Understanding Individuals' Personal Values from Social Media Word Use

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ABSTRACT
The theory of values posits that each person has a set of values, or desirable and trans-situational goals, that motivate their actions. The Basic Human Values, a motivational construct that captures people's values, have been shown to influence a wide range of human behaviors. In this work, we analyze people's values and their word use on Reddit, an online social news sharing community. Through conducting surveys and analyzing text contributions of 799 Reddit users, we identify and interpret categories of words that are indicative of user's value orientations. Using the same data, we further report a preliminary exploration on word-based prediction of Basic Human Values.

Author Keywords
Basic Human Value; word use; social media

ACM Classification Keywords
H5.3. Information Interfaces and Presentation

INTRODUCTION
Social media users are not homogenously motivated. Just because two people both "participate" on the same social media platform, it does not mean that they use it for the same reasons or interact with the platform in the same way. In fact, what they hold to be important can differ drastically and as a result they most likely will behave differently. For example, while some may be more focused on job-related uses because they are interested in advancing themselves and demonstrating their competency, others may be more likely to provide social support and be more interested in helping others who have questions or problems.

Schwartz's theory of Basic Human Values [36] provides us a rigorous framework in reasoning about these different motivations. As a theory of values [32, 34], the theory of Basic Human Values defines a motivational construct, capturing desirable, trans-situational goals of people's lives into several distinct dimensions. These value dimensions have been shown to affect a wide range of offline behaviors, including choice of degree major in college, consumer decisions [30], religiosity [6, 38], pro-environmental behavior [16], etc.

Despite these results, to date we have little knowledge on whether and how these value dimensions manifest in online social media. Do our values draw us towards certain discussions, or lead us to more frequently employ certain words? And if they do influence our word use, what words are indicative of which value dimensions? Answering these questions can lead to more effective tailored persuasive messages or incentives to tackle the under-contribution problem plaguing many social media services [22].

In this work, we present the first analysis of associations between people's Basic Human Values and their word use in online social media. We recruited users from Reddit, a popular social news sharing community, and measured their personal values through the established Portrait Values Questionnaire [35]. We also collected their posts on Reddit, and measured their word use in a number of word categories as defined by the Linguistic Inquiry and Word Count (LIWC) dictionary [27]. Following methodologies established in prior analyses (e.g. Yarkoni [44]), we correlated users' values with word use, and identified LIWC word categories that are associated with different value dimensions. We further explored the prediction of Basic Human Values based on word use.

This work contributes to both theory and practice. On the theoretical side, as the first study that relates Basic Human Values to social media word use, this work furthers our understanding of how people's values manifest in their everyday online discussions. On the practical side, this work investigates to what extent people's values can be predicted from their writing on social media. Such predictions can be potentially useful in a wide variety of practical scenarios, such as recruiting pro-social individuals for volunteer efforts or offering extrinsic recognitions to achievement-motivated contributors.

BACKGROUND AND RESEARCH QUESTIONS
In this section we describe the Basic Human Values proposed by Shalom Schwartz [34]. We then briefly review prior research that relates word use to values, personalities, and other attributes. Lastly, we introduce the two research questions that guide the rest of this paper.

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Basic Human Values

According to the theory of values, values convey what is important to an individual. Values are "desirable, trans-situational goals, varying in importance that serve as guiding principles in people's lives" [36]. Schwartz summarizes five features that are common to all values: (1) values are beliefs; (2) values are a motivational construct; (3) values transcend specific actions and situations; (4) values guide the selection or evaluation of actions, policies, people and events, and (5) values are ordered by relative importance [34].

Values have been found to correlate to a wide variety of behaviors [35]. Research suggests that people behave according to their values for two reasons. First, they seek consistency between their beliefs and actions (e.g., Rokeach [32]). Second, actions consistent with values are rewarding, since they allow people to obtain what they believe in. Studies have showed that people do want to act accordingly to their values in hypothetical situations [9, 33].

A few different values dimensions have been proposed [17, 20, 32, 34]. In this work, we focus on the Basic Human Values derived by Schwartz [34] for a number of reasons. First, Schwartz' values discriminate among individual people instead of national cultures. Second, Schwartz' values are not limited to work but also include values from different life domains. Third, they were developed through surveys of people across 67 countries, are well studied and tested, and they have been included in the European Social Survey [35].

Schwartz and colleagues propose 10 Basic Human Values, which map onto 5 higher-level value dimensions [34]. As represented in Figure 1, the circumplex structure in Schwartz' Value Theory indicates relations of conflict and congruity across values. The closer any two values are to one another, the more similar their underlying motivations, and vice versa. Below, we introduce the five value dimensions:

Self-transcendence encompasses two basic human values involving concern for the welfare and interests of others: (1) *universalism*, to pursue understanding, appreciation, tolerance and protection for the welfare of all people and for nature; and (2) *benevolence*, to pursue the preservation and enhancement of the welfare of people with whom one is in frequent personal contact.

Self-enhancement encompasses two basic human values related to the pursuit of self-interests: (1) *power*, to pursue social status and prestige, control or dominance over people and resources; and (2) *achievement*, to pursue personal success through demonstrating competence according to social standards.

Conservation encompasses three basic human values related to self-restriction, order, and resistance to change: (1) *conformity*, to pursue restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms; (2) *tradition*, to pursue respect, commitment, and acceptance of the customs and ideas that traditional culture or religion provide the self; and (3) *security*, to pursue safety, harmony, and stability of society, of relationships, and of self.

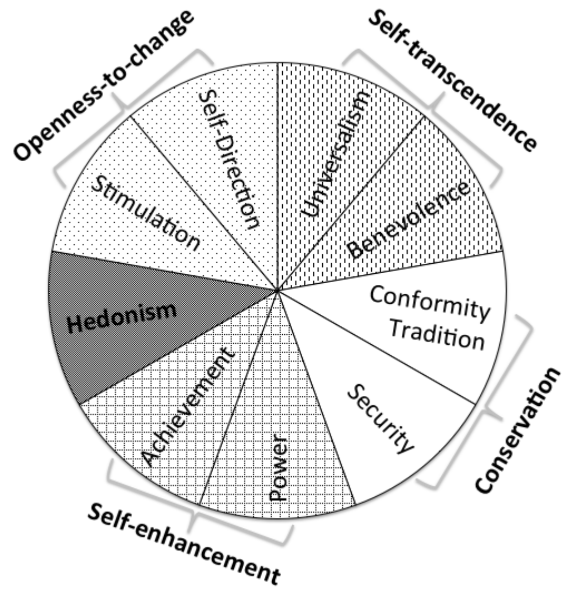

Figure 1. Schwartz' Values

Openness-to-change encompasses two basic human values related to the desire for independence and new experiences: (1) *stimulation*, to pursue excitement, novelty and challenges in life; and (2) *self-direction*, to attain independence in thought and action—to choose, create, and explore.

Hedonism refers to the pursuit of pleasure and sensuous gratification for oneself. It is about seeking pleasure, enjoying life and self-indulgence. According to Schwartz [35], hedonism can be categorized under openness-to-change 75% of the time, but may also be related to self-enhancement. To keep the effects distinct, in our analyses, we keep hedonism as a separate value.

To measure people's value orientations, we use the Portrait Value Questionnaire (PVQ) developed by Schwartz (see Schwartz [35] for review). The 21-question version takes about 5-6 minutes to answer, and has been completed by respondents from 18 nations. We describe measurements of values in more details in the methodology section.

Word Use, Value and Personality

In this work we analyze the associations between people's values and their word use in social media, guided by the hypothesis that word use is influenced by values.

The link between values and text has been proposed, but not conclusively established. Some recent research [10, 21, 41] has explored machine annotation of values expressed in text documents, as perceived by the readers. This recent research suggests that certain words are interpreted to convey certain values. In contrast to these efforts that focused on if and how readers perceive the values within text documents, our focus is on how people's own writing reveals their personal values. In other words, whether personal values influence word use in writing.

Our research methodology is borrowed from prior research that related people's word use to personality. Early works (e.g. Fast et al. [7], Mairesse et al. [25]) collected writing samples in experimental settings, and correlated the word use to writers' personality. Gill et al. [12] and Yarkoni [44] analyzed web blogs and correlated their word use with personality dimensions. Several recent papers [13, 14, 39] used text snippets on Facebook and Twitter to predict personality. A majority of these prior works followed a common research methodology: They first identified psychologically-meaningful word categories within the Linguistic Inquiry and Word Count (LIWC) dictionary [27, 28], and transformed people's writings into word counts for these word categories. The word counts were then correlated to people's personality, measured through established personality questionnaires.

We follow this methodology in analyzing the association between word use and Basic Human Values, for three reasons: 1) both personality models and value models are psychological constructs that characterize people's emotional, attitudinal and behavioral patterns on several meaningful dimensions; 2) like the case of personality, we aim to find meaningful and systematic associations between word use and psychological constructs, making LIWC an appropriate instrument; 3) like the case of personality, we can take advantage of reliable ground truth from established psychometric questionnaires.

Word-Based Prediction of Other Attributes

More broadly, prior data mining research has explored algorithms that use word-based features to predict other attributes, such as sentiment (see Pang et al. [26] and Liu [23] for reviews) and political polarization (e.g. Cohen [3]). This work complements such prior research by exploring Basic Human Values, a set of attributes that have not been studied before.

Meanwhile, our work also differs from prior data mining research on our research goals and methodology. A vast majority of data mining research on sentiment and political polarization aims to optimize prediction accuracy, and is generally uninterested in the underlying interpretation of word use; indeed, word-based features are often treated as yet another feature set and nothing else. In contrast, our investigation primarily aims to understand how and why Basic Human Values manifests in people's word use, and considers the exploration of prediction accuracy only as a secondary goal. Our work is thus more similar to what Dehghani et al. [5] and Graham et al. [15] have done on characterizing political polarization.

Research Questions

We now introduce our two research questions:

RQ1: Are there any systematic associations between people's Basic Human Values and their word use in online social media? If so, what these associations are, and why?

RQ2: To what extent can we predict people's values solely from their social media word use?

Answers to these questions are particularly valuable due to the roles of Basic Human Values in people's motivation. Researchers have long posited the matching hypothesis [4, 19, 29], i.e. effective persuasive messages and rewards need to target individual’s underlying reasons for participation. As a result, through relating people's word use to their values, this work can reveal deeper insights into people's motivation, inform more engaging designs, and lead to impacts that are lacking from existing research on other attributes such as personality and sentiment.

REDDIT AS A SOCIAL MEDIA PLATFORM

We based our word use analysis on participants recruited from Reddit. Founded in 2005, Reddit is one of the most visited social news sites. At the time of our study, Alexa ranked Reddit 8th in the News category, and 136th overall in the world.

Reddit is organized as an aggregation of over 67,000 subReddits, i.e. subcommunities built upon a specific topic, interest, or functionality. Registered users can submit content to any of these subReddits in the form of a link or user-generated text (formally known as self post). Other users can comment on each other’s posts and comments, thus giving a tree structure to the content on Reddit, with a post as the root and comments as lower level nodes.

When visiting Reddit, users are first directed to their frontpage, which shows the “hottest” submitted content. Users may also customize their frontpage by subscribing to various subReddits. They can also navigate to each subReddit, which shows only the contents posted specifically to that subReddit. Registered users can up or down-vote the submitted post or comment. The accumulated votes from all users can then affect the visibility of a post or a comment under a post.

There are two key reasons why Reddit was chosen as the focus of this work. First, the functions of Reddit are simple but representative of a wide range of different social media. Like most other sites, it enables users to submit content, comments, maintain a profile, and curate content. Thus, the findings from the study of Reddit may help us understand general social media word usage.

Second, unlike many other social media sites that oftentimes focus on specific interests or functions, Reddit welcomes users with a wide-range of interests through their subReddit design. This may provide us with a better variety of participants and texts than other interest- or function-focused social media. For example, the *r/askReddit* subReddit works like a Q&A site where people post questions and others answer the question by commenting, while the *r/worldnews* subReddit is essentially a world news aggregator where users post links from major news sites from all over the world.

METHODOLOGY

We recruited participants on Reddit through posting a public invitation. We measured the Basic Human Values of the participants through a survey, and collected their most recent posts/comments on Reddit, from which we measure their word use and general Reddit usage. We then performed a correlation analysis, a regression analysis, and a classification study to answer the two research questions.

Data Collection

We submitted a post to the *r/self* subReddit, inviting Reddit users to participate in our survey. The *r/self* subReddit is a general purpose subReddit that is "a place to put self-posts for discussion, questions, or anything else you like". Besides posting to *r/self*, we also cross-posted our survey to multiple other subReddits in order to gain more attention. Reddit users were told that they would be entered into a drawing for one of multiple $100 Amazon Gift Cards or a donation of the same amount to a charity of their choice.

The survey first invited the Reddit users to provide their Reddit username or an email address, and then asked users to fill out the Portrait Value Questionnaire (PVQ) developed by Schwartz and colleagues to measure individual's value orientations [35]. The survey also contained several questions about the demographics of the survey participants. Duplicate questions were included in our survey to help filter low quality responses.

The PVQ includes 21 items that require responses on a 6-point Likert scale. There are 2 items for each of the 10 value types discussed above, except for Universalism, which contains 3 questions. Each item describes a third person (she or he), and survey takers were asked to rate how much this person in the question is like them. As per their instructions, we used the normalized version of the rating for each respondent in our analysis as these ratings indicate the relative, and not absolute importance of various goals in individuals' lives [37].

Our calculated Cronbach's alphas (a measure of internal consistency for psychometric questionnaire results) for each of the 10 Basic Human Values range from 0.27 to 0.78. In the design of the PVQ, Schwartz has explained that these low alpha ratings are acceptable, because some of the questionnaire items are designed to measure different underlying goals [35]. Nonetheless, to further ensure the reliability of value measures, we decided to focus on the 5 higher-level value dimensions in this work, thus increasing the number of questionnaire items per dimension from 2 to 4. The resulting alphas were all above 0.50 for our final analysis dataset.

Along with the survey, we also collected the 1,000 most recent posts/comments (fewer for those with less than 1,000 total posts) for each user who provided us with a valid username in the survey (using Reddit API). The collected information is used to measure word use.

Measures

We measured word use with the Linguistic Inquiry and Word Count (LIWC) 2007 version [27]. LIWC is the most commonly used language analysis tool for investigating the relation between word use and psychological variables [40]. The LIWC 2007 dictionary defines over 60 word categories, each containing dozens or hundreds of words.

For each Reddit user we computed one LIWC measure for each LIWC category based on the user's posts/comments. First, we counted the number of times each word in that category was used by the user, and then we divided that count by the total number of the user's words for normalization. Each LIWC measure thus represents the frequency of word use in one LIWC category.

A few LIWC categories form hierarchical relationships to each other. For example, the category *pronouns* can be broken into *personal pronouns* and *indefinite pronouns*, and *personal pronouns* can be further broken into several specific categories such as *first-person plural*. Because in this case the LIWC measure of a high level category is simply the sum of the measures for all its subcategories, in our analysis we omitted 14 high-level LIWC measures to avoid duplication (e.g. *pronouns* and *personal pronouns*).

For exploring value prediction we also computed a few other generic measures per user, including the number of posts/comments, the average number of sentences per post/comment, the average number of words per sentence, and the number of up and down-votes received in total. We omit these measures in this paper as none of them showed predictive power beyond the LIWC measures.

Analytical Approach

RQ1: Values and Word Use

We identify the associations between Basic Human Values and word use through a correlation analysis and an analysis of regression coefficients.

In the correlation analysis, we correlate the LIWC measures with the five value dimensions, and use the correlation significance to measure reliability. This analytical approach has been the established way for identifying associations between word use and personality in a large body of prior work [7, 13, 14, 31, 44].

To control for the large number of concurrent statistical significance tests, we corrected significance levels using a False Discovery Rate (FDR) criterion [2], which adaptively controls the false positive rate for all correlations deemed significant. The FDR was set to 0.05; in other words, any correlation that we report as significant has only a 5% probability on average of being a false positive. The equivalent p-value on our dataset was 0.014.

We also analyze the associations through linear regressions that predict value dimensions using LIWC measures. A challenge here is the collinearity between LIWC measures. For instance, while the LIWC measure *articles* has no significant correlation with self-transcendence and is not a significant predictor in a univariate regression of self-

	Mean	Std Dev	Correlations 2	3	4	5
1.Self-Transcendence	.85	.63	**-.58**	**-.20**	**-.07**	**-.23**
2.Self-Enhancement	-.50	.73	-	**-.25**	**-.19**	-.02
3. Conservation	-.86	.66		-	**-.66**	**-.34**
4. Openness-to-Change	.44	.60			-	**.61**
5. Hedonism	.26	.95				-

Table 1. Basic Human Values of Participating Reddit Users. Significant correlations shown in bold.

transcendence, it would become significant in a full linear regression due to its collinearity with other LIWC measures. Reporting *articles* as a significant predictor from this full regression would have been highly misleading.

As a result, we have conducted a Lasso penalized linear regression [11], using the R glmnet implementation. This approach alleviates the collinearity among LIWC measures by shrinking the coefficients of weak and/or correlated measures to zero. As suggested by Wu et al. [43], while there is no well-established way to assign p-value to regression coefficients in this case, a plausible approach is to calculate the univariate p-value for each non-zero coefficient separately and then apply FDR correction. This p-value calculation is equivalent to the significance calculation we used in our correlation analysis.

To help explain the LIWC word category and illustrate actual word usage behind each LIWC measure, for each LIWC measure we counted how many times words in the LIWC category were used in our Reddit dataset, and selected a few example words from the most frequently used words.

RQ2: Prediction Potential

To understand the prediction potential of the LIWC measures, we conducted a regression analysis and a machine learning classification study. In the regression analysis, we formulated linear regressions to predict each of the five value dimensions using LIWC measures. We evaluate prediction strength through R^2 and the correlation between the regressed value and true value. These two metrics reflect overall how well the regression can approximate the value dimensions.

A few prior papers have evaluated regression results using error measures such as MAE and RMSE [13, 14, 31]. Sumner et al. [39] have however argued that such evaluation is inadequate, as these error measures can often mask large errors on a unimodal population distribution if the algorithms predict a majority of individuals around the population mean. As all of our five value dimensions had unimodel distributions, we followed the advice of Sumner et al. and supplemented the regression analysis with a machine learning classification study.

In the classification study, we used supervised binary machine learning algorithms to classify individuals with above-median levels of each value dimension. We experimented with a number of classifiers from the WEKA machine learning toolkit [42], including logistic regression, naive Bayesian classifier, a variety of support vector machines and a variety of decision tree-based classifiers. Classifiers were evaluated using Area Under the ROC Curve (AUC) values under 10-fold cross validation. The AUC value is equivalent to the likelihood that a classifier ranks a randomly chosen positive instance higher than a randomly chosen negative one, and has been widely used to indicate the practical performance of binary classifiers [8].

RESULTS

For the survey, after removing incomplete responses, those that were completed too quickly (<5 minutes), and those that failed our consistency checks (low variance across all items and high discrepancies between duplicate items), we ended up with 1305 Reddit users with valid responses. To ensure the quality of LIWC measures, we included in our final dataset only users for which we could collect at least 100 posts/comments through the Reddit API. Our final analysis dataset contained 799 Reddit users.

Participating Users

The majority of our users identified themselves as male (65%), between the ages of 21 and 29 (51%), and had at least some college education (>80%).

On average, these users had been members of Reddit for 20 months and were fairly heavy users, spending between 1 to 4 hours on the site per day (70%).

On average each user had 599 posts/comments with over 20,000 words. The median was 566 posts/comments and about 15,500 words.

Our users' posts and comments spread over more than 4,000 subReddits, covering a diverse set of topics (e.g. *r/gaming*, *r/politics*, *r/fitness*, *r/canada*, *r/android*) and functions (e.g. *r/askReddit* for Q&A, *r/worldnews* for news aggregation).

Table 1 shows the mean, standard deviation, and correlation of the participating users' value dimensions. The moderate standard deviations indicate a healthy spread of values across our Reddit users. The correlations support the circumplex structure between values (Figure 1), i.e. the opposing relationship between self-transcendence and self-enhancement (corr = -.58), the opposing relationship between conservation and openness-to-change (corr = -.66), and the proximity between openness-to-change and hedonism (corr = .61).

RQ1: Values and Word Use

Table 2 shows Pearson correlations and the standardized regression coefficients between the LIWC measures and the value dimensions. The table groups the LIWC measures by high-level LIWC categories, and each LIWC measure is accompanied with a few example words used by our Reddit users. To save space, we omitted from Table 2 LIWC measures with no significant correlations and no significant non-zero coefficients.

The correlation analysis and the regression analysis mostly agree, with a few exceptions due to collinearity among the LIWC measures. For instance, while the LIWC measures *swear words* and *anger* both significantly correlate with self-transcendence, the regression coefficient of *anger* is absorbed by *swear words* due to the collinearity between the two measures. In general, as the regression analysis handles collinearity better, below we focus our description on the regression coefficients.

We explain the significant regression coefficients in Table 2 by the five value dimensions, using the example words and the interpretations of LIWC from Tausczik et al. [40]. These significant coefficients (shown in bold in Table 2) indicate reliable associations between value dimensions and the LIWC measures: A positive coefficient between a

LIWC Measures	Example Words from Reddit Users	Self-Transcendence		Self-Enhancement		Conservation		Openness-to-Change		Hedonism	
		Corr.	Coef.	Corr.	Coef.	Corr.	Coef.	Corr.	Coef.	Corr.	Coef.
Linguistic Processes											
First-person plural	we, us, our, ours	**.150**	**.069**	**-.099**	**-.025**	-.065	-.021	.041	.014	-.071	-.011
Third-person singular	she, her, him, his	**.084**	-	-.035	-	.005	-	-.060	-	-.037	-
Common verbs	is, have, was, would, get, think	**.111**	**.020**	-.013	-	-.036	-	-.025	-	.024	-
Auxiliary verbs	is, have, would, will, could, can	**.101**	-	.019	-	-.062	-	-.024	-	.017	-
Past tense	was, had, got, thought, used, went	.022	-	-.027	.022	**.075**	-	**-.086**	**-.017**	-.002	-
Present tense	is, have, get, think, know, make	**.097**	**.025**	.001	-	-.088	-.010	.039	-	.055	-
Prepositions	to, of, in, for, on, with	**.131**	**.071**	**-.102**	**-.010**	-.050	-	.016	-	**-.154**	**-.067**
Conjunctions	and, but, if, as, or, so	**.150**	**.026**	**-.088**	-	-.015	-	-.030	-	-.052	-
Swear words	shit, fuck, hell, damn	.007	.034	-.016	-.015	**-.107**	**-.045**	**.141**	**.065**	**.158**	**.051**
Social Processes											
Family	parent, family, dad, husband	**.122**	**.007**	**-.108**	-	**.133**	**.093**	**-.160**	**-.121**	**-.140**	**-.157**
Friends	friend, girlfriend, neighbor, roommate	**.093**	-	-.064	-	-.034	-.029	.020	.028	.028	.042
Humans	people, guy, man, girl	**.128**	**.008**	-.067	-	-.077	-.015	.020	-	-.006	-
Affective Processes											
Anxiety	worry, crazy, awkward, afraid	**.177**	**.026**	**-.145**	**-.056**	.000	-	-.037	-.012	**-.110**	**-.080**
Anger	shit, fuck, kill, hate	.007	-	.010	-	**-.113**	-	**.111**	-	**.109**	-
Sadness	hurt, sad, depressing, disappointing	**.089**	**.010**	-.020	-	-.006	-	-.042	-.008	-.052	-.022
Cognitive Processes											
Insight	think, know, reason, question	**.107**	**.012**	-.015	-	-.064	-	-.008	-	-.068	-
Causation	because, why, reason, since	.016	-	.036	-	**-.083**	-	.040	-	-.012	-
Discrepancy	if, would, should, could	**.085**	-	.030	.004	-.012	-	-.074	-.014	-.082	-.049
Tentative	if, something, probably, might	**.081**	-	-.022	-	-.033	-	-.020	-	-.070	-
Certainty	all, always, never, everything	.032	-	-.025	-	**-.123**	**-.048**	**.136**	**.077**	.066	.028
Inhibition	keep, stop, wait, hold	**.103**	**.043**	-.061	-.038	-.017	-	-.009	-	-.051	-
Inclusive	and, with, we, include	**.184**	**.006**	**-.172**	**-.047**	-.039	-.034	.034	.042	**-.085**	-
Exclusive	but, without, rather, unless	**.085**	-	-.002	-	-.057	-	.008	-	.022	-
Perceptual processes											
See	see, watch, color, red	**-.135**	**-.043**	.001	-.010	**.107**	**.039**	.013	-	**.120**	**.021**
Hear	say, hear, music, song	-.005	-	-.012	-	-.008	-	.033	-	**.110**	**.044**
Feel	feel, feeling, soft, hard	**.086**	-	**-.098**	-	-.020	-	.039	-	-.017	-
Biological processes											
Health	health, doctor, medicine, drug	**.182**	**.043**	**-.091**	-	-.034	-	-.040	-	-.084	-
Sexual	love, sex, penis, porn	.032	-.008	.008	.016	-.058	-	.032	-	**.102**	**.022**
Personal concerns											
Work	work, school, job, team	**-.090**	**-.047**	**.105**	**.061**	.043	-	-.084	-.028	**-.160**	**-.132**
Leisure	game, movie, music, beer	**-.136**	**-.020**	.043	-	.049	-	.029	-	**.128**	**.042**
Home	home, family, apartment, shower	**.096**	**.031**	**-.152**	**-.075**	**.104**	**.007**	-.061	-	**-.095**	-

Table 2. Pearson Correlations and Standardized Regression Coefficients Between Value Dimensions and LIWC Measures

1) Regression coefficients are computed through Lasso penalized linear regression, which handles collinearity among LIWC measures by shrinking the coefficients of weak and/or correlated measures to zero (marked as "-" in the table).
2) **Significant** correlations and regression coefficients are shown in **bold**, for which the false discovery rate (**FDR**) was set to be **0.05**;
3) Measures with **no significant correlations** and **no significant non-zero coefficients** are **omitted** from the table;
4) **Example words** in the table are chosen from words frequently used by our Reddit users to **represent the actual word usage** that contributed toward the LIWC measures.

Value Dimensions	R^2 of Linear Regression	Correlation between the Regressed Value and the True Value
Self-Transcendence	17.0%	0.39
Self-Enhancement	13.8%	0.35
Conservation	15.4%	0.37
Openness-to-Change	18.1%	0.41
Hedonism	18.2%	0.41

Table 3. Strength of Linear Regressions.

LIWC measure and a value dimension means that people who are high on the value dimension use words in the LIWC category more frequently than the average population.

Self-Transcendence

Self-transcendence significantly associates with a number of measures. First, it is positively associated with a few word categories that indicate an attention focus on others and the larger group (*first-person plural*, *humans*, *inclusive*). Second, it is positively associated with words expressing anxiety and sadness (e.g. "worry", "sad"), and words expressing inhibition (e.g. "stop", "wait"). Third, it is positively correlated with measures that indicate more complex language and more in-depth thinking, including the use of prepositions, conjunctions, and words from the LIWC *cognitive processes* categories.

A possible explanation for these correlations is that Reddit users with high self-transcendence give more advice to others in their comments: these advice comments likely mention the group and other people more frequently, show worries, concerns and inhibition, involve more in-depth thinking, and are generally more complex. These findings complement a previous analysis of Reddit showing that people who value self-transcendence are more likely to voluntarily help newcomers on Reddit [18].

Additional associations in social processes and personal concerns categories indicate that people with high self-transcendence write more about family, health, and home-living issues, and less about work-related issues and leisure activities.

Self-Enhancement

Self-enhancement shows the opposite associations with self-transcendence on many measures. These associations indicate that Reddit users with high self-enhancement write less about the larger group, express less anxiety, and use fewer prepositions. Like the case of self-transcendence, this result may suggest that people with high self-enhancement give less advice to others in their comments compared to the average population.

Additional associations in social processes and personal concerns categories suggest that people with high self-enhancement write more about work and less about home-living issues. These results highlight both the achievement and power values in self-enhancement.

Value Dimensions	Classifier Achieving the Highest AUC	AUC	TPR	TNR
Self-Transcendence	Random Forest	.60	.67	.50
Self-Enhancement	REPTree	.56	.54	.57
Conservation	Logistic Regression	.59	.56	.57
Openness-to-Change	Logistic Regression	.61	.59	.57
Hedonism	Logistic Regression	.61	.53	.63

Table 4. Predicting the Top 50% Users on Value Dimensions.

Reporting the best performing WEKA classifier among logistic regression, naive Bayesian classifier, a variety of support vector machines and a variety of decision tree-based classifiers.

Conservation

Conservation is negatively associated with the use of swear words and the use of words suggesting absolute certainty (e.g. "always", "everything"). These associations seem to suggest that people with high conservation exhibit more self-constraint in their writing, using fewer swear words and making fewer strong absolute statements so as to avoid upsetting other people. Not upsetting other people is a defining goal of conformity, a facet under conservation.

Additional associations in social processes and personal concerns categories suggest that people with high conservation write more about family and home-living issues, indicating their elevated interest in these topics.

We also observed a significant positive association between conservation and the *see* category (e.g. "see", "red"), for which we lack a clear explanation.

Openness-to-Change

Openness-to-change shows the opposite associations with conservation. These associations suggest that people with high openness-to-change write less about the past and family, use more swear words, and use more words that suggest absolute certainty. This result seems to suggest that people who seek excitement and independence (the two facets under openness-to-change) tend to be less constrained by society's rules, and are less constrained and more confident in their writing.

Hedonism

Hedonism shares a number of common associations with self-enhancement and openness-to-change. Like the case of self-enhancement, people with high hedonism express less anxiety and use fewer prepositions. Like the case of openness-to-change, people with high hedonism also use more swear words and use fewer words about family.

In addition, we have found that people with high hedonism write more about color, music, sex and leisure activities, and less about work related issues. These findings match the common image of hedonism.

RQ2: Prediction Potential

We report the strength of regression in Table 3. The R^2 of the linear regressions were small but substantial across all five value dimensions, ranging from 13.8% to 18.2%. The correlation between the regressed value and the true value was moderate, ranging from 0.35 to 0.41.

Table 4 shows the classification results under 10-fold cross validation. Following Sumner et al. [39], for each value dimension we report the best WEKA classifier in terms of AUC, as well as the AUC value, the true positive rate (TPR) and the true negative rate (TNR) of the best classifier under 10-fold cross validation. As flipping a coin would have achieved exactly .50 for AUC, TPR and TNR, we can conclude that in this classification task, the classifiers offered a real but small improvement over random chance.

Overall, we have demonstrated that word use on Reddit indeed contains predictive information of people's values, and can potentially be used to rank people based on their values. We also found that the prediction is not strong enough to allow accurate prediction of an individual's value in the binary classification setting proposed by Sumner et al. [39].

DISCUSSION

RQ1: Values and Word Use

One of the main contributions of this work is to show that personal values can influence word use. Indeed, the results in Table 2 indicate the existence of numerous reliable associations between personal values and word use.

More importantly, these associations suggest a number of potential mechanisms through which personal values affect word use. Below we summarize two major mechanisms that seem to function across value dimensions.

One such mechanism is thinking styles. The use of words from the LIWC *cognitive processes* categories are known to reflect people's thinking process [40]. In our case, we have found that people with high self-transcendence, perhaps due to their elevated desire to help others [18], try harder to interpret other people's situations, and therefore use more *cognitive processes* words. Similarly, we have found that people with high openness-to-change, perhaps due to their elevated desire to drive their own lives, are often more confident in their reasoning, and therefore use more words indicating certainty.

Another mechanism is attention focus. The use of certain pronouns and verbs is known to indicate people's specific focus of attention [40]. In our case, we have found that people with high self-transcendence, perhaps due to their elevated interest in the wellbeing of others, pay more attentions to others, and thus use the word "we" and other group-oriented words more often. Similarly, we have found that people with high conservation, perhaps due to their elevated attachment to established status quo, pay more attention to the past, and thus use past tense more often.

Attention focus also manifests in the use of content words [40]. As Reddit users participate in discussions at will, it is likely that their increased use of certain content words is due to their elevated interest in related discussions. For instance, people with high self-enhancement, perhaps due to their elevated desire for power and achievement, care more about work-related topics, and thus participate more in work-related discussions and use more work-related words. Similarly, people with high hedonism, perhaps due to their elevated interest in leisure and entertainment, participate more in such discussions, and thus use more words related to color, music, and leisure activities.

As our analysis is based on one social media site, one may wonder how the word use patterns and mechanisms we identified may generalize to other forms of social media. First, it should be noted that people's value orientations have been shown to be trans-situational [36] and do not vary greatly between different contexts. Second, due to the wide variety of topics covered in Reddit and the wide range of subReddits our users were involved in, we believe our results will likely generalize to other forum-like social media, such as social news sites, forums, and Q&A sites. However, characteristics and affordances of various media can and do influence communication behaviors. For example, while people with high self-transcendence may write many long advice comments with in-depth thinking, they simply would not be able to write these long comments on Twitter due to the 140 character limit.

RQ2: Prediction Potential

Our regression analysis (Table 3) confirms that word use on Reddit indeed contains predictive information of people's values. This finding demonstrates the potential of ranking social media users based on their motivational values expressed in their word use. Although in this study we did not explore ranking algorithms in detail, learning-to-rank algorithms [24], a class of advanced ranking algorithms developed in recent years, may be a promising candidate for further harnessing the predictive information from word use.

Meanwhile, our classification study indicates that word use by itself cannot accurately predict an individual's value in a binary classification setting. On all value dimensions the classification was better than random, and yet no algorithms performed particularly well (Table 4). This overall result is comparable to the state-of-art results on personality classification. For example, Sumner et al. [39] explored a large number of text-based classifiers, and reported that the best classifiers they explored were only slightly better than random chance in classifying people on personality dimensions. As a result, it is perhaps more promising to explore sophisticated topic modeling (e.g. LDA with topic-in-set knowledge [1]) and/or other information sources (e.g. the social network of the users) to further improve classification accuracy.

The ranking and classification of motivational values can be useful in many practical scenarios. For instance, our linear regression of self-transcendence is strong enough that if we rank all of our Reddit users according to our prediction, the majority of the top users in the ranked list would have above-mean self-transcendent orientation. This ranking can therefore be used to find high self-transcendent people for performing volunteer work, as these people will be more intrinsically motivated to help others.

The prediction of personal values can also help other meaningful prediction tasks due to values' trans-situational nature [36]. For instance, as recently reported by Cohen et al. [3], most existing political polarization classifiers transferred poorly from political elites to ordinary people, because ordinary people do not use strong partisan-specific language and vocabularies as often as political elites. Incorporating language signals indicating personal values might improve the situation, because such signals may be more revealing of the fundamental beliefs of individuals.

CONCLUSION AND FUTURE WORK

In this work, we have analyzed people's value and word use in social media. We identified a number of word categories that are associated with each value dimension, and found reasonable explanations for a vast majority of them. We also explored and confirmed word use in social media as a potential predictor of people's values.

There are a number of promising future directions. On the theoretical side, future research can expand from the 5 high-level value dimensions in this work to the 10 low-level value dimensions (Figure 1). It would also be valuable to better understand the mechanisms through which values influence word use. In this work we have discussed such mechanisms based on prior literature; future work is needed to directly validate these proposed mechanisms. Lastly, future work could extend our investigation of word use into other important online behaviors, such as the formation of social interactions.

On the practical side, future research can employ more sophisticated topic modeling approaches such as LDA, investigate value prediction on alternative social media platforms (e.g. Twitter), and explore stronger prediction algorithms by incorporating other signals, such as social network structures and temporal activity patterns.

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