also completed measures of their self-regulatory modes and perceived supportiveness of their Twitter followers. These measures are not considered because raters did not evaluate targets on these dimensions.
3. There were significant gender differences in how targets were perceived, such that women were viewed less positively on self-esteem and anxious attachment, and more positively on avoidant attachment, as well as less accurately on both anxious and avoidant attachment. Given that the male target sample was small (N = 37; 29%), gender differences are not a focus of this study but suggest a future research direction.

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