Predicting Personality and Risk-Taking from Language Use on Twitter

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Abstract

The present research examined how well personality traits and risk-taking profile were related to language use on Twitter. Prior research has shown that social media users’ personality traits identified through analysis of word usage in social media posts. Few studies have examined the extent to which risk-taking propensity can be predicted using language used on social media. In the present study, we downloaded tweets from 76 accounts belonging to undergraduate students using the Twitter API with a python script. These participants also provided information about their personality traits and general risk-taking in daily life. We analyzed word usage using the Linguistic Inquiry Word Count (LIWC, Pennebaker et al., 2015). The results indicated relationships between personality traits and risk-taking domains and multiple LIWC categories, supporting the view that word usage can be used to identify personal characteristics of social media users. Implications and directions for future research are discussed.

Keywords: Personality, Risk-taking, Word Usage, Twitter, LIWC, Social Media

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Introduction

Over the last twenty years, the use of social media platforms has steadily increased around the world with increasing numbers of people using social media, sharing messages, news articles, and photos with others privately as well as publicly (Ortiz-Ospina, 2019; Van Dijck, 2013). Recent research has examined the extent to which personal characteristics of social media users can be predicted using language used in their social media posts (Celli & Lepri, 2018; Chen et al., 2018; Golbeck et al., 2011; Li et al., 2018; 2019; Jones et al., 2020; Park et al., 2015; Schwartz et al., 2013). Recent efforts have employed machine learning to predict user characteristics from natural language (e.g., Receptivi, 2022 and BERT, Devin et al., 2019). Accurate prediction of personal characteristics from social media posts could be leveraged for a variety of uses (e.g., targeting users with advertisements for products or services, targeting users with personalized health-related prevention or treatment information, or deriving information about prospective job applicants). The aim of the present research was to investigate how well the words used in the tweets of undergraduates could be used to predict personal characteristics, including risk-taking propensity. The latter characteristic has been the focus of few prior studies.

Individual Differences in Language Use

In the 1970s, Robin Lakoff (1975) pointed out specific differences in the language use of men and women as well as individuals varying in social status. Decades of subsequent research confirmed numerous gender differences in the use of specific words, expressions, and syntactic structures (See Tannen, 1991 for review). Women use more tag questions (e.g., *It’s cold in here, isn’t it?* or *It isn’t very expensive, is it?)* and more intensifier words (e.g., *really, just,* and *so*) than men. Men tend to use curse words more often than women. Women use polite sentence structures more than men (e.g., *If it is not too much of a bother, could you please pass the newspaper to me*). Lakoff (1975) also pointed out that differences in some words and expressions related to the social status of the speaker with low-status people more likely to use tag questions and intensifiers.

Over the last two decades, links between personal traits and word usage have been identified using Pennebaker et al.’s (2001; 2007; 2015) Linguistic Inquiry Word Count (LIWC), which computes the frequencies for dozens of word and punctuation categories for samples of text from a variety of sources, such as essays written in laboratory settings, papers from college courses, and scientific articles (Chung & Pennebaker, 2007; Mehl et al., 2006; Pennebaker & King, 1999; Tausczik & Pennebaker, 2010). For example, Pennebaker and King (1999) examined the language used in a variety of domains (e.g., personal diaries and college assignments) and found similar patterns of word usage and the Big Five personality traits (i.e., extraversion, agreeableness, conscientiousness, openness, and neuroticism) (See Widiger, 2017 & Digman, 1990 for more information about the Big Five personality model). Specifically, Pennebaker and King’s (1999) results showed that higher in levels of neuroticism (also referred to as emotional stability, Saucier, 1994) was related to more frequent use of first person singular pronouns and negative emotion words, that higher levels of extraversion was related more frequent use of positive emotion words, and that higher levels of openness was related to more frequent usage of words over six letters long.

A growing body of research has examined whether language used on social media platforms also predicts personal characteristics (See Azucar et al., 2018 for review). One of the earliest studies linking social media posts to users’ personal characteristics used text from blogs on Google’s blogger service (Yarkoni, 2010). Nearly 5,000 bloggers were invited to participate in an online survey containing questions assessing the Big Five personality factors (i.e., extraversion, agreeableness, conscientiousness, openness, and neuroticism). The participants were 694 bloggers (524 women, 170 men). The blogs contained just over 115,000 words on average. The words used in the blogs were analyzed using LIWC (Pennebaker et al., 2001; 2007; 2015). Correlations revealed relationships between personality factors and word usage for some LIWC categories and for specific words related to those categories (e.g., negative emotion category and the words *awful, stressful,* and *depressing*). Those higher in neuroticism used more negative emotion words. Those higher in extroversion used more positive emotion words, words related to interpersonal interaction (e.g., social words, such as *friends* and *family*), and 2nd person words (e.g., *you* and *your*).

Recent studies have examined word usage on Facebook (Celli & Lepri, 2018; Farnadi et al., 2013; Tadesse et al., 2018) and Twitter (Golbeck et al., 2011; Iatan, 2017; Kumar et al., 2019; Ong et al., 2017; Qiu et al., 2016), observing relationships can be found between LIWC word categories and personal traits, such as personality. For example, Golbeck et al. (2011) used LIWC to analyze the most recent 2,000 tweets from 50 Twitter users who also completed a survey in which Big Five personality factors were assessed. The results showed that higher levels of extraversion were related to more frequent use of family and social words. Higher levels of neuroticism were related to more frequent use of words related to religion and perceptual processes (e.g., seeing, hearing). Higher levels of openness were related to more frequent use of words related to causation and certainty.

Celli and Lepri (2018) explored how word usage related to multiple types of personality traits. They examined Big Five traits as well as the Myers-Briggs Type Indicator (MBTI, Myers & Myers, 20100, which involves four dimensions of personality: a) introversion-extroversion; b) sensing and intuition; c) feeling and thinking; and d) perceiving and judging. The original MBTI uses these four dimensions to categorize people into 16 possible categories of personality types. A popular derivative of the MBTI is TrueColors types (TrueColors, 2022; See Keirsay & Bates, 1979; Lowry, 1987 for more information), which categorizes people into one of four groups (i.e., warm/compassionate, wise/curious, responsible/dependable, and adventurous/spontaneous). Both the Big Five and the MBTI variants are used widely in employment settings and increasingly used in hiring decisions, despite the fact that the MBTI has been criticized for lacking extensive scientific support (Hawkins, 2021). Celli and Lepri (2018) found that in tweets: a) the Big Five’s extraversion trait was related to more frequent reference to others; b) the Big Five’s neuroticism trait was related to more frequent use of the first person singularpronoun; and c) higher levels of introversion as measured by the MBTI was related to more frequent use of anger words.

Researchers in computer science have developed algorithms, including machine learning algorithms, that can be used to predict personality traits and other characteristics of individuals using language samples, including social media posts (See Eichstaedt et al., 2021; Pennebaker, 2022 for review). Approaches include closed-vocabulary approaches, such as LIWC, which involve using a database of word categories determined through prior labeling by human participants, and open-vocabulary approaches, which involve an algorithm determining word categories using the semantic analysis of words and word clusters. Continued research is needed to determine the reliability of the algorithms and to identify any limitations.

The Present Research

In the present research, we investigated whether word use on Twitter would be related to risk-taking and self-reported personality traits. Few studies have investigated how word use relates to differences in risk-taking across individuals (Moons et al., 2013). Moons et al. (2013) found that certainty and confidence in nonverbal behaviors and use of certainty words in texts made riskier choices in a series of word problems. We are not aware of any prior study that has examined the relationship between word use on Twitter and risk-taking in daily life. Prior research has shown that there are relationships between Big Five personality traits and risk-taking (Kennison & Messer, 2017) and that individuals who report using more swear words and using aggressive humor are more likely to report higher levels of sensation-seeking personality traits and more frequent risk-taking (Kennison & Messer, 2017; 2019). We assessed both Big Five traits and TrueColors, which is based on the MBTI. TrueColors and has been used in prior research in which the four personality types are referred to as self-schemas (Brannon & Brock, 1994; Brannon & McCabe, 2002; 2003; Brock et al., 1990; Kennison et al., 2021; Miller & Brannon, 2015; Pease et al., 2006; Pilling & Brannon, 2007; York et al., 2012).

Prior research has established connections among risk-taking, impulsivity, and adverse mental health outcomes, including substance abuse disorders, problems regulating emotion, self-harm, and suicidal ideation (Abdoli et al., 2022; Hamilton et al., 2015a; 2015b; Johnson et al., 2016; Johnson et al., 2020). Abdoli et al. (2022) assessed risk-taking propensity and personality traits for 240 individuals who had attempted suicide and 376 control participants. They found that the former group reported higher levels of risk-taking propensity and more behaviors associated with suicidal ideation than the control group. Demonstrating that there are relationships between individuals’ risk-taking behavior and their social media use would be useful, as some have begun to examine the possibility that social media platforms can be used to provide mental health screenings as well as interventions (Torous et al., 2021).

In the study, we used LIWC to analyze tweets in relation to self-reported risk-taking in daily life, to Big Five traits (i.e., extraversion, conscientiousness, agreeableness, emotional stability, and openness) and to the four TrueColors types (i.e., warm/compassionate, responsible/dependable, wise/curious, and adventurous/spontaneous). We tested four hypotheses. First, we hypothesized that big five personality traits would be related to LIWC word categories with some categories being related to one of the five traits. Second, frequency of usage for LIWC categories would be related uniquely to one of the four TrueColors category. Third, self-reported risk-taking would be related to LIWC word categories with some categories being uniquely related to one of the five domains (i.e., health/safety, recreational, social, ethical, and financial).

**Method**

**Participants**

We analyzed tweets from accounts belonging to 76 undergraduates (22 men, 52 women, 2 other) who received course credit in exchange for participation. The average age of participants was 24 years (*SD* = 11.36 years)*.* The majority of the sample described themselves as White (71%). Other groups represented include Black (9%), Hispanic (5%), Native American (4%), and more than one category (11%).

**Materials**

We assessed participants’ personality using multiple measures. We used Saucier’s (1994) 40-item questionnaire to assess Big Five personality traits (i.e., extraversion, agreeableness, conscientiousness, neuroticism/emotional stability, and openness). Participants judged how well 40 adjectives described them on a 9-point scale: “1=extremely inaccurate, 2 = *very inaccurate*, 3 = *moderately inaccurate*; 4 = *slightly inaccurate*; 5 = *neither accurate nor inaccurate*; 6 = *slightly accurate*; 7 = *moderately accurate*; 8 = *very accurate,* and 9=extremely accurate.” Each Big Five trait was represented by eight adjectives. After reverse scoring for some items, the average rating was computed for each trait. Higher values reflected higher levels of extraversion, agreeableness, openness, conscientiousness, and mood instability (also called neuroticism). The measure has been generally found to have high internal consistency (i.e., Thompson et al., 2022, Cronbach alphas between α = .77 and α = .92). We also observed good internal consistency for the measure in the present study (Cronbach alphas between α = .79 and α = .90).

We asked participants to evaluate themselves in reference to the TrueColors self-schema categories (Brannon & Brock, 1994; Brock & Brannon; 2006; Keirsay & Bates, 1979; Kennison et al., 2021; Lowry, 1987; Miller & Brannon, 2015). The four self-schemas are represented in a line drawing. The line drawings were created to represent a type of person (images are provided in Brock & Brannon, 1990). Participants were presented with the following instructions: “Which of the images above best describes you? (We realize that you may feel drawn to more than one image. Select the image that is MOST like you.)” The four types are a) warm/compassionate; b) responsible/dependable; c) wise/curious; and d) adventurous/spontaneous. Prior research has shown that participants’ selection of their type (i.e., self-schema, See Brannon & Brock, 1994) has high test-retest reliability (Brock et al., 1990).

We assessed participants risk-taking behavior using Blair and Weber’s (2001; 2006) 30-item Domain-Specific Risk-Taking Attitude Scale (DOSPERT). The items reflect five domains of risk-taking (i.e., financial, social, recreational, ethical, and health). Six items were used to assess each domain. For each item, participants were asked to report how likely they were to carry out the behavior using a 7-point scale: “1 = Extremely Unlikely, 2 = Moderately Unlikely, 3 = Somewhat Unlikely; 4 = Neither Unlikely nor Likely; 5 = Somewhat Likely; 6 = Moderately Likely, and 7 = Extremely Likely.” The average rating was computed for each domain for each participant. Higher averages indicated more frequent risk-taking. The internal consistency for the DOSPERT has been shown to be adequate (Frey et al., 2017; Cronbach alphas ranging between α = .71 and α = .84,). We also observed adequate internal consistency in the present study (Cronbach alphas ranging between α = .72 and α = .88).

We included a question in the survey to identify responders not paying adequate attention to the survey. The question was worded as follows: “Sometimes researchers include a question to determine if the participant is paying adequate attention while completing the survey. In order to show us that you are paying attention please select the fourth option as the response to this question.” The following rating scale accompanied the question:“*1 = strongly disagree, 2 = slightly disagree, 3 = neither disagree nor agree, 4 = slightly agree, and 5=strongly agree.*”We also included questions about demographics (i.e., age and gender).

**Procedure**

Following receipt of IRB approval, we recruited participants for an online survey from a SONA research pool in a department of psychology. Participants were provided with information about the study as the first page of the survey. Participants were students in psychology and/or speech communication courses. The survey was implemented using a professional license of Qualtrics. The survey contained sets of questions assessing personality, demographics, cybersecurity knowledge and behavior. Results pertaining to the participants’ cybersecurity knowledge and behavior are reported in Author et al. Participants were also asked if they had a Twitter account and asked to allow the researchers to examine their tweets by providing their Twitter handle. We used the Twitter API to retrieve tweets, which allowed us to download 3200 of the most recent tweets for each account. We limited our analysis to accounts with a minimum of 100 tweets or retweets. We used python to download tweets and Java code to separate data into files containing only emojis, tweets, or retweets. We reasoned that the language used in tweets may be more reflective of the users’ characteristics than the language used in retweets. The mean number of words per account was 15,847 (*Min* = 198, *Max* = 66,599, *Mode* = 198, *SD* = 18,920). Word usage in tweets was analyzed using Pennebaker et al.’s (2001; 2007; 2015) LIWC 2015 application (Version 1.60 June 26, 2019) acquired via an academic license. The program computes the frequencies of word from a large dictionary of words, which have been grouped into categories. Each category is computed as percentage relative to total number of words.

We used G\*Power 3.1.9.7 (Faul et al., 2007) to determine the appropriate sample size for correlations and multiple regression. For correlation, using a two-tailed test, an alpha of .05 for a medium effect size (d = .05), a sample of n = 26 was needed to achieve power of .80. For multiple regression, using a two tailed test with an alpha of .05 for an effect size of f2 = .15 with as many as 30 predictors, a sample of 57 was need to achieve power of .80. We used an alpha level of .05 and did not rely on methods to control for alpha (e.g., Bonferroni correction) due to the exploratory nature of the research.

**Results**

The results supported thehypotheses that Big Five personality traits (e.g., extraversion, agreeableness, conscientiousness, openness, and emotional stability), TrueColors Type (e.g., warm/compassionate, responsible/dependable, wise/curious; and adventurous/spontaneous) and five domains of risk-taking (i.e., health/safety, recreational, social, ethical, and financial) would be related to language use in Tweets.

**Big Five Personality Traits**

The results supported the hypothesis that Big Five personality traits were related to word usage on Twitter. Table 1 displays a summary of the correlational results. None of LIWC categories were related to agreeableness. For the other traits, there were between one and six related LIWC categories.

***Extraversion.*** There was only one LIWC category related to extraversion. More frequent use of third person plural pronouns (e.g., *they* and *their*) was related to lower levels of extraversion, *r* = -.24, *p* = .036, but was not related to the other traits.

***Conscientiousness.*** There was only one LIWC category related to conscientiousness. More frequent use of *feel* words (e.g.*, feel* and *touch)* was related was related to higher levels of conscientiousness, r = .24, p = .034, but was not related to the other traits.

***Openness.*** There were six LIWC categories related to openness.More frequent use of *negate* words (e.g., *no, not,* and *never*) was related to lower levels of openness, *r* = -.24, *p* = .035, but was not related to the other traits. More frequent use of articles (e.g., *a, an,* and *the*) was related to lower level of openness, *r* = .29, *p* = .011, but was not related to the other traits. More frequent use of *sad* words (e.g., *crying, grief,* and *sad*) was related to lower levels of openness, *r* = -.23, *p* = .045. More frequent use of *emotional tone* words was related to lower levels of openness, *r* = -.26, *p* = .022, but was not related to the other traits. More frequent use of periods in tweets was related to higher levels of openness, *r* = .30, *p* = .008. Lastly, mean number of total words used per tweet was related to higher levels of openness, *r* = .35, *p* = .002, but was not related to the other traits.

To explore further the relationships how these LIWC categories are related to openness, we conducted a multiple regression analysis in which openness was the dependent variable and the six word usage categories (i.e., negate, articles, tone, sad, periods, and total words) were the independent variables, entered simultaneously. The model, *F*(6, 75) = 5.15, *p* < .001, with acceptable Tolerance and VIF values (Field, 2013). The model accounted for 24.9% of variance in openness (adjusted *R*2 = .249). There were two significant predictors in the model: *sad* words (standardized *β* = -.279 *p* = .01) and total word count (standardized *β* = .23, *p* = .044).

***Emotional stability*.** There were six LIWC categories related to mood stability. More frequent use of the first person singular pronouns (e.g., *me, mine,* and *I*) was related to higher levels of emotional stability (higher levels indicate higher neuroticism), *r* = -.26, *p* = .02, but was not related to the other traits. More frequent use of auxiliary verbs (e.g., *am, will,* and *have*) was related to lower levels of emotional stability, *r* = -.30, p = .008, but was not related to the other traits. More frequent use of interrogatives (e.g., *how, when,* and *what*) was related to lower levels of emotional stability, *r* = -.24, p = .039, but was not related to the other traits. More frequent use of *past focus* words (e.g., *ago, did,* and *talked*)was related to lower levels of emotional stability, *r* = -.29, p = .013, but was not related to the other traits. More frequent use of *present focus* words (e.g., *today, is,* and *now*) was related to lower levels of emotional stability, *r* = -.27, p = .021, but was not related to the other traits. More frequent use of *time* words (e.g., *end, until,* and *season*) was relative to lower levels of emotional stability, *r* = -.27, p = .018, but was not related to the other traits.

To explore further the relationships among mood stability and usage frequencies, we conducted a multiple regression in which mood stability was the dependent variable and the six word usage categories were independent variables, entered simultaneously. The analyses revealed high levels of collinearity involving the auxiliary verb and present focus categories with the other variable. We then conducted an exploratory stepwise linear regression, which revealed a significant model, *F*(1, 75) = 15.53, *p* < .001 with acceptable values of Tolerance and VIF (Field, 2013). The model accounting for 16.3% of the variance in mood instability (adjusted *R*2 = .163). The only significant predictor in the model was usage of first person singular pronouns, standardized *β* = -.41, *p* < .001.

**TrueColors Types**

The results supported the hypothesis that TrueColors type was related to word usage on Twitter. Only one of the four types was uniquely related to word usage – the wise/curious type. Table 2 displays a summary of results. Due to the small and unequal sample sizes (i.e., *n*s ranging from 17 to 30), we used Kruskal-Wallis H tests (Kruskal & Wallis, 1952). Mean frequency of word usage was higher for the wise/curious type than the other three types (i.e., warm/compassionate, responsible/dependable, or adventurous/spontaneous) for six categories: a) prepositions (e.g., *to, with,* and *above*): *H* (3) = 12.99, *p* = .005; b) swear words (e.g., *damn*, *shit,* and *hell*)*;* (3) = 10.78, p = .013; c) anger words: *H* (3) = 12.16, p = .007; d) sexual words; 3) = 9.94, *p* = .019; e) impersonal pronouns (e.g., *its, their,* and *theirs*): *H* (3) = 8.98, *p* = .03; and f) tentative words (e.g., *maybe* and *perhaps*): *H* (3) = 14.67, *p* = .002. Post-hoc comparisons indicated that frequencies were reliably higher for the wise/curious type than other three types for each of the six word categories: prepositions (vs. warm/compassionate, *U* = 21.93, *p* = .001, vs. responsible/dependable, *U* = 21.41, *p* = .005, and vs. adventurous/spontaneous, *U* = -22.42, *p* = .006); anger (vs. warm/compassionate, *U* = 17.56, *p* = .009, vs. responsible/dependable, *U* = 25.73, *p* = .001, and vs. adventurous/spontaneous, *U* = -17.40, *p* = .032); swear words (vs. warm/compassionate, *U* = 16.00, *p* = .017, responsible/dependable, *U* = 23.02, *p* = .003, and adventurous/spontaneous, *U* = -20.38, *p* = .012); sexual words (vs. warm/compassionate, *U* = 14.73, *p* = .027, vs. responsible/dependable, *U* = 16.10, *p* = .035, and vs. adventurous/spontaneous, *U* = -24.42, *p* = .003); impersonal pronouns (vs. warm/compassionate, *U* = 13.58, *p* = .043, vs. responsible/dependable, *U* = 19.93, *p* = .01, and vs. adventurous/spontaneous, *U* = -20.48, *p* = .012); and tentative words (vs. warm/compassionate, *U* = 15.76, *p* = .019, vs. responsible/dependable, *U* = 26.59, *p* = .001, and vs. adventurous/spontaneous, *U* = -24.79, *p* = .019). None of the other three TrueColors types were uniquely related to LIWC word usage categories.

**Risk-Taking Domains**

The results supported the hypothesis that levels of risk-taking for the five DOSPERT domains (i.e., health/safety, recreational, social, ethical, and financial) were related to frequency of word usage on Twitter. Table 3 displays a summary of the correlational results. There was between one and thirteen LIWC categories related to each of the five domains of risk-taking.

***Recreational Risk-Taking.*** For the recreational risk-taking, there was just one noteworthy LIWC category. Less frequent use of third person plural pronouns (e.g., *they* and *their*) was related to higher levels of recreational risk-taking, *r* = -.28, *p* = .015, but was not related to the other domains.

***Ethical Risk-Taking***. For ethical-risk-taking domain, there was just one noteworthy LIWC category. More frequent use of sexual wordswas related to higher levels of ethical risk-taking, *r* = .31, *p* = .007, but was not related to the other domains.

***Social Risk-Taking****.* For the social risk-taking domain, there were two LIWC categories to note. Less frequent use of you pronouns (e.g., *you, you,* and *yours*)was related to higher levels of social risk-taking, *r* = -.30, *p* = .008, but was not related to the other domains. More frequent use of *she/he* was related to higher levels of social risk-taking, *r* = .37, *p* = .001, but was not related to the other domains.

To explore further the relationships how these LIWC categories are related to social risk-taking, we conducted a multiple regression analysis in which social risk-taking was the dependent variable and the two word usage categories were independent variables, entered simultaneously. The model, *F*(2, 75) = 11.32, *p* < .001, with acceptable Tolerance and VIF values (Field, 2013). The model accounting for 21.6% of the variance in social risk-taking (adjusted *R*2 = .216). Both variables were significant predictors in the model: you pronouns (standardized *β* = -.31 *p* = .003) and she/he (standardized *β* = .38, *p* < .001).

***Health/Safety Risk-Taking***. For the health/safety risk-taking domain, there were three LIWC categories. Less frequent use of *hear words* (e.g., *listen* and *hearing*)was related to higher levels of health/safety risk-taking, *r* = -.24, *p* = .04, but was not related to the other domains. Less frequent use of words related to *work* (e.g., *job, majors,* and *Xerox)* was related to higher levels of health/safety risk-taking, *r* = -.29, *p* = .012, but was not related to the other domains. Also, having fewer tweets overall was related to higher levels of health/safety risk-taking, *r* = -.26, *p* = .022, but was not related to the other domains.

To explore further the relationships how these LIWC categories are related to health/safety risk-taking, we conducted a multiple regression analysis in which social risk-taking was the dependent variable and the three word usage categories were independent variables, entered simultaneously. The model, *F*(3, 75) = 4.47, *p* = .006, with acceptable Tolerance and VIF values (Field, 2013). The model accounting for 12.2% (adjusted *R*2 = .122) of the variance in health/safety risk-taking. There was only one significant predictor: *work* words (standardized *β* = -.24 *p* = .032).

***Financial Risk-Taking***. For the financial risk-taking domain, there were 13 LIWC categories of interest. Less frequent use of authenticwords was related to higher levels of financial risk-taking, *r* = -.26, *p* = .04, but was not related to the other domains. Less frequent use of dictionary words was related to higher levels of financial risk-taking, *r* = -.25, *p* = .028, but was not related to the other domains. Less frequent use of function words (e.g., *it, to,* and *was*) was related to higher levels of financial risk-taking, *r* = -.32, *p* = .006, but was not related to the other domains. Less frequent use of pronounswas related to higher levels of financial risk-taking, *r* = -.23, *p* = .046, but was not related to the other domains. Less frequent use of impersonal pronouns (e.g., *its, their,* and *theirs*) was related to higher levels of financial risk-taking, *r* = -.23, *p* = .04, but was not related to the other domains. Less frequent use of auxiliary verbs (e.g., *am, will,* and *have*) was related to higher levels of financial risk-taking, *r* = -.27, *p* = .021, but was not related to the other domains. Less frequent use of common adverbs (e.g., *very* and *really*) was related to higher levels of financial risk-taking, *r* = -.24, *p* = .036, but not related to the domains. Less frequent use of conjunctions (e.g., *and, but,* and *or*)was related to higher levels of financial risk-taking, *r* = -.26, *p* = .04, but was not related to the other domains. Less frequent use of words related to anxiety(e.g., *worried* and *fearful*) was related to higher levels of financial risk-taking, *r* = -.25, *p* = .03, but was not related to the other domains. Less frequent use of words related to cognitive processes(e.g., *cause, know,* and *ought*) was related to higher levels of financial risk-taking, *r* = -.26, *p* = .024, but was not related to the other domains. Less frequent use of words related to differentiation (e.g., *hasn’t, but,* and *else*) was related to higher levels of financial risk-taking, *r* = -.28, *p* = .015, but was not related to the other domains. Less frequent use of words related to the present focus (e.g., *today, is,* and *now*) was related to higher levels of financial risk-taking, *r* = -.26, *p* = .022, but was not related to the other four domains. Less frequent use of words related to nonfluency(e.g., *er*, *hm*, and *um*) was related to higher levels of financial risk-taking, *r* = -.24, *p* = .04, but was not related to the other domains.

To explore further the relationships among financial risk-taking and usage frequencies, a multiple regression was conducted in which financial risk-taking was the dependent variable and the 11 word usage categories were independent variables, entered simultaneously ((i.e., the categories of total function words and total pronouns were not entered). The analyses revealed high levels of collinearity among variables (VIFs > 5) and a non-significant model, *F*(11, 75) = 1.33, *p* = .23. We then conducted an exploratory stepwise linear regression, which revealed a significant model: *F*(1, 75) = 7.56, *p* = .008. The model accounting for 8% of the variance in financial risk-taking (adjusted *R*2 = .08). The single predictor was conjunctions (standardized *β* = -.30, *p* = .008).

**Risk-Taking Overall**

We also examined the relationships between overall DOSPERT scores (the sum across the five domains) and LIWC categories. We observed five significant relationships. Higher overall risk-taking was related to more words per sentence, *r* = .26, *p* = .023. Higher overall risk-taking was related to using achievement words (e.g., *win* and *better*) *less* often, *r* = -.317, *p* = .005; to using reward words (e.g., *prize* and *benefit*), less often, *r* = -.32, *p* = .005; and to using time (e.g., *end* and *season*) words less often, *r* = -.23, *p* = .04.

**General Discussion**

The present research investigated how self-reported Big Five personality traits; the four TrueColors Types, which are based on the MBTI; and five domains of general risk-taking in daily life were related to word usage on Twitter. The results add to the growing number of studies demonstrating that personal characteristics are related to word usage.

Regarding the results for Big Five personality traits, our results were similar to prior studies. We found that extraversion was related to more frequent use of *they,* which is similar to Celli and Lepri’s (2018) finding that higher levels of extraversion was related to more frequent references to others. We also found higher levels of that mood stability (i.e., more instability) was related to more frequent use of first person singular pronouns (e.g., *me*, *mine*, and *I*), which was also reported by Celli and Lepri (2018) in their analysis of language used on Facebook and Pennebaker and King’s (1999) analysis of multiple types of texts.

Our results are the first to show that TrueColors types, which are based on the MBTI (TrueColors, 2022; See Keirsay & Bates, 1979; Lowry, 1987), are related to word usage. The wise/curious type used six categories more frequently than other types (i.e., prepositions, anger words, sexual words, swear words, impersonal pronouns, and tentative words). These results add to the relatively small literature on word usage and MBTI types (c.f., Celli & Lepri, 2018 who also observed a relationship between anger words and introduction using the traditional MBTI). Although there is criticism of the MBTI and its derivatives due to its lack of scientific basis and psychometric rigor, our results for the TrueColors types may be of interest, due to its use in workplaces around the world. Companies that use information about TrueColors types for employee and/or clients may be interested in the question of whether these types can be predicted using samples of word usage.

Comparing the present results with prior research, we failed to observe some previously reported relationships. For example, we did not observe relationships between a) extraversion and family and social words or neuroticism; b) words related to religion or perceptual processes, and c) openness and words related to causation and certainty, which were reported by Golbeck et al. (2011) from their analysis of Tweets. We did not observe relationships between a) mood instability and negative emotion words; c) extraversion and positive emotion words; and c) extraversion and words related to interpersonal interaction, which were reported by Yakoni (2010) in an analysis of language used in blogs. We did not observe a relationship between extraversion and usage of positive emotion words, which was reported by Pennebaker and King (1999).

The present results are among the first to show that differences in self-reported risk-taking were related to word usage in 20 categories. One category was related to recreational risk-taking (i.e., third person plural pronouns), and one category was related to ethical risk-taking (i.e., sexual words). Two categories were related to social risk-taking (i.e., you pronouns and she/he pronouns); both variables were significant predictors in a multiple regression. Three categories were related to health/safety risk-taking (i.e., hear words, work words, and total tweets); only work words was a significant predictor in a multiple regression. Thirteen categories were related to financial risk-taking (i.e., authentic words, dictionary words, function words, pronouns, impersonal pronouns, auxiliary verbs, adverbs, conjunctions, anxiety words, cognitive process words, present focus, differentiation, and nonfluency). The best multiple regression model indicated that the category of function words was the only significant predictor.

There are multiple avenues available for future research, including determining whether the results can be replicated with non-university samples. With the ability to predict personality and risk-taking from language used on social media, one has possibilities of applications in business as well as public health. Businesses might find it useful to direct advertisements to individuals most likely to be interested in the service or product (e.g., insurance for the conscientious or recreational adventures for the recreational risk-takers). Public health researchers could test the benefits of targeting social media users with public health messages aimed at reducing risk-taking or increasing the utilization of mental health resources (in the case of individuals based on scores related to mood stability).

There are multiple limitations for this research. Foremost, the sample was composed of individuals with public Twitter accounts who were willing to provide their Twitter usernames for the research project. The sample is likely to be affected by volunteer bias. Those agreeing to participate may differ from those who did not consent to the analysis of their Twitter account (e.g., possibly be lower in agreeableness as well as other variables). A related issue is the fact that the sample was majority women. It is unclear whether the results would be different if gender were more balanced in the sample. An additional limitation is the fact that the sample included only undergraduates whose personality traits, self-schemas, and risk-taking may differ from those found in other populations. Lastly, the sample is relatively small containing data from only 76 participants. The small sample size reflects the difficulty in conducting this type of research in which participants provide survey data in addition to their social media usernames. Future research may find methods that yield higher rates of participation and/or rates of providing social media usernames during survey studies. Prior research with the largest sample sizes were those in which social media posts were not linked to individuals’ survey data.

Future research is also warranted to determine the extent to which language used in public spaces (e.g., social media, text messages, and conversations) may be linked to personal characteristics. While efforts to gather language by individuals who also provide self-reported personal characteristics are time-consuming, expensive, and affected by limitations, such as volunteer bias, others are demonstrating the ability of machine-learning algorithms to predict personal characteristics from modest samples of language (e.g., Reciptiviti, 2022; Devlin et al., 2019). More research is needed to test the accuracy of such algorithms and also to explore the social and ethical implications of using such algorithms in employment settings to screen prospective employees (e.g., Hawkins, 2021), for commercial enterprises to target marketing to individuals, and public health to target public health messages or information to individuals deemed to most likely to benefit.

In sum, the results suggest that it appears possible to predict personal characteristics of social media users through analysis of their word usage. Multiple prior studies have examined relationships between personality and word usage. The present study found new relationships between TrueColors Types and the five domains of general risk-taking in daily life (i.e., health/safety, recreational, social, ethical, and financial) and word usage, which may be exploited in the future by those involved in business (e.g., targeted marketing) or public health (e.g., targeted messaging and/or interventions).

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**Disclosure Statement**

The authors have no conflicts of interests to disclose.

**Data Availability Statement**

The data for the present research will be made available upon request. Direct requests to the corresponding author. The data are not publicly available in order to preserve the privacy of research participants.

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Table 1. *Summary of Correlations between Big Five Personality Traits and LIWC Word Categories.*

Big Five Personality Traits

LIWC Word Category E A C O ES

They -.24\* .003 .15 .20 .05

Feel -.13 .19 .24\* .03 .10

First person singular pronoun -.17 -.06 -.06 .01 -.26\*

Auxiliary Verbs -.18 -.09 -.12 -.09 -.30\*\*

Interrogatives -.13 -.13 -.12 -.08 -.24\*

Past -.16 -.19 -.18 -.17 -.29\*

Present -.13 -.16 -.12 -.11 -.27\*

Time -.12 -.16 -.13 -.15 -.27\*

Negative -.08 -.19 -.21 -.24\* -.17

Articles -.12 .16 .18 .29\* -.01

Sad -.05 -.05 -.02 -.23\* -.08

Tone -.03 -.12 -.08 -.26\* -.13

Period -.04 .10 -.16 .30\*\* .05

Total Words -.01 .16 .17 .35\*\* .04

*Note:* \**p* < .05, \*\**p* < .01, \*\*\**p* < .001; E = Extraversion, A = Agreeableness, C = Conscientiousness, O = Openness, ES = Emotional Stability

Table 2. *Summary of Median Frequency Results for LIWC Categories by TrueColors Type*

TrueColors Type

LIWC Category Wise/Curious Warm/Compassionate Responsible/Dependable Adventurous/Spontaneous

(n=17) (n=30) (n=16) (n=13)

Prep 8.72 7.20 7.04 6.61

Anger .68 .47 .34 .44

Swear .47 .18 .12 .24

Sexual .19 .05 .05 .03

i Pronoun 3.43 2.88 2.89 2.20

Tentative 1.85 1.35 1.23 .92

*Note*: i pronoun = impersonal pronouns; For each LIWC category, frequencies for the Wise/Curious Type were significantly different from frequencies used by each of the other TrueColors types, *p* < .05.

Table 3. *Summary of Correlations between Risk-Taking Domains and LIWC Word Categories*

Risk-Taking Domain

LIWC Word Category H/S R S E F

Total Words -.26\* .01 .18 .05 .11

Hear -.24\* .21 .06 .04 -.16

Work -.29\* -.16 .17 -.04 -.19

They -.03 .28\* .20 .14 -.17

You .09 .15 -.30\*\* -.06 -.09

She/He -.03 .01 .37\*\*\* .12 -.04

Sexual .03 -.08 .11 .31\*\* -.04

Authentic -.01 -.03 -.13 -.06 -.26\*

Dic -.11 -.07 .04 -.04 -.25\*

Function -.04 -.03 -.03 .04 -.32\*\*

Pronouns .07 .10 -.09 .02 -.23\*

I Words -.02 -.05 .09 .15 -.23\*

Auxiliary Verbs -.06 -.01 -.02 .07 -.27\*

Adverbs -.01 .03 -.05 .01 -.24\*

Conjunctions -.10 -.05 -.06 .02 -.26\*

Anxiety -.01 .20 .03 .01 -.25\*

Cognitive Processes -.01 -.08 -.03 .10 -.26\*

Differ .02 -.11 .02 .09 -.28\*

Present -.06 .01 -.11 .01 -.26\*

Nonflu -.04 .03 .01 .07 -.24\*

*Note:* \**p* < .05, \*\**p* < .01, \*\*\**p* < .001; H/S = Health/Safety, R = Recreational, S = Social, E = Ethical, F = Financial