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The impact of actively open-minded thinking on social media communication

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Abstract

Online, social media communication is often ambiguous, and it can encourage speed and inattentiveness. We investigated whether Actively Open Minded Thinking (AOT), a dispositional willingness to seek out new or potentially threatening information, may help users avoid these pitfalls. In Study 1, we determined that correctly assessing social media authors' traits was positively predicted by raters' AOT. In Study 2, we used data-driven methods to devise a three-dimensional picture of online behaviors of people high or low in AOT, finding that AOT is associated with thoughtful, nuanced, idiosyncratic actions and with resisting the typically fast pace of online interactions. AOT may be an important factor in accurate, socially responsible online behavior.

Keywords: computer-mediated communication, social media, linguistic analysis, individual differences

1 Introduction

In 1993, a famous New Yorker cartoon by Peter Steiger coined the famous axiom representing the difficulty of understanding other people online: "On the internet, nobody knows you're a dog." Although technological advancements have greatly changed online interactions in the subsequent years, the internet continues to have a number of limitations as a platform for interaction. Compared to face-to-face interaction, successful online communication requires additional attention and motivation. Social cues can be ambiguous or absent, and the variety and fleeting nature of the information can be overwhelming. In addition, users have a large degree of control over the information and people they encounter, meaning there can be minimal social consequences to misunderstandings online.

Because of this combination of an increased ability to filter content along with an overwhelming amount of ambiguous information, many researchers have expressed concern over the possibility that internet users selectively filter out or ignore material and perspectives they dislike, disagree with, or do not quickly understand (e.g., Bakshy, Messing & Adamic, 2015; Barbera, et al., 2015; Bennett & Iyengar, 2008). In other words, social media use may be particularly prone to promoting closed-mindedness.

One characteristic that might address this problem is Actively Open-Minded Thinking (AOT; Baron, 1993, in press), the dispositional willingness to seek out and thoughtfully engage with new and even threatening information. In this paper, we demonstrate explicit benefits of trait AOT in the accurate perception of other people online; then, using data-driven methods such as Natural Language Processing, we present a picture of how AOT manifests itself in online behaviors.

1.1 Challenges in computer-mediated communication (CMC)

Computer-mediated communication (CMC) using text is an inherently limited channel for interaction when compared to face-to-face interactions: it cannot convey important cues such as facial expression, tone of voice, and body language (Sproull & Kiesler, 1986). Some researchers believe that the absence of these cues presents difficulties that cannot be easily overcome, leading to miscommunication (Kruger, Epley, Parker & Ng, 2005) and misperceptions of others (Epley & Kruger, 2004; Okdie, Guadagno, Bernieri, Geers, Mclarney-Vesotski, 2011). Some evidence suggests that such misperceptions even extend to assessments of a person's membership in basic demographic categories such as age and gender, which are typically automatic and easy in face-to-face communication (Quinn et al., 2002; Tranel, Damasio & Damasio, 1988), but are more difficult when there is a dearth of vi-

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sual or audible cues, such as on social media (Flekova at al., 2016).

However, other research indicates that users can learn to attend to alternative cue systems (e.g., Walther, 1992, 1993) to form correct impressions of others online (e.g., Carpenter et al., 2016; Darbyshire et al., 2016; Tskhay & Rule, 2014). Overall, it is not clear how well these alternative cue systems work — that is, whether the impressions made through CMC are necessarily less accurate than those made face-to-face, or if people can accurately judge others based solely on text-based, online communication.

Furthermore, text-based social communicaton necessarily occurs in a digital medium, which generally facilitates a faster and shallower orientation towards information. Users have poorer retention of information they expect to be able to encounter online (Sparrow, Liu & Wegner, 2011), they focus on "ground-level information" at the expense of "big-picture construal" (Kaufmann & Flanagan, 2016), and they compensate for large amounts of information by strategically skimming content (Duggan & Payne, 2011). Heavy social media users are less likely to enjoy effortful thought and also are likely to engage in media multitasking (Zhong, Hardin & Sun, 2011), which is associated with less attentiveness and poorer performance on cognitive tasks (Vega, McCracken, Nass & Labs, 2008).

Finally, social media platforms typically allow users a degree of control over the people and information they encounter, which can result in ideological segregation (e.g., Bakshy, Messing & Adamic, 2015; Dehghani, et al., 2016; Vaccari, et al., 2016). Although the magnitude of this "echo chamber effect" is debated (e.g., Barbera, et al., 2015; Flaxman, Goel & Rao, 2016), the consequences may be severe: online extremism has been linked to devaluing science (Helmuth, Gouhier, Scyphers & Mocarski, 2016), the spread of misleading political information (Shin, Jian, Driscoll & Bar, 2016), and ultimately might lead to less competent citizenship (Flynn, Nyhan & Reifler, 2017).

In sum, not only are some basic types of social cognition more difficult in text, but the digital, online medium can facilitate a closed-minded mindset (Kruglanski, 2004) characterized by inattentiveness and avoidance of challenging information. However, individual differences may affect the extent to which users draw on useful cues within the CMC context despite these limitations.

1.2 Actively open-minded thinking

One potentially promising antidote to this closed-mindedness is users' willingness to attend to new information and adopt a thoughtful, methodical mindset. This cognitive style is known as Actively Open-Minded Thinking (AOT). People high in AOT on the trait level (measured by the AOT scale used by Haran, Ritov & Mellers, 2013, and other similar scales) are more accurate at a variety of judgments, such as estimating amounts (Haran, Ritov & Mellers, 2013), distinguishing between good and bad arguments (Stanovich & West, 1997), and forecasting world events (Mellers et al., 2015).[1] In short, this cognitive style has real-world benefits: by ignoring biases and being open to sources of information, people are more likely to make accurate inferences.

AOT is one of many constructs related to trait-level, epistemic orientations. Other commonly used scales are Need for Cognition (Cacioppo & Petty, 1982), which measures a motivation to cognitively elaborate on information; Need for Closure (Webster & Kruglanski, 1994), which measures intolerance for ambiguity and uncertainty; and Personal Fear of Invalidity (Thompson, Naccarato, Parker & Moskowitz, 2001), which measures the aversion to reaching erroneous conclusions. AOT is correlated with these measures (e.g., Haran, Ritov & Mellers, 2013), but it is distinct in that it specifically describes a preference towards taking in more diverse amounts of information, especially information that may conflict with previous intuitions. This tendency is in direct contrast to the hasty, inattentive mindset typically facilitated by digital communication (e.g., Sparrow, Liu & Wegner, 2011; Zhong, Hardin & Sun, 2011). Therefore, AOT may play a beneficial role in CMC by increasing users' tendency to attend to the distinctively scarce social cues online, via either more fair-minded or more extensive search.

If AOT is indeed beneficial for understanding others online, the next step in understanding its influence on social media behavior is to take advantage of the enormous amounts of information produced on social media to reveal the patterns of behavior associated with high and low levels of AOT. Data-driven, unrestricted techniques can allow us to visualize how AOT's thoughtful and tolerant orientation has distinct effects on the ways people communicate online in the real world; in particular, the behavior of people high in AOT may be distinguished by their preference to avoid impulsive conclusions.

1.3 Current goals

The present study had two aims. First, we used quasi-experimental methods to investigate whether having high AOT would facilitate drawing accurate conclusions about others based only on their social media activity. Second, we applied data-driven methods to explore and visualize the ways that AOT manifests itself across people's general social media behavior: its effect on linguistic expression, visual self-representation, and interpersonal behaviors. We therefore focused on both sides of social media participation: responding to content and creating content. In other words, we sought to answer: (1) is AOT beneficial for CMC? and (2) what general, real-world social media behavior is associated with AOT?

[1] For a longer list, see Baron (in press), and Stanovich (2016).

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2 Study 1

The goal of Study 1 was to investigate whether AOT is associated with drawing objectively accurate conclusions about other people online. Specifically, we predicted that high-AOT individuals would be better at guessing targets' basic demographic traits relying solely on the targets' social media posts. Because these basic categorizations are often automatic and easy in face to face interactions (e.g., Tranel, Damasio & Damasio, 1988), it is especially useful to examine if AOT is associated with greater accuracy in a social media context, where sparser cues make people more likely to fail.

2.1 General methods and materials

Study 1 consists of four sub-studies, all of which followed the same procedure and had the same hypothesis. Participants were shown a series of tweets by target authors and asked to guess each author's status on a selected characteristic (1a: gender; 1b: age; 1c: education level; 1d: political orientation). Each set of authors's tweets was rated on only a single characteristic, and participants signed up to rate one of the four characteristics, and after signing up, rated tweets on that characteristic only. For all studies, we hypothesized that participants' levels of trait AOT would be positively associated with more accurate guesses.

Participants were recruited via Amazon Mechanical Turk and underwent a brief training explaining the task and the trait they were to identify (1a: gender; 1b: age; 1c: education level; 1d: political orientation). Participants then completed a short demographic survey and the 9-item Actively Open-Minded Thinking questionnaire (Haran et al., 2013; see Supplement A for items). Reliability for AOT, which was measured across studies on a 1–7 scale, was acceptable in each sample (Study 1a $\alpha = .77$; Study 1b $\alpha = .75$; Study 1c $\alpha = .77$; Study 1d $\alpha = .83$).

Participants then completed the rating task, in which they were shown a set of 20 randomly chosen tweets out of a battery of 100 tweets posted by a single author in the past year (user mentions and URLs, which might disclose personal information, were replaced with placeholders). Based only on these tweets, participants attempted to guess the author's demographics. To discourage blind guessing, participants were not allowed to submit an answer until a minimum of 10 seconds had passed.

Participants were paid \$0.02 for each task and were allowed to perform the task as many times as they wished, but never for the same author. They were presented with an initial bonus after filling in the training and surveys (\$0.25) and another bonus after completing 10 ratings (\$0.25).[2] Figure 1 shows a screenshot of an example task from Study 2d.

To control for the fact that outcomes regarding the same authors would likely be intercorrelated, we used hierarchical linear regression (Dai, Li & Rocke, 2006) to predict binary outcomes (correct/incorrect), from raters' trait AOT. Because each author was rated by more than one participant, we used a model with both rater and author as crossed random effects.

2.2 Study 1a: Gender

Tweets from 2,607 authors who could be identified as male or female were collected. An objective gender label (male/female) was determined by linking their Twitter profile to self-reported information available on Twitter or similar apps (Burger et al., 2011).[3]

Participants (n = 1,078) were asked to guess each label using a forced, binary choice and thus had a 51.9% chance of being correct if always guessing female (there were slightly more female authors in our dataset). Participants completed the task an average of 21 times.

Results. Participants with higher trait AOT were more likely to assign the correct gender to authors. The odds ratio estimate was 1.064 (95% confidence interval [CI] = 1.014, 1.117) indicating that for each 1-unit increase in raters' AOT (on the 1–7 scale), each guess was 1.064 times more likely to be correct; a guess by a rater whose AOT was 7 was almost 50% more likely to be correct than a rater whose AOT was 1. Overall, participants' guesses were correct 75.70% of the time.

2.3 Study 1b: Age

Tweets from 826 authors were collected; authors reported their own ages in an online survey. Because age is a scalar variable, participants' accuracy was not measured on a binary correct/incorrect scale. Instead, they were asked to guess each author's age in years, and their accuracy was assessed as the absolute value of the difference between the author's actual age and the participant's guess. Participants (n = 691) completed the task an average of 11 times.

[2] For quality control, we interspersed several authors who directly stated their group category (e.g., a male author saying "My beard is almost to the point where I can make other men jealous of my sweet beard"). If participants misidentified two of these unambiguous authors, they were unable to participate further and their data are not included in our results. 16, 8, 20, and 40 raters failed the attention checks in Studies 1a, 1b, 1c, and 1d, respectively.

[3] Because each response is nested both in the author of the tweet and the worker who rated the tweet, each of these datasets are cross-classified. However, low ICCs at the worker level (0.05 – 0.005) provided insufficient evidence of dependency to require nesting, compared to the high ICCs observed at the author level (0.19 – 0.62). As the ICC for cross-classified models is calculated pooling variances across all levels, this does not imply a lack of any significant effects at the worker level – merely that the variance at the author level is far larger.

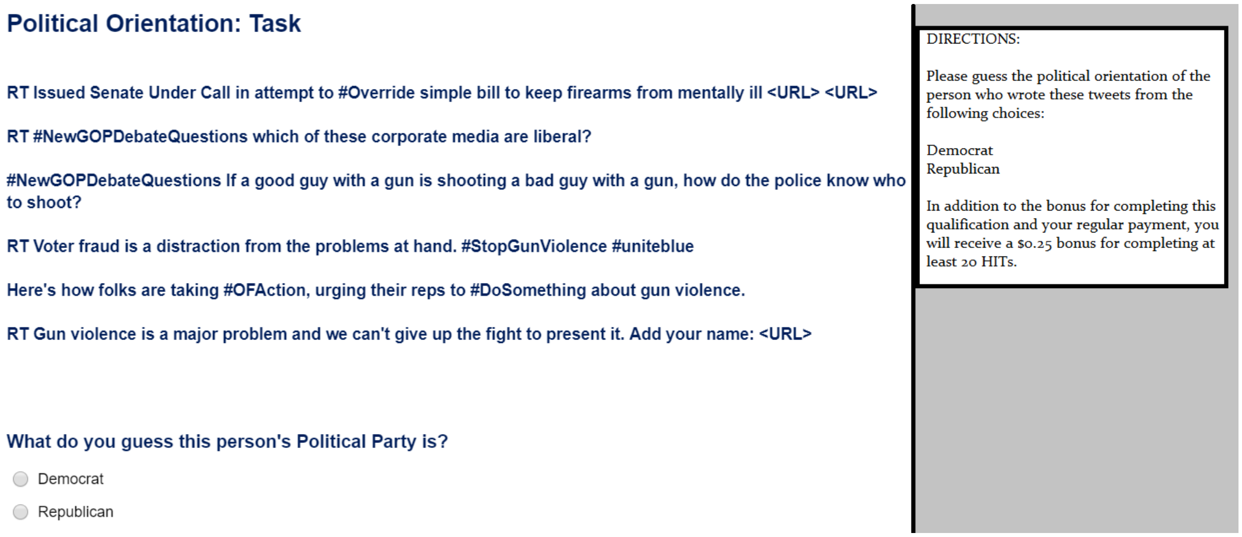

FIGURE 1: Sample task for Study 1.

Results. Participants with higher trait AOT were overall more accurate at guessing authors' ages, b = −0.237, p = .002, indicating that for each unit increase in AOT, each guess was approximately a quarter of a year closer to the author's actual age. Overall, participants' guesses diverged from authors' actual ages by an average of 7.25 years.

2.4 Study 1c: Education level

Education information was available for 900 Twitter authors, based on self-reported occupations in the user description field on Twitter (Preotiuc-Pietro, Lampos & Aletras, 2015). We mapped an estimated education level (no bachelor's degree, bachelor's degree or equivalent, advanced degree), based on the education level required for occupations listed in the UK Social Occupation Classification (SOC, 2000). The three groups were evenly split. Participants (n = 482) were asked to assign one of the three labels. Participants completed the task an average of 49 times and had a 33.33% chance of being correct.

Results. Trait AOT was positively associated with correct categorizations. The odds ratio estimate was 1.141 (95% CI = 1.065, 1.223), indicating that for each one-unit increase in rater AOT, the likelihood of a guess being correct was 1.141 times more likely to be correct. In general, guesses were correct 54% of the time.

2.5 Study 1d: Political orientation

Political orientation (Republican or Democrat) could be determined for 2,500 Twitter authors, based on their patterns of following political leaders on Twitter in August of 2015. We selected four politicians associated with the American Democratic party (@SenSanders, @JoeBiden, @CoryBooker, @JohnKerry) and four politicians associated with the American Republican party (@marcorubio, @tedcruz, @RandPaul, @RealBenCarson). Authors labelled "Democrats" followed all four of the Democrat politicians and none of the Republicans, while authors labelled "Republicans" followed all four of the Republican politicians and none of the Democrats. Participants (n = 943) were asked to guess each author's political orientation; they had a 50% chance of being correct. Participants performed the task an average of 23 times.

Results. Raters' AOT was strongly related to the accuracy of their guesses. The estimated odds ratio was 1.240 (95% CI = 1.154, 1.333): for each one-unit increase in AOT, raters' guesses were 1.240 times more likely to be correct. Overall, guesses were correct 81.69% of the time.

2.6 Discussion

Across four sub-studies, correctly assessing social media authors' traits was significantly associated with raters' AOT. In other words, people with higher AOT were more skilled at drawing correct conclusions about people solely based on social media behavior.

These results suggest that being motivated to think deeply and search for new information can help overcome the ambiguous aspects of much online communication. Although the tasks in Study 1 were not very difficult -- participants generally performed better than chance across the board -- participants higher in AOT were better at using the cues in online text to draw accurate conclusions about authors.

In other words, being low in actively open-minded thinking was associated with lower accuracy about social cate-

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gorizations online, despite the relative ease of these categorizations overall; even very basic kinds of social cognition were hindered by the combination of low AOT and the online social media setting. Therefore, the decision-making and reasoning benefits to AOT extend to social perception in a social media setting.

3 Study 2

Study 1 established AOT's relationship with how people perceive and respond to social media information. Study 2 explored how AOT is related to social media behaviors directly; that is, how it is reflected in people's actions online. To create a broad picture of social media behaviors, we considered three dimensions: platform usage, language use, and profile image choice. While the exploratory nature of Study 2 kept us from making specific hypotheses about our results, we had particular interest in AOT's relationship to closed-mindedness and thoughtlessness.

3.1 Participants

Participants (n = 1,464)[4] were recruited via online platforms (Amazon Mechanical Turk and Qualtrics). Because of our focus on uncontrolled, field data, we expected the effect sizes of our results to be somewhat small. Using the standards of a small effect size ($\rho = .10$), a two-tailed test, power of .80, and $\alpha = .05$, G*Power determined a minimum sample size of 779 participants (Faul, Buchner & Lang, 2009). Because data-driven language analysis requires especially large samples (e.g., Schwartz & Ungar, 2015), we included all participants we could access.

Mean age was 31.1 years old (SD = 11.03, range = 13, 72), and 67.9% (994) of participants were female. For our analysis, we downloaded up to the most recent 3,200 public tweets using the Twitter API per the API restrictions. Participants had posted an average of 1,109 tweets in total.

3.2 Methods and materials

Participants were asked to share their Twitter handles and to complete a basic demographic survey including age, gender, and a 9-item version of the Actively Open-minded Thinking scale (Haran et al., 2013; Cronbach's $\alpha = .71$). We then collected three types of information about each user: platform related behaviors, language use, and profile image.

[4]This sample was taken from a larger set of 4026 participants. Participants were eliminated from analysis if they chose not to share their Twitter handle with the researchers or if they listed a handle with over 5000 followers or if the handle was a verified account (suggesting that they listed a celebrity's account) or if they failed to complete the survey.

Platform related behaviors. One approach to gaining insight about online behavior involves querying the general ways that people tend to use the social media platform itself, such as the number of posts they make in a day, the average length of their posts, and the frequency of retweeting (i.e., passing along someone else's tweet to a new audience). These kinds of behaviors have been shown to be associated both with demographic characteristics (e.g., Preoţiuc-Pietro, Volkova, Lampos, Bachrach, & Aletras, 2015) and personality traits (e.g., Farnadi, Zoghbi, Moens & de Cock, 2013; Quercia, Kosinski, Stillwell, & Crowcroft, 2011).

Table 1 indicates the behaviors measured for each user, grouped by type.[5] Most variables had extremely skewed distributions. For instance, the average tweets per day was close to three, but the most prolific user posted over 300 times per day. We thus log-transformed or logit-transformed each variable (proportion variables were logit-transformed; count variables were log transformed; cases of 0 or 1 for logit-transformed variables were deleted (Aitchison, 1986)). Analyses were a series of univariate, linear regressions predicting each behavior from AOT.

Language use. A second type of social media behavior is language use: the words and topics that characterize different users. The large-scale text data found in social media make it possible for data-driven analyses to automatically identify words that tend to be used by people high or low in certain traits (Kern et al., 2016, Park et al., 2015).

Language analysis in psychology has most commonly been performed using the Linguistic Inquiry and Word Count (LIWC), a set of theory-driven dictionaries which categorize words in psychologically meaningful ways (Pennebaker, Francis & Booth, 2001; Tausczik & Pennebaker, 2010). For example, the 'Positive Emotion' LIWC dictionary contains words such as 'happy', 'good', 'love' and 'lol'. By counting how often words in the dictionary are used by a certain group, one can determine which group expresses more positive emotions in their writing. LIWC has been used to reveal group differences in spontaneous language: for instance, men are more likely than women to use articles such as the or an, while women are more likely to use social words and first-person pronouns (Newman, Groom, Handelman & Pennebaker, 2008).

However, methods based on Natural Language Processing can be used to discover a wider breadth of words and topics associated with a specific group or trait, especially in the context of the diversity in language use that exists in social media. Using Natural Language Processing and statistical analysis, one can identify all words or phrases that are associated with a given trait (Park et al., 2015). To aid interpretation, we followed the procedure introduced in

[5]To keep low-activity users from skewing the sample, we eliminated from all analysis involving text-derived features 275 participants who had posted less than 1000 words in total.

Table 1: Twitter behavioral measures and descriptive information, grouped by type.

Behavior	Mean	SD
Descriptors of overall Twitter behavior:		
The average number of characters per tweet	14.83	3.09
The average number of tweets per day	3.34	14.64
Whether or not the user enables geolocation, usually associated with using Twitter from a mobile device	32.9%	
The number of different profile images a user had in the last month	1.17	.69
Features of tweets:		
The proportion of tweets that use hashtags, which are a method of thematically organizing tweets for others to easily search or discover	.24	.20
The proportion of tweets with @-replies, which indicate direct replies to specific tweets made by another user	.016	.014
The average number of URLs in a tweet	.39	.39
Features of social network size:		
The number of followers ('following' a Twitter account allows a user to automatically be shown new tweets from that account as they are made)	278.65	518.88
The number of people followed by the user	350.32	515.09
The ratio of the user's followers to the number of people followed by the user	1.29	6.51
Social behaviors:		
The average number of times the user's tweets were liked by others (liking is a way to express support for or enjoyment of a particular tweet)	.37	.86
The average number of times the user's tweets were retweeted by others	.15	.48
The proportion of tweets that are retweets as opposed to original	.26	.22

Preoţiuc-Pietro, Lampos, and Aletras (2015) which automatically groups words that are semantically or syntactically similar into clusters. Specifically, we used the GloVe algorithm (Pennington, Socher & Manning, 2014), which generates 1,000 discrete sets of words called topics, with each word belonging to a single topic. We then used these 1,000 topics to quantify the language use of users on Twitter by aggregating all the words in a user's tweets and representing the user as a distribution of the fraction of words which belong to each topic. All analyses were performed on the topics, and not individual words.

To find the most discriminative features of AOT, we then correlated each individual topic with the AOT score of the authors. Because our method involves calculating thousands of independent, univariate regression equations, all language analysis was corrected using the Simes p-correction (Simes, 1986). Our sample size is appropriate for our analyses and fits accepted standards of big-data language correlations (e.g., Eichstaedt et al., 2017).

Profile image. Twitter allows users to represent themselves with profile pictures; these pictures are a form of self-presentation online and are related to individual differences of users (e.g., Liu, Preotiuc-Pietro, Samani, Moghaddam & Ungar, 2016). Profile images were automatically downloaded on the same day as the tweets using the public Twitter API. Out of 1,474 users, 104 users had the default Twitter profile image and 16 users' pictures could not be opened, leaving 1,354 profile images for analysis.

A number of high-level features of the pictures were automatically extracted. These features describe basic aspects of the pictures' composition and content. The analyzed features were:

Brightness: the amount of light in the picture, ranging from 0 (totally black) to 255 (totally white) (M = 116.01, SD = 41.02)

Contrast: the relative variation of luminance, ranging from 0 (entirely dark or light) to 57,303 (M = 10032.70, SD = 7034.18)

Saturation: the level of vividness and chromatic purity in the picture, ranging from 0 (very sharp distinctions between objects) to 1 (no distinction between objects) (M = 0.30, SD = 0.17)

Colorfulness: the amount of shades of red, green, and blue compared to shades of grey, ranging from 0 (entirely grayscale) to 33,394 (complete color) (M = 10401.13, SD = 4298.50).

Faces: the presence or absence of at least one photographed human face.[6] 75.3% of analyzed profile images contained at least one human face.

3.3 Results

Participants' AOT had a significant, positive correlation with age, $r(1464) = .100$, $p < .001$, 95% CI = .05, .15. Men's AOT scores (M = 4.91) were slightly higher than women's (M =

[6] The researchers originally used an automatic face recognition program, Face++ (faceplusplus.com), but it was unreliable, falsely rejecting images that clearly contained faces. Thus, two human raters coded each picture for the presence of faces. For the 39 pictures on which they disagreed (mostly due to heavily shadowed figures or pictures where slivers of a face are visible), a third rater broke the tie.

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TABLE 2: Aot's relationships, above and beyond age and gender.

	B with AOT (95% LCL | 95% UCL)	R^2
A. AOT's relationship with overall Twitter behavior.		
Characters per tweet	.04** (.03 | .06)	.16
Avg. tweets per day	−.26** (−.40 | −.12)	.08
Enabled geolocation	−.03* (−.06 | −.00)	.01
Discrete profile images / 1 mo.	−.02** (−.04 | −.01)	.05
Discrete profiles / 1 mo.	−.01 (−.04 | .01)	.01
B. AOT's relationship with features of tweets.		
Proportion of tweets with hashtags	.00 (−.10 | .10)	.02
Proportion of tweets with @-replies	.02 (−.13 | .09)	.02
C. AOT's relationship with features of social network size.		
Number of followers	−.15** (−.26 | −.04)	.03
Number of users followed	−.12* (−.21 | −.03)	.01
Ratio of followers/followed	−.06 (−.12 | .01)	.02
D. AOT's relationship with social behaviors.		
Avg. times tweets were liked	.16** (.05 | .27)	.05
Avg. times tweets were retweeted	.00 (−.20 | .20)	.11
Proportion of tweets that were retweets	−.02 (−.13 | .09)	.02

Note: * indicates p < .05. ** indicates p < .01.

4.64), t(1474) = 6.15, p < .001, r = .158. Because of these relationships, age and gender were entered as covariates for all results presented in Study 2.

Platform related behaviors. In general, higher AOT was associated with less frequent tweeting but longer tweets. Users high in AOT had fewer followers and followed fewer people themselves, but their tweets were liked more often. They also were less likely to have geo-location enabled, suggesting that they tweet on desktops or laptops rather than handheld devices. We uncovered no relationship between AOT and users' hashtags and retweeting behaviors. Full results for platform behaviors are presented in Tables 2a-2d.

Language use. Interpretable and coherent patterns in language were apparent for both high and low levels of AOT. The twelve topics most strongly correlated with low AOT are presented in Figure 2, and the twelve topics most strongly correlated with high AOT are presented in Figure 3. The topics are visually presented such that the most frequently used words in our dataset and thus the ones most likely to drive the association are larger. The number of topics for each direction was chosen to present an illustrative range of responses. For ease of interpretation, we have arranged the topics post-hoc into categories; these categories and their labels are open to interpretation, but they highlight clearly distinct linguistic patterns of users high or low in AOT.

TABLE 3: AOT's relationship with profile picture features, above and beyond age and gender.

	B with AOT (95% LCL | 95% UCL)	R^2
Brightness	−.35 (−3.10 | 2.39)	.007
Contrast	18.96 (−452.39 | 490.31)	.002
Saturation	.00 (0.01 | .01)	.005
Colorfulness	−10.65 (−.299.33 | 278.04)	<.001
Presence of human face	−.06** (−.08 | −.03)	.06

** indicates p < .01.

Users low in AOT used topics consisting of informal words that are often used in conversational settings ("Casual Speech" category in Figure 2) or that display a tendency of positively referencing valued personal relationships (such as expressions of gratitude, birthday wishes, positive personal traits, or family and friends). Overall, low AOT involved a focus on personal or social interests, expressed through casual language use.

In contrast, high AOT was associated with elevated diction and broad ideas. Individuals high in AOT used relatively sophisticated words, particularly modifiers such as adverbs, suggesting a tolerance for shades of grey and nuance. They also described wide-focus issues and ideas such as religion, political ideologies, education, nature and imagination. Users high in AOT also expressed their views on social issues such as injustice and economic inequality, and their consequences and outcomes. One topic specifically consisted of ways to quote or allude to other people's statements or points of view (e.g., "referred," "admitted," "stated").

Profile image. Users high in AOT were less likely to have human faces in their profile images. Because a portrait of oneself is the most common and expected kind of profile picture, AOT predicts a more unorthodox manner of visually presenting oneself. AOT was not significantly related to any other descriptive features of profile image. (See Table 3 for full results.)

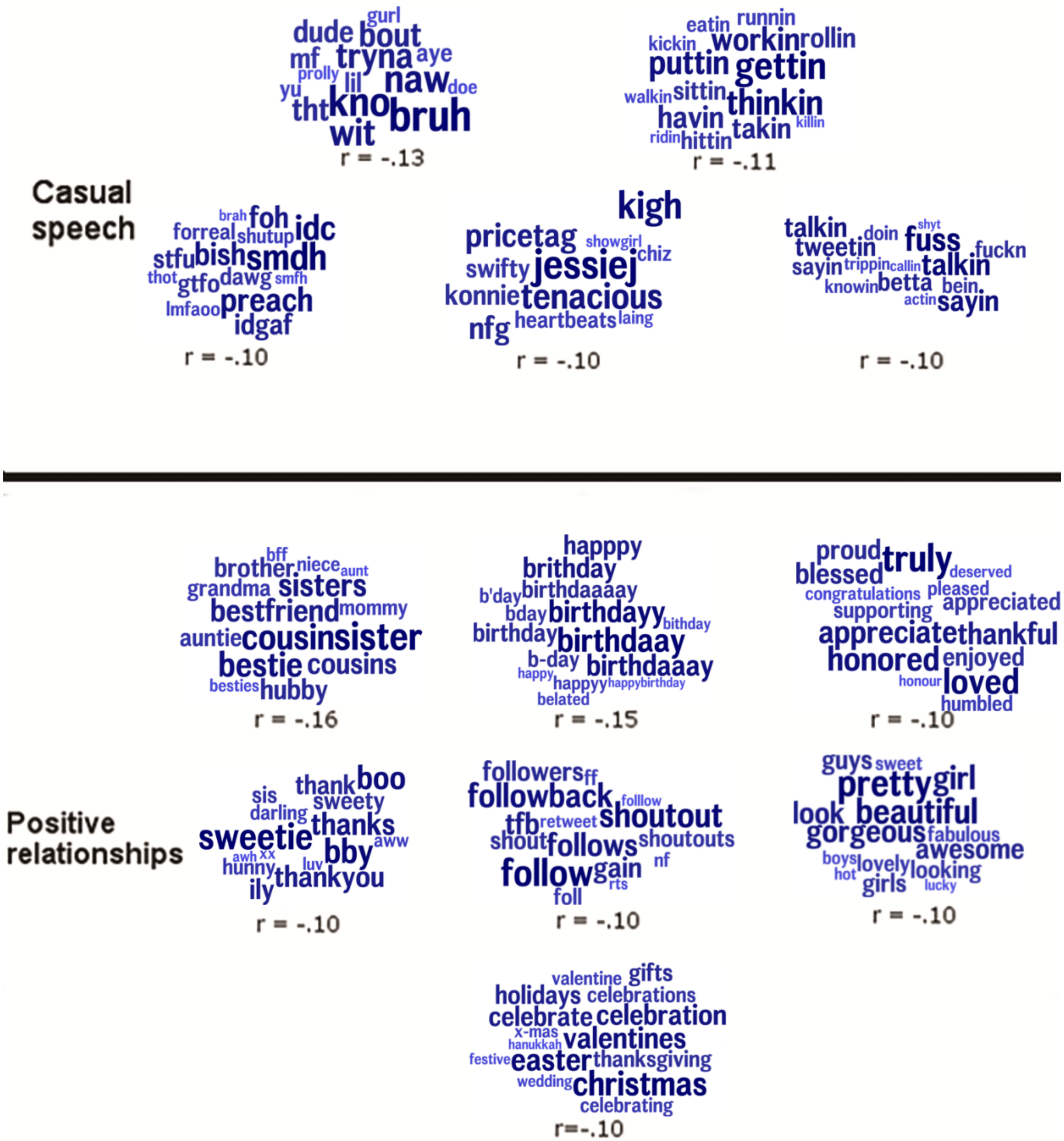

FIGURE 2: The 12 topics most strongly negatively correlated with AOT. All topics significant at Simes-corrected p < .01. Size of word within topic indicates frequency within data.

3.4 Discussion

Overall, our data-driven methods revealed a distinct picture of high AOT users as thoughtful in their expression, intellectually curious, oriented towards the big picture rather than personal issues, and somewhat unorthodox in their manner of self-presentation. In their language, users high in AOT demonstrated a focus on broad, abstract ideas rather than the immediate situation. AOT was positively associated with a willingness to talk about unpleasant things, particularly perceived systematic injustices like "Islamophobia" or "pa-

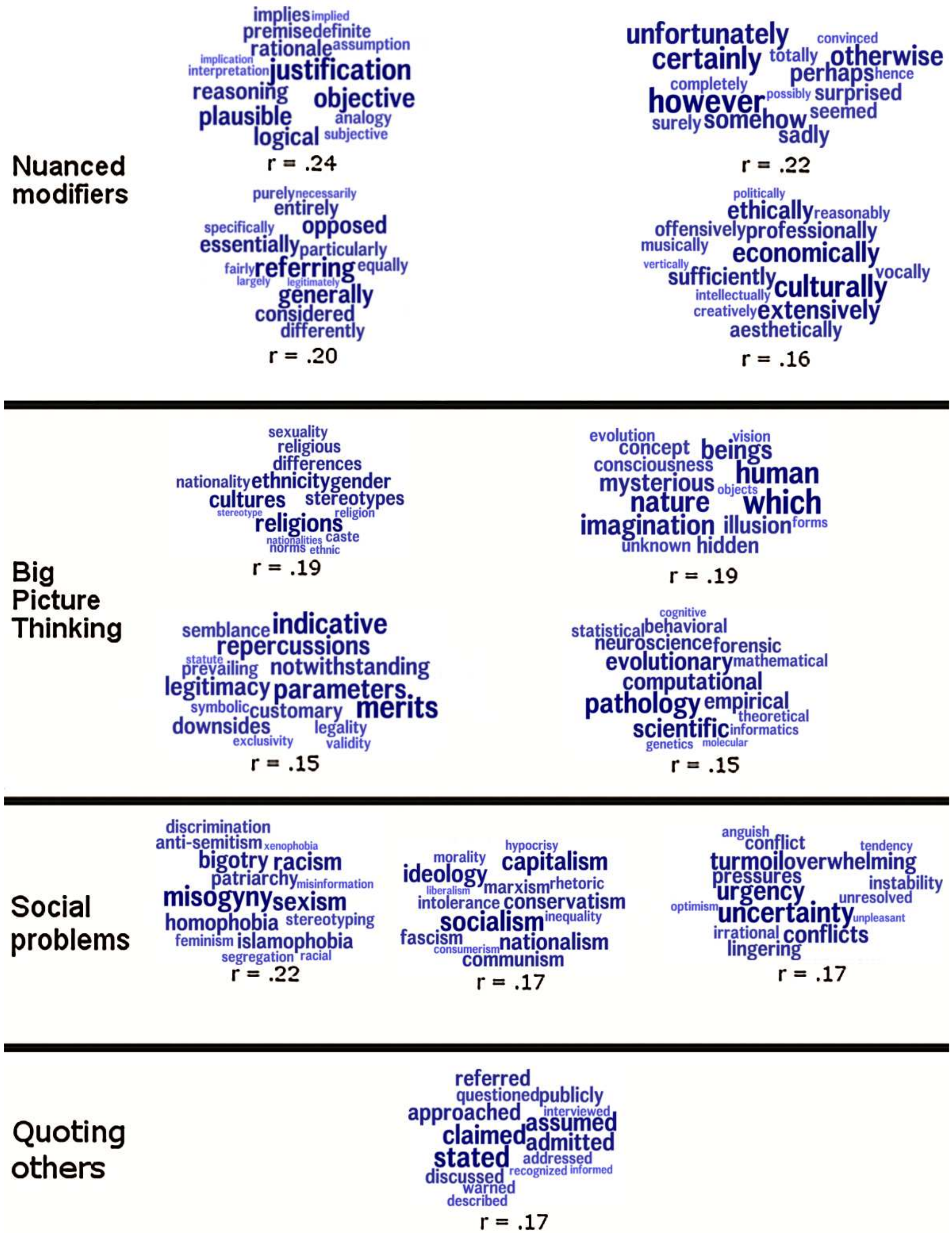

FIGURE 3: The 12 topics most strongly positively associated with AOT. All topics significant at Simes-corrected p < .01. Size of word within topic indicates frequency within data.

triarchy", and it was negatively associated with happy, optimistic communication and references to friends and family. This may be another instance in which people high in AOT are willing to expose themselves to information others would rather ignore. It may also reflect a left wing political orientation, which is consistent with previous research connecting political liberalism with openness (Jost, 2017).

Notably, participants high in AOT were also characterized by a focus on big picture ideas and concepts, precisely the level of construal that people are prone to avoid on digital media compared to analog (Kaufmann & Flanagan, 2016). Low-AOT users, on the other hand, were more likely to discuss their immediate relationships. Because AOT's definition includes an orientation towards an expanded breadth of information, it may help people to avoid "losing the forest for the trees" online. Finally, high-AOT users were more likely to use words referring to others' speech or quotes. This finding directly demonstrates an interest in others' perspectives.

Although the focus of this paper is on AOT's effects, it is plausible that these specific effects may be more directly related with other individual differences correlated with AOT, particularly education level (Carpenter, et al., 2016).

Users high in AOT were less likely to visually present themselves in the conventional manner: they were less likely to follow the typical behavior of having a human face in their profile image, instead using other kinds of pictures, such as cartoon characters, pets, or landscapes. Also, they posted less frequently but made longer posts. Importantly, their posts were also more likely to be liked by others, suggesting social benefits to having high AOT on social media.

In general, these results are consistent with ways that AOT manifests in other contexts (e.g., Baron, in press; Stanovich, 2017). We do not mean to imply that the behaviors negatively associated with AOT are necessarily maladaptive; in particular, positive personal relationships are a key aspect of well-being (e.g.,. Ryff, 1995). However, high-AOT users are specifically distinguished by their avoidance of the fast-pace and immediacy of much online communication, both in terms of frequency of posting and the breadth of their objects of discussion, consistent with a trait tendency to cognitively reflect (Campitelli & Labollita, 2010).

It is important to reiterate that our methods in study 2 are correlational, and therefore we cannot make any claims of causality between AOT and these behaviors. Even more important, however, is to acknowledge the difficulty of isolating the single individual difference most directly related to behavioural outcomes. As we discuss above, AOT is conceptually similar to and strongly intercorrelated with a number of other constructs (e.g. need for cognition and need for closure); it also is related to demographic variables such as gender and education level. For these two reasons, it is beyond the scope of this paper to determine whether AOT (or any other construct) is the fundamental causal factor of these outcomes. Rather, our focus is on providing insight to the potential psychological reasons a person may use social media in different ways.

4 General discussion

Across two studies, we demonstrated that Actively Open-Minded Thinking was associated with benefits both in responding to and at creating social media content. In Study 1, AOT was found to enable more accurate assessments of other users, based solely on social media text: in other words, high-AOT people were better able to interpret and reason about social media text. In Study 2, we composed a three-dimensional picture of how AOT affects online behavior in general social media tendencies, language use, and profile image selection. AOT was associated with more thoughtful, better-liked tweets; high-AOT people were more skillful at writing tweets that people react well to. Although these results do not suggest that high AOT is beneficial in all situations that may arise on social media, these results are a first step for studying individual differences that allow social media users to navigate the potentially overwhelming amount of information inherent to social media platforms such as Twitter (e.g., Jones, Ravid & Rafaeli, 2004). AOT may serve as an "antidote" to the detail-level, fast-paced, inattentive mindset facilitated by digital social media (e.g., Jones, Ravid & Rafaeli, 2004; Kaufman & Flanagan, 2016; Zhong, Hardin & Sun, 2011).

One particularly compelling future direction involves analyzing the effect of trait AOT on how people identify or deal with the increasingly troubling problem of biased or false information available on social media (e.g., Maheshwari, 2016; El-Bermawi, 2016). AOT may moderate the extent to which people are open to new perspectives and viewpoints instead of treating their social media spaces as "echo chambers" which merely reinforce and ossify their pre-existing views and values (Barbera et al. 2015; Dehghani et al. 2016). Also, users motivated to think more deeply about information may be more likely to recognize and ignore unsubstantiated or false information online (e.g., Qazvinian, Rosengren, Radev & Mei, 2011; Starbird et al., 2014). A promising step in this direction has been recently reported by Bronstein and colleagues (2018), who found that users' AOT is positively associated with their ability to distinguish 'fake news' headlines from real headlines. The skills involved in being a good citizen, community member, and consumer of information increasingly are needed on social media; a closed-minded mindset can interfere with these skills. Our studies provide an important first look at traits that facilitate them on text-based social media. Eventually, it may be possible to use these findings to automatically track AOT and its related behaviors over time using supervised learning techniques (Mcauliffe & Blei, 2008).

Our studies do have limitations. For ethical reasons, we recruited only Twitter users who willingly shared their Twitter handles, which means our sample may not be fully representative of the general population; likewise, the Twitter population itself is a non-representative sample of the English-speaking population. Also, despite Twitter's popularity, its format is primarily short messages, and so AOT's effect may not be identical to those on other social media platforms, which allow longer messages or have a greater emphasis on pictures or video. In the future, it will be important to extend these methods to other forms of social media. Furthermore, as we stated above, our interpretations in Study 2 were made in light of AOT's effect on the outcomes, but it is possible other traits or characteristics correlated with AOT may be more direct factors (or they may exert their effects in part through AOT itself).

The benefits of widespread mediated communication are obvious: it connects people to new communities, facilitates the convenient and fast spread of information, and allows people to start to build relationships that otherwise could not exist. However, the downsides — information overload, an overly fast pace of communication, distant and abstract communication partners — can be dangerous. Our studies begin to suggest that an orientation toward thinking deeply and openly allows users to sidestep some of these problems and have online interactions characterized by depth, accuracy, and openness.

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