Spring March 10th, 2017

Predicting Employee Performance Using Text Data from Resumes

Joshua D. Weaver
Seattle Pacific University

Predicting Employee Performance Using Text Data from Resumes

Joshua D. Weaver

A dissertation submitted in partial fulfillment

Of the requirements for the degree of

Doctor of Philosophy

In

Industrial/Organizational Psychology

Seattle Pacific University

April 2017

Approved by:
Dana Kendall Ph.D.
Assistant Professor, Industrial/Organizational Psychology
Dissertation Chair

Christopher Roenicke Ph.D.
Assessment & Evaluation Program Manager at Amazon
Committee Member

Ryan C. LaBrie Ph.D.
Associate Professor - MIS
Committee Member

Reviewed by:

Robert B. McKenna Ph.D.
Chair, Industrial/Organizational Psychology

Katy Tangenberg Ph.D.
Dean, School of Psychology, Family & Community

Acknowledgements

I have been fortunate to be surrounded by a cadre of supporters and advisers who have shaped and continue to shape who I am. These acknowledgments are presented in no particular order. Each of these individuals has had a meaningful (statistically significant) impact on my life, without which I would not be the person I am today…

My advisor, Dr. Dana Kendall. Her unwavering support, passion for truth, theory, and quantitative prowess have been a source of inspiration, emotional support, and healthy tension throughout this journey.

The SPU faculty who have pushed, pulled, challenged, and supported me over the years. The tools you have given me to make sense of myself, the world and people in organizations have had a huge impact. Keep up the great work.

Kira, for being an academic confidant, a reliable colleague with whom I could discuss our unconventional views of IO psychology and our desire to make a lasting impact on our worlds, and for being a friend to share in the difficulties of graduate school and young professional life.

Diana, thanks, roomie. Sharing our love of musicals and upbringing has been a source of support and much laughter.

Katie, for being an awesome co-author and research partner. Her support early on in the Ph.D. program was key to helping me survive those turbulent early years.

Robleh, thanks, roomie. It has been a remarkable experience to support each other over the years and to cheer on our successes and problem solve through setbacks.

Emily, for being a great friend, and happy hour buddy. Who else would I talk to about structural equation modeling while drinking bourbon?

Serena, for being a great friend, who always brings a unique perspective to the world of work or academia. I am looking forward to more spirited conversations in the future.

Matt, who thought meeting on Twitter (will Twitter be relevant in 10 years?) would lead to us being friends 5 years later. Thanks for great times and looking forward to more, even if Twitter ceases to be relevant.

Tyler, Dan, and Aaron for being a much-needed distraction from the crazy-making that can be graduate school. Cheers, mates.

To the rest of the group, outside of graduate school (you know who you are), you guys are awesome, and I would not trade you for anything. Thanks for putting up with me all these years.

Preface

The impetus for this dissertation came in 2011 while working as an entry-level consultant with a local Seattle consulting company. I was assigned to work on a project with an intellectual property firm to help the US Patent Office more quickly process patent applications. In 2011, it took about 3 years for a patent to be officially accepted or rejected. We used text analytics to try and identify patent applications that should be rejected because the idea had already been patented. Up until that point, I was not aware that text could be used in such a way. I was fascinated with the potential for text to be analyzed and mined for insight and immediately began considering its application to IO psychology as a tool for automating resume reviews.

Initially, I considered text analytics as a tool to add rigor to keyword searches applicant tracking systems (ATS) used to crudely screen resumes, as well as a way to deliver value to organizations by reducing time spent hiring talent, while also protecting applicants from recruiter or hiring manager bias by doing a “blind” resume review. Truthfully, I was more interested in applying the technique to resumes than extending and building on IO psychology theory. After all, text analytics had been used to identify sex (Cheng, Chandramouli, & Subbalakshmi, 2011), mood (Nguyen, Phung, Adams, & Venkatesh, 2014), and even predict stock prices (Bollen, Mao, Zeng, 2010). My rationale was to use the transitive property to argue that if text analytics could be used for those purposes, why not extend its use to evaluating resumes? However, I knew this would not fly; my advisor would never allow such a flimsy theoretical argument as the basis for a dissertation (…and rightly so I might add).

In digging deeper into IO psychology selection research, I happened upon biodata and immediately saw a connection (albeit a tenuous one) between text analytics and biodata, and the rest—well the rest, as they say, is history…or at least I hope so!

Table of Contents

List of Tables

List of Figures

List of Appendices

Joshua David Weaver

346

Abstract

Text analytics using term frequency was proposed as an extension of biodata for predicting job performance and addressing criticisms of biodata and predictor methods—that they do not identify the constructs they are measuring or their predictive elements. Linguistic Inquiry and Word Count software was used to analyze and sort text into validated categories. Prolific Academic was used to recruit full-time workers who provided a copy of their resume and were assessed on impression management (IM), cognitive ability, and job performance. Predictive analyses used resumes with 100+ words (*n* = 667), whereas correlational analyses used the full sample (*N* = 809). Third-person plural pronouns, impersonal pronouns, sadness words, certainty words, non-fluencies, and colons emerged as significant predictors of job performance (χ^2 = 26.01 (10), *p* = .006). As hypothesized, impersonal pronouns were positively correlated with self-oriented IM (*r* = .07, *p* < .05), and first-person singular pronouns were positively correlated with other-oriented IM (*r* = .07, *p* < .05), however, first-person plural pronouns were negatively correlated (*r* = -.07, *p* < .05). Pronouns and verbs were not predictive of job performance. Positive and negative emotion words did not show hypothesized relationships to OCBs, CWBs, or job performance. Finally, differentiation words (*r* = .09, *p* < .01), conjunctions (*r* = .28, *p* < .01), words longer than six characters (*r* = .29, *p* < .01), prepositions (*r* = .20, *p* < .01), cognitive process words (*r* = .19, *p* < .01), causal words (*r* = .20, *p* < .01), and insight words (*r* = .06, *p* < .05) correlated with cognitive ability, but did not predict job performance. An exploratory regression analysis in which cognitive ability as measured by the Spot-The-Word Test (*β* = .10, *p* < .05) and a composite of cognitive ability created from text analytics (*β* = .15, *p* < .05) both uniquely and significantly predicted job performance ($F(1,805) = 18.79$, $p < .001$), demonstrating that word categories can serve as a proxy for cognitive ability. Overall, the method of text analytics sidesteps some of the limitations of biodata predictor methods, while demonstrating the potential to automate resume reviews and mitigate unconscious bias inherent in human judgment.

CHAPTER 1

Introduction

In the 20 years since scholars at McKinsey and Company coined the term "war for talent" (Chambers, Foulon, Handfield-Jones, Hankin, & Michaels, 1997), the war has not abated. Rather, it has intensified. Employee selection remains a top strategic imperative for human resources (HR) leaders (Ray et. al., 2012); yet hiring the right individuals remains challenging due time constraints (Bullhorn, 2014; Virgina, 2014) and finances (Galbreath, 2000). Although resume screening is one popular approach for selecting employees, it is only the first step in the process. Applicants must also pass phone screens and structured on-site interviews, to name a few of the typical hurdles in the employee selection process.

In this study, I will integrate evidence and methods from the long-standing study of biodata in industrial-organizational (IO) psychology, with the relatively new field of text analytics to make a case for a new method that transforms resume text into quantifiable predictors of an applicant's job performance. One benefit of this research is the automation of the resume review process, enabling fast and efficient resume screening at scale. A potential theoretical contribution is that this new method identifies and quantifies underlying applicant attributes and skills that are job-relevant, by analyzing resumes. I make a case for text analytics as a potential method for employee selection by first defining and describing the biographical data method. Next, I review the applicant attributes captured by biodata that predict job performance, noting that it is unclear which specific constructs are being captured. Next, I describe the text analytics method, highlighting benefits that other scientific fields have gained from using this method. Because text analytics can potentially infer attributes of a person by analyzing their writing, it holds promise for alleviating some of the costs associated with selecting employees, and the potential for being more effective than human evaluation of resumes. I then explore the possibility of analyzing a resume in a manner that captures an applicant's job-relevant knowledge, skills, and abilities based on the words used. Finally, I propose a series of hypotheses that test the idea that these word choices can be quantified and used to predict applicants' future job performance. Ultimately, the goal of this study is to extend existing biodata theory and method and equip HR practitioners with a powerful tool for employee selection.

Biographical Data

Defining and describing the biodata method. The biodata method involves selecting and scoring a set of questions asked of applicants to create an index that will successfully predict outcomes like future job performance (See Table 1 for other criterion examples; Becton, Matthews, Hartley, & Whitaker, 2009; Cucina, Caputo, Thibodeaux, & MacLane, 2012). Many types of biodata can be solicited from applicants for the purpose of prediction, and resumes are one example (Brown & Campion, 1994; Stokes, Mumford, & Owens, 1994). The biodata method involves collecting information from applicants regarding their developmental experiences and typical behavior, both in and out of the workplace (Becton et al., 2009; Barrick & Zimmerman, 2009; Mael, 1991; Zaccaro, Gilbert, Zazanis, & Diana, 1995). Developmental questions focus on experiences that theoretically shape an individual's behavior, for example, living abroad (Zaccaro et al., 1995). An example of a general behavioral question is: "How many non-fiction books did you read in the past year?" (Zaccaro et al.). Finally, an example of a job-related behavior question would be: "How many people have you managed in past jobs?" (Barrick & Zimmerman, 2009; Parish & Drucker, 1957).

Exploring applicant attributes captured by biodata. Biodata seeks to capture applicant attributes, behaviors, and experiences that are theoretically expected to predict their future performance on the job. The primary rationale for this link is that past behavior is the best predictor of future behavior (Owens, 1976; Wernimont & Campbell, 1968) because behavior is shaped by an individual's values, volitional choices, goals (Mumford & Owens, 1987; Mumford & Stokes, 1992), and perceived membership to social groups (Ashforth & Mael, 1989; Mael, 1991; Mael & Ashforth, 1992). Thus, biodata indirectly captures the aspects of the applicant's personality and cognitive ability (Dean & Russell; Kilcullen, 1995) that predict job performance (Barrick & Mount, 1991; Hogan & Holland, 2003; Judge et al., 2013; Schmidt & Hunter, 1998; Schmidt & Hunter, 2004).

Limitations of biodata: the conflation of method and construct. In scholarly work, the biodata technique is characterized as a selection method, as opposed to a construct. Selection constructs are specific behavioral domains like personality, whereas selection methods are the techniques by which domain-relevant behavioral information is collected, quantified, and used to select applicants (Arthur & Villado, 2008). Although predictor methods like biodata are useful for identifying predictors of job performance (Allworth & Hesketh, 2000; Becton, Matthews, Hartley, & Whitaker, 2009; Reilly & Chao, 1982; Zaccaro, Gilbert, Zazanis, & Diana, 1995), the nature of the constructs they actually capture remain unidentified (Lievens & Patterson, 2011; Shultz, 1996). This stymies the progress of scholarly and applied work because we remain ignorant to the specific predictor constructs that are being captured by a particular method. For instance, in the case of biodata and resumes, we do not know exactly which applicant characteristics are driving performance—all we know is that something is driving it. The current study represents a step toward making this link explicit by examining if applicants' choice of words can serve as indirect indicators of predictors of performance such as cognitive ability.

Biodata summary. In summary, the biodata method is useful for predicting job performance and thus is a promising method for selection (see Table 2 for additional evidence of this). To improve its effectiveness and reduce its limitations, we need more efficient, objective ways to aggregate and quantify job-relevant applicant data provided on resumes. Text analytics represents a potential way to achieve these goals simultaneously.

Text Analytics

Text analytics refers to methods used to identify patterns and relationships within text (Hotho, Nurnberger, & Paab, 2013). For a detailed discussion of text analytics methods see Aggarwal and Zhai (2012). The text analytic technique employed in this study is *term frequency*. Term frequency refers to the process of counting the number of times a word appears in a document (Hotho et al., 2005). This number is then used to predict the personal characteristics or future behavior of the document's author. This technique has been used in clinical psychology to diagnose patients (Oxman, Rosenberg, Schnurr, & Tucker, 1988), and in other fields (see Table 3). The utility of text analytics in clinical psychology (e.g., Oxman et al., 1988) and other fields, suggests that text analytics may benefit IO psychology by providing the missing link between method and construct, thereby yielding an empirical approach to linking certain words to job performance. Therefore, I hypothesize the following:

Hypothesis 1: Variables derived from term frequency text analytics will add explanatory power above and beyond control variables to differentiate high job performers from low job performers.

Term frequency using linguistic inquiry and word count software. This study used Linguistic Inquiry and Word Count (LIWC) software (Pennebaker, Boyd, Jordan, & Blackburn, 2015; Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007) to analyze text. The software was originally developed to “analyze the emotional, cognitive, and structural components of individuals’ verbal and written speech” (Pennebaker et al., 2007, p. 3), and contains 6,400 words, word stems, and select emoticons grouped into over 80 categories (Pennebaker, Boyd et al., 2015, pp. 3-4, 11-12). These words and word stems have been curated and agreed upon by independent judges (see Pennebaker et al., 2007; Pennebaker, Boyd et al., 2015; Tausczik & Pennebaker, 2010 for detailed information on the development of LIWC). The major categories include: (a) linguistic processes such as articles and pronouns, (b) psychological processes (e.g., positive and negative emotion), (c) personal concerns like work and leisure, (d) spoken categories for example assent and fillers, as well as (e) punctuations such as commas and periods. See Appendix A for examples of words in these categories.

Overview of how LIWC software analyzes text. The Linguistic Inquiry and Word Count software counts the number of times each of the 6,400 words, word stems, and select emoticons occur across the 80 plus categories and sub-categories in each document. Because words can be categorized into multiple categories, the final output is the percentage of words in each category for a given text (Tausczik & Pennebaker, 2010). For example, the word *sad* can be placed in the following categories: Sadness, negative emotion, overall affect, and adjective. *Sad* would increase the count in each of these categories by one, and the integer value of these categories would be divided by the total number of words in the text to arrive at a final percentage of words in the text for a given category.

Linking the predictor method to the construct. Beyond transforming resume data into quantifiable predictors of an applicant’s job performance, text analytics provides a way to link predictor method and predictor construct by identifying specific word types (e.g. conjunctions) as proxies for known predictors of job performance. For example, rather than administering a direct assessment of an applicant's cognitive ability, selection practitioners may be bale to use text analytics to infer the level of cognitive ability from the content of a resume. In the following sections, I identify and describe several specific LIWC word categories that are likely to predict job performance. In addition, I contend that some of these categories may be proxies for specific predictor constructs such as impression management and cognitive ability. The LIWC categories reviewed are: (a) pronouns, (b) verbs, (c) positive emotion words, (d) negative emotion words, (e) differentiation words, (f) conjunctions, (g) words longer than six characters, (h) prepositions, (i) cognitive process words, (j) causal words, and (k) insight words.

Pronouns as proxies for impression management. Pronouns (e.g., I, we, you, etc.) have been linked to impression management (IM) styles (Ickes, Reidhead, & Patterson, 1986; Tausczik & Pennebaker, 2010), and IM is positively related to job performance (Wayne & Liden, 1995; Huang, Zhao, Niu, Ashford, & Lee, 2013). Taken together, this suggests that pronouns may be proxies for IM. Impression management is defined as "behaviors individuals employ to protect their self-image and influence the way they are perceived by important others" (Wayne & Liden, 1995, p. 232). Use of first-person pronouns (e.g., I, me) have been found to be positively associated with a self-IM style (Ickes et al., 1986)—a style characterized by IM tactics designed to bring others' behavior in line with one's own objectives. While second- and third-person pronouns (e.g., you, your, he, she) are correlated with an "other"-IM style; a style characterized by IM tactics intended to curry approval from others and align one's own behavior to the goals and objectives of others. Given the findings in text analytic research linking pronouns to these IM styles (Ickes et al., 1986) and the association between IM and job performance (Wayne & Liden, 1995; Huang et al., 2013) I proposed the following hypothesis.

Hypothesis 2a-b: The use of pronouns in individuals' resumes, will correlate positively *with (a) self and other impression management styles, and (b) job performance behaviors.*

Verbs as predictors of job performance. Verbs are associated with a thinking style called “categorical thinking” (Pennebaker, 2011; pp. 285-286). This style is methodical, structured, and impersonal and predictive of academic success (i.e. GPA; Pennebaker, 2011; Pennebaker, Chung, Frazee, Lavergne, & Beaver, 2014). Although Pennebaker (2011) refers to this as a thinking style, it is clear from his description that this thinking style is not synonymous with cognitive ability. Given that resumes and biodata are theorized to tap into specific skills and abilities (Mumford & Owens, 1987; Mumford & Stokes, 1992), it stands to reason that the verbs in a resume may be related to job performance, given their link to academic achievement (Pennebaker et al., 2014).

Hypothesis 2c: The number of verbs used in resumes will positively predict job performance.

Emotion words as predictors of organizational citizenship behaviors and counterproductive work behaviors. Prior text analytic work using LIWC has shown that positive and negative emotions can be extracted from text (Nguyen, Phung, Adams, & Venkatesh, 2014). Thus, it is worthwhile to investigate whether positive and negative emotion can also be extracted from resumes. Doing so could enable the prediction of work outcomes such as organizational citizenship behaviors (OCBs) and counterproductive work behaviors (CWBs). Organizational citizenship behaviors are positive employee actions that extend beyond the scope of an individual's formal job description. Examples of OCBs include staying late to help a colleague or volunteering for extra assignments, whereas counterproductive work behaviors harm an organization (e.g., bullying, incivility, etc.). According to a prior meta-analysis, positive mood is positively related to both job performance (ρ = 0.19) and OCBs (ρ = 0.23; Kaplan, Bradley, Luchman, & Haynes, 2009). Conversely, negative mood is negatively associated with job performance (ρ = -0.21) and positively related to CWBs (ρ = 0.30). Given that authors' moods can be ascertained from their writings (Nguyen et al., 2014) and moods have been demonstrated to predict work outcomes (Kaplan et al., 2009), I hypothesized the following:

Hypothesis 3a: Positive emotion words will positively predict job performance and OCBs.

Hypothesis 3b: Negative emotion words will negatively predict job performance and positively predict CWBs.

Accompanying Hypothesis 3 is a caveat. Conventional wisdom recommends eliminating emotional language from resumes (Knouse, 1994, Koeppel, 2002). Thus, it is possible that positive and negative emotion words will not show up on resumes in sufficient quantities to be useful predictors of performance indicators.

LIWC categories that may serve as proxies for cognitive ability. Researchers have identified seven LIWC categories as indicators of cognitive complexity (Pennebaker, Boyd, et al., 2015; Pennebaker & King, 1999; Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010). They are: (a) differentiation words, (b) conjunctions, (c) words longer than six characters, (d) prepositions, (e) cognitive process words, (f) causal words, and (g) insight words. Conjunctions are used by writers when creating a narrative thread, and exclusion words are used to make distinctions between categories of things (e.g. political candidates in political ads; Tausczik & Pennebaker, 2010), whereas prepositions appear with greater frequency in the discussion section of a journal in which authors are integrating current and past findings (Hartley, Pennebaker, & Fox, 2003). Similarly, causal and insight words indicate cognitive processing and reappraisal of an event or idea (Pennebaker, Mayne, & Francis, 1997).

Although researchers refer to these seven LIWC categories as indicators of cognitive complexity (Pennebaker, Boyd et al., 2015; Pennebaker & King, 1999; Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010), their descriptions are better characterized as indicators of meta-cognition that reflect an aspect of cognitive processing rather than cognitive ability. Nevertheless, this body of research leads to a logical and intuitive question—do these categories reflect actual underlying cognitive ability?

This question is particularly pertinent to employee selection because cognitive ability has been consistently found to be one of the best predictors of job performance (Schmidt & Hunter, 1998; Schmidt & Hunter, 2004; Hunter & Hunter, 1984). Thus it is useful to explore whether cognitive ability can be measured by proxy via text analytics. This would allow selection practitioners to infer cognitive ability from a resume via text analytics and potentially obviate the need to administer a cognitive ability measure.

Hypothesis 4a-g: The frequency of words that fall into LIWC categories (a) differentiation words, (b) conjunctions, and (c) words longer than six characters, (d) prepositions, (e) cognitive process words, (f) casual words, and (g) insight words, can be used as proxies of verbal intelligence; and consequently, positively predict job performance.

Chapter One Summary and Introduction to the Present Study

In summary, biodata is a promising method for selection (see Table 2); however, one of its primary liabilities is a lack of clarity between the specific applicant attributes being captured and their empirical links to job performance (Lievens & Patterson, 2011; Shultz, 1996). Text analytics represents a technique to potentially improve biodata's effectiveness and reduce its limitations by using an objective method for aggregating and quantifying applicant data provided in resumes. In this investigation, I examine whether text analytics is capable of extracting job-relevant individual differences that can be empirically linked to current levels of job performance.

CHAPTER 2

Method

Participants Characteristics, Text Data Characteristics, Sample Size, and Power

Inclusion and exclusion criteria. Data collection occurred between November 2015 and January 2016. One thousand, five participants provided data (*N* = 1,005). To be included, participants had to be at least 18 years of age and work more than 32 hours a week. Of the 1,005 participants who completed the survey, 196 provided unusable data and were excluded. Participants were excluded if any of the following conditions were met: (a) the participant did not provide a resume (i.e. submitted blank files or a file that was not a resume), or (b) the resume provided was not in a format that could be analyzed (e.g., resume was not written in English). In summary, 809 participants provided usable data, meeting the minimum sample size needed for tolerable statistical power based on a power analysis (Faul, Erdfelder, Buchner, & Lang, 2009).

Working with distributions found in text data. The nature of written speech means that text data is sparse; ideas, words, and phrases are not repeated more times than necessary in times in a conversation or a document (Pennebaker et al., 2015). This results in non-normal data that has a stark positive skew and is leptokurtic. This shape is common in text analytics (see Corral, Boleda, & Ferrer-i-Cancho, 2015; Piantadosi, 2015) and is addressed by setting a minimum number of words per document ranging from 100 – 1,000 depending on the analyses (see Mahmud, 2015; Schultheiss, 2013; Schwartz et al., 2013), and log transforming the data (Tabachnick & Fidell, 2013). Sample sizes greater than 200 do not require transformations for kurtosis (Waternaux, 1976). For the regression analyses resumes with fewer than 100 words were not included. However, to maximize power, all 809 resumes were included in correlation analyses. This exclusion was applied for the regression analyses, but not for the correlation analyses, because regression models require more robust estimates of central tendency when modeling data (Field, 2009).

Demographic characteristics. For the full sample (*N* = 809), most participants were white (*n* = 512, 63% of the final sample), a majority were males (*n* = 529, 65% of the final sample), the most common level of academic achievement was an undergraduate degree (*n* = 356, 44% of the final sample), and average tenure was 3.5 years (*SD* = 3.52). These proportions remained the same for the logistic-regression subsample (*n* = 667). Most were white (*n* = 462, 69% of the sub-sample), a majority were males (*n* = 407, 61% of the sub-sample), the most common level of academic achievement was an undergraduate degree (*n* = 325, 49% of the sub-sample), and average tenure was 3.4 years (*SD* = 3.52). A detailed exploration of demographics for the total sample can be explored online.

Sampling Procedures. Participants were recruited online using Prolific Academic (Bradley & Damer, 2014), a cloud-based participant recruitment platform that is similar to Amazon's Mechanical Turk, but built specifically for social science research by researchers from the University of Sheffield and backed by the University of Oxford. Given the similarities between Prolific Academic and Amazon's Mechanical Turk and the intent of the platforms, it was assumed that the same findings on Mechanical Turk applied to Prolific Academic, namely that Prolific Academic participants were (a) similar to participants recruited using traditional approaches (Buhrmester, Kwang, & Gosling, 2011; Goodman, Cryder, & Cheema, 2013), (b) representative of the larger population researchers wished to study (Buhrmester et al., 2011; Paolacci, Chandler, & Ipeirotis, 2010), and (c) able to provide data of quality and integrity equivalent to data obtained by traditional approaches (Buhrmester et al., 2011; Chandler, Mueller, & Paolacci, 2013; Goodman et al., 2013). Participants were paid $1.56 (USD) for completing the study. Average completion time was 17 minutes. Participants consented to the study and then clicked on a link, which opened the survey. They were asked to share a copy of their resume, they answered demographic questions (sex, race, education, tenure), and completed the following assessments: (a) 18-item self-reported job performance behavior assessment, (b) 10-item impression management assessment, and (c) 60-item verbal intelligence assessment.

Measures

Control variables. Control variables included: (a) sex, (b) race, (c) education, and (d) tenure. These control variables were selected based on their links to job performance demonstrated in prior research (Ng, Eby, Sorensen, & Feldman, 2005).

LIWC variables. Seventeen LIWC variables were used as predictors for Hypotheses 2-4. Table 4 reports their means, standard deviations, skew, and kurtosis, as well as information on the average base rates identified by Pennebaker et al. (2015). Example words for these categories can be found in Appendix A. In general, base rates reported by Pennebaker, et al. for the word categories proposed in Hypotheses 2-5 are higher than those found in this study. Words longer than six characters were the notable exception this category, making up 40.18 percent of all word categories in resumes, as opposed to only 15.60 percent across the writing contexts such as blogs, books, and news articles analyzed in by Pennebaker et al. This is not surprising, given that resumes constitute a writing context with relatively well-defined parameters and objectives, and where longer and more descriptive words are encouraged. Thus, it is intuitive that the base rates for the resumes sampled in this study would be dissimilar to the base rates reported by Pennebaker et al. Additionally, LIWC contains both categories (i.e., cognitive process word category) and sub-categories (insight words, causal words, etc.) of words. I conducted analyses to determine if sub-categories should be rolled up to the higher-order category. The details of these decision rules and the results of these analyses can be found in Appendix B.

Impression management. Impression management was assessed using a 10-item scale developed by Wayne and Liden (1995). This measure was chosen because it captured both self- and other-oriented impression management in a workplace context and was longitudinally related to job performance (Wayne & Liden, 1995). See Table 5 for a list of all items for this scale. Participants were asked to report how often they had engaged in 10 impression management behaviors during the past three months using a 7-point scale ranging from 1 (*never)* to 7 (*always)*. Scores for each subscale were summed to yield an overall score for each type of impression management behavior (supervisor or self). Higher values indicated greater impression management. Cronbach's alpha (Cronbach, 1951) was 0.87 for the supervisor-focused impression management subscale and 0.84 for the self-focused impression management subscale. Examples of supervisor-focused impression management items include "To what extent do you praise your immediate supervisor on his or her accomplishments?" and "To what extent do you take an interest in your supervisor's personal life?" Examples of self-focused impression management items include "To what extent do you let your supervisor know that you try to do a good job in your work?" and "To what extent do you work hard when you know the results will be seen by your supervisor?"

Verbal intelligence. Verbal intelligence is language-based skills that reflect general latent cognitive abilities (Dawson, 2013). Verbal intelligence was measured using the spot-the-word test (Baddeley et al., 1993; STW; Cronbach's α = .87). See Table 6 for a list of all items. Participants were presented with 60 pairs of words and asked to select the word in each pair that was the real word. Scores on the STW ranged from 0-60 and were derived by summing the number of correct word choices. See Appendix C for additional validity evidence.

Job performance. Self-reported job performance behaviors were measured using the Individual Work Performance Questionnaire (IWPQ; Koopmans et al., 2013; Koopmans et al., 2015), an 18-item measure that assesses task performance (5 items; Cronbach's α = .87), contextual performance (8 items; Cronbach's α = .85), and counter-productive work behaviors (5 items; Cronbach's α = .87). See Table 7 for the full list of items and scales in the IWPQ. Task performance are those behaviors that directly support the conceptualization, design, creation, and dissemination of an organization's products and services (e.g., writing computer code, designing marketing materials; Motowidlo & Van Scotter, 1994). Contextual performance supports the organizational, social, and psychological environment in which the development and distribution of the organization's products and services occur (Motowidlo & Van Scotter). These include pro-social behaviors such as taking on extra tasks that are not formally part of the job, volunteering to help coworkers, etc. Counterproductive work behaviors are those behaviors that harm an organization and people in the organization such as bullying etc. (Kaplan et al., 2009).

Given the applied nature of this research, I primarily focused on task performance as the outcome, except where other outcomes were specified (e.g., OCBs). Such a focus makes sense in a selection context, where one is selecting for job performance rather than a proclivity for OCBs or CWBs. In addition, biodata research has primarily focused on predicting task performance. As such, the inclusion of OCBs and CWBs that were not specified a priority would not directly contribute to building biodata theory.

The IWPQ was chosen for its close alignment with Campbell's (2012) model of job performance, along with its reliability and validity (Koopmans et al., 2013; Koopmans, Bemaards, Hildebrandt, van Buuren et al., 2014; Koopmans, Coffeng et al., 2014; Landers & Callan, 2014) and suitability for use in cross-sectional research (Koopmans, Coffeng et al.).

Examples of items include “I managed to plan my work so that it was done on time” (task performance), “I started new tasks myself when my old ones were finished” (contextual performance, OCB), and “I complained about minor work-related issues at work” (CWB). Scale items, reliability and validity evidence, and scale anchors/scoring procedures can be found in Table 8, Table 9, and Appendix D respectively.

CHAPTER 3

Results

Data Preparation

The final dataset was created by merging the results of the LIWC output file, which is the result of processing participants' resumes (see Appendix E for an example of the LIWC output) with the survey data, which included job performance, impression management, verbal intelligence, and demographic data.

Preparing resume files for analysis. The LIWC software has the capacity to process Portable Data Files (PDFs, .pdf file extension), Microsoft Word files (.doc and .docx file extensions) and plain text files (.txt file extension). Since LIWC cannot process text from an image file (e.g., jpg, .png, .gif, etc.), the twenty-four resumes that were submitted as image files were transcribed by hand as text files (.txt) for processing and analyses by LIWC. Additionally, approximately 30 text-type files (.doc, .docx, .pdf) had view/read permissions associated with them that had to be removed before they could be processed and analyzed.

Cleaning and preparing survey data. Data preparation also included creating a dataset structured for analysis and online visualization in Tableau (2015). I converted the data from a wide format (each row represents a participant and each column a variable or survey item) to a long format, in which all numeric values were placed in a single column with a second column containing their respective labels. Categorical variables were not restructured.

Creating the training and holdout samples. The logistic regression subsample (*n* = 667) which represented resumes with more than 100 words was split into a training and holdout samples following standard biodata assessment development procedures (e.g. Cucina et al., 2012; Dean, 2013). Seventy percent of the data were randomly selected for the training sample, whereas the remaining 30% of cases were assigned to the holdout sample using a feature in SPSS (Version 23; IBM, 2015) that produces a random sample of cases.

Data Diagnostics

As mentioned in the working with distributions found in text data section, the distribution of text data is usually positively skewed and leptokurtic. An inspection of the skewness and kurtosis metrics in (see Tables 10-164) demonstrated this to be the case for the current study's data. A plurality of the predictor variables showed positive skew above the ±2 threshold and was primarily leptokurtic in width (Field, 2009). The Kolmogorov-Smirnov test and the Shapiro-Wilk tests were used to confirm this (see Table 22). To mitigate the significant positive skew of the variables in the logistic regression analyses, all LIWC predictor variables were log-transformed, following recommendations in Tabachnick and Fidell (2013).

Comparing resume text sparseness to previously reported base rates for LIWC analyzed text. As noted previously, text data for this study was sparse—perhaps because resume writing is restricted to a very specific context (i.e. the workplace), and brevity and clarity are typically prioritized over lengthy and descriptive prose. Visual inspection of the histograms for the 17 LIWC categories used in the present study illustrates this (see Figures 1-14). This can also be observed by comparing the average word category usage for resumes against the base rates reported by Pennebaker et al. (2015; see Table 4 and Table 23).

Preliminary Analyses

Descriptive statistics for the control variables (sex, race, education, & tenure) are summarized in Tables 10-13b. Tables 14-17b summarize the demographics for the subset of data that was used in the logistic regression analyses (i.e., Hypothesis 2a-b, Hypothesis 2c, Hypothesis 3a-b, Hypothesis 4a-g).

Empirical linkages of the control variables to job performance was confirmed by running an independent samples *t*-test (sex), one-way analysis of variances (ANOVA; race and education), and bivariate correlations (tenure) with task performance as the outcome (dependent variable). Female participants reported more task performance behaviors than males (*t(391)* = -3.65, *p* < .001, see Table 18). There were no statistically significant differences for race, *F*(4, 388) = 1.84, *p* = .121 (see Table 19), or education *F*(7, 385) = 0.31, *p* = .950 (see Table 20). Tenure was not significantly correlated with task performance (*r* = -.09, *p* = .069, see Table 13b and Table 17b).

Bivariate correlations are provided in Table 21. Overall, correlations were in the expected directions. Salary as expected, was positively and significantly correlated with age (*r* = .19, *p* < .01), education (*r* = .19, *p* < .01), and tenure (*r* = .20, *p* < .01). While cognitive ability as measured by the spot-the-word test showed expected relationships with task (*r* = .17, *p* < .01) and counterproductive work behaviors (*r* = -.16, *p* < .01). Additionally, task performance as measured by the IWPQ showed expected positive correlations with key primary study variables: words longer than six characters (*r* = .15, *p* < .01), prepositions (*r* = .16, *p* < .01), conjunctions (*r* = .19, *p* < .01), positive emotion words (*r* = .12, *p* < .01), and cognitive process words (*r* = .13, *p* < .01).

Primary Analyses

Hypothesis one. To test the proposition that word categories can be employed to classify individuals into high and low job performance categories, a logistic regression model was fitted to the data and tested using the cross-validation procedure described in the creating training and holdout samples section. Backward logistic regression was used for variable selection after entering the covariates. Any job performance score of 3.0 or higher was designated as high performance, whereas any score less than 3.0 was designated as low job performance. Sex was included as a covariate, and it was a significant predictor in block one (-2 LL [log-likelihood] = 593.51; χ^2 (1) = 13.27, $p < .001$). Tenure was not a significant covariate once task performance was dichotomized and was thus excluded from the logistic regression model for parsimony and to conserve degrees of freedom.

Using covariates in logistic regression requires checking for statistical differences in log-likelihood between two models: one model that includes all focal variables and one model that includes only control variables. In this case, the test is to see if the focal variables selected using backward logistic regression resulted in a lower LL score, as opposed to using sex alone. Log-likelihood is an indication of the badness of fit; thus, the lower the number, the better the model fit of the data (Field, 2009). Checking for a significant difference between the models (control variables v. focal variables) requires subtracting the LL score from the control variable model from the log-likelihood in the focal variable model. This result and the degrees of freedom in the focal variable model is then compared with the chi-square distribution to ascertain if the score exceeds the critical chi-square value needed to be statistically significant.

For hypothesis one, the focal variables yielded a significantly improved model over sex alone on the training data set (n = 462) with an LL of 549.30 compared to an LL of 593.51 when using sex. Significance was determined by subtracting the LL of the first model with sex from the final model with all relevant variables. Thus 593.51 - 549.30 = 44.21 with 10 degrees of freedom, one degree of freedom for each additional variable included in the model, resulted in $\chi^2_{\text{critical}} = 25.19$, $p = .005$, suggesting the 10 additional variables added significant explanatory power and model fit (final model with sex and 10 additional variables: χ^2 (11)= 549.30, $p < .001$, see Table 24).

The 10 variables fit to the training data set included third-person plural pronouns, impersonal pronouns, auxiliary verbs, adverbs, sadness words, certainty words, non-fluencies, colons, dashes, and parentheses. These same variables were applied to the holdout sample of the data (*n* = 205). The model retained significance $\chi^2 = 26.01$ (10), *p* = .006, see Table 25. To evaluate whether the 10 variables remained statistically significant predictors, I tested the difference between the B weights from the training and test data following the method recommended by Cohen, Cohen, West, and Aiken (2003). Table 26 presents the results of this test (Soper, 2016; Cohen et al., 2003). The test checks to see if the significant predictors from the training sample become insignificant in the hold-out sample. A value of less than 0.05 indicates that a specific predictor was no longer a statistically significant predictor in the holdout sample. Only sex, third-person plural pronouns, impersonal pronouns, sadness words, certainty words, non-fluencies, and colons remained statistically significant predictors in the testing sample. Overall, the results suggest that word categories can be used to classify individuals into high and low job performance categories; therefore, Hypothesis 1 was supported.

Hypothesis 2a-c

Hypothesis 2a. For Hypothesis 2a, I proposed that use of pronouns in individual resumes would be positively related to self and other impression management styles. The data showed that impersonal pronouns (e.g., it, its, those) were positively correlated with self-oriented impression management, whereas first-person plural pronouns (e.g., we, us, our) were negatively correlated with self-oriented impression management. First-person singular pronouns (e.g., I, me, mine) usage was positively correlated with other-oriented impression management. See Table 27 for correlation results. In sum, the results were consistent with the expectation that pronoun use would positively predict impression management, except that first-person *plural* pronouns negatively predicted self-oriented impression management. Thus, Hypothesis 2a received partial support.

Hypothesis 2b. I predicted that the prevalence of pronouns in applicants' resumes would positively predict self-reported job performance. Results of the hierarchical regression analysis for Hypothesis 2b regressing task performance on pronoun word categories are presented in Table 28. The control variables, sex, and tenure were added as the first step in the regression model, and the log-transformed pronoun predictors (first-person singular pronouns, first-person plural pronouns, second-person pronouns, third-person singular pronouns, third-person plural pronouns, and impersonal pronouns) were added. See **Appendix A** for example words in each of these categories. Interpreting log-transformed (natural log) predictors are similar to the interpretation of non-log transformed predictors, except that coefficients are interpreted as percent changes. That is, a one percent increase in the predictor variable(s) either increases or decreases the dependent variable by (coefficient/100) units (UCLA Statistical Consulting Group, n.d.). Taking tenure as an example, a one percent increase in tenure would result in a -0.00018 decrease in job performance (-0.018/100).

The pronoun predictors accounted for a non-significant amount of variance in task performance ($\Delta R^2 = .010$, $p = .312$); therefore, Hypothesis 2b was not supported. Because no types of pronoun variables emerged as significant predictors, I did not explore simple regression models using individual pronoun variables.

Hypothesis 2c. Hypothesis 2c predicted that verbs were positively predictive of job performance. Results of the hierarchical regression analysis for Hypothesis 2c for task performance regressed on verbs are presented in Table 29. The control variables, sex, and tenure were added as the first step in the regression model, and the log-transformed verb variable was added as the second step. The addition of the verb predictor did not account for additional variance over sex or tenure (ΔR^2 change = .000, p = .818); hypothesis 2c was not supported.

Hypotheses 3a-b

Hypothesis 3a. For hypothesis 3a, I proposed that positive emotion words would positively predict task and contextual performance. Results for this hierarchical regression analysis are presented in Tables 30 and 31. For task performance, the control variables, sex, and tenure were added as the first step in the regression model, and the log-transformed positive emotion word predictor was added as the second step. The positive emotion variable (CI [-0.176, 0.421] for B weights) did not account for a significant portion of task performance variability.

For contextual performance, the control variable, sex, was added as the first step in the regression model, and the log-transformed positive emotion word predictor was added as the second step. The positive emotion variable (CI [-0.241, 0.391] for *B* weights) resulted in a non-significant amount of variance in contextual performance. In summary, positive emotion words did not significantly predict either task or contextual performance; thus, Hypothesis 3a was not supported.

Hypothesis 3b. For Hypothesis 3b, I proposed that negative emotion words would positively predict counterproductive job performance and negatively predict task performance. Results of the simple regression analysis for Hypothesis 3b are presented in Table 32 and Table 33. For counterproductive performance, negative emotion words (CI [-0.923, 0.091] for *B* weights) did not positively predict counterproductive job performance. Negative emotion words (CI [-0.061, 0.135] for *B* weights) also did not negatively predict job performance. Thus, Hypothesis 3b was not supported.

Hypotheses 4a-g

Hypotheses 4a-g predicted that (a) differentiation words, (b) conjunctions, and (c) words longer than six characters, (d) prepositions, (e) cognitive process words, (f) causal words, and (g) insight words, can be used as proxies of verbal intelligence; and consequently, they will positively predict self-reported job performance (see Appendix A for example words for each of the categories).

Results indicated that verbal intelligence was significantly related to differentiation words (r = .09, p < .001; supporting Hypothesis 4a), conjunctions (r = .28, p < .001; supporting Hypothesis 4b), words longer than six characters (r = .29, p < .001; supporting Hypothesis 4c), prepositions (r = .19, p < .001; supporting Hypothesis 4d), cognitive process words (r = .19, p < .00; supporting Hypothesis 4e), and insight words (r = .06, p < .05; supporting Hypothesis 4g). In contrast, the use of prepositions and causal words were not significantly related to verbal ability (see Table 34 for bivariate results). However, when job performance was regressed on these word categories (controlling for sex and tenure), none of these word categories were statistically significant predictors (see Table 35). In summary, although many of the proposed LIWC word categories were positively associated with verbal ability, they were not effective predictors of job performance. Therefore, Hypotheses 4a-g received partial support.

Ancillary Analyses

As noted in chapter 1, research on the LIWC categories (a) differentiation words, (b) conjunctions, and (c) words longer than six characters, (d) prepositions, (e) cognitive process words, (f) casual words, and (g) insight words leads to the question of whether these categories are capable of reflecting an individual’s cognitive ability. This is relevant to employee selection because cognitive ability is one of the best predictors of job performance (Schmidt & Hunter, 1998; Schmidt & Hunter, 2004; Hunter & Hunter, 1984). The analyses shown in Table 34 suggest a connection between these text categories and cognitive ability. However, this evidence on its own does not confirm that these text categories are proxies for cognitive ability that can predict performance. To test this directly, I conducted a regression analysis, in which cognitive ability and a composite score of the 5 LIWC categories used in Hypothesis 4 simultaneously predicted task performance. This composite score or Written Cognitive Ability Index (WCAI) was created by taking the average of the sum of the LIWC categories: (a) differentiation words, (b) conjunctions, (c) words longer than six characters, (d) prepositions, and (e) cognitive process words. The lower order word categories under cognitive process words (i.e. casual and insight words) were excluded. The WCAI was calculated as follows: Mean(differentiation words + conjunctions + words longer than six characters + prepositions + cognitive process words).

I ran an ordinary least squares regression analysis in which gender was controlled. Results indicated that both verbal ability (B = 0.007, *p* = .005) and the WCAI (B = 0.030, *p* < .001) significantly predicted job performance (see Table 36). Specifically, a one-point increase on the cognitive ability test (spot-the-word test) translates to an increase in job performance by 0.007, and an increase of one point on the WCAI was associated with a 0.030 increase in job performance. Thus, given that both cognitive ability and the WCAI positively predicted job performance, it can be tentatively inferred that the WCAI can serve as a proxy for cognitive ability and potentially preclude the necessity of costly cognitive ability assessments.

CHAPTER 4

Discussion, Limitations, and Future Research

Summary of Results

The overall objective of this research was to investigate the potential to analyze resumes using text analytics to capture job-relevant traits (e.g. cognitive ability), and then empirically link these attributes to job performance. The findings of the current study indicate that the text analytics method is potentially useful for accomplishing these objectives. Specifically, third-person plural pronouns, impersonal pronouns, sadness words, certainty words, non-fluencies, and colons (See Appendix A for examples of these word categories) emerged as key predictors, differentiating high and low performers. This research also evaluated whether or not specific word categories (e.g., cognitive process words) could function as proxies for known predictors of job performance (e.g., cognitive ability).

Pronouns as predictors of job performance. Pronouns were hypothesized to be predictive of performance based on prior research that suggested they were proxies for Impression management (Ickes et al., 1986; Tausczik & Pennebaker, 2010), and research showing that IM was predictive of job performance (Wayne & Liden, 1995; Huang et al., 2013). The present study did not find support for this (see Table 28).

However, some pronoun types were correlated with IM (see Table 27), although not all correlations were in the expected direction. First person plural pronouns (we, us, our, etc.) were *negatively* correlated with self-impression management. Whereas this runs counter to prior findings such as Ickes et al.(1986), it is in line with more recent research suggesting that individuals who are less devious tend to use more inclusive language like we, us, etc. (Steffens & Haslam, 2013; Grant, 2013).

Verbs as predictors of job performance. Verb usage has been shown to be negatively related to academic success (Pennebaker, 2011). The present study sought to see if this relationship held in a non-academic setting, to predict performance in the workplace. The current data did not support this (see Table 29). This is likely because verb use is associated with an analytical thinking style (Pennebaker, 2011), a style typified by a methodical and structured approach to writing and breaking down concepts and problems into component parts.

This style is reinforced and rewarded in higher education and work. Given this reinforcement, it is possible that individuals working full-time already met the minimum threshold for thinking style, resulting in range restriction and lower variance. This would have made it difficult to find an effect. However, it is also possible that lower verb usage is related to academic success but not job performance as a histogram of verb usage (see Figure 7) shows verb usage across resumes and verbs were not significantly correlated with job performance (r = .04, p > .05).

Positive and negative emotion words as predictors of job performance, contextual performance, and counterproductive performance. Positive and negative moods have been found to predict task performance, contextual performance, and counterproductive performance (Kaplan et al., 2009). However, their closer, visible behavioral counterparts—positive and negative words, did not predict job performance (see Table 30, and Table 31). Although there is strong prior evidence demonstrating that text can predict mood (Nguyen et al., 2014), there are a few possibilities for why this relationship was not observed in the current study. First, emotional words are unlikely to occur in resumes, resulting in low variance and significant skew. A review of the histograms for the positive and negative emotion word categories shows this to be true for the present data. The majority of resumes used positive emotion words less than 2.5% of the time, and the majority of resumes used negative emotion words less than 1% of the time. Most career advice around resumes recommends eliminating emotional language from resumes (Knouse, 1994, Koeppel, 2002). Thus any overtly emotional language in resumes is likely to be an extreme exception rather than the rule. A second reason that emotion words failed to predict performance has to do with the actual words and word stems that make up the positive and negative word category. A review of the words in the LIWC dictionary for these word categories indicates that, while face valid, these words were unlikely to be used in a resume, e.g. faith, sunshine, jaded or annoying. A third plausible alternative explanation for the findings is that the current approach may not have been sophisticated enough to link mood expressed in a resume to job performance. Identifying emotion in text is difficult. An in-depth discussion about why this is the case is beyond the scope of this paper, but interested readers should consult Chapter 26 in the Handbook of Natural Language Processing (Liu, 2010). Part of the difficulty stems from the variety of ways mood is encoded in text. Furthermore, identifying mood in texts usually requires more complex analyses than those employed in the present study.

Word categories that are proxies for cognitive ability. The LIWC word categories (a) differentiation words, (b) conjunctions, and (c) words longer than six characters, (d) prepositions, (e) cognitive process words, (f) casual words, and (g) insight words were hypothesized to be proxies for cognitive ability based on prior research (Pennebaker, Boyd et al., 2015; Pennebaker & King, 1999; Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010). These word categories did correlate with cognitive ability. Unfortunately, they did not predict job performance after controlling for tenure and gender (see Table 35). However, exploratory regression analyses found that a composite combination of these word categories could be used as a proxy for cognitive ability (see Table 36).

Theoretical Implications

This research represents a potential path to addressing two critical limitations of biodata and predictor methods in general. First, biodata does not identify the specific constructs measured (Lievens & Patterson, 2011; Shultz, 1996). Second, biodata does not specify the elements that make it predictive (Arthur & Villado, 2008; Christian; Edwards, & Bradley, 2010; Ployhart 2006; Whetzel & Daniel, 2006).

A theory based case was made that the text analytics method could address these limitations by linking word categories (specific elements of the text analytics method) to known constructs predictive of job performance (identifying specific constructs measured). These linkages were then empirically evaluated (Huffcutt, Conway, Roth, & Stone, 2001). For example, I argued that specific word categories were linked to cognitive ability. Cognitive ability was chosen because it has consistently been found to predict job performance (Hunter & Hunter, 1984; Hunter & Schmidt, 1998). In addition, research suggests that multiple predictor methods such as structured interviews (Huffcutt et al., 2001), assessment centers (Hoffman, Kennedy, LoPilato, Monahan, Lance, 2015), and situational judgment tests (SJTs; Lievens, & Reeve, 2012) capture some aspect of cognitive ability. Regression was used to provide empirical evidence that a composite of these word categories (Table 35) was an appropriate proxy for cognitive ability.

Practical Implications

Use of this new method (text analytics) to review resumes may reduce costs for organizations by obviating the need to administer cognitive ability tests. Consider the following:

According to the Corporate Executive Board (CEB), the hourly cost for a vacant job position is $62.50 dollars an hour (as cited in iCIMS, 2015). The Wonderlic Personnel Test (WPT), a cognitive ability assessment, can be administered via the internet at a cost of $200 for

100 tests (Reilly, n.d.). The WPT takes approximately 12 minutes to complete (Reilly, n.d.). A mid-sized company of 500 employees growing at a rate of 35% year-over-year with 15% attrition would need to hire 250 people (175 due to growth and 75 due to attrition), resulting in a cost of $3,625 ($500 in assessment fees and $3,125 in assessment time). Text analytics could eliminate 12 minutes of assessment time per candidate, resulting in a potential savings of $3,125, assuming the cost per year to implement text analytics is $500 for this organization. Now consider a Fortune 50 company like Intel with 100,000 employees. Assuming 10% year-over-year growth (*n* = 10,000) with 15% attrition (*n* = 15,000), the cost for the WPT would be $362,500 ($50,000 in assessment fees and $312,500 in assessment time). Therefore, using text analytics could potentially result in a savings of $312,500.

Beyond cost savings for organizations, this method could also provide another lever to drive diversity efforts, as this method removes the possibility of evaluating resumes based on applicant attributes protected by federal employment discrimination laws. These attributes include race, color, religion, sex, national origin (Title VII of the Civil Rights Act of 1964); age (Age Discrimination in Employment Act [ADEA] of 1967); and disability status (Americans with Disabilities Act [ADA] of 1990). A seminal study published in 2004 showed that resumes with white-sounding names were 50% more likely to receive a call back (or email back) compared to black sounding names (Bertrand & Mullainathan, 2004). A comprehensive literature review on experiments like this one conducted across multiple countries from 2000-2013 concluded that majority race/ethnic applicants received more positive responses compared to minority applicants across all countries (Rich, 2014). In addition, most of the discrimination occurred at resume review process (Rich). Thus, by removing names from resumes and analyzing the text contained in resumes for markers of job performance (e.g. cognitive ability), it is possible to reduce bias early in the hiring process and thereby improve the odds that more minority candidates are hired.

Beyond automating resume evaluation, text analytics may also be applicable to talent sourcing (i.e. proactively reaching out to candidates about open positions). Sourcing often takes place before an applicant officially applies to a position. Sourcing tends to focus on a small subset of talent pools (e.g., Ivy League schools, Fortune 50 companies, etc.). Text analytics may allow an organization to proactively evaluate resumes from larger, more demographically-diverse talent pools by evaluating potential candidates on LinkedIn or other public job forums, thereby enabling greater democratization of talent sourcing. Additionally, this approach would allow organizations to target specific individuals (e.g., women, minorities, principal engineers, etc.) without being constrained to highly competitive talent pools.

Employer brand may also be impacted by the automation of resume reviews via text analytics. Potential employees may react negatively to learning that processes have been automated which were previously undertaken by humans (Hausknecht, Day, & Thomas, 2004). However, negative reactions may not be a foregone conclusion. Recent survey research on the use of social media (SM) in selection suggests that younger workers have fewer concerns than older employees do regarding employers using SM for selection decisions (Davison, Maraist, & Bing, 2011; Turkle, 2011). This perception by younger employees is worth noting as individuals born between 1981-1997, known as the “Millennial” generation, currently comprise a majority of the workforce (Fry, 2015). Organizations should consider how a selection system will impact their employer brand and whether or not applicant reactions should influence choices on the selection and validation of a selection system.

Ethical Implications

The use of text analytics and empirically driven approaches to employee selection, in general, raise ethical questions of (a) informed consent and privacy, (b) the scope of data employers can use in hiring decisions, and (c) applicant reactions. However, before embarking on a discussion of these topics, it is necessary to set the context for this discussion.

Implications of text analytics for employment decisions extend beyond resume data. The potential for using text analytics to evaluate resumes efficiently raises the possibility of applying text analytics to more than just resumes. Public information about job applicants is potentially available in the form of blog posts, tweets, Reddit posts, LinkedIn posts, and Facebook posts. Moreover, non-text public information (e.g. videos and pictures) are available on platforms like Instagram, SnapChat, Periscope, etc. Thus, a discussion of ethical implications of using text analytics must address information beyond the domain of resumes and consider other sources of information available on SM platforms.

Informed consent and privacy in the era of easy access to mass quantities of candidate information. The potential to use text analytics to evaluate SM data raises the question of informed consent. Informed consent originates from medical ethics and describes the process of disclosing information to a patient so that they may make a choice to accept or refuse treatment (Appelbaum, 2007). It includes the following elements (a) information about the treatment, (b) alternatives to the proposed treatment, (c) risks and benefits of the proposed treatment and alternatives, (d) assessment of whether the patient understood the information, and (e) acceptance or rejection of the proposed treatment. In the case of text analytics of SM and resumes, the necessity and appropriateness of informed consent depend on the security of the user’s information within a given SM platform.

Informed consent is necessary in cases in which an employer needs an applicant to grant the employer access to their information. For example, Instagram accounts set to private are not available for public viewing. Thus, employers seeking access to an applicant's Instagram data would need to obtain his or her express permission and disclose why they wanted to use this information. For example, an employer could inform the applicant that they are requesting access to their Instagram photos to evaluate culture fit. Obtaining this information without permission or disclosing how the information would be used in the selection decision would be identity theft; as an employer would have to impersonate a job applicant to access their information. Informed consent is also inappropriate in certain states where asking for such information is illegal. As of 2014, 20 states had passed laws prohibiting employers from asking job applicants or employees for their SM account passwords (Workplace Fairness, 2016). Thus, for some types of SM data, employers must obtain explicit, and voluntary permission from job applicants to access their data, or there are laws prohibiting employers from asking for this information.

The necessity of obtaining informed consent is less clear (and becomes closely coupled with questions of privacy) when SM platforms allow a mixture of both publicly-searchable information and information that requires a membership (i.e., user login). This is the case with SM platforms like LinkedIn or Facebook. These SM platforms allow users and potential job applicants to make certain information publicly available (and thus accessible via search engines like Google) while keeping other information private. In the case of these SM platforms, informed consent is less important, and privacy is more important because the question is about the flows of information (Noam, 1997) which can be both public and private.

The scope of data employers can use in hiring decisions. Here at the liminal space between informed consent and privacy, the chief concern is what information employers *should* *use*, rather than what information they *could use*. Availability of information is not a mandate for use, even if it significantly predicts job performance. For example, researchers published a study in 2014 that suggested for heterosexual couples, partner's level of conscientiousness was predictive of income (*b* = 0.04), likelihood of promotion (*b* = 0.05), and job satisfaction (*b* = 0.11; Solomon & Jackson, 2014). Does this mean that an applicant's partner's conscientiousness levels should be used in the employment decision?

The Uniform Guidelines on Employee Selection Procedures (Equal Employment Opportunity Commission, 1978) provide some guidance. They state that criterion measures, selection procedures that have not been validated and alternative selection procedures must be job relevant. Although they do not address the types of data currently available to employers (e.g. social media text data), the guidelines clearly state that employers must provide evidence that the data used in hiring decisions is job-relevant. Hence, in the case of the research conducted by Solomon and Jackson (2014), an employer would need to demonstrate how an employee's partner's level of conscientiousness is job-relevant. Given this, existing employment law seems to preclude the use of data that are predictive of job performance, but not job-related.

While the Uniform Guidelines do not offer guidance on how selection methods and tools should be developed, the Society for Industrial and Organizational Psychology (2003) has published a set of principles that provide such guidance. Guiding principles are important because mechanized approaches are not perfect. For example, the algorithm behind Google's ad machine showed high paying jobs to men more frequently than to women (Datta, Tschantz, & Datta, 2015). In another instance, advertisements for public records websites were more likely to imply criminal activity (e.g., arrest records) when searching for black-sounding names compared to white-sounding ones (Sweeney, 2013). Thus, using a mechanized approach to employee selection does not absolve practitioners or the academics who assist them, from critical thinking and ensuring that bias is not encoded into these approaches.

However, encoding bias in mechanized approaches to decision making is fundamentally a data problem. Text analytics algorithms learn based on the data provided to them. If text analytic algorithms are only trained using resumes from one group of people (e.g. Caucasians), those models will likely have a harder time predicting outcomes of people from other groups. Conversely, an algorithm could also be trained to reduce bias in selection. Thus, algorithms are not inherently biased or unethical but are dependent on the values and intent of the organization creating them. As such, how an organization defines success (see Katz & Kahn, 1978 for various conceptualizations of organizational success) and the ethical decision-making frameworks they bring to bear (see Velasquez et al., 2015 for ethical decision-making frameworks) will determine their approach in developing these kinds of algorithms and mechanistic approaches.

Taken together, informed consent and the Uniform Guidelines provide an outline for a way forward in an era of algorithms and mechanized approaches to employee selection. First, if employers wish to use social media data that requires a job applicants' login information, they must obtain informed consent by explicitly requesting access, specifying what data will be gathered, what it will be used for, and provide job applicants the choice to provide or not provide this information. Second, in cases where information is not restricted by login information (e.g. publicly-searchable information from SM platforms like LinkedIn or Twitter), employers should take care to ensure the information they use is job relevant per the Uniform Guidelines. Even beyond social media (e.g. resumes), employers should ensure the job relevance of the data they use. Third, employers should look to their ethical values for guidance, in order to make decisions that are both legally defensible and in alignment with their mission and values.

Future Research Directions

Because this study is the first of its kind and was limited in scope, this study should be replicated, employing a larger sample size (10,000+ resumes). Future researchers would also be wise to enforce requirements on the length and type of content provided in the resumes. For example, a summary and a minimum number of words could be required. Additionally, it would be worth exploring if the word count of a resume varied as a function of someone's relative level of job performance. For example, do people who write more verbose resumes also tend to be high performers? (Note: the present study did not address this inquiry, due to a limited sample size).

Researchers continuing this work should identify job-relevant predictor constructs beyond cognitive ability and impression management. Personality, specifically the Big Five model of personality would be an ideal start, given prior research, which suggests that personality is encoded in text (e.g. Tomlinson, Hinote, & Bracewell, 2013). For researchers interested in exploring constructs outside of personality, the framework proposed by Huffcutt and colleagues (2001) may be a useful guide.

Additionally, researchers should consider utilizing text analytics methods and software other than LIWC. An immediate and logical next step is to use a more robust form of the term frequency methodology called term frequency-inverse document frequency (TF-IDF). This method uses term frequency but also weights words based on how often they occur in a document (Salton, Wong, Yan, 1975). This method helps ensure that important words are not drowned out by frequently occurring words (e.g., the). This may enable text analytics to identify words beyond LIWC category words. For example, another type of term frequency method involves creating pairs groups of words called bigrams and assessing the frequency of their occurrence. This method can also use TF-IDF. Use of bigrams is highly recommended for classifying individuals into high and low-performance categories as bigrams tend to represent text better (Naji, 2013).

Beyond term frequency, text analytics methodologies researchers seeking to extend this work are encouraged to explore using latent semantic analysis (Aggarwal & Zhai, 2012, pp. 52-53), or topic modeling (e.g. Blei, Ng, & Jordan, 2003) as well. These approaches provide new approaches to word profile that can be used as proxies for various psychological constructs.

Affect, given its strong link to positive and negative work outcomes (Kaplan, et. al., &, 2009), may be one such construct to explore with the these more advanced methodologies. Particularly, as the software used in this study was relatively rudimentary and affect, in a business context, is likely to be expressed in more subtle ways than what the LIWC software could detect. For example, one could assess people in an organization, whose peers have identified as frequently showing positive and negative affect, by applying latent semantic analysis (LSA) to documents these individuals have written. Next, the resulting LSA dimensions could be run through a clustering algorithm like DBSCAN, and then human evaluation could evaluate the resulting clusters. Ideally, this evaluation would reveal that some clusters are more distinctively positive versus negative.

Future work on this topic should explore using text generated and hosted on social media platforms such as LinkedIn or Twitter. Provided job applicants consent to employers accessing their LinkedIn or Twitter accounts; these additional sources of text data may provide additional insight into job relevant traits, as social media can capture individuals in a range of contexts beyond work or professional contexts.

Beyond using text content domains other than resumes, future work should also explore making a version of the LIWC specifically for business writing focusing on text written in a business setting. This would enable the software to be much more applicable to business problems and have the benefit of rigorous external validation by SMEs (similar to the LIWC development process.).

Limitations

Typically, text analytic projects include thousands (10k+) of participants with many more words per text (Nguyen et al., 2014; Pennebaker et al., 2014; Schultheiss, 2013). Thus, sample size was a critical limitation. However, the current approach allowed me to obtain measures of impression management, verbal intelligence, and task performance. This enabled a theory-driven exploration into the effectiveness of text analytics as a selection method—something that would not have been possible without obtaining data on these measures.

A second limitation of this research was the method of obtaining resumes. The participants for this study were told to upload copies of their resumes but were not given any instructions on the format or length of the resume. Consequently, resume content and format varied widely, which likely played a role in the results or lack thereof. Had the research protocol asked participants for specific pieces of information such as a summary, education, and jobs for the past 5 years, with minimum word counts, for example, more than 500 words, the results would likely have been different.

A third limitation of this research was the use of a self-reported measure of job performance as I did not have access to performance ratings given by managers at a company. However, as job performance ratings are fraught with issues (Campbell & Wiernik, 2015; Murphy & Deckert, 2013), a self-reported measure of job performance with construct validity evidence arguably provides a more consistent and accurate measurement of job performance.

A fourth limitation of this research was the skewness of the data. This skewness likely caused the study to be underpowered (Aguinis 2004; Maruo, Yamabe, Yamaguchi, 2016); even after applying a log transformation to the data (Tabachnick & Fidell, 2013). As a result, the reported population effects are likely underestimated, and some effects may have been not been found.

A final identified limitation of this research was that the sample was comprised of job incumbents rather than job applicants. However, most selection methods utilize job incumbents first to obtain initial evidence that the selection method works. This limitation was also, to some degree, unavoidable given the difficulty of obtaining job applicant samples. Practically, recruiting a sufficient number of job applicants, even equivalent to the meager sample size in the present study, would have been exceedingly difficult and would have required more resources than were available.

Conclusion

Text analytics was a new method proposed as a solution to common critiques of biodata and predictor methods in general because it proffers an objective way to aggregate and quantify resume text and empirically link this data to job performance. The current study demonstrated that it is possible for predictor methods and predictor constructs to be empirically linked—specifically that particular word categories were indicators of cognitive ability. Using this new biodata method provides employers a powerful new employee selection method that not only enables the automation of resume reviews, but also provides employers another approach to driving diversity efforts, through truly blind resume reviews, and delivering cost savings.

References

Aggarwal, C., & Zhai, C. (Eds.). (2012). *Mining text data*. New York, NY: Springer doi:10.1007/978-1-4614-3223-4

Aguinis, H. (2004). *Regression analysis for categorical moderators* (Methodology in the social sciences). New York: Guilford Press.

Allworth, E., & Hesketh, B. (1999). Construct oriented biodata: Capturing change related and contextually relevant future performance. *International Journal of Selection and Assessment, 7*, 97–111. doi:10.1037/apl0000049

Allworth, E., & Hesketh, B. (2000). Job requirements biodata as a predictor of performance in customer service roles. *International Journal of Selection and Assessment, 8,* 137–147. doi:10.1111/1468-2389.00142

Amundson, S. D. (1998). Relationships between theory-driven empirical research in operations management and other disciplines. *Journal of Operations Management, 16*, 341-359. doi:10.1016/S0272-6963(98)00018-7

Appelbaum, P. (2007). Clinical practice. Assessment of patients' competence to consent to treatment. *New England Journal of Medicine, 357*(18), 1834-1840.

Arthur, W. J., & Villado, A. J. (2008). The importance of distinguishing between constructs and methods when comparing predictors in personnel selection research and practice. *Journal of Applied Psychology, 93(2)*, 435-442. doi:10.1037/0021-9010.93.2.435

Ashforth, B. E., & Mael, F. (1989). Social identity theory and the organization. *Academy of Management Review, 27,* 519-533. doi:10.5465/AMR.1989.4278999

Baddeley, A., Emslie, H., & Nimmo-Smith, I. (1993). The spot-the-word test: A robust estimate of verbal intelligence based on lexical decision. *British Journal of Clinical Psychology,* *32*, 55-65. doi:10.1111/j.2044-8260.1993.tb01027.x

Baehr, M. E., & Williams, G. B. (1968). Prediction of sales success from factorially determined dimensions of personal background data. *Journal of Applied Psychology*, *52,* 98-103. doi:10.1037/h0020587

Bandura, A. (1989). Human agency in social cognitive theory. *American Psychologist, 44*(9), 1175-1184. doi:10.1037/0003-066X.44.9.1175

Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: A meta-analysis. *Personnel Psychology, 44,* 1-26. doi:10.1111/j.1744-6570.1991.tb00688.x

Barrick, M. R., & Zimmerman, R. D. (2005). Reducing voluntary, avoidable turnover through selection. *Journal of Applied Psychology, 90,* 159–166. doi:10.1037/0021-9010.90.1.159

Barrick, M. R., & Zimmerman, R. D. (2009). Hiring for retention and performance. *Human Resource Management, 48,* 183–206. doi:10.1002/hrm

Beall, G. E. (1991). Validity of the weighted application blank across four job criteria: A meta-analysis. *Applied H.R.M. Research, 2*(1), 18-26.

Becker, T. E., & Colquitt, A. L. (2006). Potential versus actual faking of a biodata form: An analysis along several dimensions of item type. *Personnel Psychology, 45,* 389–406. doi:10.1111/j.1744-6570.1992.tb00855.x

Becton, J. B., Matthews, M. C., Hartley, D. L., & Whitaker, D. H. (2009). Using biodata to predict turnover, organizational commitment, and job performance in healthcare. *International Journal of Selection and Assessment, 17,* 189–202. doi:10.1111/j.1468-2389.2009.00462.x

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine*

Learning Research, 3, 993-1022.

Bliesener, T. (1996). Methodological moderators in validating biographical data in personnel selection. *Journal of Occupational and Organizational Psychology*, *69*, 107–120. doi:10.1111/j.2044-8325.1996.tb00603.x

Biber, D. (1988). *Variation across speech and writing*. Cambridge, UK: Cambridge University Press.

Bobko, P., Roth, P., & Potosky, D. (1999). Derivation and implications of a meta-analytic matrix incorporating cognitive ability, alternative predictors, and job performance. *Personnel Psychology, 52*, 561–588. doi:10.1111/j.1744-6570.1999.tb00172.x

Bollen, J., Mao, H., Zeng, XJ. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2, 1–8

Bradley, P., & Damer. E. (2014). Prolific academic [Computer software]. Available from https://www.prolific.ac/

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6*, 3–5. doi:10.1177/1745691610393980

Bullhorn. (2014). *A numbers game: North America staffing and recruiting trends report*. Retrieved from http://pages.bullhorn.com/rs/bullhorninc/images/2014_NorthAmericanTrendsReport.pdf

Burt, R. S. (1980). Models of network structure. *Annual Review of Psychology, 6*, 79-141. doi:10.1146/annurev.so.06.080180.000455

Campbell, J. P. (1990). Modeling the performance prediction problem in industrial and organizational psychology. In M. D. Dunnette & L. M. Hough (Eds), Ha*ndbook of*

Industrial and Organizational Psychology (pp. 687-732). Palo Alto: CA: Consulting Psychologists Press.

Campbell, J. P. (2012). Behavior, performance, and effectiveness in the twenty-first century. In S. W. J. Kozlowski (Eds.), *The Oxford handbook of organizational psychology, volume 1* (pp. 159-194). Oxford, UK: Oxford University Press. doi:10.1093/oxfordhb/9780199928309.013.0006

Campbell, J. P. & Wiernik, B. M. (2015). The modeling and assessment of work performance. *The Annual Review of Organizational Psychology and Organizational Behavior, 2*, 47-74. doi: 10.1146/annurev-orgpsych-032414-111427

Carlson, K. D., Scullen, S. E., Schmidt, F. L., Rothstein, H., & Erwin, F. (1999). Generalizable biographical data validity can be achieved without multi-organizational development and keying. *Personnel Psychology, 52*, 731–755. doi:10.1111/j.1744-6570.1999.tb00179.x

Cascio, W. F. (1976). Turnover, biographical data, and fair employment practice. *Journal of Applied Psychology, 61*, 576–580. doi:10.1037//0021-9010.61.5.576

Chambers, E. G., Foulon, M., Handfield-Jones, H., Hankin, S. M., & Michaels, E., III. (1997). The war for talent. *The McKinsey Quarterly*. Retrieved from http://www.mckinseyquarterly.com

Chandler, J., Mueller, P., & Paolacci, G. (2014). Nonnaïveté among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers. *Behavior Research Methods, 46*, 112–130. doi:10.3758/s13428-013-0365-7

Chartrand, T. L., & Bargh, J. A. (1999). The chameleon effect: The perception-behavior link and social interaction. *Journal of Personality and Social Psychology, 76*, 893-910. doi:10.1037/0022-3514.76.6.893

Chen, C.-C., Huang, Y.-M., & Lee, M.-I. (2011). Test of a model linking applicant résumé information and hiring recommendations. *International Journal of Selection and Assessment, 19,* 374–387. doi:10.1111/j.1468-2389.2011.00566.x

Cheng, N., Chandramouli, R., & Subbalakshmi, K. P. (2011). Author sex identification from text. *Digital Investigation, 8,* 78–88. doi:10.1016/j.diin.2011.04.002

Christian, M. S., Edwards, B. D., & Bradley, J. C. (2010). Situational judgment tests: Constructs assessed and a meta-analysis of their criterion-related validities. *Personnel Psychology, 63*(1), 83-117. doi:10.1111/j.1744-6570.2009.01163.x

Cohen, J., Cohen, P., West, S., & Aiken, L. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). New York, NY: Routledge.

CoinNews. (n.d.). *US Inflation Calculator.* Retrieved from http://www.usinflationcalculator.com/

Cole, M. S., Rubin, R. S., Feild, H. S., & Giles, W. F. (2007). Recruiters' perceptions and use of applicant resume information: Screening the recent graduate. *Applied Psychology, 56,* 319–343. doi:10.1111/j.1464-0597.2007.00288.x

Corral, Á., Boleda, G., & Ferrer-i-Cancho, R. (2015). Zipf's law for word frequencies: Word forms versus lemmas in long texts. *PLoS ONE, 10*(7), e0129031. http://doi.org/10.1371/journal.pone.0129031

Costa, P. T., Jr., & McCrae, R. R. (1992). *The NEO-PI–R professional manual.* Odessa, FL: Psychological Assessment Resources.

Cronbach, I. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*, 297-333. doi:10.1007/BF02310555

Cucina, J. M., Caputo, P. M., Thibodeaux, H. F., & Maclane, C. N. (2012). Unlocking the key to biodata scoring: A comparison of empirical, rational, and hybrid approaches at different sample sizes. *Personnel Psychology*, *65*, 385–428. doi:10.1111/j.1744-6570.2012.01244.x

Cucina, J. M., Caputo, P. M., Thibodeaux, H. F., Maclane, C. N., & Bayless, J. M. (2013). Scoring Biodata: Is it rational to be quasi-rational? *International Journal of Selection and Assessment*, *21*(2), 226-232. doi:10.1111/ijsa.12032

Dalessio, A. T., Crosby, M. M., & McManus, M. A. (1996). Stability of biodata keys and dimensions across English-speaking countries: A test of the cross-situational hypothesis. *Journal of Business and Psychology, 10*, 289–296. doi:10.1007/BF02249604

Danner, D. D., Snowdon, D. A., & Friesen, W. V. (2001). Positive emotions in early life and longevity: Findings from the nun study. *Journal of Personality and Social Psychology, 80*, 804–813. doi:10.1037/0022-3514.80.5.804

Datta, A., Tschantz, M. C., Datta A. (2015). Automated experiments on ad privacy settings. *Proceedings on Privacy Enhancing Technologies*, 92-112.

Dawson, M. (2013). Verbal intelligence. In Volkmar, F. R., Paul, R., Pelphrey, K., & Powers, M. D. (Eds.), *Encyclopedia of autism spectrum disorders Vols. 1-5* (pp. 3243-3250). New York, NY, US: Springer Science + Business Media. doi:10.1007/978-1-4419-1698-3

Davis, S. J., Faberman, R. J., & Haltiwanger, J. C. (2013). The establishment-level behavior of vacancies and hiring. *Quarterly Journal of Economics, 128*(2), 581-622.

Davison, H. K., Maraist, C., & Bing, M. N. 2011. Friend or foe? The promise and pitfalls of using social networking sites for HR decisions. *Journal of Business and Psychology*, 26: 153-159.

Dean, M. A. (2004). An assessment of biodata predictive ability across multiple performance criteria. *Applied H.R.M. Research, 9(1)*, 1-12.

Dean, M. A. (2013). Examination of ethnic group differential responding on a biodata instrument. *Journal of Applied Social Psychology, 43*, 1905–1917. doi:10.1111/jasp.12212

Devlin, S. E., Abrahams, N. M., & Edwards, J. E. (1992). Empirical keying of biographical data: Cross-validity as a function of scaling procedure and sample size. *Military Psychology, 4*, 119–136. doi:10.1207/s15327876mp0403_1

Drakeley, R. J., Herriot, P., & Jones, A. (1988). Biographical data, training success and turnover. *Journal of Occupational Psychology, 61*, 145–152. doi:10.1111/j.2044-8325.1988.tb00278.x

Drasgow, F. (2013). Intelligence and the workplace. In I. B. Weiner (Ed.), *Handbook of psychology* (pp. 184-210). Hoboken, NJ: Wiley and Sons, Inc.

Dunnette, M. D. (1962). Personnel management. *Annual Review of Psychology, 13*, 285-313. doi:10.1111/j.1468-232X.1963.tb00292.x

Equal Employment Opportunity Commission (1978). *Uniform guidelines on employee selection procedures.* Retrieved from http://www.uniformguidelines.com/uniformguidelines.html

Fassinger, R. E. (2005). Paradigms, praxis, problems, and promise: Grounded theory in counseling psychology research. *Journal of Counseling Psychology, 52*, 156-166. doi:10.1037/0022-0167.52.2.156

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149-1160. doi:10.3758/BRM.41.4.1149

Field, A. (2009). *Discovering statistics using SPSS* (3^{rd} ed.). Thousand Oaks, CA: Sage Publications.

Finch, D. M., Edwards, B. D., & Wallace, J. C. (2009). Multistage selection strategies: Simulating the effects on adverse impact and expected performance for various predictor combinations. *Journal of Applied Psychology, 94*, 318-340. doi:10.1037/a0013775

Fisher, R. A. (1930). *The genetical theory of natural selection.* Oxford, UK: Oxford University Press.

Fisher, C. (2008). What if we took within-person performance variability seriously? *Industrial and Organizational Psychology, 1*, 185–189. doi:10.1111/j.1754-9434.2008.00036.x

Fry, R. (2015). Millennials surpass gen xers as the largest generation in U.S. labor force. Retrieved from http://www.pewresearch.org/fact-tank/2015/05/11/millennials-surpass-gen-xers-as-the-largest-generation-in-u-s-labor-force/

Goldberg, L. R. (1992). The development of markers for the big-five factor structure. *Psychological Assessment, 4*, 26-42. doi:10.1037/1040-3590.4.1.26

Goodman, J. K., Cryder, C. E., & Cheema, A. (2013). Data collection in a flat world: The strengths and weaknesses of mechanical turk samples. *Journal of Behavioral Decision Making, 26*, 213–224. doi:10.1002/bdm.1753

Grant, A. M. (2013). *Give and take: A revolutionary approach to success*. New York, N.Y: Viking.

Hausknecht, J. P., Day, D. V., & Thomas, S. C. (2004). Applicant reactions to selection procedures: An updated model and meta-analysis. *Personnel Psychology, 57*, 639-683. doi:10.1111/j.1744-6570.2004.00003.x

Harold, C. M., McFarland, L. A., & Weekley, J. A. (2006). The validity of verifiable and non-verifiable biodata items: An examination across applicants and incumbents. *International Journal of Selection and Assessment*, *14*, 336–346. doi:10.1111/j.1468-2389.2006.00355.x

Hartley, J., Pennebaker, J. W., & Fox, C. (2003). Abstracts, introductions, and discussions: How far do they differ in style? *Scientometrics, 57*, 389-398. doi:10.1023/A:1025008802657

Harvey-Cook, J. E., & Taffler, R. J. (2000). Biodata in professional entry-level selection: Statistical scoring of common format applications. *Journal of Occupational and Organizational Psychology, 73*, 103–118. doi:10.1348/096317900166903

Hausknecht, J. P., Day, D. V., & Thomas, S. C. 2004. Applicant reactions to selection procedures: An updated model and meta-analysis. *Personnel Psychology*, 57: 639-683.

Highhouse, S. (2008). Stubborn reliance on intuition and subjectivity in employee selection. *Industrial And Organizational Psychology: Perspectives On Science And Practice, 1(3)*, 333-342. doi:10.1111/j.1754-9434.2008.00058.x

Himelstein, P., & Blaskovics, T. (1960). Prediction of an intermediate criterion of combat effectiveness with a biographical inventory. *Journal of Applied Psychology, 44*, 166–168. doi:10.1037/h0048009

Hoffman, B. J., Kennedy, C. L., LoPilato, A. C., Monahan, E. L., & Lance, C. E. (2015). A review of the content, criterion-related, and construct-related validity of assessment center exercises. *Journal of Applied Psychology*, *100*(4), 1143-1168. doi:10.1037/a0038707

Hogan, J., & Holland, B. (2003). Using theory to evaluate personality and job performance relations: A socioanalytic perspective. *Journal of Applied Psychology, 88*, 100-112. doi:10.1037/0021-9010.88.1.100

Holtgraves, T. (2011). Text messaging, personality, and the social context. *Journal of Research in Personality, 45*, 92–99. doi:10.1016/j.jrp.2010.11.015

Hotho, A., Nürnberger, A., & Paaß, G. (2005). A brief survey of text mining. *Machine Learning, 20*(1), 19–62. doi:10.1111/j.1365-2621.1978.tb09773.x

Hough, L. M., & Paullin, C. (1994). Construct-oriented scale construction. In G. S. Stokes, M. D. Mumford, & W. A. Owens (Eds.), *Biodata handbook* (pp. 109–146). Palo Alto, CA: Consulting Psychologists Press.

Huang, G., Zhao, H. H., Niu, X., Ashford, S. J., & Lee, C. (2013). Reducing job insecurity and increasing performance ratings: Does impression management matter?. *Journal of Applied Psychology, 98*(5), 852-862. doi:10.1037/a0033151

Huffcutt, A. I., Conway, J., Roth, P. L., & Stone, N. 2001. Identification and meta-analysis of constructs measured in employment interviews. *Journal of Applied Psychology*, 86: 897-913.

Hunter, J. E., & Hunter, R. F. (1984). Validity and utility of alternative predictors of job performance. *Psychological Bulletin, 96*(1), 72–98. doi:10.1037//0033-2909.96.1.72

IBM SPSS Statistics for Windows (Version 23.0) [Computer software]. Armonk, NY: IBM Corp.

I. Naji. (2013, January 21). 10 tips to improve your text classification algorithm accuracy and performance. Retrieved from http://thinknook.com/10-ways-to-improve-your-classification-algorithm-performance-2013-01-21/

iCIMS. (2015). U.S. hiring trends q1-q4 2015. Retrieved from: https://www.icims.com/sites/www.icims.com/files/public/iCIMS%20Quarterly%20Report%20Q4%202015%20Final2_1.pdf

Ickes, W., Reidhead, S., & Patterson, M. (1986). Machiavellianism and self-monitoring: As different as “me” and “you.” *Social Cognition, 4*, 58–74. doi:10.1521/soco.1986.4.1.58

Ilies, R., & Judge, T. A. (2002). Understanding the dynamic relationships among personality, mood, and job satisfaction: A field experience sampling study. *Organizational Behavior & Human Decision Processes, 89*, 1119-1139. doi:10.1016/S0749-5978(02)00018-3

Illingworth, A., Morelli, N., Scott, J., & Boyd, S. (2015). Internet-based, unproctored assessments on mobile and non-mobile devices: Usage, measurement equivalence, and outcomes. *Journal of Business & Psychology, 30*(2), 325-343. doi:10.1007/s10869-014-9363-8

Imus, A., Schmitt, N., Kim, B., Oswald, F. L., Merritt, S., & Wrestring, A. F. (2010). Differential item functioning in biodata: Opportunity access as an explanation of sex and race related DIF. *Applied Measurement in Education*, *24*, 71–94. doi:10.1080/08957347.2011.532412

Indurkhya, N., & Damerau, F. J. (Eds.). (2010). *Handbook of natural language processing* (2nd ed.). New York, NY: CRC Press.

Judge, T. A., & Kammeyer-Mueller, J. D. (2012). Job Attitudes. *Annual Review of Psychology, 63,* 341-367. doi:10.1146/annurev-psych-120710-100511

Judge, T. A., Rodell, J. B., Klinger, R. L., Simon, L. S., & Crawford, E. R. (2013). Hierarchical representations of the five-factor model of personality in predicting job performance: Integrating three organizing frameworks with two theoretical perspectives. *Journal of Applied Psychology, 98,* 875-925. doi:10.1037/a0033901

Kaplan, S., Bradley, J. C., Luchman, J. N., & Haynes, D. (2009). On the role of positive and negative affectivity in job performance: A meta-analytic investigation. *Journal of Applied Psychology, 94*, 162–176. doi:10.1037/a0013115

Karas, M., & West, J. (1999). Construct-oriented biodata development for selection to a differentiated performance domain. *International Journal of Selection and Assessment, 7,* 86–96. doi:10.1111/1468-2389.00109

Katz, D., & Kahn, Robert L. (1978). *The social psychology of organizations* (2d ed.). New York: Wiley.

Kriska, S.D. (2001, April). The validity-adverse impact trade-off: Real data and mathematical model estimates. *Paper presented at the Society for Industrial and Organizational Psychology meeting, San Diego, CA.*

Kleiman, L., & Faley, R. (1990). A comparative analysis of the empirical validity of past-and present-oriented biographical items. *Journal of Business and Psychology, 4,* 431–437. doi:10.1007/BF01013606

Kluger, A. N., Reilly, R. R., & Russell, C. J. (1991). Faking biodata tests: Are option-keyed instruments more resistant? *Journal of Applied Psychology, 76,* 889–896. doi:10.1037//0021-9010.76.6.889

Knouse, S. B. (1994). Impressions of the resume: The effects of applicant education, experience, and impression management. *Journal of Business and Psychology, 9*(1), 33-45. doi:10.1007/BF02230985

Koeppel, D. (2002, November 24). On a Résumé, Don't Mention Moon Pies or Water Cannons. *New York Times*. p. 1.

Koopmans, L., Bernaards, C., Hildebrandt, V., van Buuren, S., van der Beek, A. J., & de Vet, H. C. W. (2013). Development of an individual work performance questionnaire.

International Journal of Productivity and Performance Management, 62, 6–28. doi:10.1108/17410401311285273

Koopmans, L., Bemaards, C. M., Hildebrandt, V. H., van Buuren, S., van der Beek, A. J., & de Vet, H. W. (2014). Improving the individual work performance questionnaire using rasch analysis. *Journal of Applied Measurement, 15*, 160-175. doi:10.1136/oemed-2013-101717.51

Koopmans, L., Bernaards, C. M., Hildebrandt, V. H., de Vet, H. C. W., & van der Beek, A. J. (2014). Construct validity of the individual work performance questionnaire. *Journal of Occupational and Environmental Medicine, 56*, 331–337. doi:10.1097/JOM.0000000000000113

Koopmans, L., Bernaards, C. M., Hildebrandt, Lernger, D., de Vet, H. C. W., & van der Beek, A. J. (2016). Cross-cultural adaptation of the individual work performance questionnaire. *Work, 53*, 609-619. doi:10.3233/WOR-152237

Koopmans, L., Coffeng, J. K., Bernaards, C. M., Boot, C. L., Hildebrandt, V. H., de Vet, H. W., & van der Beek, A. J. (2014c). Responsiveness of the Individual Work Performance Questionnaire. *BMC Public Health, 14*(1), 1099-1118. doi:10.1186/1471-2458-14-513

Kriedt, P. H., & Gadel, M. S. (1953). Prediction of turnover among clerical workers. *Journal of Applied Psychology, 37*, 338–340. doi:10.1037/h0062274

Landers, R. N., & Callan, R. C. (2014). Validation of the beneficial and harmful work-related social media behavioral taxonomies: Development of the work-related social media questionnaire. *Social Science Computer Review, 32,* 628-646. doi:10.1177/0894439314524891

Lang, J. B., Kersting, M., Hülsheger, U. R., & Lang, J. (2010). General mental ability, narrower cognitive abilities, and job performance: The perspective of the nested factors model of cognitive abilities. *Personnel Psychology, 63*, 595-640. doi:10.1111/j.1744-6570.2010.01182.x

LeBreton, J. M., Hargis, M. B., Griepentrog, B., Oswald, F. L., & Ployhart, R. E. (2007). A multidimensional approach for evaluating variables in organizational research and practice. *Personnel Psychology, 60*, 475-498. doi:10.1111/j.1744-6570.2007.00080.x

Lievens, F., & Reeve, C. L. (2012). Where I-O psychology should really (re)start its investigation of intelligence constructs and their measurement. *Industrial and Organizational Psychology: Perspectives On Science And Practice*, *5*(2), 153-158. doi:10.1111/j.1754-9434.2012.01421.x

Liu, B. (2010). Sentiment analysis and subjectivity. In N. Indurkhya & F. J. Damerau (Eds.), *Handbook of natural language processing* (2nd ed.; pp. 627-665). New York, NY: CRC Press.

Mael, F. A. (1991). A conceptual rationale for the domain and attributes of biodata items. *Personnel Psychology, 44*, 763–793. doi:10.1111/j.1744-6570.1991.tb00698.x

Mael, F. & Ashforth, B. E. (1992). Alumni and their alma mater: A partial test of the reformulated model of organizational identification. *Journal of Organizational Behavior, 13*, 103-123. doi:10.1002/job.4030130202

Mael, F. & Ashforth, B. E. (1995). Loyal from day one: Biodata, organizational identification, and turnover among newcomers. *Personnel Psychology, 48*, 309-333. doi:10.1111/j.1744-6570.1995.tb01759.x/full

Mahmud, J. (2015, March 23). IBM Watson personality insights: The science behind the service [Web log post]. Retrieved from https://developer.ibm.com/watson/blog/2015/03/23/ibm-watson-personality-insights-science-behind-service

Maruo, K., Yamabe, T. & Yamaguchi, Y. (2016). Statistical simulation based on right-skewed distributions. *Comput Stat*. doi:10.1007/s00180-016-0664-4

McKinney, W. (2010). Data structures for statistical computing in Python. In S. van der Walt & J. Millman (Eds.), *Proceedings of the 9th Python in Science Conference* (pp. 51-56). Retrieved from http://conference.scipy.org/proceedings/

Mitchell, T. W., & Klimoski, R. J. (1982). Is it rational to be empirical? A test of methods for scoring biographical data. *Journal of Applied Psychology, 67*, 411–418. doi:10.1037//0021-9010.67.4.411

Mount, M., Witt, L., & Barrick, M. (2000). Incremental validity of empirically keyed biodata scales over GMA and the five-factor personality constructs. *Personnel Psychology, 43*, 299–323. doi:10.1111/j.1744-6570.2000.tb00203.x

Mumford, M. D. (1999). Construct validity and background data: Issues, abuses, and future directions. *Human Resource Management Review, 9*, 117-145. doi:10.1016/S1053-4822(99)00015-7

Mumford, M., Costanza, D. P., Connelly, M. S., & Johnson, J. F. (1996). Item generation procedures and background data scales: Implications for construct and criterion-related validity. *Personnel Psychology*, *49*, 361–399. doi:10.1111/j.1744-6570.1996.tb01804.x

Mumford, M. D., & Owens W.A. (1987). Methodology review: Principles, procedures, and findings in the application of background data measures. *Applied Psychological Measurement, 11*, 1-31. doi:10.1177/014662168701100101

Mumford, M. D., & Stokes, G. S. (1992). Developmental determinants of individual action: Theory and practice in the application of background data measures. In M. Dunnette & L.

M. Hough (Eds.), *Handbook of Industrial and Organizational Psychology* (Vol. 3; pp. 61–138). Palo Alto, CA: Consulting Psychologists Press.

Murphy, K. R. & Deckert, P. J. (2013). Performance appraisal. In K. F. Geisinger et al. (Eds.), *APA handbook of testing and assessment in psychology, Vol. 1: Test theory and testing and assessment in industrial and organizational psychology, volume 1: Test theory and testing and assessment in industrial and organizational psychology*. (pp. 611–627). American Psychological Association. doi: http://dx.doi.org/10.1037/14047-033

Nisbett, R. E., Aronson, J., Blair, C., Dickens, W., Flynn, J., Halpern, D. F., & Turkheimer, E. (2012). Intelligence: New findings and theoretical developments. *American Psychologist, 67*, 130–159. doi:10.1037/a0026699

Ng, T. H., Eby, L. T., Sorensen, K. L., & Feldman, D. C. (2005). Predictors of objective and subjective career success: A meta-analysis. *Personnel Psychology, 58*, 367-408. doi:10.1111/j.1744-6570.2005.00515.x

Nguyen, T., Phung, D., Adams, B., & Venkatesh, S. (2014). Mood sensing from social media texts and its applications. *Knowledge and Information Systems, 39*, 667-702. doi:10.1007/s10115-013-0628-8.

O'Boyle, E. H., Jr., Humphrey, R. H., Pollack, M. J., Hawver, T. H., & Story, P. A. (2010). The relationship between emotional intelligence and job performance: A meta-analysis. *Journal of Organizational Behavior, 32*, 788-818. doi:10.1002/job.714

Owens, W. A. (1976). Background data. In M. D. Dunnette (Ed.), *Handbook of Industrial and Organizational Psychology* (pp. 609–644). Chicago, IL: Rand McNally.

Owens, W. A., & Schoenfeldt, L. F. (1979). Towards a classification of persons. *Journal of*

Applied Psychology, *64*, 569–607. doi:10.1037/0021-9010.64.5.569

Oxman, T. E., Rosenberg, S. D., Schnurr, P. P., & Tucker, G. J. (1988). Diagnostic classification through content analysis of patients' speech. *American Journal of Psychiatry*, *145*, 464-468. doi:10.1176/ajp.145.4.464

Oxman, T. E., Rosenberg, S. D., & Tucker, G. J. (1982). The language of paranoia. *American Journal of Psychiatry*, *139*, 275-282. doi:10.1176/ajp.139.3.275

Pace, L. A., & Schoenfeldt, L. F. (1977). Legal concerns in the use of weighted applications. *Personnel Psychology*, *30*, 159-166. doi:10.1111/j.1744-6570.1977.tb02085.x

Pannone, R. D. (1984). Predicting test performance: A content valid approach to screening applicants. *Personnel Psychology*, *37*, 507–514. doi:10.1111/j.1744-6570.1984.tb00526.x

Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon Mechanical Turk. *Judgment and Decision Making*, *5*, 411–419. Retrieved from http://ssrn.com

Parish, J., & Drucker, A. (1957). *Personnel research of Officer Candidate School* (TAGO Personnel Research Branch Technical Research Report No. 117).Retrieved from http://oai.dtic.mil/oai/oai?verb=getRecord&metadataPrefix=html&identifier=AD0149319

Pennebaker, J. W. (2011) *The secret life of pronouns: What our words say about us* (p. 368). New York, NY: Bloomsbury Press

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*. Austin, TX: University of Texas at Austin.

Pennebaker, J. W., Chung, C. K., Frazee, J., Lavergne, G. M., & Beaver, D. I. (2014). When small words foretell academic success: The case of college admissions essays. *PLoS ONE*, *9*, e115844. doi:10.1371/journal.pone.0115844

Pennebaker, J. W., Chung, C. K., Ireland, M., Gonzales, A., & Booth, R. J. (2007). *The development and psychometric properties of LIWC2007*. Retrieved from http://homepage.psy.utexas.edu/HomePage/Class/Psy301/Pennebaker/HRtraining/LIWC2007_LanguageManual.pdf

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology, 77*, 1296-1312. doi:10.1037/0022-3514.77.6.1296

Pennebaker, J. W., Mayne, T. J., & Francis, M. E. (1997). Linguistic predictors of adaptive bereavement. *Journal of Personality and Social Psychology*, *72*, 863–871. doi:10.1037/0022-3514.72.4.863

Pennebaker, J. W., Mehl, M. R., & Neiderhoffer, K. G. (2003). Psychological aspects of natural language use: Our words, ourselves. *Annual Review of Psychology, 54*, 547-577. doi:10.1146/annurev.psych.54.101601.145041

Pennebaker, J. W., & Stone, L. D. (2003). Words of wisdom: Language use over the lifespan. *Journal of Personality and Social Psychology, 85*, 291–301. doi:10.1037/0022-3514.85.2.291

Piantadosi, S. T. (2015). Zipf's word frequency law in natural language: A critical review and future directions. *Psychonomic Bulletin & Review, 21*(5), 1112-1130.

Ployhart R. (2006). Staffing in the 21st century: New challenges and strategic opportunities. *Journal of Management*, *32*(6), 868–897.

Potosky, D., Bobko, P., & Roth, P. L. (2005). Forming composites of cognitive ability and alternative measures to predict performance and reduce adverse impact: Corrected estimates and realistic expectations. *International Journal of Selection and Assessment,* *13*, 304–315. doi:10.1111/j.1468-2389.2005.00327.x

Potter, J. (2015). *The big five personality test*. Retrieved from http://www.outofservice.com/bigfive/

Prolific. (2015). *How Prolific works.* Retrieved from https://www.prolific.ac/about/prolific

Python language reference (Version 2.7.11) [Computer software]. (2015). Available from http://www.python.org

Ray, R. L., Mitchell, C., Abel, A. L., Phillips, P., Lawson, E., Hancock, B.,…Weddle, B. (2012). The war for talent. *The McKinsey Quarterly*. Retrieved from http://www.mckinseyquarterly.com

Reilly, R. R., & Chao, G. T. (1982). Validity and fairness of some alternative employee selection procedures. *Personnel Psychology, 35*, 1–62. doi:10.1111/j.1744-6570.1982.tb02184.x

Reilly, N. P (n.d.). Cognitive ability tests. Retrieved from: http://nreilly.asp.radford.edu/

Rich, J. (2014). What do field experiments of discrimination in markets tell us? A meta-analysis of studies conducted since 2000. *IZA Discussion Paper No. 8584*. Bonn, Germany. IZA. Retrieved from http://ftp.iza.org/dp8584.pdf

Roth, P. L., Bobko, P., Van Iddekinge, C. H., Thatcher, J. B. (2013). Social media in employee selection related decisions: A research agenda for uncharted territory. *Journal of Management, 42*(1), 269-298.

Rothstein, H., & Schmidt, F., Erwin, F. W., Owens, W. A., & Sparks, C. P. (1990). Biographical data in employment selection: Can validities be made generalizable? *Journal of Applied Psychology, 75*, 175–184. doi:10.1037/0021-9010.75.2.175

Salton, G., Wong, A., Yang, C. S. (1975). A vector space for automatic indexing. *Communications of the ACM, 18,* 613-620. doi: 10.1145/361219.361220

SAS faq: How can I interpret log transformed variables in terms of percent change in linear regression?. *UCLA: Statistical Consulting Group*. from http:// http://www.ats.ucla.edu/stat/sas/faq/sas_interpret_log.htm/ (accessed May 28, 2016).

Scherwitz, L., Graham, L. E., Grandits, G., Buehler, J., & Billings, J. (1986). Self-involvement and coronary heart disease incidence in the multiple risk factor intervention trial. *Psychosomatic Medicine*, *48*, 187–199.

Schlomer, G. L., Bauman, S., & Card, N. A. (2010). Best practices for missing data management in counseling psychology. *Journal of Counseling Psychology*, *57*, 1-10. doi:10.1037/a0018082

Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin*, *124*, 262–274. doi:10.1037//0033-2909.124.2.262

Schmidt, F. L., & Hunter, J. E. (2004). General mental ability in the world of work: Occupational attainment and job performance. *Journal of Personality & Social Psychology*, *86*, 162-173. doi:10.1037/0022-3514.86.1.162

Schneider, B. (1987). The people make the place. *Personnel Psychology*, *40*(3), 437-453. doi:10.1111/j.1744-6570.1987.tb00609.x

Schoenfeldt, L. (1999). From dustbowl empiricism to rational constructs in biographical data. *Human Resource Management Review*, *9*, 147–167. doi:10.1016/S1053-4822(99)00016-9

Schultheiss, O. C. (2013). Are implicit motives revealed in mere words? Testing the marker-word hypothesis with computer-based text analytics. *Frontiers in Psychology, 4*, 748. doi:10.3389/fpsyg.2013.00748

Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Ramones, S. M., Agrawal, M., …Ungar, L. H. (2013). Personality, sex, and age in the language of social media: The open-vocabulary approach. *PLoS ONE, 8*, e73791. doi:10.1371/journal.pone.0073791

Shaffer, G. S., Saunders, V., & Owens, W. A. (1986). Additional evidence for the accuracy of biographical data: Long-term retest and observer ratings. *Personnel Psychology, 39*, 791–809. doi:10.1111/j.1744-6570.1986.tb00595.x

Shultz, K. S. (1996). Distinguishing personality and biodata items using confirmatory factor analysis of multitrait-multimethod matrices. *Journal of Business and Psychology, 10,* 263–288. doi:10.1007/BF02249603

Society for Industrial and Organizational Psychology. (2003). *Principles for the validation and use of personnel selection measures* (4th ed.). Bowling Green, OH: Society for Industrial and Organizational Psychology.

Solomon, B. C., & Jackson, J. J. (2014). The long reach of one's spouse: Spouses' personality influences occupational success. *Psychological Science, 25*(12), 2189-2198. doi:10.1177/0956797614551370

Soper, D. S. (2016). *Significance of the difference between two slopes calculator* [Software]. Available from http://www.danielsoper.com/statcalc

Steinhaus, S. D., & Waters, B. K. (1991). Biodata and the application of a psychometric perspective. *Military Psychology, 3*, 1–23. doi:10.1207/s15327876mp0301_1

Steffens NK, Haslam SA (2013) Power through ‘us’: Leaders’ use of we-referencing language predicts election victory. *PLoS ONE 8*(10): e77952. doi:10.1371/journal.pone.0077952

Stirman, S., & Pennebaker, J. (2001). Word use in the poetry of suicidal and nonsuicidal poets. *Psychosomatic Medicine, 63*, 517–522.

Stokes, G. S., & Searcy, C. A. (1999). Specification of scales in biodata form development: Rational vs. empirical and global vs. specific. *International Journal of Selection and Assessment, 7*, 72–85. doi:10.1111/1468-2389.00108

Sweeney, L. (2013). Discrimination in online ad delivery. *Communications of The ACM, 56*(5), 44-54. doi:10.1145/2447976.2447990

Tableau (Version 9.1.3) [Computer software]. (2015). Seattle, WA: Tableau Software Inc.

Tabachnick, B. G. & Fidell, S. F. (2013). *Using multivariate statistics.* Boston: Pearson Education.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analytics methods. *Journal of Language and Social Psychology, 29,* 24-54. doi:10.1177/0261927X09351676

Tippins, N. T. (2009a). Internet alternatives to traditional proctored testing: Where are we now? *Industrial and Organizational Psychology, 2,* 2–10. doi:10.1111/j.1754-9434.2008.01097.x

Tippins, N. T. (2009b). Where is the unproctored internet testing train headed now? *Industrial and Organizational Psychology, 2*, 69–76. doi:10.1111/j.1754-9434.2008.01111.x

Tippins, N. T., Beaty, J., Drasgow, F., Gibson, W. M., Pearlman, K., Segall, D. O., & Shepherd, W. (2006). Unproctored Internet testing in employment settings. *Personnel Psychology, 59,* 189-225. doi:10.1111/j.1744-6570.2006.00909.x

Tomlinson, M., Hinote, D., & Bracewell, D. (2013, July). *Predicting conscientiousness through semantic analysis of facebook posts.* Paper presented at the Seventh International AAAI Conference on Weblogs and Social Media, Cambridge, MA. Retrieved from http://www.aaai.org/ocs/index.php/ICWSM/ICWSM13/paper/download/6255/6313

Turckle, S. 2011. *Alone together: Why we expect more from technology and less from each other*. New York: BasicBooks.

Virgina. (2014, March 1). What's the average time to hire? [Web log comment]. Retrieved from http://blog.talentpuzzle.com/recruitment-agencies/what-is-the-average-time-to-hire/

Waternaux, C. M. (1976). Asymptotic distribution of the sample roots for nonnormal population. *Biometrika, 63*(3), 639-645.

Wayne, S. J., & Ferris, G. R. (1990). Influence tactics, affect, and exchange quality in supervisor-subordinate interactions: A laboratory experiment and field study. *Journal of Applied Psychology, 75,* 487-499. doi:10.1177/1059601195203003

Wayne, S. J., & Liden, R. C. (1995). Effects of impression management on performance ratings: A longitudinal study. *Academy of Management Journal, 38,* 232-260. doi:10.2307/256734

Wernimont, P. F., & Campbell, J. P. (1968). Signs, samples, and criteria. *Journal of Applied Psychology, 52,* 372-376. doi:10.1037/h0026244

West, J., & Karas, M. (1999). Biodata: Meeting clients' needs for a better way of recruiting entry-level staff. *International Journal of Selection and Assessment, 7,* 126–131. doi:10.1111/1468-2389.00112

Weick, K. E. (1999). Theory construction as disciplined reflexivity: Tradeoffs in the 90s. *Academy of Management Review, 24,* 797-806. doi:10.5465/AMR.1999.2553254

Whetzel, D. L., & McDaniel, M. A. (2009). Situational judgment tests: An overview of current research. *Human Resource Management Review, 19(*3), 188-202. doi:10.1016/j.hrmr.2009.03.007

Whitney, D. J., & Schmitt, N. (1997). Relationship between culture and responses to biodata employment items. *Journal of Applied Psychology, 82*, 113–129. doi:10.1037//0021-9010.82.1.113

Wilkinson, L. J. (1997). Generalizable biodata? An application to the vocational interests of managers. *Journal of Occupational and Organizational Psychology, 70*, 49–60. doi:10.1111/j.2044-8325.1997.tb00630.x

Workplace Fairness (2016). *Social networking and computer privacy*. Retrieved from http://www.workplacefairness.org/social-network-computer-privacy-workplace#3

Yuspeh, R. L., & Vanderploeg, R. D. (2000). Spot-the-word: A measure for estimating premorbid intellectual functioning. *Archives of Clinical Neuropsychology, 15*, 319-326. doi:10.1016/S0887-6177(99)00020-7

Zaccaro, S. J., Zazanis, M. M., Diana, M., & Gilbert, J. A. (1995). *Investigating a background data measure of social intelligence* (Technical Report No. 1024). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Table 1

Detailed Biodata Research Findings Reproduced from Mumford, Costanza, Connelly, & Johnson (1996)

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V^d	CV^c
1)	Uhlman & Mumford (1993) (n_v^f = 5,246, nc_{vg} = 5,246, n_{rep}^h = 2,583)						
	Cognition		Problem-solving with:	Empirical constructs, Concurrent design	Undergrad GPA	0.37	0.36
	Memory (3)	.35 (.35)	Job knowledge (.15)		Graduate GPA	0.2	0.1
	Oral Communication (12)	.68 (.66)	written comprehension (.56)		Months of overseas experience	0.17	0.18
	Planning (15)	.68 (.65)	cultural adaptation (.37)				
	Problem Solving (13)	.65 (.62)					
	Written comprehension (7)	.47 (.36)					
	Social						
	Cultural adaptation (14)	.67 (.69)					
	Interviewering (7)	.62 (.60)					
	Handling difficult situations (18)	.69 (.69)					
	Leadership (15)	.73 (.72)					
	Negotiation (15)	.75 (.74)					
	Personality						
	Initiative and persistence (16)	.66 (.62)					
	Personal Integrity (17)	.67 (.66)					
	Personal style (15)	.65 (.62)					
	Work flexibility (5)	.56 (.50)					

a Constructs used in validation and cross-validation analysis.

b Cronbach alphas for each scale.

c Second column of alphas included in studies where replication samples were obtained.

d Validation sample multiple *R*.

e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.

g Number of subjects in cross-validation sample.

h Number of subjects in the replication sample.

Table 1 continued

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V[d]	CV[c]
2)	Costanza & Mumford (1993) (n_v^f=10,487)						
	Cognition		Planning with:	Empirical constructs, Predictive design	Assessment center performance ratings	0.38	N/A
	Memory (3)	.35 (.35)	Job Knowledge (.10)		Foreign service institute performance ratings	0.58	N/A
	Oral Communication (12)	.68 (.66)	assessment center score (.15)		Months of overseas experience		
	Planning (15)	.68 (.65)	personal interview (.09)				
	Problem Solving (13)	.65 (.62)					
	Written comprehension (7)	.47 (.36)	Written comprehension with:				
	Social		job knowledge (.26)				
	Cultural adaptation (14)	.67 (.69)	assessment center score (.05)				
	Interviewing (7)	.62 (.60)	personal interview (.07)				
	Handling difficult situations (18)	.69 (.69)					
	Leadership (15)	.73 (.72)	Negotiation with:				
	Negotiation (15)	.75 (.74)	Job knowledge (.00)				
	Personality		assessment center score (.13)				
	Initiative and persistence (16)	.66 (.62)	personal interview (.07)				
	Personal Integrity (17)	.67 (.66)					
	Personal style (15)	.65 (.62)					
	Work flexibility (5)	.56 (.50)					

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
					V^d	CV^c
3) Kilcullen (1993) (n_v^f = 1,022, n_{cv}^g=1,022)						
Cognition		Practical intelligence with:	Theoretical constructs; Concurrent design	Supervisory ratings	0.22	0.21
Cognitive Ability (37)	0.82	cognitive ability (.79)		Performance records	0.38	0.31
Management skills (9)	0.65	planning/organizing (.60)				
Planning /organizing (18)	0.73	harm avoidance (-.49)				
Practical intelligence (28)	0.81					
Supervisory skills (10)	0.69	Supervisory skills with:				
Motivation		cognitive ability (.53)				
Achievement (22)	0.77	planning/organizing (..37)				
Dependability (23)	0.79	harm avoidance (-.32)				
Dominance (24)	0.76					
Energy level (11)	0.73	Achievement with:				
Social maturity (14)	0.69	cognitive ability (.75)				
Stress tolerance (27)	0.85	planning/organizing (.41)				
Work motivation (15)	0.69	harm avoidance (-.51)				
Self-Confidence						
Defensiveness (17)	0.74					
Harm Avoidance (19)	0.7					
Need for approval (15)	0.76					
Need for security (25)	0.83					
Self-esteem (18)	0.69					
Social Skills						
Consideration (17)	0.78					
Interpersonal monitoring (29)	0.82					
Self-monitoring (25)	0.79					
Social alienation (14)	0.79					

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.

e Cross-validation sample multiple *R*.
f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

Predictors and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
					V^d	CV^c
4) Kilcullen, White, & O'Connor (1994) (n_v^f=213)						
Achievement (22)	0.85	Achievement with:	Theoretical constructs; Concurrent design	Rank	0.4	N/A
Physical Strength (7)	0.74	work orientation (.45)		Career achievement record	0.41	N/A
Anxiety (8)	0.72	dominance (.44)		Physical readiness	0.25	N/A
		Physical strength with Physical endurance (.61)				
		Anxiety with: adjustment (-.49)				
5) Zaccaro, Zazanis, Diana, & Gilbert (1995) (n_v^f = 189)						
Interpersonal perceptiveness (15)	0.82	Interpersonal perception with:	Theoretical constructs; Concurrent design)	Peer rankings of team performance (9 to 11 judges)	0.22	N/A
Systems perception (9)	0.72	social transition (.11)				
Behavioral flexibility (10)	0.76	sensitivity to expressive behavior (.59)				
Social competence (6)	0.72	intelligence (-.01)				
		Systems perception with:				
		social transition (.24)				
		sensitivity to expressive behavior (.51)				
		intelligence (.24)				
		Social Competence with:				
		social transition (.10)				
		sensitivity to expressive behavior (.42)				
		intelligence (-.05)				

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V^d	CV^c
6)	Kilcullen, White, Mumford, & Mack (1995) (n_v^f=229)						
	Stress tolerance (17)	0.76	Stress tolerance with:	Theoretical constructs; Concurrent design	Performance records	0.31	(17)
	Energy level (9)	0.41	emotional stability (.66)				(9)
	Social maturity (14)	0.52	energy level (.40)				(14)
	Work motivation (11)	0.5	dominance (.36)				(11)
	Self-esteem (9)	0.45	Energy level with:				(9)
	Dominance (12)	0.61	emotional stability (.43)				(12)
			energy level (.62)				
			dominance (.37)				
			Dominance with:				
			emotional stability (.51)				

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
					V^d	CV^c
7) Mumford, Zaccaro, Harding, & Fleishman (1994) (n_V^f = 853, n_{cv}^g =414)						
Practical Intelligence						
Troubleshooting (8)	0.75	Systems perception with:	Theoretical constructs; Concurrent design	Career achievement record	0.43	0.51
Planning under ambiguity (8)	0.64	intuiting (.22)			0.48	0.51
Monitoring (6)	0.54	openness (.17)				
Information gathering (4)	0.54	verbal reasoning (.11)				
Selection of solution components (3)	0.59	Troubleshooting with:		Rank		
Social Intelligence		intuiting (.17)				
Interpersonal perceptiveness (12)	0.86	openness (.26)				
Social adroitness (5)	0.58	verbal reasoning (.16)				
Harmony facilitation (6)	0.56					
Behavioral flexibility (4)	0.64					
Wisdom		Behavioral flexibility with:				
Self-reflectivity (7)	0.75	intuiting (.21)				
Insight (4)	0.7	openness (.25)				
Judgment under uncertainty (8)	0.69	verbal reasoning (.15)				
Systems perception (4)	0.51					

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.
f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V^d	CV^c
8)	Mumford, Gessner, O'Connor, Johnson, Holt, & Smith (1994) (n_v^f = 195, n^f_{cv} = 97)						
	Fear (10)	0.75	Fear with:	Theoretical constructs; Concurrent design	Integrity Tests		
	Narcissism (11)	0.68	personal adjustment (-.48)		Reid		
	Need for power (11)	0.68	authoritarianism (.42)		Honesty	0.22	0.22
	Negative life themes (7)	0.43	Power with:		Theft	0.26	0.24
	Object beliefs (19)	0.73	authoritarianism (.43)		PSI		
	Outcome uncertainty (15)	0.71	Object beliefs with:		Honesty	0.34	0.35
	Self-regulation (9)	0.42	Object beliefs with:		Theft	0.19	0.19
			Machiavellianism (.26)				
			authoritarianism (.35)				

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
					V^d	CV^c
9) Baughman,Costanza, Uhlman, Threlfall, & Mumford (1992) (n_v^f = 567)						
Category flexibility (9)	0.72	Problem anticipation with:	Theoretical constructs; Concurrent design	High school GPA	0.36	0.29
Delay of gratification (8)	0.65	intellectual confidence (.23)		College GPA	0.45	0.4
Ego control (12)	0.78	learning orientation (.39)				
Ego resiliency (8)	0.59					
Energy (7)	0.63	Mastery motives with:				
Internal locus of control (8)	0.7	intellectual confidence (.34)				
Mastery motives (6)	0.67	learning orientation (.45)				
Maturity (13)	0.7					
Need for achievement (9)	0.7	Anxiety with:				
Openness (11)	0.67	intellectual confidence (-.41)				
Persistence (12)	0.73	performance orientation (.41)				
Positive emotionality (10)	0.7					
Problem anticipation (6)	0.7	Naivete with:				
Self-esteem (14)	0.85	intellectual confidence (-.44)				
Tolerance for ambiguity (11)	0.71	performance orientation (.33)				
Anxiety (9)	0.74					
Defensive reappraisal (9)	0.66					
Defensiveness (9)	0.76					
Depression (13)	0.75					
Envy (10)	0.76					
Greed (10)	0.78					
Judgmentalism (12)	0.74					
Naivete (8)	0.62					
Need for status (10)	0.76					
Neuroticism (9)	0.68					
Self-assessment (11)	0.69					
Shame (7)	0.67					
Suspicion (13)	0.74					

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.

e Cross-validation sample multiple *R*.
f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V^d	CV^c
10)	Mumford, Baughman, Threlfall, Uhlman, & Costanza (1993) ($n_v^f = 167$, $n_{cv}^g = 83$)						
	Evaluation apprehension (34)	0.94	Evaluation apprehension with:	Theoretical constructs; Predictive design	Quality of novel problem solving	0.24	0.22
	Self-discipline (51)	0.96	neuroticism (.25)				
	Creative achievement (19)	0.89	anxiety (.24)				
			self-esteem (-.18)				
			Self-discipline with:				
			delay of gratification (.44)				
			tolerance for ambiguity (.39)				
			greed (-.37)				
			Creative achievement with:				
			energy (.25)				
			openness (.43)				
			achievement motivation (.29)				

a Constructs used in validation and cross validation analyses.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V^d	CV^c
11)	Mumford, Baughman, Uhlman, Costanza, & Threlfall (1993) (n_v^f = 117)						
	Competitiveness (31)	0.94	Creative achievement with:	Theoretical constructs; Predictive design	Amount of milk processed in a simulated milk pasteurizer task		
	Creative achievement (12)	0.84	competitiveness (.22)		hour 1	0.49	
	Defensive rigidity (30)	0.93	defensive rigidity (-.26)		hour 2	0.43	
	Positive temperament (16)	0.87	Positive temperament with:		hour 3	0.61	
	Self-discipline (12)	0.86	competitiveness (-.81)		hour 4	0.61	
			defensive rigidity (.79)				

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Table 1 continued

	Predictors[a] and # items in scales	r_u^{bc}	Correlations of constructs with reference measures	Validation strategy	Criteria	Multiple R	
						V[d]	*CV*[c]
12)	Connelly, Marks, & Mumford (1993) (n_{v1}^{f} = 100, n_{cv1}^{g} = 67, n_{v3}^{h} = 83)						
	Accommodation (8)	.66 (.58)	Judgment under uncertainty with:	Theoretical constructs; Concurrent design	Interpretations of Aesop's Fables (wisdom related performance)	0.55	0.42
	Contextual morality (9)	.68 (.45)	openness (.50)				
	Judgment under uncertainty (10)	.72 (.65)	deductive reasoning (.34)				
	Problem construction (19)	.70 (.54)	creativity (.24)				
	Reasoning (10)	.82 (.84)	Self-reflectivity with:				
	Self-objectivity (12)	.70 (.50)	openness (.32)				
	Self-reflectivity (13)	.72 (.68)	deductive reasoning (.21)				
	Sensitivity to fit (10)	.59 (.61)	creativity (.10)				
	Social commitment (19)	.70 (.69)	Social perception with:				
	Social perception (10)	.70 (.71)	openness (.50)				
	Style of information processing (7)	.60 (.53)	deductive reasoning (.36)				
			creativity (.23)				

a Constructs used in validation and cross-validation analysis.
b Cronbach alphas for each scale.
c Second column of alphas included in studies where replication samples were obtained.
d Validation sample multiple *R*.
e Cross-validation sample multiple *R*.

f Number of subjects in the validation sample.
g Number of subjects in the cross-validation sample.
h Number of subjects in the replication sample.

Link back to manuscript

Table 2

Overview of Biodata Research Findings

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
1953	Kriedt et al.	Predict turnover	Turnover	Empiric	.37**	--	358	Self-created	--	Yes	Insurance	Not reported	No
1960	Himelstein et al.	Combat effectiveness	Combat effectiveness	--	0.41	0.98	57	Torrance-Ziller risk scale	--	--	Military	Not reported	No
1976	Cascio	Predict tenure in minority and non-minority female clerical workers	Turnover	Empiric	0.57	--	260	Self-created	Yes	--	Insurance	Not reported	Yes
1982	Mitchell et al.	Test of rational v empirical keying	Job perf	Rational& Empiric	.41**	--	698	Combined existing biodata banks	--	--	Real Estate	Not reported	No
1982	**Reilly & Chao**	**Meta-analysis of biodata**	**Varied**	**--**	**0.35**	**--**	**46,526**	**--**	**Yes**	**--**	**Varied**	**--**	**Used only cross-validated validities**
1984	Pannone	Bio data predicts performance	Job perf	Rational	.39	0.96	221	Self-created	--	--	Electrician	--	--
1984	**Hunter & Hunter**	**Meta-analysis of biodata**	**Manager ratings, promotion, training success, tenure**	**--**	**.30****	**--**	**30,392**	**--**	**--**	**--**	**Varied**	**--**	**--**

*Average reliability.

**Average effect size.

***Organizational Identification

Bolded rows indicate e meta-analyses

Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.

Rational Keying: based on prior theoretical linkages between items/options and criterion

Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Table 2 continued

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
1986	Shaffer et al.	Are biodata items accurate over time	--	--	--	0.77	237	Owens Biographical Questionnaire		--	--	Not reported	No
1988	Drakeley et al.	Biodata to predict turnover and training performance	Voluntary turnover Training	Empirical	.26**		702						Yes
1990	Kleiman et al	Present life v past life questions	--	--	--	--	96	Military Bio Questionnaire	--	--	Military	Not reported	--
1990	**Rothstein et al.**	**Meta-analysis; making biodata validities generalizable**	**Job perf**	**Rational**	**0.33**	**--**	**11,000**	**Supervisory Profile Record**	**--**	**--**	**Varied**	**Not reported**	**No**
1991	Steinhaus et al.	Attrition in military	Attrition	Empirical	0.24	0.74	26,000	Edu & Bio Information Survey	Yes	--	Military	Not reported	Yes
1991	Kluger et al.	Reducing faking	--	Empirical	--	--	85	Russell & Domm (1990) store manager scale	--	--	Public sector	Not reported	No
1991	**Beall**	**Meta-analysis of biodata**	**Job perf, tenure, credit risk, theft**	**--**	**.38****	**--**	**92,111**	**--**	**--**	**--**	**--**	**--**	**--**

*Average reliability.

**Average effect size.

***Organizational Identification

Bolded rows indicate e meta-analyses

Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.

Rational Keying: based on prior theoretical linkages between items/options and criterion

Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Table 2 continued

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
1992	Becker et al.	Reducing faking	--	Empirical	0.39	0.79	289	Self-created	--	--	Retail	Not reported	Yes
1992	Devlin et al.	Test empirical keying methods	School Perf	Empirical	.29**	--	775	Personal History Questionnaire	--	--	Military	Not reported	Yes
1995	Mael & Ashforth	Behavioral and experiential antecedents of org identification	Turnover, OID***	Hybrid	0.24	--	2,535	Self-created	---	Yes	Military	Not reported	Yes
1996	**Bliesener**	**Analysis of method moderators in biodata validities**	--	--	**0.22**	--	**106,302**	**Varied**	--	--	**Varied**	**Not reported**	--
1996	Dalessio et al.	Transporting alpha coefficients for scoring and factor structure	--	Empirical	0.15	0.65	25,474	Career Profile Questionnaire	--	--	Insurance	0.06	Yes
1997	Whitney et al.	Black/White cultural differences in differential item functioning	--	--	--	0.82	216	Combined based on existing biodata banks	--	--	Public sector	Not reported	No

*Average reliability.

**Average effect size.

***Organizational Identification

Bolded rows indicate e meta-analyses

Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.

Rational Keying: based on prior theoretical linkages between items/options and criterion

Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Table 2 continued

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
1997	Wilkinson	Do biodata questions predict career interest regardless of job or organization	Career interest	Hybrid	.63**	--	148	Self-created	--	--	Managers	Not reported	No
1999	**Bobko et al.**	**Meta-analysis of GMA & other predictors of job perf**	**Job perf**	**Varied**	**.33**	**--**	**6,115**	**Varied**	**--**	**--**	**Varied**	**Not reported**	**No**
1999	Schoen-feldt	Test of keying methods	Job perf	Empirical/Rational	0.41	--	867	Self-created	--	--	Customer Service		Yes
1999	Allworth et al.	Biodata for context and culture selection	Job perf	Hybrid	0.35	.82*	325	Self-created	Yes	Yes, 9% above	Hospitality	0.1	Yes
1999	Karas et al.	Differential impact of keying procedures	Job perf	rational and empirical	0.29	0.84*	2,904	Self-created	--	Yes, 13% above	Public sector	0.7	Yes
1999	Stokes et al.	Test of rational v empirical keying and global v specific items	sales and Overall job perf	Varied	.21**	0.73	1,621	Self-created	--	--	Retail	Not reported	Yes

*Average reliability.
**Average effect size.
***Organizational Identification
Bolded rows indicate e meta-analyses
Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.
Rational Keying: based on prior theoretical linkages between items/options and criterion
Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Table 2 continued

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
1999	West et al.	Assess GMA and non-cognitive abilities with Biodata to max. validity and fairness of recruiting process	Job perf	Hybrid	0.37	0.7	1094	Self-created	Yes	--	--	--	--
1999	**Carlson et al.**	**Validity generalization can be achieved for biodata within a single org as opposed to multiple orgs**	**Promotion rate**	**Hybrid**	**0.53**	**--**	**7,334**	**Manager Profile Record**	**--**	**--**	**Varied**	**Not reported**	**Yes**
2000	Mount et al.	Incremental validity of biodata over gma and personality	Job perf, retention	Hybrid	0.41	0.54	376	Self-created	Yes	Yes, by up to 9%	Administration	Not reported	Yes
2000	Allworth et al.	Biodata test construction approach	Job Perf	Construct from JA only	0.28	0.67	245	Self-created	--	Yes, 6.5% above	Customer Service	Not reported	No
2000	Harvey-Cook et al.	Professional entry level selection	Job perf	Hybrid	0.23	--	686	Standard Application Form	--	--	Varied	0.3	Yes

*Average reliability.

**Average effect size.

***Organizational Identification

Bolded rows indicate e meta-analyses

Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.

Rational Keying: based on prior theoretical linkages between items/options and criterion

Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Table 2 continued

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
2004	Dean	Validating biodata across multiple performance criteria:	Training perf	Empirical	.39**	0.79	6,036	Self-created	--	Yes, 9% above and beyond gma	Manu-facturing	0.11***	Yes
2005	Barrick et al.	Biodata to predict turnover	Turnover	---	0.33	---	445	Self-created	---	--	Varied	Not reported	No
2006	Harold et al.	Validity of verifiable and non-verifiable biodata items, with incumbents and applicants	Job perf	Hybrid	.54**	--	835	Proprietary Kenex scale	--	--	Customer Service	Not reported	Yes
2009	Barrick et al.	Assess the usefulness of pre-hire variables in predicting performance and voluntary turnover	Job Performance, Turnover	--	.26**	--	354	Self-created	--	--	Customer Service	Not reported	No

*Average reliability.
**Average effect size.
***Organizational Identification
Bolded rows indicate e meta-analyses
Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.
Rational Keying: based on prior theoretical linkages between items/options and criterion
Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Table 2 continued

Year	Author	Study Purpose	Outcome Variable	Keying Type	Effect Size	Alpha	N	Scale	Meet Fairness Standards	Over GMA	Industry	Shrinkage	Cross Validated
2009	Becton et al.	Biodata to predict turnover, org commitment, and performance in healthcare	Turnover, Org Commit, Job Perf	Empirical	.33**	0.72	896	Self-created	yes	--	Healthcare	Not reported	Yes
2011	Chen et al.	Recruiters inferences as mediators of biodata	Hiring recs	--	0.23	0.77	62	Modified Cole et al. (2007)	--	--	Varied	Not reported	No
2012	Levashina et al.	Reducing faking	--	--	--	0.95	16,304	Self-created	--	--	Public sector	Not reported	--
2013	Dean	Biodata fairness v GMA fairness	Training Perf	Empirical	0.42	--	3,401	--	Yes	--	Public Sector	Not reported	Yes

*Average reliability.
**Average effect size.
***Organizational Identification
Bolded rows indicate e meta-analyses
Empirical Keying: items and options are weighted based on the empirical relationship between a selected item/option and scores on a criterion.
Rational Keying: based on prior theoretical linkages between items/options and criterion
Hybrid Keying: combines both empirical and rational keying approaches to establish a biodata scoring key. See Cucina, Caputo, Thibodeaux, & Maclane (2012) for an in-depth review and evaluation of these three types of keying approaches

Link back to manuscript

Table 3

Overview of Text analytics and the Marker Word Hypothesis Used in Psychological and Computer Science Research

Year	Author	Study Purpose	Hypothesis/Theory	Method	Findings
1975	Tucker & Rosenberg	Differentiate the speech of schizophrenics from non-schizophrenics via text analytics	No theory cited, referenced past works that attempted to use language used to diagnose a mental health disorder, past work focused on the structure of language (e.g. grammar and syntax) or content analysis of themes.	Used the General Inquirer Computer Content Analysis Program with the Harvard III Psychosocial Dictionary. Only analyzed 600 words from each person. Used mean comparisons and factor analysis.	Categories like “time reference,” “sense,” and “attempt” differentiated between schizophrenics and non-schizophrenics. Overall, the categories demonstrated themes around confusion, distress, and self-concern, and were consistent with clinical experience.
1982	Oxman et al.	Test 3 theories about paranoia via text analytics.	Discussed three theories of paranoia. Paranoia as a subtype of schizophrenia, a separate mental disorder, or on a continuum from normal to abnormal.	Used the General Inquirer Computer Content Analysis Program with the Harvard III Psychosocial Dictionary. Only analyzed 600 words from each person. Used mean comparisons and factor analysis.	Results suggested paranoia as a separate mental disorder rather than a sub-type of schizophrenia or on a scale from normal to abnormal. Paranoid participants used more abstract self-reference words, used neutral affect words when discussing others, and tended to use more words expressing warmth and intimacy. Paranoid participants were classified correctly 80% of the time when using speech samples.
1986	Scherwitz et al.	Assess risk factor of Type A for coronary heart disease (CHD)	Type A behavior predicts CHD	Count of first, person pronouns (I, me, my) and logistic regression to predict (CHD) and heart attack.	Use of first-person pronouns (I, me, my) predicted CHD, mortality from CHD, and fatal heart attacks.
1997	Pennebaker et al.	Examined the extent to which discussing the death of a loved one was predictive of later physical and mental health	Disclosure theory: confronting upsetting topics reduces the constraints or inhibitions associated with not talking about the events. Differential emotion: using more negative words leads to health improvements.	LIWC correlated with self-reports of mental and physical health	Use of more positive words and insight words like “think,” “know,” “consider” were associated with health.
2001	Cheng et al.	Accurately predict a person’s sex based on text data.	Can the sex of an author be identified from a short text document?	LIWC to identify psycholinguistic and sex cues and computer science algorithms for sex identification based on the authors chosen LIWC categories and sub-categories	Able to predict author sex with 85% accuracy. Words indicative of sex were function words (articles, conjunctions, etc.), word features (total number of words, avg character length per word, etc.), and structural features (number of sentences, paragraphs, etc.)
2001	Danner et al.	Examine the relationship between emotional text content and mortality in late adulthood (75-95)	Emotions reflect patterns of adaptive or maladaptive coping	Self-created coding process developed for study and regression analysis	Positive emotion words (accomplishment, happiness, hope, love) were related to longevity 60 years later. 1% increase in positive words decreased mortality rate by 1.4%.

Table 3 continued

Year	Author	Study Purpose	Hypothesis/Theory	Method	Findings
2001	Pennebaker & Stone	Investigate links between aging and language use	Theories and hypothesis centered on aging and: affect, social relationships, time orientation, and cognitive ability	LIWC (14 categories only) correlated with and regressed on age	As age increased, use of positive affect words, present, and future tense verb use increased
2001	Stirman & Pennebaker	Investigated whether word usage and word styles differentiated poets who committed suicide versus those who did not.	Social Integration/disengagement Theory	Used LIWC to identify words and stylometric features that distinguished poets who committed suicide from those who did not	Poets who committed suicide tended to use more first-person, singular pronouns (I, me, my) than poets who did not.
2010	Holtgraves	Investigated how language used in text messaging varies as a function of personality, sex, interpersonal context.	Hypothesis based on prior findings looking at the links between language use and extraversion, agreeableness, and neuroticism	Used LIWC correlated with Goldberg's (1992) measure of the Big Five looking at extraversion, agreeableness, and neuroticism only.	Extraversion was correlated with personal pronouns, agreeableness with positive emotion words and swearing, neuroticism with negative emotion words. Females used more social words, personal pronouns, and used more emoticons. Males used more swear words, more overall words. Slang and emoticons were used more with friends and romantic partners
2013	Schultheiss	Looked to see if motivations (specifically, McClelland's need typology) could be inferred from language use.	Sought to extend McClelland's need theory using new methodology (computerized text analytics)	Used LIWC categories correlated with measures of McClelland's needs.	Power was related to anger categorized words. Achievement with achievement, positive emotion, optimism, and occupation words. Affiliation with social, friend, third-person pronouns, and positive feeling words.
2013	Tomlinson et al.	Examined whether it was possible to predict conscientious using Facebook posts.	No theory cited; hypothesis was that verb usage that is less specific is predictive of conscientiousness.	Used WordNet and parsed Facebook posts into subjects and verbs.	More specific and less objective verbs were correlated .27 with conscientious. Specific verb examples: donated, stabbed versus gave and hurt.

Link back to manuscript

Table 4.

Descriptive Statistics: LIWC Categories for Hypothesis 2-5 with Base Rate Comparisons (Sub-Sample)

LIWC categories for hypothesis 2-5	M	SD	Skew	Kurtosis
1st person singular pronouns	1.22 (4.99)	1.66 (2.46)	1.81	**2.97**
1st person plural pronouns	0.08 (0.72)	0.19 (0.83)	**4.46**	**27.39**
2nd person pronouns	0.04 (1.70)	0.14 (1.35)	**5.02**	**30.36**
3rd person singular pronouns	0.02 (1.88)	0.11 (1.53)	**8.57**	**100.38**
3rd person plural pronouns	0.20 (0.66)	0.32 (0.60)	**2.60**	**8.90**
Impersonal pronouns	0.92 (5.26)	0.71 (1.62)	1.24	**2.07**
Auxiliary verbs	1.42 (8.53)	1.33 (2.04)	1.56	**2.79**
Verbs	4.79 (16.44)	2.32 (2.93)	0.83	0.97
Positive emotion words	2.83 (3.67)	1.22 (1.63)	0.41	-0.00
Negative emotion words	0.53 (1.84)	0.52 (1.09)	**2.05**	**6.49**
Differentiation words	0.55 (2.99)	0.50 (1.18)	1.91	**5.93**
Conjunctions	6.25 (5.90)	2.04 (1.57)	-0.41	0.44
Words longer than 6 characters	40.18 (15.60)	6.29 (3.76)	-0.78	**3.06**
Prepositions	12.05 (12.93)	3.08 (2.11)	-1.00	**3.07**
Cognitive process words	5.73 (10.61)	2.03 (3.02)	0.47	1.56
Causal words	1.96 (1.40)	1.01 (0.73)	0.83	1.77
Insight words	1.98 (2.16)	1.00 (1.08)	1.14	**3.86**

Note. Bolded values indicate skewness and kurtosis exceed ±2. N = 667. Values in parentheses are LIWC reported average base rates and standard deviations

Link back to manuscript

Table 5.

Impression Management Questionnaire (Wayne & Liden, 1995)

Dimensions	Item Text
Other-Impression Management *In the past 3 months, to what extent did you*	
O-IM1	Do personal favors for your supervisor (for example, getting him or her a cup of coffee or coke, etc.)
O-IM2	Offer to do something for your supervisor which you were not required to do; that is, you did it as a personal favor to him or her
O-IM3	Complimented your immediate supervisor on his or her dress or appearance
O-IM4	Praise your immediate supervisor on his or her accomplishments
O-IM5	Take an interest in your supervisor's personal life
Self-Impression Management *In the past 3 months, to what extent did you*	
S-IM1	Try to be polite when interacting with your supervisor
S-IM2	Try to be a friendly person when interacting with your supervisor
S-IM3	Try to act as a "model" employee by, for example, never taking longer than the established time for lunch
S-IM4	Work hard when you know the results will be seen by your supervisor
S-IM5	Let your supervisor know that you try and do a good job in your work

Link back to manuscript

Table 6

The Spot-The-Word Test (Baddeley et al., 1993)

Items	
slank – chariot	coracle – prestasis
lentil – glotex	paramour – imbulasm
stamen - dombus	dallow – ocatroon
loba – comet	fleggary – carnation
pylon – strion	liminoid – agnostic
scrapten – flannel	naquescent – plinth
fender – ullus	thole – leptine
ragsupr – joust	crattish – reform
milliary – mantis	wraith – stribble
sterile – palth	metulate – pristine
proctive – monotheism	pauper – progotic
gilivular – stallion	aurant – baleen
intervantation – rictus	palindrome – lentathic
byzantine – chloriant	hedgehog – mordler
monologue – rufine	prassy – ferret
elegy – festant	torbate – drumlin
malign – vago	texture – disenrupted
exonize – gelding	isomorphic – thassiary
bulliner – trireme	fremoid – vitriol
visage – hyperlistic	farrago – gesticity
frion – oratory	minidyne – hermeneutic
meridian – phillidism	pusality – chaos
grottle – strumpet	devastate – prallage
equine – psynomy	peremptory – paralepsy
baggalette – riposte	chalper – camera
valance – plesmiod	roster – falluate
introvert – vinadism	scaline – accolade
penumbra – rubiant	methagenate – pleonasm
breen – maligner	drobble – infiltrate
gammon - unterried	mystical – harreen

Link back to manuscript

Table 7

The Individual Work Performance Questionnaire (Koopmans et al., 2013)

Dimensions	Item Text
Task Performance (TP)	
In the past 3 months	
TP1	I managed to plan my work so that it was done on time.
TP2	I managed my time well.
TP3	I kept in mind the results that I had to achieve in my work.
TP4	I was able to set priorities.
TP5	I was able to carry out my work efficiently.
Contextual Performance (CP)	
In the past 3 months	
CP1	I took on extra responsibilities.
CP2	I started new tasks myself when my old ones were finished.
CP3	I took on challenging work tasks, when available.
CP4	I worked at keeping my job knowledge up-to-date.
CP5	I worked at keeping my job skills up-to-date.
CP6	I came up with creative solutions to new problems.
CP7	I kept looking for new challenges in my job.
CP8	I actively participated in work meetings.
Counterproductive Work Behavior (CWB)	
In the past 3 months	
CWB1	I complained about minor work-related issues at work.
CWB2	I made problems greater than they were at work.
CWB3	I focused on the negative aspects of a work situation, instead of on the positive aspects.
CWB4	I spoke with colleagues about the negative aspects of my work.
CWB5	I spoke with people from outside the organization about the negative aspects of my work.

Link back to manuscript

Table 8

Overview of Evidence for the Validity and Reliability of the Individual Work Performance Questionnaire (Koopmans et al., 2013).

Year	Author	Article Title	Sample Size	Demographics	Reliability	Validity	Dimensions	Items
2013	Koopmans et al.	Development of an individual work performance questionnaire	1,181	Dutch workers, jobs spanned blue to white collar	0.78-0.85[1] across all dimensions	N/A	TP CP AP CWB	14 total 4 (TP) 2 (CP) 3 (AP) 5 (CWB)
2014	Koopmans et al.	Improving the individual work performance questionnaire using Rasch analysis.	1,424	Dutch workers, jobs spanned blue to white collar	0.81 (TP)[1] 0.85 (CP)[1] 0.74 (CWB)[1]	N/A	TP CP CWB	18 Total 5 (TP) 8 (CP) 5 (CWB)
2014	Koopmans et al.	Responsiveness of the individual work performance questionnaire.	412	Financial workers in the Netherlands	0.78 (TP)[2] 0.85 (CP)[2] 0.79 (CWB)[2]	**Convergent Validity** Presenteeism: 0.18 (TP), 0.22 (CP), -0.11 (CWB) Job Sat: 0.12 (TP), 0.17 (CP), -0.24 (CWB) Work Engagement: 0.19 (TP), 0.29 (CP), -0.23 (CWB) Work Ability: 0.16 (TP), 0.26 (CP), -0.23 (CWB) Manager Rating: 0.16 (TP), 0.26 (CP), -0.02 (CWB) Work Quality: 0.20 (TP), 0.18 (CP), -0.06 (CWB) Work Quantity: 0.11 (TP), 0.19 (CP), -0.02 (CWB) **Discriminant Validity** Need for Recovery: -0.15 (TP), -0.11 (CP), 0.16 (CWB) General Health: -0.07 (TP), 0.08 (CP), 0.02 (CWB) Vitality: 0.23 (TP), 0.29 (CP), -0.03 (CWB) Exhaustion: -0.23 (TP), -0.13 (CP), 0.23 (CWB) Sickness absenteeism: -0.14 (TP), -0.08 (CP), -0.09 (CWB)	TP CP CWB	18 Total 5 (TP) 8 (CP) 5 (CWB)
2014	Koopmans et al.	Construct validity of the individual work performance questionnaire.	1,424	Dutch workers, jobs spanned blue to white collar	N/A	**Convergent Validity** HPQ Absolute Presenteeism: 0.39 (TP), 0.33 (CP) -0.16 (CWB) HPQ Relative Presenteeism: 0.09 (TP), 0.11) (CP), 0.07 (CWB) UWES: 0.35 (TP), 0.43 (CP), -0.31 (CWB) **Discriminant Validity** Defined as the extent to which a measure can differentiate known groups. For example, higher job satisfaction would have a higher task and contextual scores and lower scores than individuals with low job satisfaction. (see p. 332 for definition and pp. 334-335 for results and figures)	TP CP CWB	18 Total 5 (TP) 8 (CP) 5 (CWB)
2015	Koopmans et al.	Cross-cultural adaptation of the individual work performance questionnaire	40	American workers, jobs spanned blue to white collar	0.79 (TP)[2] 0.83 (CP)[2] 0.89 (CWB)[2]	N/A	TP CP CWB	18 Total 5 (TP) 8 (CP) 5 (CWB)
2014	Landers et al.	Validation of the beneficial and harmful work-related social media behavioral taxonomies: Development of the work-related social media questionnaire.	100	Mturk sample, mostly White, older (*M* = 31.5)	0.86 (TP)[2] 0.77 (CP)[2] 0.86 (CWB)[2] 0.87 (AP)[2]	Correlated with the Work-related Social Media Questionnaire (WSMQ, + or -). **WSMQ(+) short form** 0.02 (task), 0.10 (contextual), 0.12 (adaptive), -0.01 (CWB) **WSMQ(-) short form** -0.40 (task), -0.45 (contextual), -0.48 (adaptive), 0.32 (CWB)		

TP = Task Performance. CP = Contextual Performance. CWB = counterproductive work behavior. AP = adaptive performance

1: person separation index (PSI) estimates the internal consistency of a scale, it's similar to Cronbach's alpha, only it uses the logit scale estimates as opposed to the raw scores. It is interpreted in a similar manner, a minimum value of 0.70 is required for group use and 0.85 for individual use.

2: Cronbach's Alpha

Link back to manuscript

Table 9

Benchmark Scores for the Individual Work Performance Questionnaire

	Blue Collar			Pink Collar (service industry)			White Collar		
	TP	CP	CWB	TP	CP	CWB	TP	CP	CWB
Very Low (≤ 10th percentile)	≤2.00	≤ 1.25	≤ 0.20	≤ 1.83	≤ 1.25	≤ 0.00	≤ 1.83	≤ 1.37	≤ 0.40
Low (10-25th percentile)	2.01-2.49	1.26-1.74	0.21-0.59	1.84-2.32	1.26-1.74	0.01-0.59	1.84-2.16	1.38-1.87	0.41-0.79
Average (25-75th percentile)	2.50-3.16	1.75-2.99	0.60-1.39	2.33-2.99	1.75-2.87	0.60-1.59	2.17-2.99	1.88-.287	0.80-1.59
High (75-90th percentile)	3.17-3.49	3.00-3.24	1.40-1.79	3.00-3.49	2.88-3.12	1.60-1.99	3.00-3.32	2.88-3.24	1.60-1.99
Very High (≥ 90th percentile)	≥ 3.50	≥ 3.25	≥ 1.80	≥ 3.50	≥ 3.13	≥ 2.00	≥ 3.33	≥ 3.25	≥ 2.00

TP= Task Performance. CP= Contextual Performance. CWB= Counter Productive Work Behaviors

Link back to manuscript

Table 10

Descriptive Statistics: Primary Study Variables by Sex (Full Sample)

	Gender							
	Female				Male			
Primary study variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables								
Impression Management Other	16.22	7.64	0.30	-0.90	16.36	7.60	0.27	-0.74
Impression Management Self	27.84	5.95	-1.39	**2.29**	26.13	6.11	-0.83	0.91
Verbal Intelligence	48.50	9.10	**-2.90**	**10.49**	44.27	12.98	-1.84	**2.99**
Independent Variables								
1st person singular pronouns	1.11	1.77	**2.03**	**3.96**	0.85	1.50	**2.38**	**5.96**
1st person plural pronouns	0.06	0.19	**5.70**	**40.83**	0.05	0.18	**5.51**	**38.56**
2nd person pronouns	0.03	0.14	**6.36**	**45.46**	0.04	0.21	**7.04**	**57.91**
3rd person singular pronouns	0.02	0.07	**5.11**	**28.64**	0.01	0.08	**15.20**	**274.16**
3rd person plural pronouns	0.20	0.34	**2.38**	**6.94**	0.10	0.26	**4.25**	**23.68**
impersonal pronouns	0.74	0.73	1.35	**2.21**	0.64	0.75	1.41	**2.05**
auxiliary verbs	1.34	1.57	**2.26**	**7.42**	1.09	1.45	**2.57**	**11.87**
verbs	4.64	2.65	0.75	0.70	4.04	3.14	1.73	**8.41**
positive emotion words	2.70	1.61	1.02	**3.44**	2.24	1.77	0.95	**2.44**
negative emotion words	0.43	0.50	1.74	**4.83**	0.44	0.68	**3.14**	**14.44**
differentiation words	0.54	0.55	1.69	**4.47**	0.38	0.61	**4.30**	**36.53**
conjunctions	5.81	2.49	-0.47	0.02	4.48	3.02	-0.13	-0.98
words longer than 6 characters	41.13	7.78	-0.91	**3.47**	36.81	11.85	-1.05	1.25
prepositions	11.25	3.97	-0.93	1.09	9.30	5.31	-0.52	-0.59
cognitive process words	5.30	2.44	0.29	0.84	4.43	3.04	0.36	0.59
causal words	1.69	1.10	1.12	**4.31**	1.50	1.34	0.78	0.39
insight words	1.82	1.19	1.21	**3.93**	1.68	1.46	1.27	**3.11**
Dependent Variables								
Task Performance	3.11	0.69	-0.84	0.63	2.85	0.79	-0.62	0.06

Note. Bolded values indicate skewness and kurtosis exceeds ±2. Female (*n* = 280 / 35%), Male (*n* = 530 / 65%)

Link back to manuscript

Table 11

Descriptive Statistics: Primary Study Variables by Race: White, Asian, Hispanic/Latino (Full Sample)

	White				Asain				Hispanic/Latino			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables												
Impression Management Other	15.73	7.65	0.36	-0.80	18.05	7.27	-0.04	-0.74	13.79	5.19	0.92	1.56
Impression Management Self	27.05	6.15	-1.17	1.76	25.95	5.93	-0.64	0.12	24.14	7.03	-0.88	0.76
Verbal Intelligence	47.90	8.86	**-2.77**	**9.92**	40.56	16.86	-1.12	0.05	43.39	12.31	-1.80	**4.02**
Independent Variables												
1st person singular pronouns	1.11	1.72	1.97	**3.71**	0.70	1.45	**2.91**	**9.41**	0.31	0.51	**1.78**	**2.36**
1st person plural pronouns	0.06	0.20	**5.52**	**38.28**	0.04	0.16	**5.85**	**38.72**	0.04	0.11	**2.84**	**6.89**
2nd person pronouns	0.03	0.15	**8.78**	**97.58**	0.06	0.27	**5.52**	**34.49**	0.00	0.00	0.00	0.00
3rd person singular pronouns	0.01	0.07	**5.79**	**37.40**	0.01	0.11	**13.95**	**198.78**	0.00	0.00	0.00	0.00
3rd person plural pronouns	0.16	0.32	**3.13**	**12.86**	0.06	0.20	**3.82**	**14.37**	0.13	0.33	**3.30**	**11.98**
impersonal pronouns	0.77	0.80	1.31	1.70	0.48	0.62	1.18	0.39	0.40	0.45	0.76	-0.68
auxiliary verbs	1.34	1.52	**1.87**	**5.02**	0.92	1.56	**3.86**	**22.54**	0.67	0.75	1.12	0.70
verbs	4.59	2.99	**1.51**	**7.92**	3.61	3.09	1.51	**4.94**	2.71	1.92	0.22	-0.80
positive emotion words	2.64	1.64	0.83	**2.41**	1.87	1.91	1.46	**4.31**	2.12	1.58	0.16	-0.90
negative emotion words	0.45	0.58	**2.56**	**11.17**	0.38	0.76	**3.59**	**16.28**	0.39	0.47	**2.17**	**7.24**
differentiation words	0.50	0.63	**3.75**	**30.21**	0.32	0.53	**2.48**	**7.88**	0.37	0.54	**2.25**	**6.84**
conjunctions	5.57	2.70	-0.49	-0.20	3.35	2.98	0.30	-1.11	4.38	2.57	-0.50	-0.76
words longer than 6 characters	40.61	7.98	-0.66	**3.91**	31.96	13.91	-0.59	-0.77	39.39	11.88	**-2.10**	**4.43**
prepositions	10.79	4.31	-0.86	0.61	8.08	6.12	-0.15	-1.23	8.13	4.21	-0.68	-0.73
cognitive process words	5.18	2.61	0.28	0.89	3.65	3.31	0.69	0.92	4.53	3.02	0.43	-0.07
causal words	1.76	1.24	0.89	1.95	1.06	1.22	1.04	0.58	1.40	1.50	1.12	0.85
insight words	1.80	1.30	1.48	**4.71**	1.53	1.55	1.06	1.79	2.18	1.65	0.99	1.97
Dependent Variables												
Task Performance	3.01	0.72	-0.79	0.73	2.76	0.81	-0.37	-0.60	2.93	0.91	-1.11	1.14

Note: Bolded values indicates skewness and kurtosis exceeds ±2. White (*n* = 530 / 63%). Asian (*n* = 222 / 26%). Hispanic/Latino (*n* = 28 / 3%).

Link back to manuscript

Table 11

Descriptive Statistics: Primary Study Variables by Race: Other, Black, Hawaiian/Pacific Islander, American Indian/Alaskan Indian (Full Sample) Cont'd

	Other				African American				Hawaiin/Pacific Islander				American Indian/Alaskan Indian			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables																
Impression Management Other	16.81	9.07	0.33	-0.93	15.80	8.08	0.69	-0.14	16.00	-	-	-	13.00	-	-	-
Impression Management Self	27.10	6.07	-0.62	-0.01	28.64	4.61	-0.09	-1.20	34.00	-	-	-	28.00	-	-	-
Verbal Intelligence	45.58	8.35	-1.12	0.84	47.56	5.68	-0.38	0.79	55.00	-	-	-	50.00	-	-	-
Independent Variables																
1st person singular pronouns	0.88	1.31	1.57	1.20	0.43	0.91	**3.24**	**12.02**	-	-	-	-	-	-	-	-
1st person plural pronouns	0.08	0.18	**2.08**	**3.00**	0.01	0.05	**5.00**	**25.00**	-	-	-	-	-	-	-	-
2nd person pronouns	0.07	0.24	**4.06**	**17.96**	0.04	0.17	**4.38**	**19.87**	-	-	-	-	-	-	-	-
3rd person singular pronouns	0.00	0.00	0.00	0.00	0.01	0.05	**5.00**	**25.00**	-	-	-	-	-	-	-	-
3rd person plural pronouns	0.13	0.27	**2.90**	**9.16**	0.17	0.30	**2.76**	**8.89**	-	-	-	-	-	-	-	-
impersonal pronouns	0.62	0.48	0.12	-1.22	0.62	0.58	0.73	-0.66	-	-	-	-	0.53	-	-	-
auxiliary verbs	1.05	1.27	1.68	**3.45**	0.93	1.00	1.80	**3.92**	-	-	-	-	0.53	-	-	-
verbs	4.48	2.62	0.82	1.12	4.16	2.33	**2.16**	**7.68**	0.85	-	-	-	3.74	-	-	-
positive emotion words	2.25	1.59	1.09	1.10	2.46	1.29	0.46	0.04	1.71	-	-	-	2.67	-	-	-
negative emotion words	0.48	0.52	0.69	-0.91	0.53	0.45	0.54	-0.05	-	-	-	-	1.60	-	-	-
differentiation words	0.35	0.42	1.23	0.94	0.33	0.32	0.98	1.16	-	-	-	-	0.53	-	-	-
conjunctions	4.88	2.67	-0.13	-0.47	6.00	2.26	-0.22	1.36	4.27	-	-	-	8.56	-	-	-
words longer than 6 characters	37.15	11.38	-1.49	**4.16**	44.25	6.58	-0.06	-0.26	52.14	-	-	-	48.66	-	-	-
prepositions	10.25	4.54	-0.30	1.12	10.88	3.64	-1.21	**2.34**	11.11	-	-	-	11.23	-	-	-
cognitive process words	4.35	2.38	0.12	-0.36	5.60	2.15	-0.05	0.18	1.71	-	-	-	3.21	-	-	-
causal words	1.43	0.92	-0.13	-0.87	2.12	1.22	0.39	-0.18	0.85	-	-	-	1.60	-	-	-
insight words	1.43	1.00	0.48	-0.15	1.99	1.09	0.98	0.98	0.85	-	-	-	1.07	-	-	-
Dependent Variables																
Task Performance	2.77	0.99	-0.55	-0.68	3.21	0.62	-0.56	-0.28	3.00	-	-	-	2.80	-	-	-

Note: bolded values indicates skewness and kurtosis exceeds ±2. Other (n = 31 / 4%). African American (n = 25 / 3%). Native Hawaiian or Other Pacific Islander (n = 1 / 0.001%). American Indian or Alaska Native (n = 1 / 0.001%).

Link back to manuscript

Table 12

Descriptive Statistics: Primary Study Variables by Education: Bachelor's, Master's, Some College, Doctorate (Full Sample)

	Bachelors				Masters				Some College				Doctorate			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables																
Impression Management Other	15.92	7.34	0.23	-0.86	16.00	7.34	0.40	-0.69	16.69	8.39	0.33	-0.77	18.67	7.27	-0.13	-0.75
Impression Management Self	27.20	5.76	-0.94	1.01	26.62	5.35	-0.63	0.26	28.37	5.85	-1.17	1.86	26.12	6.54	-1.14	1.97
Verbal Intelligence	46.63	10.38	**-2.37**	**6.19**	46.85	11.13	**-2.07**	**5.36**	45.85	11.53	**-2.12**	**4.44**	39.17	20.04	-0.94	-0.71
Independent Variables																
1st person singular pronouns	0.89	1.46	**2.10**	**4.08**	0.67	1.11	**2.22**	**5.20**	1.29	2.03	1.69	**2.06**	0.88	1.63	1.96	**2.94**
1st person plural pronouns	0.05	0.17	**4.37**	**23.47**	0.04	0.20	**7.26**	**59.41**	0.06	0.18	**3.81**	**16.19**	0.02	0.05	**3.83**	**14.61**
2nd person pronouns	0.04	0.20	**7.59**	**66.98**	0.05	0.19	**4.92**	**27.12**	0.03	0.22	**9.19**	**88.74**	0.05	0.22	**4.40**	**18.88**
3rd person singular pronouns	0.01	0.10	**11.05**	**147.90**	0.01	0.04	**5.32**	**27.55**	0.01	0.07	**5.47**	**32.22**	0.00	0.03	**7.62**	**58.00**
3rd person plural pronouns	0.14	0.29	**3.00**	**11.22**	0.11	0.27	**3.51**	**15.34**	0.17	0.35	**3.18**	**13.75**	0.04	0.10	**3.38**	**12.84**
impersonal pronouns	0.74	0.74	1.15	1.15	0.64	0.68	1.63	**4.32**	0.79	0.87	1.11	0.60	0.30	0.62	**3.27**	**13.10**
auxiliary verbs	1.16	1.25	1.67	**3.76**	1.03	1.43	**3.33**	**17.33**	1.52	1.77	1.38	1.51	1.32	2.42	**3.08**	**11.47**
verbs	4.35	2.56	0.60	0.65	3.68	2.53	1.03	**2.39**	4.77	3.00	0.44	-0.11	4.31	4.17	1.57	**3.37**
positive emotion words	2.55	1.45	0.28	-0.25	2.12	1.49	1.33	**5.30**	2.78	2.13	0.90	**2.23**	1.55	2.28	**2.71**	**9.85**
negative emotion words	0.44	0.53	**2.67**	**14.21**	0.45	0.71	**2.80**	**9.29**	0.43	0.48	0.87	-0.21	0.30	0.81	**4.67**	**25.93**
differentiation words	0.46	0.50	1.56	**3.20**	0.38	0.50	**2.50**	**10.22**	0.59	0.92	**4.41**	**29.17**	0.22	0.51	**3.99**	**19.75**
conjunctions	5.46	2.60	-0.40	-0.07	4.54	2.82	-0.05	-0.52	5.35	3.00	-0.66	-0.67	3.08	3.08	0.39	-1.35
words longer than 6 characters	39.93	7.82	-1.05	**3.65**	40.61	11.04	-1.33	**4.19**	36.58	10.63	-0.90	1.41	28.65	15.17	-0.05	-1.38
prepositions	10.91	4.09	-0.87	1.00	9.92	5.11	-0.62	-0.21	9.83	4.95	-0.82	-0.18	7.56	6.58	0.15	-1.17
cognitive process words	5.18	2.51	0.04	0.48	4.66	2.70	0.14	0.24	4.82	3.06	-0.01	-0.58	2.61	3.65	**2.26**	**7.05**
causal words	1.75	1.19	0.53	0.57	1.56	1.28	0.76	0.41	1.47	1.28	1.05	1.29	0.80	1.26	**2.28**	**6.05**
insight words	1.86	1.23	1.14	**3.31**	1.88	1.52	1.20	**2.39**	1.54	1.12	0.31	-0.41	1.14	1.78	**2.52**	**7.74**
Dependent Variables				0.00												
Task Performance	3.01		-0.77	0.70	2.97	0.69	-0.94	1.01	2.85	0.88	-0.43	-0.73	2.82	0.84	-0.77	0.16

Note. Bolded values indicates skewness and kurtosis exceeds ±2. Bachelors (*n* = 356 / 44%). Masters (*n* = 149 / 18%). Some College (*n* = 104 / 13%). Doctorate (*n* = 58 / 7%).

Link back to manuscript

Table 12

Descriptive Statistics: Primary Study Variables by Education: Professional, Associates, High School, Trade/Vocational/Technical (Full Sample)

	Professional				Associates				High School				Trade, Vocational, or Technical			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables																
Impression Management Other	16.53	7.32	0.07	-0.89	16.18	8.70	0.43	-0.98	15.43	7.12	0.20	-0.96	17.71	9.10	0.44	-0.91
Impression Management Self	23.75	6.89	-0.41	-0.84	24.61	7.45	-1.35	1.58	23.73	6.99	-0.88	1.01	27.39	6.87	-1.52	3.00
Verbal Intelligence	39.83	16.67	-1.30	0.59	47.74	7.90	**-2.44**	**8.46**	45.73	8.27	-1.99	**5.86**	47.32	8.94	**-2.93**	**11.24**
Independent Variables																
1st person singular pronouns	1.17	2.18	**2.63**	**6.84**	0.69	1.08	1.68	**2.14**	1.03	1.85	**2.48**	**6.71**	1.78	2.42	1.45	1.06
1st person plural pronouns	0.04	0.15	**4.38**	**19.14**	0.12	0.38	**3.79**	**14.72**	0.02	0.08	**3.63**	**12.36**	0.05	0.15	**3.10**	**9.37**
2nd person pronouns	0.01	0.05	**4.88**	**24.40**	0.02	0.11	**4.62**	**21.57**	0.05	0.19	**3.75**	**13.31**	0.01	0.04	**4.26**	**18.76**
3rd person singular pronouns	0.01	0.03	**4.38**	**18.41**	0.01	0.04	**6.16**	**38.00**	0.01	0.04	**6.08**	**37.00**	0.02	0.06	**3.11**	**8.76**
3rd person plural pronouns	0.10	0.26	**2.80**	**7.61**	0.11	0.26	**2.38**	**4.60**	0.19	0.46	**3.00**	**9.19**	0.15	0.20	1.30	1.02
impersonal pronouns	0.47	0.55	1.04	0.09	0.61	0.70	1.39	1.81	0.53	0.68	0.88	-0.70	0.82	0.95	1.85	4.15
auxiliary verbs	0.76	1.12	**2.03**	**4.94**	1.04	1.34	1.80	**2.96**	1.12	1.59	1.80	**3.11**	1.55	1.68	1.05	0.33
verbs	3.80	4.81	**3.65**	**18.05**	3.71	2.44	0.59	0.08	4.56	3.81	1.15	1.93	4.74	3.35	0.08	-0.90
positive emotion words	1.95	1.85	0.78	0.11	2.26	1.76	0.65	0.79	2.18	1.85	0.47	-0.59	3.28	1.94	-0.07	-0.35
negative emotion words	0.31	0.50	**2.36**	**6.81**	0.61	1.04	**2.58**	**7.32**	0.46	0.65	1.55	1.91	0.51	0.52	0.61	-0.75
differentiation words	0.24	0.30	1.09	0.13	0.59	0.71	1.54	**2.26**	0.36	0.54	**2.21**	**5.38**	0.55	0.68	1.95	3.81
conjunctions	3.46	3.14	0.27	-1.38	5.13	3.20	-0.23	-0.89	3.94	3.20	0.21	-1.13	5.99	2.92	-0.88	-0.15
words longer than 6 characters	32.03	13.69	-0.67	-0.98	39.36	12.19	-1.72	**3.07**	37.92	13.29	-1.23	1.97	39.75	8.10	-0.72	1.35
prepositions	8.17	6.34	-0.15	-1.26	9.15	5.11	-0.64	-0.36	8.05	5.66	-0.26	-1.48	10.06	4.72	-0.65	-0.59
cognitive process words	3.14	2.60	0.11	-1.42	5.16	3.01	-0.01	-0.10	4.59	3.37	0.69	1.46	5.31	2.70	0.71	1.51
causal words	1.11	1.02	0.37	-1.00	1.83	1.28	0.17	-0.71	1.60	1.73	1.80	**5.12**	1.47	0.98	-0.24	-1.25
insight words	1.31	1.24	0.49	-1.03	1.59	1.20	0.62	-0.12	1.66	1.71	1.76	**5.08**	2.05	1.67	1.11	2.23
Dependent Variables																
Task Performance	2.70	0.76	-0.30	-0.51	2.91	0.79	-1.00	0.99	2.73	0.84	-0.08	-0.94	3.18	0.62	-0.70	0.34

Note: bolded values indicate and kurtosis exceeds ±2. Professional (n = 40 / 5%). Associates (n = 39 / 5%). High School (n = 37 / 5%). Trade, Vocational, or Technical (n = 28 / 3%).

Link back to manuscript

Table 13a

Descriptive Statistics: Tenure (Full Sample)

	M	*SD*	Skew	Kurtosis
Tenure	3.45	3.52	**2.56**	**9.66**

Note. Bolded values indicate skewness and kurtosis exceeds ±2. *N* = 809

Table 13b

Descriptive Statistics: Tenure Correlated with Hypothesis Variables (Full Sample)

Primary Study Variables	Tenure
Corroboration Variables	
Impression Management Other	0.03
Impression Management Self	**-0.14**
Verbal Intelligence	-0.02
Independent Variables	
1st person singular pronouns	0.01
1st person plural pronouns	0.03
2nd person pronouns	-0.01
3rd person singular pronouns	0.05
3rd person plural pronouns	-0.05
impersonal pronouns	*-0.08*
auxiliary verbs	0.06
verbs	0.01
positive emotion words	-0.06
negative emotion words	-0.05
differentiation words	-0.05
conjunctions	*-0.10*
words longer than 6 characters	-0.04
prepositions	-0.06
cognitive process words	**-0.14**
causal words	*-0.08*
insight words	**-0.13**
Dependent Variables	
Task Performance	**-0.09**

Italics values indicate *p* < .05, bolded values indicate *p* < .001, *N* = 809

Link back to manuscript

Table 14

Descriptive Statistics: Hypothesis Variables by Sex (Sub-Sample)

	Gender							
	Female				Male			
Primary Study variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables								
Impression Management Other	16.36	7.42	0.24	-1.00	15.59	7.24	0.53	-0.32
Impression Management Self	28.60	5.25	-1.37	2.67	26.65	5.82	-0.83	1.17
Verbal Intelligence	49.38	7.90	**-3.12**	**13.34**	47.17	9.22	**-2.40**	**7.66**
Independent Variables								
1st person singular pronouns	1.39	1.89	1.66	**2.25**	1.10	1.47	1.84	**3.13**
1st person plural pronouns	0.08	0.21	**5.88**	**44.03**	0.08	0.19	**3.10**	**10.40**
2nd person pronouns	0.03	0.12	**6.51**	**55.08**	0.05	0.15	**4.37**	**21.96**
3rd person singular pronouns	0.03	0.09	**3.92**	**16.55**	0.02	0.12	**9.67**	**110.94**
3rd person plural pronouns	0.25	0.33	1.94	**4.42**	0.16	0.30	**3.30**	**14.68**
impersonal pronouns	0.89	0.69	1.45	**3.04**	0.94	0.74	1.11	1.58
auxiliary verbs	1.51	1.45	1.76	**3.39**	1.36	1.23	1.25	1.35
verbs	5.15	2.38	1.02	1.31	4.53	2.24	0.66	0.46
positive emotion words	2.88	1.24	0.53	0.19	2.80	1.21	0.32	-0.16
negative emotion words	0.50	0.50	1.92	**6.56**	0.55	0.54	**2.13**	6.48
differentiation words	0.60	0.48	1.94	**8.25**	0.51	0.51	1.96	**4.85**
conjunctions	6.71	1.89	-0.69	1.06	5.91	2.08	-0.21	0.38
words longer than 6 characters	40.80	6.06	-0.35	0.16	39.73	6.43	-1.03	**4.64**
prepositions	12.50	2.99	-0.82	**2.99**	11.72	3.11	-1.14	**3.17**
cognitive process words	5.70	2.14	0.83	**2.22**	5.76	1.96	0.12	0.93
causal words	1.80	0.90	0.51	0.29	2.07	1.08	0.90	1.98
insight words	1.95	1.06	1.61	**7.00**	2.00	0.95	0.68	0.32
Dependent Variables								
Task Performance	3.19	0.67	-0.90	0.72	2.96	0.74	-0.81	1.21

Note. Female (*n* = 260 / 39%), Male (*n* = 407 / 61%) bolded values indicate skewness and kurtosis exceed ±2

Link back to manuscript

Table 15

Descriptive Statistics: Hypothesis Variables by Race: White, Asian, Hispanic/Latino, Other (Sub-Sample)

	White				Asain				Hispanic/Latino			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables												
Impression Management Other	15.80	7.46	0.44	-0.61	16.11	6.77	0.08	-1.12	14.73	5.12	1.49	**2.56**
Impression Management Self	27.88	5.63	-1.32	**2.67**	26.03	5.21	-0.17	-0.82	22.18	7.03	-0.12	-1.03
Verbal Intelligence	49.09	8.18	**-3.24**	**13.73**	45.94	8.70	-1.22	**2.29**	39.82	16.88	-1.38	1.46
Independent Variables												
1st person singular pronouns	1.43	1.80	1.57	1.98	0.76	1.14	**2.38**	**6.27**	0.35	0.43	1.91	**4.39**
1st person plural pronouns	0.08	0.20	**4.86**	**31.98**	0.07	0.19	**3.41**	**11.49**	0.09	0.16	1.34	-0.04
2nd person pronouns	0.03	0.09	**4.09**	**18.81**	0.10	0.26	**3.03**	**8.84**	0.00	0.00	0.00	0.00
3rd person singular pronouns	0.02	0.09	**4.20**	**19.23**	0.03	0.19	**7.77**	**61.74**	0.00	0.00	0.00	0.00
3rd person plural pronouns	0.22	0.33	2.50	**8.63**	0.11	0.24	**2.84**	**8.23**	0.22	0.45	**2.93**	**9.05**
impersonal pronouns	0.97	0.77	1.21	1.77	0.89	0.59	0.47	-0.47	0.57	0.43	0.60	-0.89
auxiliary verbs	1.56	1.43	1.40	**2.02**	1.12	0.91	1.13	1.34	0.65	0.50	0.33	-1.11
verbs	5.05	2.42	0.65	0.45	4.14	1.87	1.10	3.04	3.41	1.54	-0.63	1.87
positive emotion words	2.93	1.23	0.31	-0.15	2.53	1.07	0.63	0.23	2.66	1.39	0.14	0.71
negative emotion words	0.52	0.50	1.87	**5.61**	0.57	0.68	**2.25**	**5.89**	0.46	0.28	-0.11	-1.07
differentiation words	0.57	0.52	1.95	**5.81**	0.53	0.48	1.86	**6.56**	0.38	0.40	0.65	-1.18
conjunctions	6.55	1.93	-0.56	1.16	5.36	2.00	-0.10	-0.28	5.25	2.09	-1.44	2.78
words longer than 6 characters	39.99	6.12	-0.27	-0.26	39.68	6.59	**-3.06**	**15.84**	44.55	4.35	0.13	-1.06
prepositions	12.23	3.04	-1.15	**3.28**	11.90	3.02	-0.85	**2.70**	9.64	3.76	-1.88	**4.20**
cognitive process words	5.66	2.03	0.59	1.94	6.25	2.07	0.28	1.43	5.78	2.14	-0.92	1.44
causal words	1.92	1.00	0.93	**2.27**	2.14	1.05	0.57	0.74	2.19	1.28	1.08	0.82
insight words	1.89	0.97	1.59	**6.55**	2.34	0.99	0.10	-0.04	2.68	1.22	-0.60	0.19
Dependent Variables												
Task Performance	3.08	0.70	-0.89	1.36	2.95	0.74	-0.56	-0.05	2.87	1.10	-1.33	1.35

Note: Bolded values indicates skewness and kurtosis exceeds ±2. White (*n* = 462 / 69%). Asain (*n* = 129 / 19%). Hispanic/Latino (*n* = 22 / 4%). Other (*n* = 27 / 4%). American Indian/Alaskan Indian ethnicities not represented in the sub-sample

Link back to manuscript

Table 15

Descriptive Statistics: Hypothesis Variables by Race: Black, Hawaiian/Pacific Islander (Sub-Sample) cont'd

	Other				Black				Hawaiin/Pacific Islander			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables												
Impression Management Other	17.07	7.82	-0.04	-1.33	17.07	8.60	0.70	-0.10	16.00	-	-	-
Impression Management Self	29.07	4.43	-0.03	-1.32	29.14	5.53	-0.47	-1.56	34.00	-	-	-
Verbal Intelligence	45.36	9.25	-1.06	0.17	48.71	4.34	0.94	0.93	55.00	-	-	-
Independent Variables												
1st person singular pronouns	0.93	1.48	1.64	1.21	0.43	0.58	1.22	0.31	0.00	-	-	-
1st person plural pronouns	0.12	0.21	1.59	1.13	0.02	0.07	**3.74**	**14.00**	0.00	-	-	-
2nd person pronouns	0.06	0.15	**2.68**	**6.76**	0.02	0.07	**3.74**	**14.00**	0.00	-	-	-
3rd person singular pronouns	0.00	0.00	0.00	0.00	0.02	0.07	**3.74**	**14.00**	0.00	-	-	-
3rd person plural pronouns	0.14	0.15	0.60	-0.73	0.26	0.37	**2.22**	**5.29**	0.00	-	-	-
impersonal pronouns	0.66	0.43	0.21	-0.90	0.68	0.44	1.16	0.85	0.00	-	-	-
auxiliary verbs	1.33	1.38	**2.17**	**5.98**	0.88	0.79	1.57	**3.06**	0.00	-	-	-
verbs	5.12	2.42	1.78	**4.97**	3.65	1.03	0.38	-1.16	0.85	-	-	-
positive emotion words	2.65	1.48	1.67	**3.06**	2.62	1.14	-0.20	-0.09	1.71	-	-	-
negative emotion words	0.51	0.47	0.70	-0.11	0.59	0.38	0.37	0.35	0.00	-	-	-
differentiation words	0.55	0.44	1.03	0.80	0.50	0.30	0.98	1.76	0.00	-	-	-
conjunctions	5.61	2.74	0.33	-1.55	6.14	2.09	0.71	0.87	4.27	-	-	-
words longer than 6 characters	37.17	6.46	0.88	1.26	45.85	5.22	0.40	0.04	52.14	-	-	-
prepositions	12.03	3.11	**2.37**	**6.71**	11.30	3.01	-1.19	1.74	11.11	-	-	-
cognitive process words	5.21	1.96	-0.08	-1.06	5.17	1.74	0.31	-0.70	1.71	-	-	-
causal words	1.73	0.89	-0.35	0.00	1.71	0.82	-0.06	-1.06	0.85	-	-	-
insight words	1.56	0.93	0.74	1.10	1.82	0.75	0.34	-0.50	0.85	-	-	-
Dependent Variables												
Task Performance	3.01	0.80	-0.01	-1.66	3.37	0.51	-0.18	-1.31	3.00	-	-	-

Note: bolded values indicates skewness and kurtosis exceeds ±2. African American (n = 25 / 4%). American Indian/Alaskan Indian ethnicities not represented in the sub-sample.

Link back to manuscript

Table 16

Descriptive Statistics: Hypothesis Variables by Education: Bachelor's, Master's, Some College, Doctorate (Sub-Sample)

	Bachelors				Masters				Some College				Doctorate			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables																
Impression Management Other	16.19	7.20	0.20	-0.95	15.16	6.68	0.51	-0.30	17.53	8.56	0.50	-0.64	15.64	7.84	0.25	-1.02
Impression Management Self	27.98	5.17	-0.88	1.11	27.18	5.24	-0.67	0.24	29.11	5.46	-1.37	**2.33**	27.91	6.93	-1.86	**4.73**
Verbal Intelligence	47.34	9.60	**-2.47**	**7.24**	49.64	6.28	-0.96	0.58	47.56	8.72	**-2.99**	**12.98**	49.32	10.07	**-2.39**	**6.68**
Independent Variables																
1st person singular pronouns	1.17	1.55	1.65	**2.18**	0.90	1.24	1.86	**3.34**	1.81	2.00	1.01	-0.08	0.64	1.17	**2.82**	**8.41**
1st person plural pronouns	0.07	0.16	**3.14**	**10.83**	0.08	0.27	**5.20**	**29.76**	0.11	0.22	**3.36**	**14.29**	0.04	0.08	**2.05**	**3.27**
2nd person pronouns	0.04	0.13	**5.50**	**36.73**	0.06	0.15	**3.59**	**15.90**	0.03	0.10	**4.02**	**16.50**	0.09	0.27	**3.38**	**11.48**
3rd person singular pronouns	0.03	0.14	**7.95**	**76.65**	0.02	0.06	**3.55**	**11.42**	0.03	0.10	**3.64**	**14.01**	0.01	0.04	**4.69**	**22.00**
3rd person plural pronouns	0.20	0.29	**2.17**	**5.26**	0.18	0.33	**2.80**	**9.52**	0.30	0.46	**2.74**	**9.50**	0.10	0.15	1.76	**3.26**
impersonal pronouns	0.95	0.67	1.08	1.46	0.79	0.65	1.79	**6.01**	1.23	0.88	0.67	-0.21	0.50	0.54	1.50	1.88
auxiliary verbs	1.40	1.20	1.36	1.93	1.21	1.07	1.68	**3.59**	2.23	1.90	1.12	1.21	0.79	1.00	**2.60**	**8.65**
verbs	4.91	2.18	0.84	0.77	4.38	2.12	1.45	**3.80**	5.92	2.43	0.90	0.79	3.04	1.97	0.63	0.89
positive emotion words	2.96	1.18	0.46	-0.22	2.40	0.93	0.39	-0.01	3.43	1.08	0.03	-0.40	1.96	1.05	0.18	-1.49
negative emotion words	0.51	0.45	1.48	**2.69**	0.52	0.65	**2.99**	**10.93**	0.62	0.46	0.60	-0.25	0.44	0.59	**2.29**	**6.40**
differentiation words	0.55	0.45	1.66	**5.33**	0.54	0.56	**2.58**	**9.91**	0.74	0.60	0.86	0.86	0.33	0.35	1.69	**2.52**
conjunctions	6.49	1.91	-0.11	0.27	5.80	2.00	-0.14	0.22	6.85	1.61	-0.50	0.87	5.50	2.44	-0.52	-0.39
words longer than 6 characters	39.87	5.83	-0.11	-0.19	41.88	5.30	-0.50	-0.32	38.29	7.18	0.05	0.26	40.24	9.92	**-2.85**	**10.86**
prepositions	12.20	2.75	-0.51	1.80	11.92	3.17	-1.13	**2.85**	12.87	2.60	-0.51	0.79	11.31	3.14	**-2.22**	**7.71**
cognitive process words	5.95	2.05	0.77	2.24	5.71	1.84	-0.26	0.63	6.17	2.10	0.41	-0.38	4.27	2.01	0.07	0.46
causal words	2.08	1.08	0.90	2.04	1.95	0.94	0.58	0.73	1.85	0.84	0.90	0.09	1.40	0.88	0.72	0.73
insight words	2.02	1.03	1.57	**6.24**	2.10	0.91	0.75	0.97	1.92	0.90	0.75	1.74	1.69	1.11	0.68	0.43
Dependent Variables																
Task Performance	3.07	0.74	-0.92	1.47	3.05	0.68	-0.98	0.88	3.13	0.78	-0.83	0.14	2.99	0.75	-1.29	3.74

Note: Bolded values indicate skewness and kurtosis exceeds ±2. Bachelors (*n* = 325 / 49%). Masters (*n* = 122 / 18%). Some College (*n* = 83 / 12%). Doctorate (*n* = 27 / 4%).

Link back to manuscript

Table 16

Descriptive Statistics: Hypothesis Variables by Education Professional, Associates, High School, Trade/Vocational/Technical (Sub-Sample) Cont'd

	Professional				Associates				High School				Trade, Vocational, or Technical			
Primary Study Variables	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis	*M*	*SD*	Skew	Kurtosis
Corroboration Variables																
Impression Management Other	14.22	6.03	-0.09	-1.24	15.73	8.68	0.77	-1.06	15.73	8.68	0.77	-1.06	18.18	8.53	0.56	-0.47
Impression Management Self	22.67	6.56	-0.23	-0.40	25.18	7.04	-1.35	**3.08**	25.18	7.04	-1.35	3.08	28.88	4.86	-1.01	1.79
Verbal Intelligence	44.94	12.82	**-2.37**	**7.29**	50.73	3.20	0.98	0.90	50.73	3.20	0.98	**0.90**	49.59	2.81	-0.13	-0.21
Independent Variables																
1st person singular pronouns	1.51	2.32	**2.24**	**4.84**	0.78	0.90	1.25	0.96	0.78	0.90	1.25	0.96	2.48	2.76	0.97	-0.45
1st person plural pronouns	0.08	0.23	**2.78**	**7.07**	0.13	0.22	**2.17**	**5.10**	0.13	0.22	**2.17**	**5.10**	0.09	0.18	**2.26**	**4.42**
2nd person pronouns	0.02	0.07	**3.16**	**9.84**	0.03	0.10	**3.32**	**11.00**	0.03	0.10	**3.32**	**11.00**	0.02	0.05	**3.26**	**10.74**
3rd person singular pronouns	0.02	0.04	**2.78**	**6.59**	0.02	0.08	**3.32**	**11.00**	0.02	0.08	**3.32**	**11.00**	0.03	0.07	**2.25**	**3.85**
3rd person plural pronouns	0.09	0.19	1.80	**2.03**	0.24	0.38	1.27	-0.07	0.24	0.38	1.27	-0.07	0.18	0.18	0.64	-0.53
impersonal pronouns	0.73	0.61	0.54	-0.96	1.19	0.80	0.68	0.56	1.19	0.80	0.68	0.56	1.15	1.04	1.55	2.63
auxiliary verbs	1.10	1.33	1.93	**4.23**	1.16	1.23	**2.46**	**7.18**	1.16	1.23	**2.46**	**7.18**	2.03	1.56	0.97	0.62
verbs	4.07	2.52	0.61	0.88	3.74	2.40	1.23	1.31	3.74	2.40	1.23	1.31	6.02	2.49	0.06	-0.23
positive emotion words	2.33	1.26	-0.10	-0.73	2.56	1.14	-0.79	0.11	2.56	1.14	-0.79	0.11	3.72	1.57	-0.21	0.25
negative emotion words	0.51	0.60	**2.05**	**5.13**	0.58	0.73	**2.33**	**6.49**	0.58	0.73	**2.33**	**6.49**	0.55	0.52	0.77	-0.13
differentiation words	0.33	0.30	0.97	0.42	0.54	0.41	0.72	-0.72	0.54	0.41	0.72	-0.72	0.64	0.64	**2.16**	**5.42**
conjunctions	4.89	2.74	-0.44	-0.87	5.35	2.52	-0.37	1.77	5.35	2.52	-0.37	1.77	6.94	1.61	-1.21	1.73
words longer than 6 characters	40.13	6.80	-0.61	0.84	43.43	5.56	-0.77	0.01	43.43	5.56	-0.77	0.01	37.78	5.62	-0.66	-0.55
prepositions	11.48	4.99	-1.02	**2.48**	10.44	4.28	-1.31	**3.43**	10.44	4.28	-1.31	**3.43**	11.96	3.29	-0.82	1.05
cognitive process words	4.79	1.89	-0.68	-0.06	5.29	2.42	0.84	0.53	5.29	2.42	0.84	0.53	5.95	1.95	1.56	5.64
causal words	1.65	0.79	-0.27	0.12	2.09	1.35	0.85	0.51	2.09	1.35	0.85	0.51	1.74	0.87	-0.51	-0.66
insight words	2.01	0.93	0.11	-0.33	1.51	1.04	1.74	**4.32**	1.51	1.04	1.74	**4.32**	2.02	1.08	0.38	-0.08
Dependent Variables																
Task Performance	2.78	0.66	-0.18	-0.25	3.04	0.77	-1.28	**2.56**	3.04	0.77	-1.28	**2.56**	3.15	0.61	-0.27	-0.55

Note: Bolded values indicate skewness and kurtosis exceeds ±2. Professional (n = 28 / 4%). Associates (n = 32 / 5%). High School (n = 25 / 4%). Trade, Vocational, or Technical (n = 25 / 4%).

Link back to manuscript

Table 17a

Descriptive Statistics: Tenure (Sub-Sample)

	M	*SD*	Skew	Kurtosis
Tenure	3.38	3.52	**2.37**	**7.69**

Note. Bolded values indicate skewness and kurtosis exceeds ±2. *N* = 667

Table 17b

Descriptive Statistics: Tenure by Hypothesis Variables (Sub-Sample)

Primary Study Variables	Tenure
Corroboration Variables	
Impression Management Other	.03
Impression Management Self	**-.12**
Verbal Intelligence	.00
Independent Variables	
1st person singular pronouns	-.01
1st person plural pronouns	.05
2nd person pronouns	.00
3rd person singular pronouns	.06
3rd person plural pronouns	-.*08*
impersonal pronouns	-.06
auxiliary verbs	-.01
verbs	-.72
positive emotion words	-.05
negative emotion words	-.04
differentiation words	-.03
conjunctions	-.*09*
words longer than 6 characters	.01
prepositions	-.06
cognitive process words	**-.13**
causal words	-.06
insight words	**-.12**
Dependent Variables	
Task Performance	*-0.1*

Italics values indicate $p < .05$, Bolded values indicate $p < .001$, $N = 667$

Link back to manuscript

Table 18

Results of t-Test and Descriptive Statistics for Task Performance by Sex

	Sex						95% CI for Mean Difference		
	Male			Female					
	M	*SD*	n	*M*	*SD*	n		*t*	df
Task Performance	2.91	0.748	407	3.15	0.666	260	-0.347, -0.124	-4.14*	665

* *p* < .001. Males coded as 0 and females as 1

Link back to manuscript

Table 19

Omnibus ANOVA Results for Task Performance by Race

	Sum of Squares	df	Mean Square	F
Between Groups	5.56	6	0.93	1.77
Within Groups	345.30	660	0.52	
Total	350.87	666		

p = .102

Link back to manuscript

Table 20

Omnibus ANOVA Results for Task Performance by Education

	Sum of Squares	df	Mean Square	F
Between Groups	1.85	7	0.26	0.50
Within Groups	349.02	659	0.53	
Total	350.87	666		

p = .836

Link back to manuscript

Table 21

Correlation Matrix of All Study Variables and Control Variables

	Age	Gender	Race	Education	Tenure	Salary	Impression Management - Other	Impression Management - Self	Task Performance	Contextual Performance	Counterproductive Work Behaviors	Cognitive Ability	Words Longer Than 6 Characters	Pronouns	Personal Pronouns	1st Person Pronouns	1st Person Plural Pronouns	2nd Person Pronouns	3rd Person Singular Pronouns	3rd Person Plural Pronouns	Impersonal Pronouns	Prepositions	Conjunctions	Verbs	Positive Emotion Words	Negative Emotion Words	Cognitive Process Words	Insight Words	Causal Words	Auxilary Verbs	Differentiation Words
Age																															
Gender	.061																														
Race	.105**	.243**																													
Education	.107**	-.027	-.150**																												
Tenure	.505**	-.041	.020	.037																											
Salary	.192**	-.034	.005	.188**	.199**																										
Impression Management - Other	-.098**	-.009	-.072*	.030	.034	.039																									
Impression Management - Self	-.147**	.134**	.099**	-.045	-.143**	.066	.279**																								
Task Performance	-.042	.161**	.100**	.012	-.090*	-.015	.090*	.367**																							
Contextual Performance	-.004	.126**	.053	.074*	.005	.072*	.291**	.319**	.557**																						
Counterproductive Work Behaviors	-.125**	-.116**	-.107**	.098**	.026	-.073*	.315**	-.043	-.124**	.039																					
Cognitive Ability	.131**	.167**	.229**	-.094**	-.015	.015	-.160**	.106**	.165**	.034	-.159**																				
Words Longer Than 6 Characters	.047	.189**	.254**	-.085*	-.040	.014	-.172**	.105**	.145**	.056	-.221**	.285**																			
Pronouns	.025	.105**	.176**	-.118**	-.023	-.094**	.038	.037	.048	.012	-.037	.070*	-.142**																		
Personal Pronouns	.045	.106**	.152**	-.105**	.003	-.091**	.052	.020	.037	.008	-.012	.045	-.204**	.957**																	
1st Person Pronouns	.041	.085*	.144**	-.094**	.007	-.088*	.065	.017	.031	.003	.000	.019	-.214**	.923**	.973**																
1st Person Plural Pronouns	.065	.031	.067	-.040	.034	.021	-.014	-.071*	-.034	.016	-.026	.042	-.038	.255**	.250**	.132**															
2nd Person Pronouns	.006	-.028	-.039	.020	-.006	-.075*	-.002	.016	.021	-.015	.017	.026	-.043	.200**	.214**	.117**	-.008														
3rd Person Singular Pronouns	.046	.049	.030	-.024	.053	-.012	-.037	.022	.062	-.019	-.076*	.060	.024	.100**	.092**	.049	-.001	-.003													
3rd Person Plural Pronouns	-.006	.167**	.114**	-.106**	-.053	-.032	-.021	.055	.044	.038	-.042	.108**	-.022	.450**	.432**	.274**	.169**	.006	.035												
Impersonal Pronouns	-.033	.063	.168**	-.102**	-.077*	-.066	-.010	.065	.055	.016	-.083*	.104**	.057	.732**	.504**	.465**	.173**	.092**	.083*	.328**											
Prepositions	.070*	.185**	.223**	-.028	-.062	.027	-.113**	.130**	.162**	.098**	-.160**	.200**	.366**	.334**	.274**	.235**	.146**	.014	.060	.257**	.356**										
Conjunctions	.061	.216**	.275**	-.130**	-.094**	.008	-.081*	.172**	.190**	.098**	-.190**	.278**	.408**	.310**	.251**	.215**	.126**	.000	.116**	.238**	.338**	.652**									
Verbs	.077*	.094**	.166**	-.076*	.007	-.063	.053	.080*	.038	.039	.001	.056	-.098**	.575**	.553**	.535**	.145**	.050	.065	.293**	.418**	.363**	.301**								
Positive Emotion Words	-.053	.126**	.167**	-.144**	-.058	-.042	.002	.097**	.123**	.064	-.088*	.150**	.225**	.335**	.285**	.271**	.040	.048	.030	.182**	.331**	.439**	.453**	.299**							
Negative Emotion Words	-.001	-.003	.045	-.048	-.051	.017	-.081*	.063	.086*	.084*	-.121**	.076*	.235**	.073*	.029	.018	-.042	.046	.024	.063	.152**	.224**	.238**	.074*	.227**						
Cognitive Process Words	-.053	.143**	.182**	-.136**	-.140**	-.023	-.051	.165**	.165**	.092**	-.168**	.190**	.404**	.311**	.209**	.163**	.133**	.092**	.030	.221**	.436**	.542**	.546**	.303**	.464**	.355**					
Insight Words	-.072*	.047	.024	-.028	-.131**	.002	-.044	.100**	.094**	.030	-.077*	.064	.390**	.152**	.075*	.058	.020	.028	.019	.103**	.276**	.383**	.338**	.118**	.357**	.362**	.780**				
Causal Words	.002	.070*	.193**	-.082*	-.078*	.024	-.127**	.119**	.130**	.062	-.184**	.199**	.355**	.114**	.038	.009	.122**	-.008	.019	.105**	.252**	.432**	.454**	.188**	.297**	.218**	.747**	.442**			
Auxilary Verbs	.052	.079*	.129**	-.067	.056	-.095**	.055	.054	.025	.034	-.001	.031	-.190**	.701**	.695**	.689**	.156**	.061	.093**	.293**	.456**	.222**	.205**	.666**	.224**	.011	.193**	.025	.038		
Differentiation Words	-.018	.122**	.113**	-.128**	-.045	-.054	.034	.078*	.076*	.030	-.076*	.094**	.087*	.313**	.233**	.183**	.118**	.228**	.018	.182**	.387**	.231**	.294**	.198**	.220**	.119**	.476**	.230**	.158**	.191**	

* *p* < .05, ***p* < .001, N = 809

bivariates for
manuscript_30Jan17

Link back to manuscript

Table 22

Test for Normality for Predictor Variables

	Kolmogorov-Smirnov Test			Shapiro-Wilk Test		
Primary Study Variables	*D*	*df*	*p*	*D*	*df*	*p*
Independent Variables						
1st person singular pronouns	.337	847	*p* < .001	.426	847	*p* < .001
1st person plural pronouns	.470	847	*p* < .001	.309	847	*p* < .001
2nd person pronouns	.457	847	*p* < .001	.076	847	*p* < .001
3rd person singular pronouns	.506	847	*p* < .001	.091	847	*p* < .001
3rd person plural pronouns	.396	847	*p* < .001	.515	847	*p* < .001
Impersonal pronouns	.207	847	*p* < .001	.787	847	*p* < .001
Auxiliary verbs	.269	847	*p* < .001	.578	847	*p* < .001
Verbs	.118	847	*p* < .001	.799	847	*p* < .001
Positive emotion words	.090	847	*p* < .001	.937	847	*p* < .001
Negative emotion words	.310	847	*p* < .001	.413	847	*p* < .001
Differentiation words	.325	847	*p* < .001	.359	847	*p* < .001
Conjunctions	.111	847	*p* < .001	.943	847	*p* < .001
Words longer than 6 characters	.137	847	*p* < .001	.904	847	*p* < .001
Prepositions	.119	847	*p* < .001	.912	847	*p* < .001
Cognitive process words	.076	847	*p* < .001	.882	847	*p* < .001
Causal words	.117	847	*p* < .001	.924	847	*p* < .001
Insight words	.130	847	*p* < .001	.825	847	*p* < .001

Link back to manuscript

Table 23

Descriptive Statistics: LIWC Categories for Hypothesis 2-5 with Base Rate Comparisons (Full Sample)

LIWC categories for hypothesis 2-5	M	SD	Skew	Kurtosis
1st person singular pronouns	0.94 (4.99)	1.60 (2.46)	**2.25**	**5.18**
1st person plural pronouns	0.05 (0.72)	0.18 (0.83)	**5.59**	**39.55**
2nd person pronouns	0.04 (1.70)	0.19 (1.35)	**7.23**	**62.76**
3rd person singular pronouns	0.01 (1.88)	0.08 (1.53)	**12.32**	**208.80**
3rd person plural pronouns	0.13 (0.66)	0.29 (0.60)	**3.31**	**14.02**
Impersonal pronouns	0.67 (5.26)	0.74 (1.62)	1.37	**2.05**
Auxiliary verbs	1.18 (8.53)	1.50 (2.04)	**2.44**	**9.93**
Verbs	4.24 (16.44)	2.99 (2.93)	1.45	**6.58**
Positive emotion words	2.39 (3.67)	1.73 (1.63)	0.91	**2.58**
Negative emotion words	0.43 (1.84)	0.62 (1.09)	**2.97**	**14.13**
Differentiation words	0.44 (2.99)	0.59 (1.18)	**3.47**	**26.80**
Conjunctions	4.94 (5.90)	2.91 (1.57)	-0.30	-0.75
Words longer than 6 characters	38.30 (15.60)	10.81 (3.76)	-1.20	2.14
Prepositions	9.97 (12.93)	4.98 (2.11)	-0.70	-0.16
Cognitive process words	4.73 (10.61)	2.88 (3.02)	0.26	0.65
Causal words	1.57 (1.40)	1.27 (0.73)	0.82	1.21
Insight words	1.73 (2.16)	1.37 (1.08)	1.24	**3.37**

Note. Bolded values indicate skewness and kurtosis exceeds ±2. *N* = 809 Values in parentheses are LIWC reported average base rates and standard deviations

Link back to manuscript

Table 24

Logistic Regression Model for Training Data (n = 462)

			95% CI for Odds Ratio		
	B	*SE*	*Lower*	*Odds Ratio*	*Upper*
Included in final training model					
Constant	-0.02	0.24			
Sex	0.67	0.22	1.27	**1.95**	3.01
Third-person plural pronouns	5.45	3.12	0.51	**232.545**	105267.46
Impersonal pronouns	-0.34	0.19	0.49	0.72	1.04
Auxiliary verbs	0.33	0.12	1.10	**1.40**	1.77
Adverbs	-0.43	0.21	0.44	**0.65**	0.98
Sadness words	1.69	0.84	1.05	**5.43**	28.15
Certainty Words	0.30	0.17	0.96	**1.35**	1.90
Nonfluencies	0.79	0.46	0.90	2.21	5.43
Colon	-0.10	0.04	0.83	**0.91**	0.99
Dash	-0.04	0.02	0.93	0.97	1.00
Parentheses	0.13	0.04	1.05	**1.14**	1.24

Note. R^2 = .09 (Hosmer & Lemeshow), .12 (Cox & Snell), .16 (Nagelkerke). Model $\chi^{2\,=}$ 57.48, p < .001. Bolded odds ratios numbers indicate that coefficient doesn't cross 1, suggesting a significant predictor in logistics regression equation. Training model sample size n = 462

Link back to manuscript

Table 25

Logistic Regression Model for Testing Data (n = 205)

			95% CI for Odds Ratio		
	B	*SE*	*Lower*	*Odds Ratio*	*Upper*
Included in final testing model					
Constant	0.67	0.41			
Sex	0.45	0.33	0.82	**1.57**	3.00
3rd person plural pronouns	-1.08	3.55	0.00	0.34	356.20
Impersonal pronouns	-0.22	0.26	0.48	0.80	1.33
Auxiliary verbs	-0.40	0.16	0.49	0.67	0.91
Adverbs	0.61	0.29	1.05	**1.84**	3.24
Sadness words	2.41	1.25	0.96	**11.14**	128.83
Certainty Words	-0.03	0.27	0.57	0.97	1.64
Nonfluencies	0.22	0.70	0.31	1.25	4.94
Colon	-0.12	0.07	0.78	0.89	1.02
Dash	0.10	0.06	0.97	**1.10**	1.25
Parentheses	-0.14	0.08	0.75	0.87	1.01

Note. R^2 = .10 (Hosmer & Lemeshow), .12 (Cox & Snell), .16 (Nagelkerke). Model $\chi^{2\,=}$ 13.12, p = .041. Bolded odds ratios numbers indicate that coefficient doesn't cross 1, suggesting a significant predictor in logistics regression equation. Testing model sample size n= 205

Link back to manuscript

Table 26

Testing for Significant Differences in B-weights from Training to Test Models

	B (training model)	*B (testing model)*	*t*	*p*
Comparison B weights				
Sex	0.67	0.45	0.55	**0.58**
3rd person plural pronouns	5.45	-1.08	1.38	**0.17**
Impersonal pronouns	-0.34	-0.22	0.35	**0.72**
Auxiliary verbs	0.33	-0.40	3.74	0.00
Adverbs	-0.43	0.61	2.94	0.00
Sadness words	1.69	2.41	0.48	**0.63**
Certainty words	0.30	-0.03	1.04	**0.30**
Nonfluencies	0.79	0.22	0.68	**0.49**
Colon	-0.10	-0.12	0.24	**0.81**
Dash	-0.04	0.10	2.16	0.03
Parentheses	0.13	-0.14	3.00	0.00

Note. See Soper (2016) and Cohen, Cohen, West, & Aiken (2003) for how to tell significance. Bolded *p*-values indicate predictors are retaining significance from training to testing model tests. Predictors are considered to be still significant if the *p* value is above .05

Link back to manuscript

Table 27

Pronouns Correlated with Impression Management

Hypothesis 2b	1st person singular pronouns	1st person plural pronouns	2nd person pronouns	3rd person singular pronouns	3rd person plural pronouns	Impersonal pronouns
Impression Management Self	.02	**-.07**	.02	.02	.06	**.07**
Impression Management Other	**.07**	-.01	.00	-.04	-.02	-.01

Note. Bolded values indicate correlations that were significant at *p* < .05. *N* = 809

Link back to manuscript

Table 28

Task Performance Regressed on Pronouns

Variables	*R*	R^2	ΔR^2	*B*	SE_B	*β*	sr^2
Step 1 - control variables	.178	.032	.032**				
Sex				0.231**	0.057	0.156	.024
Tenure				-0.017*	0.008	-0.081	.007
Step 2 - log-transformed pronoun predictors	.205	.042	.010				
Sex				0.22**	0.058	0.148	.021
Tenure				-0.018*	0.008	-0.087	.007
Pronouns							
1st person singular pronouns				0.097	0.127	0.034	.001
1st person plural pronouns				-0.666	0.470	-0.055	.003
2nd person pronouns				-0.021	0.550	-0.001	.000
3rd person singular pronouns				1.868	1.042	0.069	.005
3rd person plural pronouns				0.108	0.337	0.013	.000
Impersonal pronouns				-0.279	0.203	-0.063	.003

Note. All predictors were log-transformed. Sex was a dichotomous variable with males coded as 0 and females as 1.
* $p < .05$. ** $p < .001$.

Link back to manuscript

Table 29

Task Performance Regressed on Verbs

Variables	R	R^2	ΔR^2	B	SE_B	β	sr^2
Step 1 - control variables	.178	.032	.032**				
Sex				0.231**	0.057	0.156	.024
Tenure				-0.017*	0.008	-0.081	.007
Step 2 - log-transformed verb predictors	.178	.032	.000				
Sex				0.230**	0.057	0.155	.024
Tenure				-0.017*	0.008	-0.080	.006
Verbs				0.029	0.126	0.009	.000

Note. All predictors were log-transformed. Sex was a dichotomous variable with males coded as 0 and females as 1.
* $p < .05$, ** $p < .001$.

Link back to manuscript

Table 30

Task Performance Regressed on Positive Emotion Words

Variables	R	R^2	ΔR^2	B	SE_B	β	sr^2
Step 1 - control variables	.178	.032	.032**				
Sex				0.231**	0.057	0.156	.024
Tenure				-0.017*	0.008	-0.081	.007
Step 2 - log-transformed positive emotion words	.181	.033	.001				
Sex				0.228**	0.057	0.154	.023
Tenure				-0.016*	0.008	-0.079	.006
Positive emotion words				0.123	0.152	0.031	.001

Note. All predictors were log-transformed. Sex was a dichotomous variable with males coded as 0 and females as 1.
* p < .05. ** p < .001.

Link back to manuscript

Table 31

Contextual Performance Regressed on Positive Emotion Words

Variables	*R*	R^2	ΔR^2	*B*	SE_B	β	sr^2
Step 1 - control variable	.126	.016	.016**				
Sex				0.197**	0.060	0.126	.016
Step 2 - log-transformed positive emotion words	.183	.033	.000				
Sex				0.195**	0.060	0.125	.015
Positive emotion words				0.075	0.161	0.018	.000

Note. All predictors were log-transformed. Sex was a dichotomous variable with males coded as 0 and females as 1.
** $p < .01$.

Link back to manuscript

Table 32

Counterproductive Job Performance Regressed on Negative Emotion Words

Variables	*R*	R^2	ΔR^2	*β*	*SE B*	*β*	sr^2	*p*
Negative emotion words	.062	.004	.004	-0.416	0.258	-0.062	.004	.11

Note. All predictors were log-transformed.

Link back to manuscript

Table 33

Task Performance Regressed on Negative Emotion Words

Variables	*R*	R^2	ΔR^2	*B*	*SE B*	β	sr^2	*p*
Negative emotion words	.029	.001	.001	0.037	0.505	0.029	.001	.16

Note. All predictors were log-transformed.

Link back to manuscript

Table 34

Verbal Intelligence Correlated with Differentiation Words, Conjunctions, and Words Longer than Six Characters, Prepositions, Cognitive Process Words, Causal Words, and Insight Words

Hypothesis 4a-g	Differentiation Words	Conjunctions	Words longer than 6 characters	Prepositions	Cognitive Process Words	Causal Words	Insight Words
Verbal Intelligence	**.094**	**.278**	**.285**	**.200**	**.190**	**.199**	*.064*

Note. Bolded values indicate correlations that were significant at $p <$ .001. Italics indicate correlations that were significant at $p <$ .05. N = 809

Link back to manuscript

Table 35

Task Performance Regressed on Differentiation Words, Conjunctions, and Words Longer than Six Characters, Prepositions, Cognitive Process Words, Causal Words, and Insight Words

Variables	*R*	R^2	ΔR^2	*B*	*SE B*	β	sr^2
Step 1 - control variables	.178	.032	.032**				
Sex				0.231**	0.057	0.156	.024
Tenure				-0.017*	0.008	-0.081	.007
Step 2 - log transformed verbal intelligence proxy predictors	.215	.046	.015				
Sex				0.218**	0.058	0.147	.022
Tenure				-0.015	0.008	-0.073	.005
Verbal Intelligence proxy predictors							
differentiation words				-0.359	0.251	-0.066	.004
conjunctions				0.027	0.014	0.087	.008
words longer than 6 characters				-0.024	0.283	-0.003	.000
prepositions				-0.172	0.165	-0.052	.003
cognitive process words				0.606	0.360	0.163	.027
insight words				-0.480	0.252	-0.117	.014
causal words				-0.058	0.235	-0.015	.000

Note: Sex was a dichotomous variable with males coded as 0 and females as 1.**p* < .05. ** *p* < .001.

Link back to manuscript

Table 36

Task Performance Regressed on Cognitive Ability and the Written Cognitive Ability Index

Variables	*R*	R^2	ΔR^2	*B*	*SE B*	β	sr^2
Step 1 - control variable	.161	.026	.026**				
Sex				0.258**	.056	.161	.026
Step 2 - cognitive ability and WCAI text analytics composite variable	.256	.065	.040**				
Sex				0.176*	.057	.109	.012
Cognitive ability				0.007*	.002	.102	.010
WCAI				0.030**	.007	.150	.023

Note. * $p < .005$, ** $p < .001$. Sex was a dichotomous variable with males coded as 0 and females as 1.

Link back to manuscript

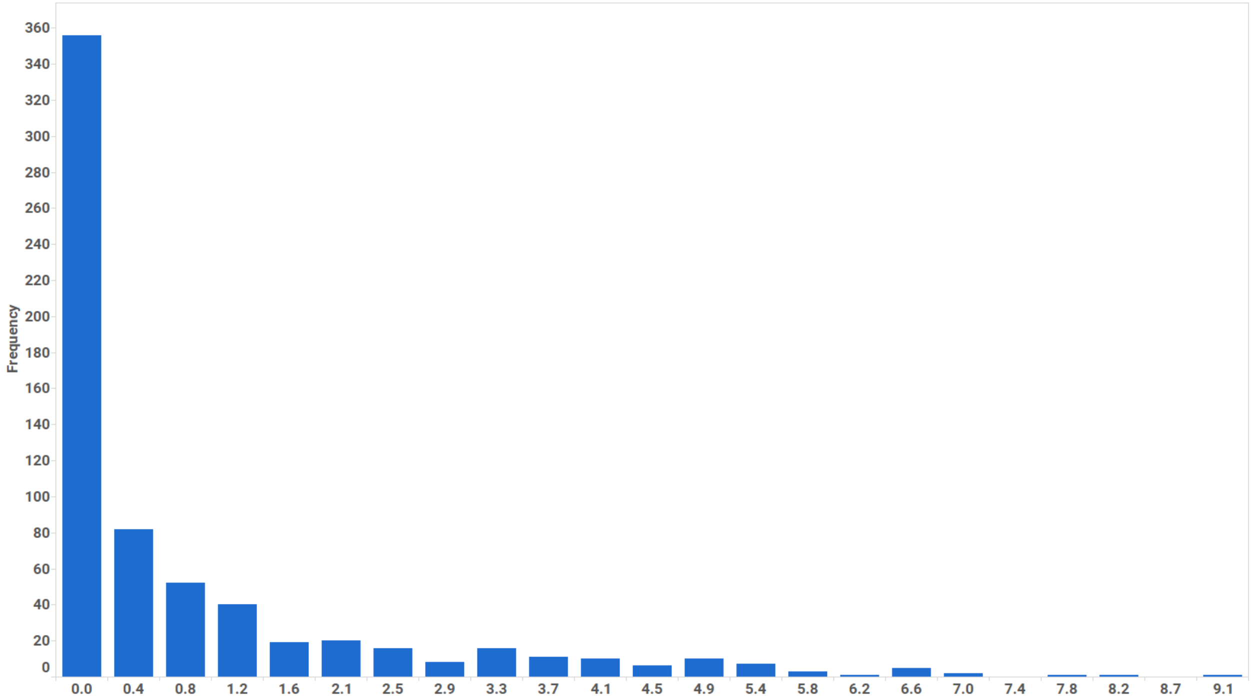


Figure 1. The frequency of first-person singular pronoun usage in aggregate resume text.

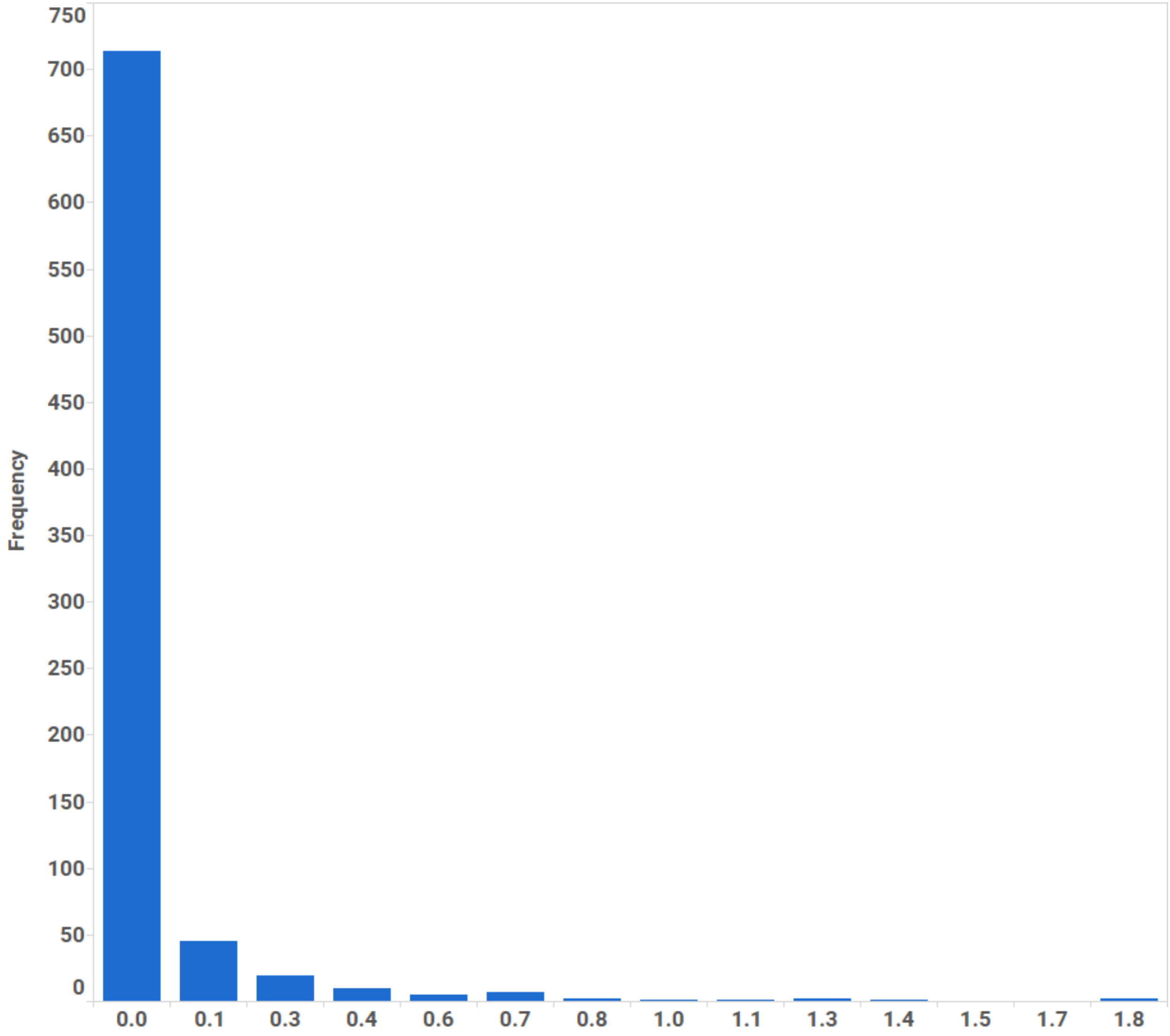


Figure 2. The frequency of first-person plural pronoun usage in aggregate resume text.

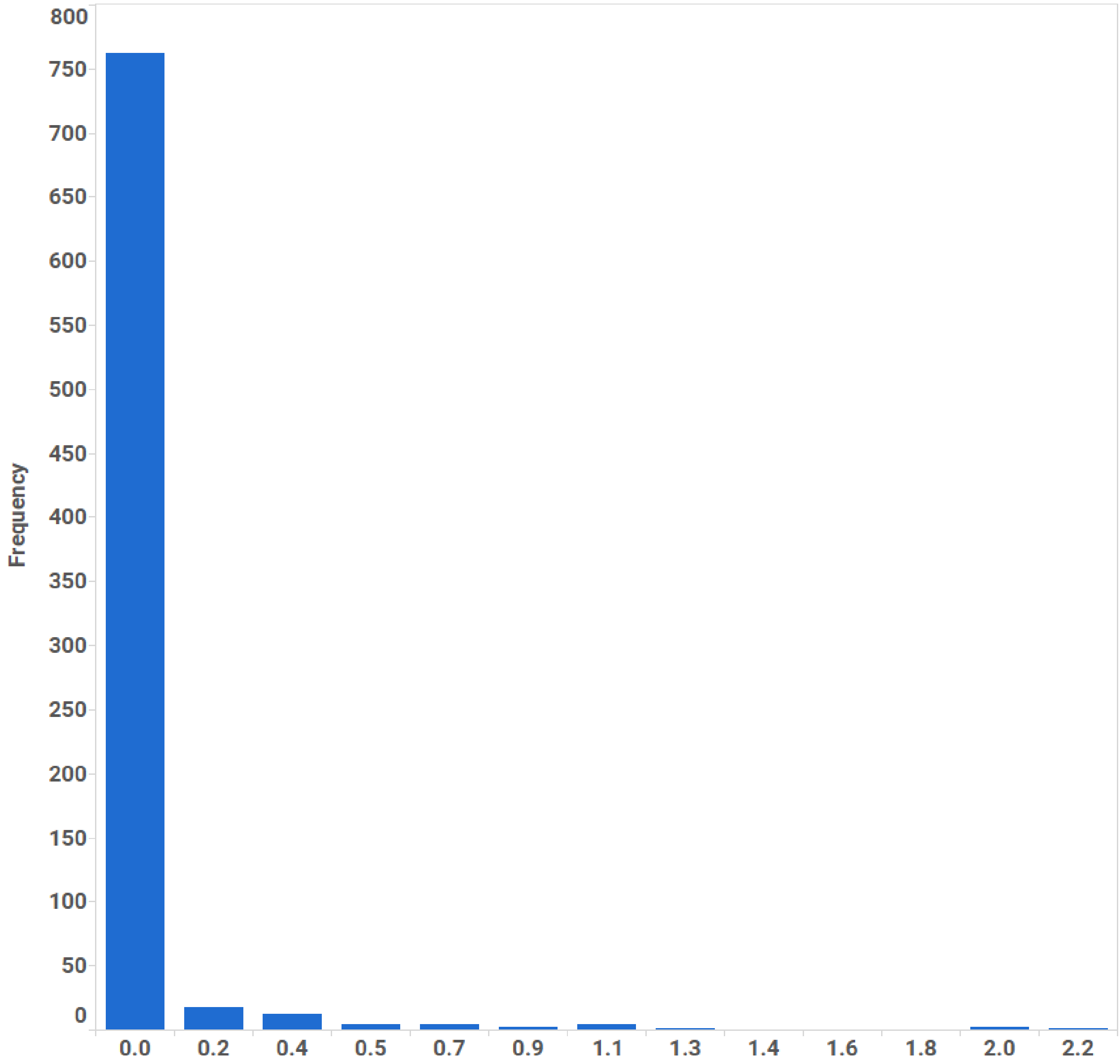


Figure 3. The frequency of second-person pronoun usage in aggregate resume text.

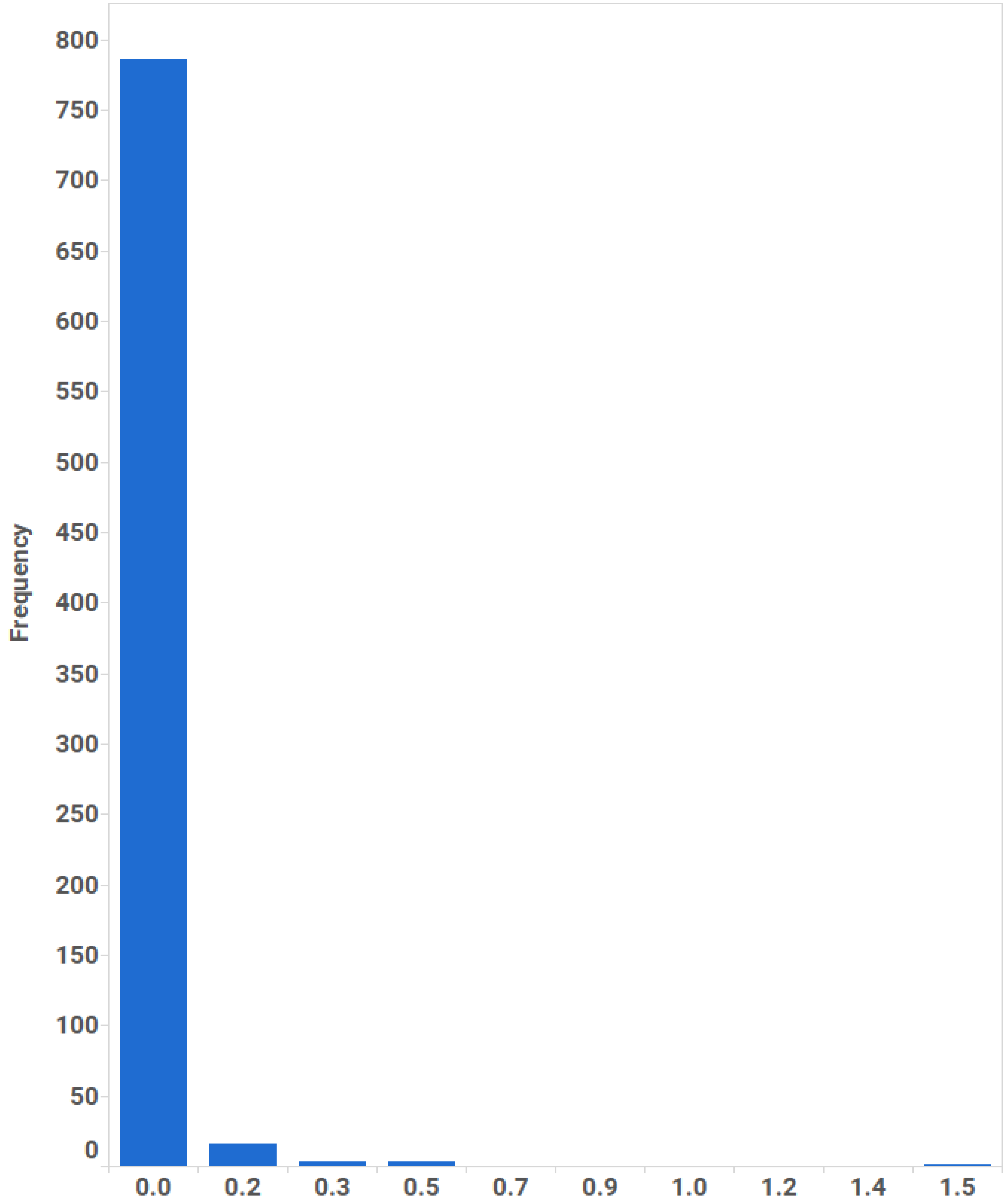


Figure 4. The frequency of third-person singular pronoun usage in aggregate resume text.

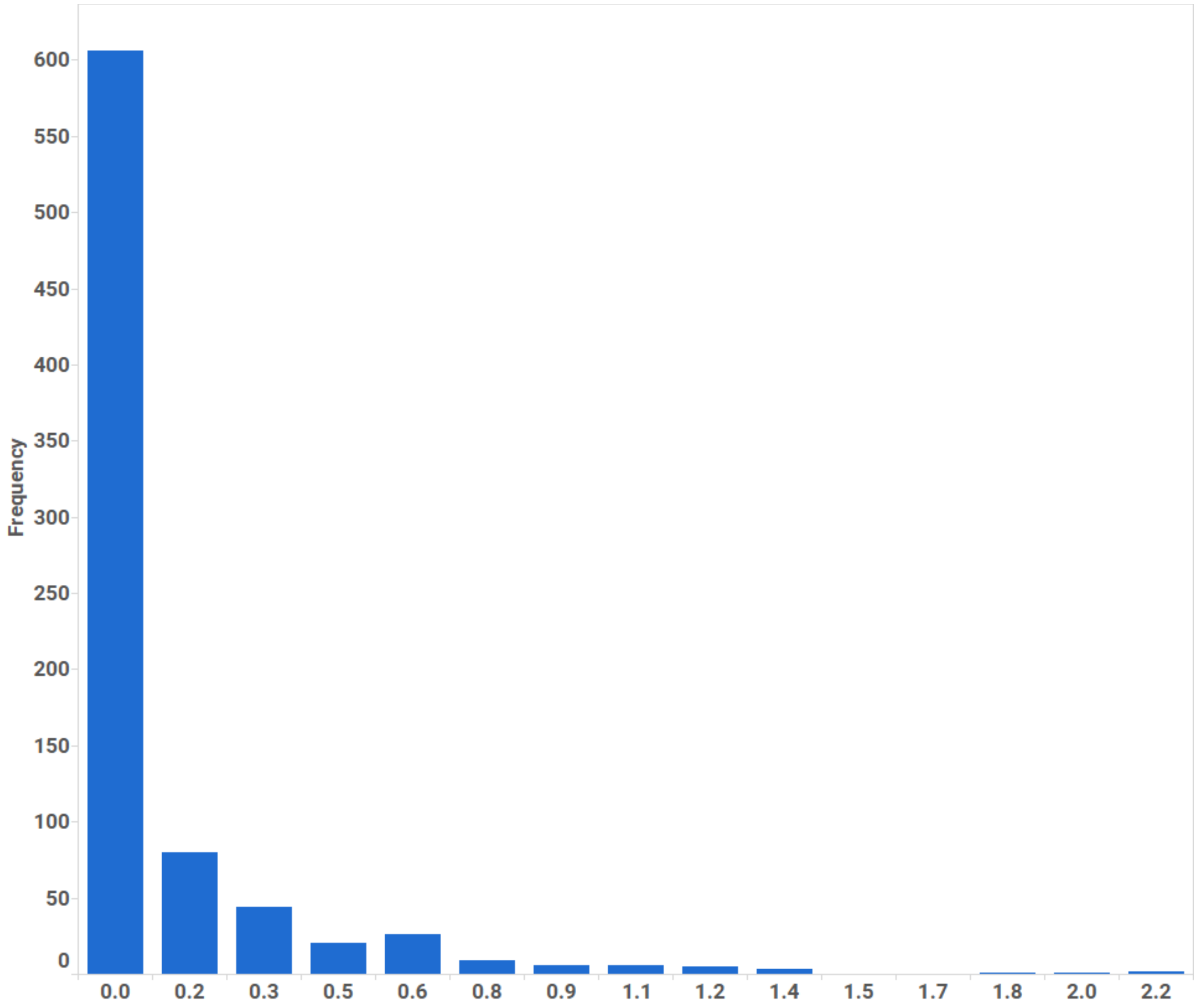


Figure 5. The frequency of third-person plural pronoun usage in aggregate resume text.

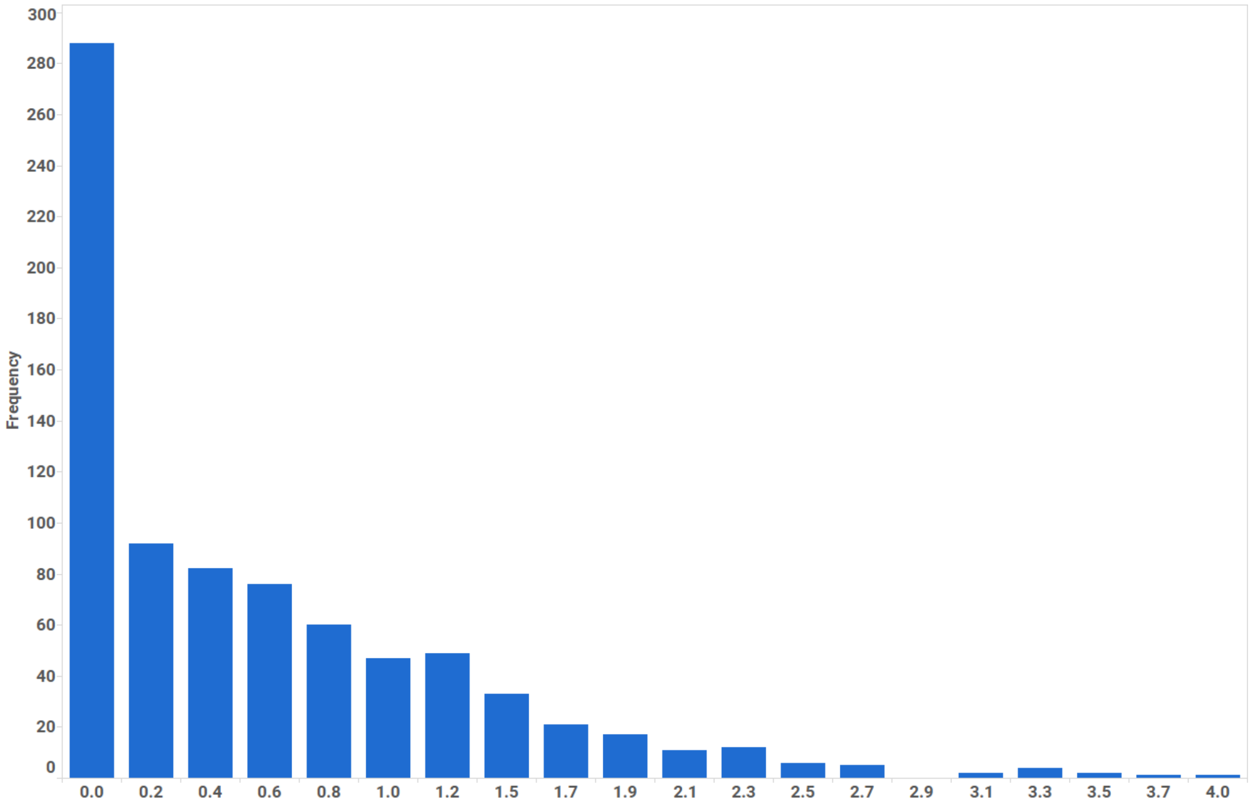


Figure 6. The frequency of impersonal pronoun usage in aggregate resume text.

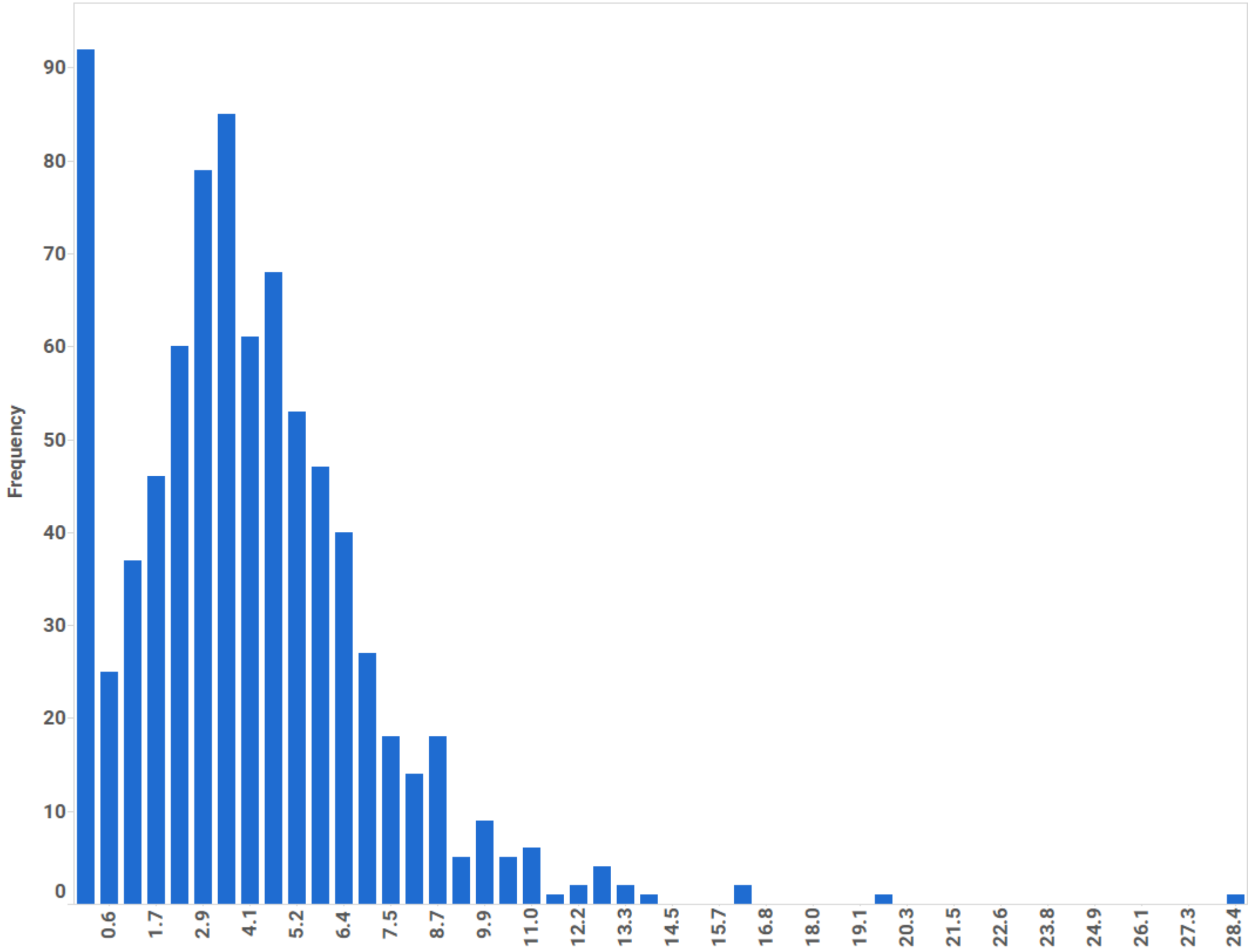


Figure 7. The frequency of verb usage in aggregate resume text.

Link back to manuscript

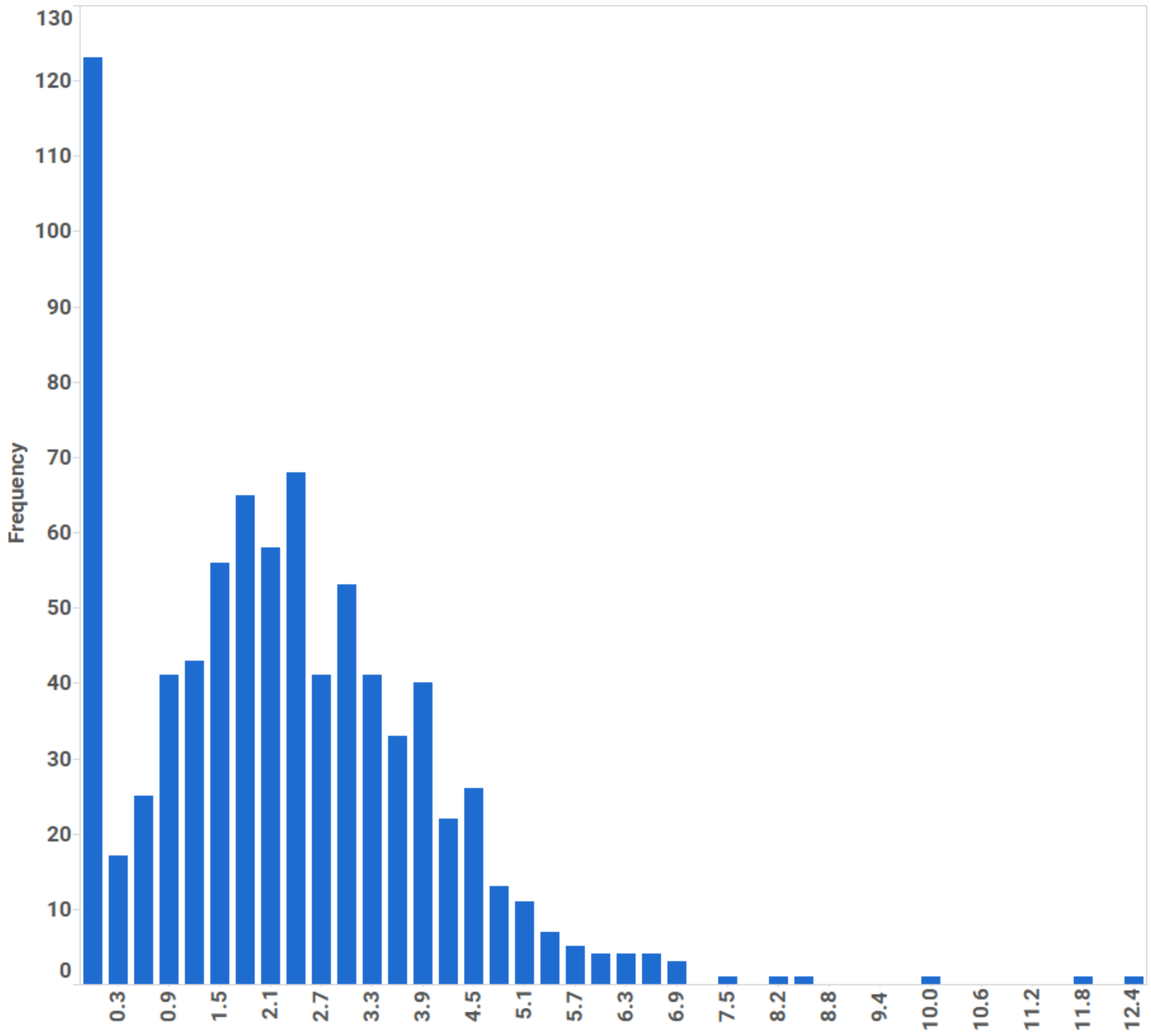


Figure 8. The frequency of positive emotion word usage in aggregate resume text.

Link back to manuscript

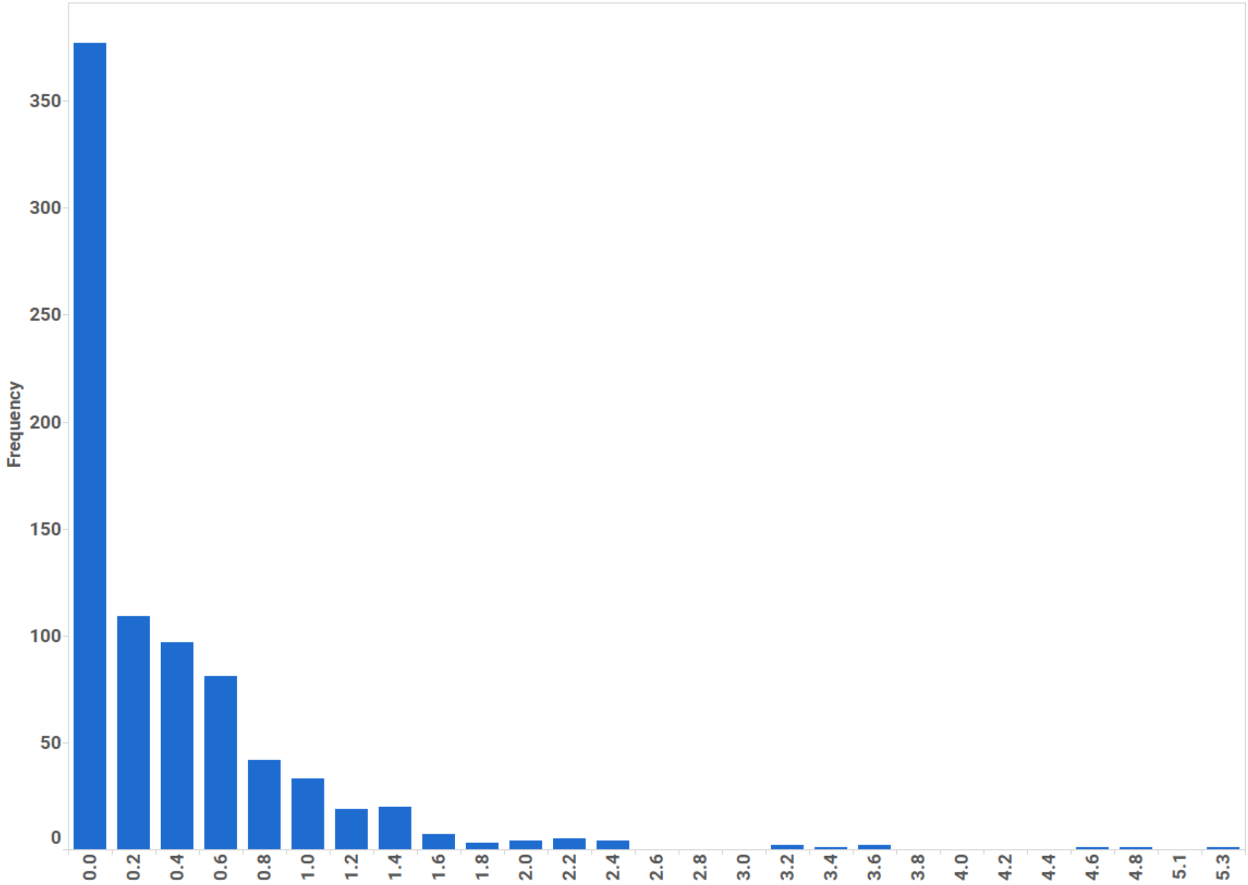


Figure 9. The frequency of negative emotion word usage in aggregate resume text.

Link back to manuscript

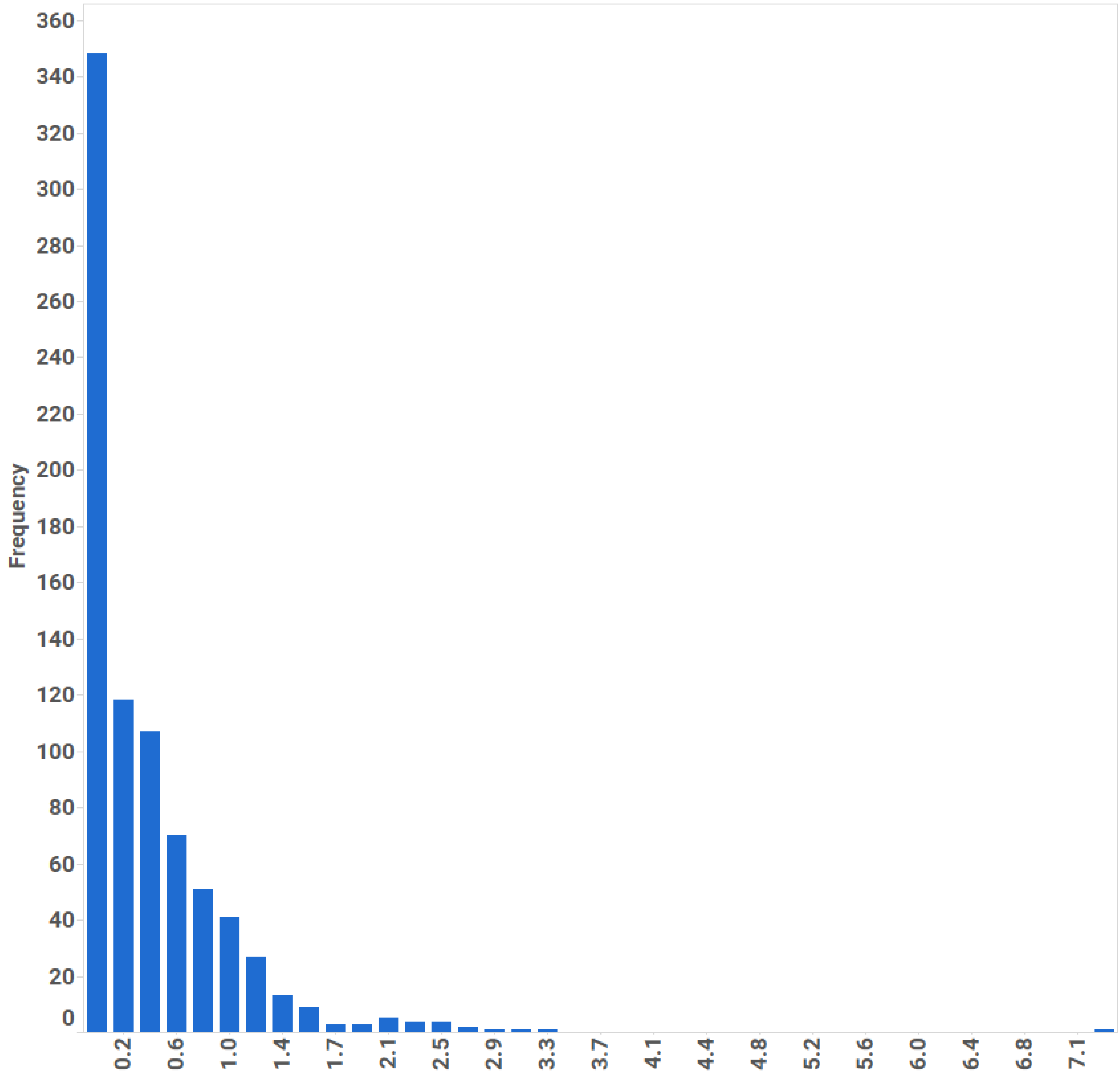


Figure 10. The frequency of differentiation word usage in aggregate resume text.

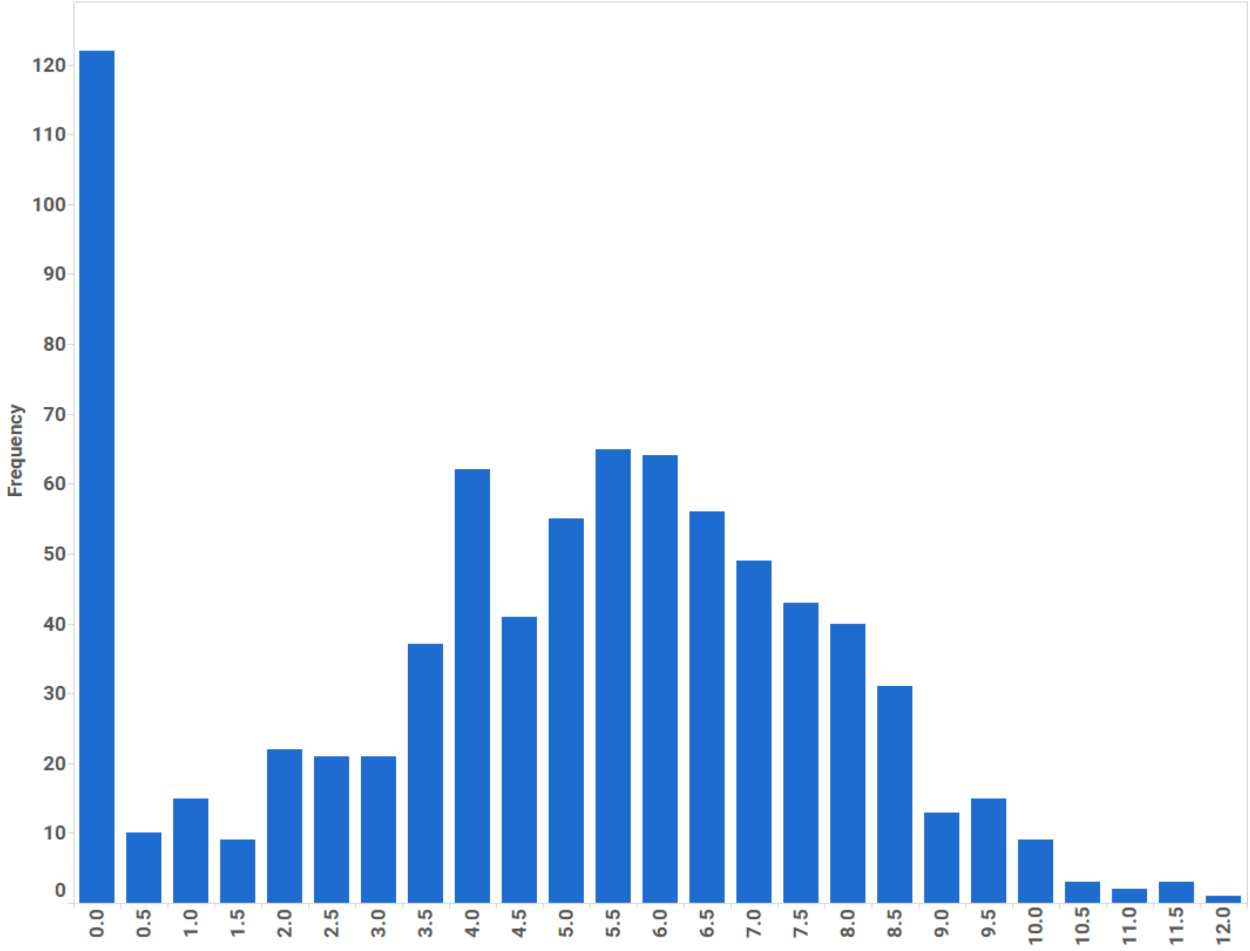


Figure 11. The frequency of conjunction usage in aggregate resume text.

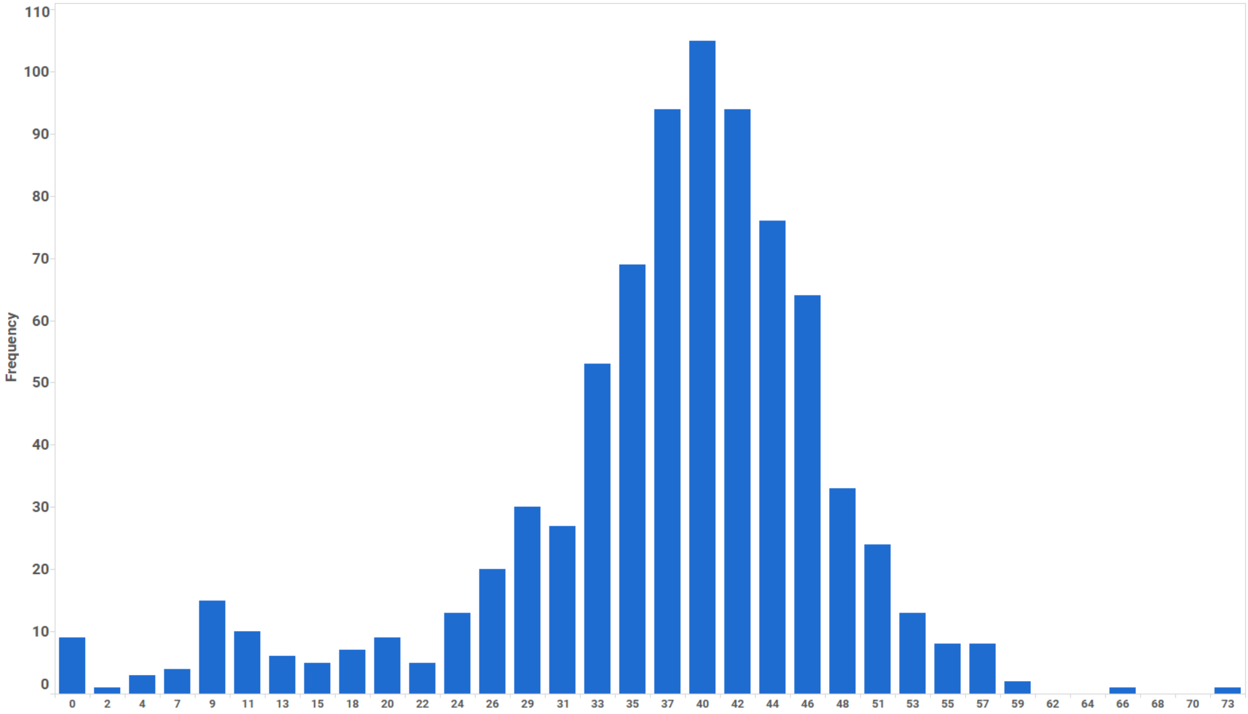


Figure 12. The frequency of words longer than six characters in aggregate resume text.

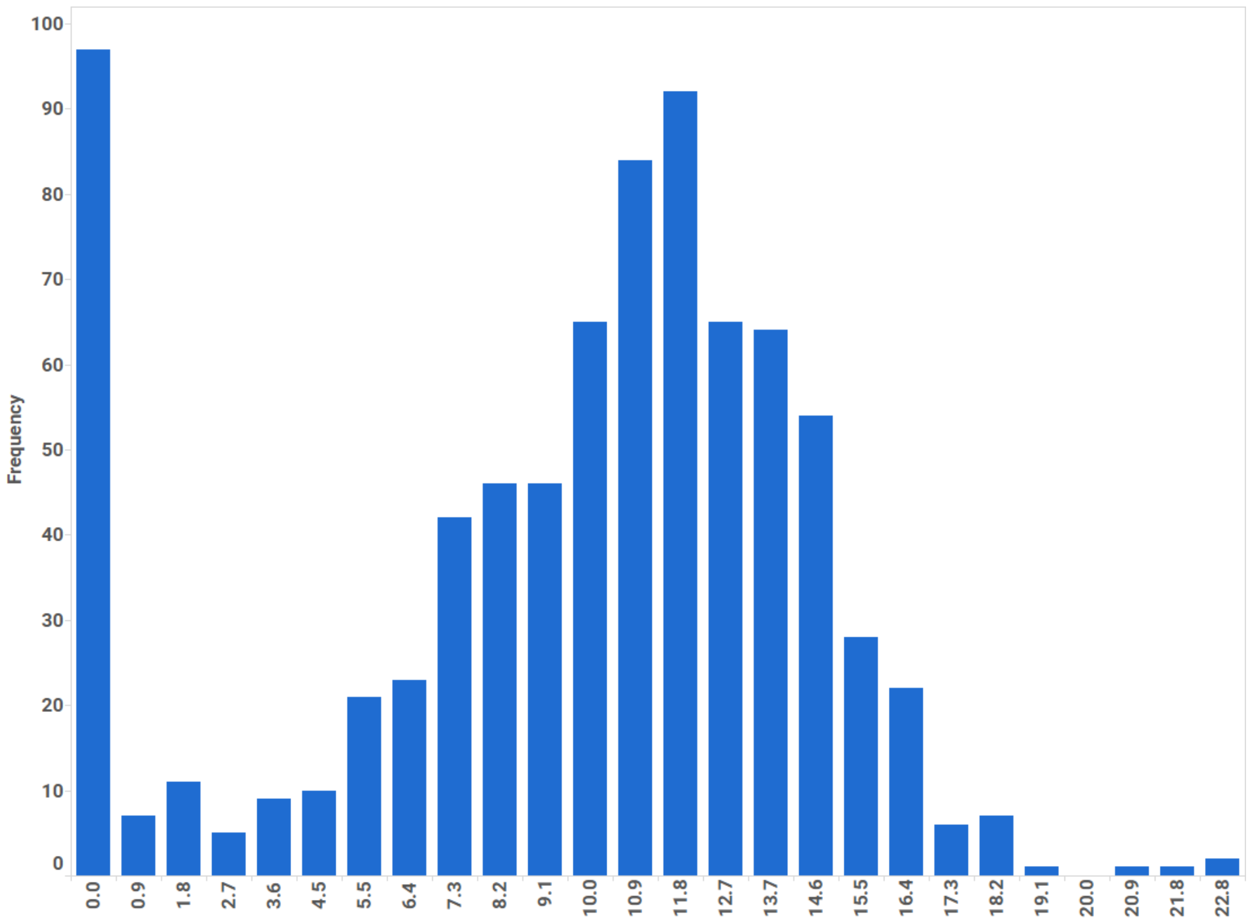


Figure 13. The frequency of preposition usage in aggregate resume text.

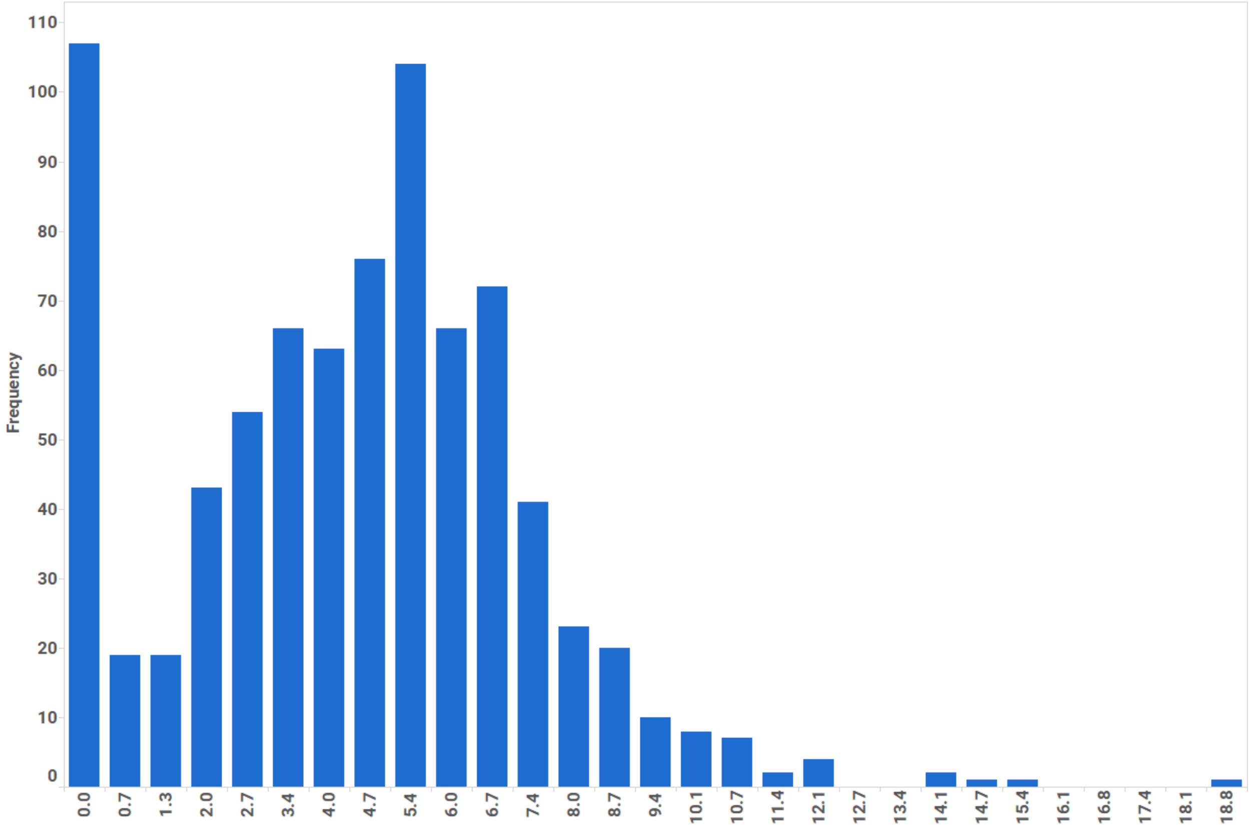
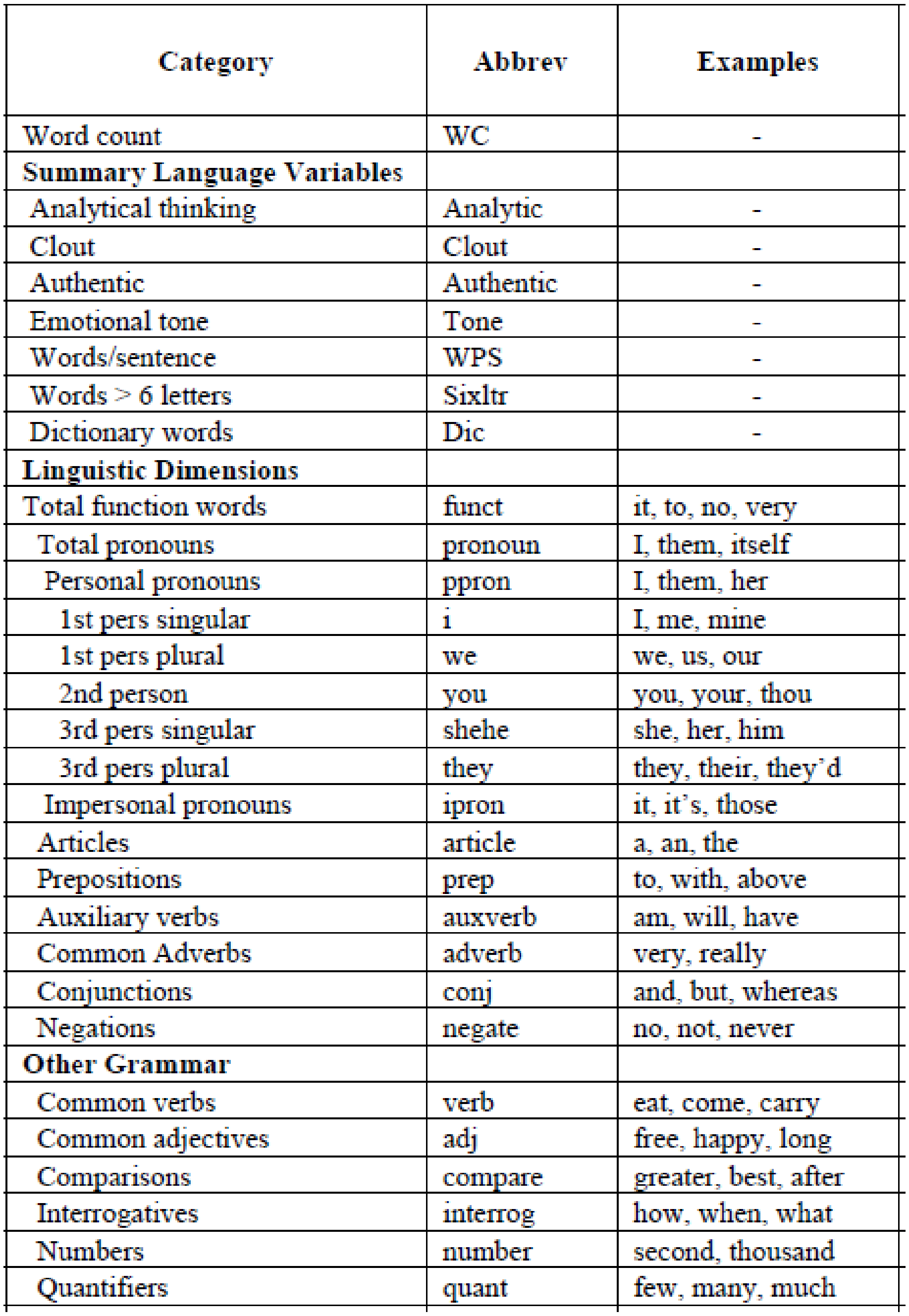


Figure 14. The frequency of cognitive process words in aggregate resume text.

Appendix A

LIWC Word Categories and Example Word for Each Category



Category	Abbrev	Examples
Word count	WC	-
Summary Language Variables		
Analytical thinking	Analytic	-
Clout	Clout	-
Authentic	Authentic	-
Emotional tone	Tone	-
Words/sentence	WPS	-
Words > 6 letters	Sixltr	-
Dictionary words	Dic	-
Linguistic Dimensions		
Total function words	funct	it, to, no, very
Total pronouns	pronoun	I, them, itself
Personal pronouns	ppron	I, them, her
1st pers singular	i	I, me, mine
1st pers plural	we	we, us, our
2nd person	you	you, your, thou
3rd pers singular	shehe	she, her, him
3rd pers plural	they	they, their, they'd
Impersonal pronouns	ipron	it, it's, those
Articles	article	a, an, the
Prepositions	prep	to, with, above
Auxiliary verbs	auxverb	am, will, have
Common Adverbs	adverb	very, really
Conjunctions	conj	and, but, whereas
Negations	negate	no, not, never
Other Grammar		
Common verbs	verb	eat, come, carry
Common adjectives	adj	free, happy, long
Comparisons	compare	greater, best, after
Interrogatives	interrog	how, when, what
Numbers	number	second, thousand
Quantifiers	quant	few, many, much

Psychological Processes		
Affective processes	affect	happy, cried
Positive emotion	posemo	love, nice, sweet
Negative emotion	negemo	hurt, ugly, nasty
Anxiety	anx	worried, fearful
Anger	anger	hate, kill, annoyed
Sadness	sad	crying, grief, sad
Social processes	social	mate, talk, they
Family	family	daughter, dad, aunt

Category	**Abbrev**	**Examples**
Friends	friend	buddy, neighbor
Female references	female	girl, her, mom
Male references	male	boy, his, dad
Cognitive processes	cogproc	cause, know, ought
Insight	insight	think, know
Causation	cause	because, effect
Discrepancy	discrep	should, would
Tentative	tentat	maybe, perhaps
Certainty	certain	always, never
Differentiation	differ	hasn't, but, else
Perceptual processes	percept	look, heard, feeling
See	see	view, saw, seen
Hear	hear	listen, hearing
Feel	feel	feels, touch
Biological processes	bio	eat, blood, pain
Body	body	cheek, hands, spit
Health	health	clinic, flu, pill
Sexual	sexual	horny, love, incest
Ingestion	ingest	dish, eat, pizza
Drives	drives	
Affiliation	affiliation	ally, friend, social
Achievement	achieve	win, success, better
Power	power	superior, bully
Reward	reward	take, prize, benefit
Risk	risk	danger, doubt
Time orientations	TimeOrient	
Past focus	focuspast	ago, did, talked
Present focus	focuspresent	today, is, now
Future focus	focusfuture	may, will, soon
Relativity	relativ	area, bend, exit
Motion	motion	arrive, car, go
Space	space	down, in, thin
Time	time	end, until, season
Personal concerns		

Work	work	job, majors, xerox
Leisure	leisure	cook, chat, movie
Home	home	kitchen, landlord
Money	money	audit, cash, owe
Religion	relig	altar, church
Death	death	bury, coffin, kill
Informal language	informal	
Swear words	swear	fuck, damn, shit
Netspeak	netspeak	btw, lol, thx
Assent	assent	agree, OK, yes
Nonfluencies	nonflu	er, hm, umm
Fillers	filler	Imean, youknow

Appendix B

Decision Rules for Selecting Independent Variables and LIWC Categories

LIWC word categories were hierarchical in nature, with higher order categories representing a combination of lower order categories. For example, cognitive processes, a category which focused on word markers of cognitive activity (Pennebaker, 2015), is an aggregate measure of the cognitive process sub-categories of insight, causation, discrepancy, tentativeness, certainty, and differentiation. This approach has only recently been clarified in the latest LIWC manual (Pennebaker, 2015). The prior documentation suggested higher order categories but did not indicate that the higher order categories were created by summing the lower level categories.

This is problematic for hypotheses that posit a linear model that includes both higher and lower order word categories (e.g. the cognitive process category and the causal category) because the inclusion of these categories introduces a high degree of multicollinearity. This makes a test of a linear or curvilinear relationship untenable. Additional categories increase the predictor to sample size ratio, decreasing power, and degrees of freedom. Therefore, business rules were developed when deciding whether to use the higher order or lower order categories. They are described below as follows.

1) If the lower order categories (e.g. insight, causation, discrepancy) have a correlation that exceeds $|r = .65|$, use the higher order category, e.g. cognitive process. Otherwise, use the lower order categories.
2) Lower order categories are preferred to higher order categories due to greater explanatory capability and theory building. For example, it is preferable to discuss how first-person pronouns drive job performance rather than pronouns.

These business rules applied to all hypotheses in this study. However, it should be noted that these decisions resulted in what initially appeared to be a random assortment of predictors for job performance (Hypothesis 1). However, this is not the case for the following reasons. First, understanding the bivariate correlations between lower and higher order word categories is standard practice. Redundant predictors are often collapsed into a single predictor. Second, while one would prefer greater precision in an applied context, a more robust regression model is preferred to a brittle model. That is to say, the inclusion of terms with multicollinearity not only represents an incorrectly specified model but also adds unnecessary complexity, violating the principle of parsimony. Thus, parsimony and a correctly specified model are more important in practice than extreme precision. Finally, given the small sample size (*N* = 393), using higher order categories aided in dimensionality reduction of the predictor space.

Correlation
matrices checking tc

Appendix C

Validity Evidence for the Spot-The-Word Test

The Spot-The-Word test has strong convergent validity with established measures of verbal intelligence, including (a) the National Adult Reading Test, (*r* = 0.83 with Form A; *r* = 0.86 with Form B; Baddeley et al., 1993), (b) the American National Adult Reading Test (*r* = 0.56; Yuspeh & Vanderploeg, 2000), (c) the Wechsler Adult Intelligence Scale-Revised Vocabulary subtest (*r* = 0.58; Yuspeh & Vanderploeg), and (d) the Shipley Institute of Living Scale Vocabulary subtest (*r* = 0.66; Yuspeh & Vanderploeg). In addition, the STW has strong alternate forms reliability (*r* = 0.88, Baddeley, et al., 1993). Finally, the STW has also shown to be an adequate measure of general intelligence; Yuspeh and Vanderploeg reported a validity coefficient of 0.35 between the STW and the Wechsler Adult Intelligence Scale.

Appendix D

Summary of the Development and Validation Research for the Individual Work Performance Questionnaire

Development of the IWPQ employed classic scale development approaches (e.g. factor analysis) in addition to Rasch modeling, a type of item response theory (IRT) modeling, and was initially developed on a sample of 1,181 Dutch workers ranging from blue to white collar (e.g. mechanic, manager, service industry; Koopmans et al., 2013). Rasch modeling was used to refine the IWPQ to the final 18-item measure used in this study (Koopmans et al., 2014a), using a sample of 1,424 Dutch workers ranging from blue to white collar jobs (Koopmans et al., 2014a, 2014b). This version is more sensitive to variance in job performance across individuals and better differentiates between employees within each subscale (Koopmans et al., 2014a, 2014b). See Table 6 for a detailed list of IWPQ development studies and reliability estimates.

Reliability of the IWPQ is adequate for research and has been measured using Cronbach's alpha (Cronbach, 1951) and the person separation index (PSI). The PSI is used to ascertain reliability when developing a scale using Rasch modeling. Like Cronbach's alpha, the PSI estimates the internal consistency of a scale, only using logit scale estimates as opposed to raw scores (Koopmans et al., 2013). It is interpreted in a manner similar to Cronbach's alpha; a minimum value of 0.70 is required for group use and 0.85 for individual use (Koopmans et al., 2013). Reliability metrics reported for the IWPQ in prior research ranged from 0.78-0.86 for task performance (Koopmans et al., 2013; Landers & Callan, 2014), 0.77-0.85 for contextual performance (Koopmans et al., 2014c; Landers & Callan, 2014), and 0.74-0.86 for CWB (Koopmans et al., 2014a; Landers & Callan, 2014). Validation work on the IWPQ used multiple constructs, including (a) presenteeism, (b) job satisfaction, (c) work engagement, and (d) manager ratings of performance. See Table 6 for a detailed list of IWPQ validation studies and corresponding validity coefficients.

Respondents were asked to recall their job performance behaviors from the past three months and respond to Likert-scaled items ranging from 0 (*seldom/never*) to 4 (*always/often*). Mean scores were obtained for each sub-scale by summing the item scores and dividing the total by the number of items in that particular subscale. This resulted in a sub-scale score with a range of 0 to 4. Higher scores reflected higher task and contextual performance and higher counterproductive work behavior. A single overall score was not computed as current job performance theory conceptualizes job performance as multidimensional (Campbell, 1990, 2012; Koopmans et al., 2014a). What is more, computing a single overall score would necessarily include the counterproductive work behavior subscale, and its inclusion would result in sub-optimal psychometrics due to its negative correlation with the other two sub-scale scores.

Appendix E

Sample Output from the LIWC Software

Response_ID	**Sixltr**	**ppron**	**i**	**we**	**you**	**shehe**	**they**	**ipron**	**article**	**prep**	**auxverb**
41194514	31.75	0	0	0	0	0	0	0	2.84	12.32	0.95
41194519	37.16	4.65	3.67	0	0	0.24	0.73	1.47	5.13	15.4	3.67
41194604	32.76	3	3	0	0	0	0	1.71	6.85	11.56	0.86
41194663	38.05	0.13	0	0	0.13	0	0	0.38	3.88	11.26	0.63
41194668	30.89	1.39	0	0	1.09	0.1	0.2	3.27	10.1	14.26	6.14
41194701	42.29	1.49	1.49	0	0	0	0	1	2.49	9.95	1
41194703	33.33	0	0	0	0	0	0	0	0	0	0
41194755	30.57	3.07	1.38	0.77	0	0	0.92	1.84	2.61	7.22	2.61
41194759	43.7	0.42	0.42	0	0	0	0	0.84	3.57	11.34	1.26
41194805	35.81	0.31	0	0	0.31	0	0	0	7.91	13.02	1.09
41194866	41.7	0.36	0.36	0	0	0	0	1.09	5.33	12.85	0.85
41194876	37.01	0.15	0.15	0	0	0	0	0	2.32	13.93	0.15
41194912	43.68	0.18	0	0.18	0	0	0	1.44	2.89	14.62	1.08
41194945	41.78	0	0	0	0	0	0	0.47	0.94	13.62	0.94
41194960	26.15	4.36	2.06	0	0	0	2.29	3.21	8.26	12.61	4.13
41194974	38.15	0	0	0	0	0	0	0.8	4.82	14.06	0.8
41195002	33.76	0.25	0.25	0	0	0	0	0	1.78	0.51	0.76
41195044	41.42	1.72	1.47	0.25	0	0	0	0.49	5.39	16.42	0.74
41195078	50.93	0	0	0	0	0	0	0	1.85	14.81	1.39

Appendix F

Python Code for Cleaning Up Survey Data

```
# -*- coding: utf-8 -*-
"""
Created on Thu Dec 17 16:28:00 2015
"""
'''
IMPORT AND CONCATENATE/UNION ALL 5 EXCEL FILES  IMPORT AND
CONCATENATE/UNION ALL 5 EXCEL FILES
IMPORT AND CONCATENATE/UNION ALL 5 EXCEL FILES  IMPORT AND
CONCATENATE/UNION ALL 5 EXCEL FILES
IMPORT AND CONCATENATE/UNION ALL 5 EXCEL FILES  IMPORT AND
CONCATENATE/UNION ALL 5 EXCEL FILES

note: the raw CSV files had the following edits done to them
1) removed first 3 rows that included download and metadata information
   (this was included from the survey platform)
2) moved all header columns to a single row, the header column was two rows
3) item column headers had sequential numbers appended to them (e.g.
   "15 - Job Performance1", "15 - Job Performance2") this was done as a
   precautionary step to ensure that the columns would concatenate/union
   all correctly using the for loop
'''

#import required packages and set parameters for creating data visualizations and set
visualization style color
import glob
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

plt.rcParams['figure.figsize'] = (10, 8)
plt.rcParams['font.size'] = 14
plt.style.use('bmh')

#verify csv files are showing up
glob.glob('C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey/*.csv')

'''
the code commented out below is code to help check that the
concatenation/union all of the survey files was happening correctly
i.e. making sure columns were being mapped to the correct columns
'''
```

```
##read in each file individually into it's own data frame
#df =
pd.read_csv('C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey/11.13.15_Responses
_340.csv', index_col=False, header=0, encoding='utf-8')
#df1 =
pd.read_csv('C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey/11.21.15_Responses
_235.csv', index_col=False, header=0, encoding='utf-8')
#df2 =
pd.read_csv('C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey/11.28.15_Responses
_196.csv', index_col=False, header=0, encoding='utf-8')
#df3 =
pd.read_csv('C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey/12.07.15_Responses
_134.csv', index_col=False, header=0, encoding='utf-8')
#df4 =
pd.read_csv('C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey/01.08.16_Responses
_36.csv', index_col=False, header=0, encoding='utf-8')
#
##append each dataframe to the data frame before it to create a single data frame of all data
#dat = df.append(df1, ignore_index=True)
#dat1 = dat.append(df2, ignore_index=True)
#dat2 = dat1.append(df3, ignore_index=True)
#
##write dataframe to file
#dat2.to_csv("dissertation_test_ind.csv", encoding='utf-8', index=False, header=True)


#loop through all csv files in the folder and combine them into a single data frame
path = "C:/Users/Joshuaw/Documents/PhD_Year_5/Data/Raw_Survey"
files = glob.glob(path + "/*.csv")
df = pd.DataFrame()
for file_ in files:
    f = pd.read_csv(file_,index_col=False, header=0, encoding='utf-8')
    df = df.append(f, ignore_index=True)

#write dataframe created with a loop to file
df.to_csv("dissertation_merge", encoding='utf-8', index=False, header=True)

'''
DATA CLEAN UP   DATA CLEAN UP   DATA CLEAN UP   DATA CLEAN UP   DATA
CLEAN UP
DATA CLEAN UP   DATA CLEAN UP   DATA CLEAN UP   DATA CLEAN UP   DATA
CLEAN UP
DATA CLEAN UP   DATA CLEAN UP   DATA CLEAN UP   DATA CLEAN UP   DATA
CLEAN UP

split the '8 - Location' column into multiple columns to obtain the city as a
```

```
separate column
Note: the split isn't clean, but since we already have a country code all we need is the city for
visualization in Tableau.
'''
s = df['8 - Location'].str.split(',').apply(pd.Series,1)
s.name = '8 - Location' #we need a name to be able to join it to the original dataframe
del df['8 - Location'] #drop the location column
#df1 = df.join(s) #join the 10 columns back to the dataframe
dat = pd.concat([df, s], axis=1)
df = dat #rename the dataframe back to df, for consistency

'''
delete columns: these columns were part of the survey but don't contain
relevant data
'''
df.drop(['Response Status', 'Seq. Number', 'External Reference',
    'Respondent Email', 'Email List', '1 - INTRO', '3 - Demographics_header',
    '14 - Work_Behavior_Header',
    'Spot_The_Word_Test:...........1',   'Spot_The_Word_Test:...........2',
    'Spot_The_Word_Test:...........3',   'Spot_The_Word_Test:...........4',
    'Spot_The_Word_Test:...........5',   'Spot_The_Word_Test:...........6',
    'Spot_The_Word_Test:...........7',   'Spot_The_Word_Test:...........8',
    'Spot_The_Word_Test:...........9',   'Spot_The_Word_Test:...........10',
    'Spot_The_Word_Test:...........11',   'Spot_The_Word_Test:...........12',
    'Spot_The_Word_Test:...........13',   'Spot_The_Word_Test:...........14',
    'Spot_The_Word_Test:...........15',   'Spot_The_Word_Test:...........16',
    'Spot_The_Word_Test:...........17',   'Spot_The_Word_Test:...........18',
    'Spot_The_Word_Test:...........19',   'Spot_The_Word_Test:...........20',
    'Spot_The_Word_Test:...........21',       'Spot_The_Word_Test:...........22',
    'Spot_The_Word_Test:...........23',       'Spot_The_Word_Test:...........24',
    'Spot_The_Word_Test:...........25',       'Spot_The_Word_Test:...........26',
    'Spot_The_Word_Test:...........27',       'Spot_The_Word_Test:...........28',
    'Spot_The_Word_Test:...........29',       'Spot_The_Word_Test:...........30',
    'Spot_The_Word_Test:...........31',       'Spot_The_Word_Test:...........32',
    'Spot_The_Word_Test:...........33',       'Spot_The_Word_Test:...........34',
    'Spot_The_Word_Test:...........35',       'Spot_The_Word_Test:...........36',
    'Spot_The_Word_Test:...........37',       'Spot_The_Word_Test:...........38',
    'Spot_The_Word_Test:...........39',       'Spot_The_Word_Test:...........40',
    'Spot_The_Word_Test:...........41',       'Spot_The_Word_Test:...........42',
    'Spot_The_Word_Test:...........43',       'Spot_The_Word_Test:...........44',
    'Spot_The_Word_Test:...........45',       'Spot_The_Word_Test:...........46',
    'Spot_The_Word_Test:...........47',       'Spot_The_Word_Test:...........48',
    'Spot_The_Word_Test:...........49',       'Spot_The_Word_Test:...........50',
    'Spot_The_Word_Test:...........51',       'Spot_The_Word_Test:...........52',
    'Spot_The_Word_Test:...........53',       'Spot_The_Word_Test:...........54',
    'Spot_The_Word_Test:...........55',       'Spot_The_Word_Test:...........56',
    'Spot_The_Word_Test:...........57',         'Spot_The_Word_Test:...........58',
    'Spot_The_Word_Test:........... 59'], axis =1, inplace=True)

#rename the columns to make them more pythonic and easy to type
#first create a list that contains the new names for the columns
df_cols = ['Response_ID', 'IP_Address', 'Timestamp', 'Device_Data',
        'SecondsToComplete', 'Country_Code', 'Region', 'Resume',
        'Age', 'Sex', 'Race', 'Education', 'Industry', 'Job_Level',
        'Years_Experience', 'Hours_Week', 'Salary','Job_Performance1',
        'Job_Performance2', 'Job_Performance3',    'Job_Performance4',
        'Job_Performance5', 'Job_Performance6',    'Job_Performance7',
        'Job_Performance8', 'Job_Performance9',    'Job_Performance10',
        'Job_Performance11', 'Job_Performance12', 'Job_Performance13',
        'Job_Performance14', 'Job_Performance15', 'Job_Performance16',
        'Job_Performance17', 'Job_Performance18', 'Impression_Work1',
        'Impression_Work2', 'Impression_Work3',  'Impression_Work4',
        'Impression_Work5', 'Impression_Work6',  'Impression_Work7',
        'Impression_Work8', 'Impression_Work9',  'Impression_Work10',
        'Spot_The_Word_Test:slank', 'Spot_The_Word_Test:chariot',
        'Spot_The_Word_Test:lentil', 'Spot_The_Word_Test:glotex',
        'Spot_The_Word_Test:stamen',       'Spot_The_Word_Test:dombus',
        'Spot_The_Word_Test:loba','Spot_The_Word_Test:comet',
        'Spot_The_Word_Test:pylon',        'Spot_The_Word_Test:stroin',
        'Spot_The_Word_Test:scrapten',     'Spot_The_Word_Test:flannel',
        'Spot_The_Word_Test:fender',       'Spot_The_Word_Test:ullus',
        'Spot_The_Word_Test:ragspur',      'Spot_The_Word_Test:joust',
        'Spot_The_Word_Test:milliary',     'Spot_The_Word_Test:mantis',
        'Spot_The_Word_Test:sterile',      'Spot_The_Word_Test:palth',
        'Spot_The_Word_Test:proctive',     'Spot_The_Word_Test:monotheism',
        'Spot_The_Word_Test:glivular',     'Spot_The_Word_Test:stallion',
        'Spot_The_Word_Test:intervantation', 'Spot_The_Word_Test:rictus',
        'Spot_The_Word_Test:byzantine',    'Spot_The_Word_Test:chloriant',
        'Spot_The_Word_Test:monologue', 'Spot_The_Word_Test:rufine',
        'Spot_The_Word_Test:elegy',        'Spot_The_Word_Test:festant',
        'Spot_The_Word_Test:malign',       'Spot_The_Word_Test:vago',
        'Spot_The_Word_Test:exonize',      'Spot_The_Word_Test:gelding',
        'Spot_The_Word_Test:bulliner',     'Spot_The_Word_Test:trireme',
        'Spot_The_Word_Test:visage',       'Spot_The_Word_Test:hyperlisitc',
        'Spot_The_Word_Test:froin',        'Spot_The_Word_Test:oratory',
        'Spot_The_Word_Test:meridian',     'Spot_The_Word_Test:phillidism',
        'Spot_The_Word_Test:grottle',      'Spot_The_Word_Test:strumpet',
        'Spot_The_Word_Test:equine',       'Spot_The_Word_Test:psynomy',
        'Spot_The_Word_Test:baggalette',   'Spot_The_Word_Test:riposte',
        'Spot_The_Word_Test:valance',      'Spot_The_Word_Test:plesmoid',
        'Spot_The_Word_Test:introvert',    'Spot_The_Word_Test:vinadism',
        'Spot_The_Word_Test:penumbra',     'Spot_The_Word_Test:rubiant',
        'Spot_The_Word_Test:breen',          'Spot_The_Word_Test:malinger',
        'Spot_The_Word_Test:gammon',         'Spot_The_Word_Test:unterried',
        'Spot_The_Word_Test:coracle',        'Spot_The_Word_Test:prestasis',
        'Spot_The_Word_Test:paramour',       'Spot_The_Word_Test:imbulasm',
        'Spot_The_Word_Test:dallow',         'Spot_The_Word_Test:octaroon',
        'Spot_The_Word_Test:fleggary',       'Spot_The_Word_Test:carnation',
        'Spot_The_Word_Test:liminoid',       'Spot_The_Word_Test:agnostic',
        'Spot_The_Word_Test:naquescent',     'Spot_The_Word_Test:plinth',
        'Spot_The_Word_Test:thole',          'Spot_The_Word_Test:leptine',
        'Spot_The_Word_Test:crattish',       'Spot_The_Word_Test:reform',
        'Spot_The_Word_Test:wraith',         'Spot_The_Word_Test:stribble',
        'Spot_The_Word_Test:metulate',       'Spot_The_Word_Test:pristine',
        'Spot_The_Word_Test:pauper',         'Spot_The_Word_Test:progotic',
        'Spot_The_Word_Test:aurant',         'Spot_The_Word_Test:baleen',
        'Spot_The_Word_Test:palindrome',     'Spot_The_Word_Test:lentathic',
        'Spot_The_Word_Test:hedgehog',       'Spot_The_Word_Test:mordler',
        'Spot_The_Word_Test:prassy',         'Spot_The_Word_Test:ferret',
        'Spot_The_Word_Test:torbate',        'Spot_The_Word_Test:drumlin',
        'Spot_The_Word_Test:texture',        'Spot_The_Word_Test:disenrupted',
        'Spot_The_Word_Test:isomorphic',     'Spot_The_Word_Test:thassiary',
        'Spot_The_Word_Test:fremoid',        'Spot_The_Word_Test:vitriol',
        'Spot_The_Word_Test:farrago',        'Spot_The_Word_Test:gesticity',
        'Spot_The_Word_Test:minidyne',       'Spot_The_Word_Test:hermeneutic',
        'Spot_The_Word_Test:pusality',       'Spot_The_Word_Test:chaos',
        'Spot_The_Word_Test:devastate',      'Spot_The_Word_Test:prallage',
        'Spot_The_Word_Test:peremptory',     'Spot_The_Word_Test:paralepsy',
        'Spot_The_Word_Test:chalper',        'Spot_The_Word_Test:camera',
        'Spot_The_Word_Test:roster',         'Spot_The_Word_Test:fallulate',
        'Spot_The_Word_Test:scaline',        'Spot_The_Word_Test:accolade',
        'Spot_The_Word_Test:methagenate',          'Spot_The_Word_Test:pleonasm',
        'Spot_The_Word_Test:drobble',        'Spot_The_Word_Test:infiltrate',
        'Spot_The_Word_Test:mystical',       'Spot_The_Word_Test:harreen',
        'Grit1',       'Grit2', 'Grit3', 'Grit4', 'Grit5', 'Grit6', 'Grit7',
        'Grit8',       'Location1',   'Location2',   'Location3',   'Location4',
        'Location5',   'Location6',   'Location7',   'Location8',   'Location9',
        'Location10']

#rename columns using the list that was just created
df.columns = df_cols


'''
RECODE VARIABLES, CREATE CATEGORICAL STRING VARIABLES, & AGGREGATE
ITEMS TO VARIABLE
LEVEL
RECODE VARIABLES, CREATE CATEGORICAL STRING VARIABLES, & AGGREGATE
```

```
ITEMS TO VARIABLE
LEVEL
RECODE VARIABLES, CREATE CATEGORICAL STRING VARIABLES, & AGGREGATE
ITEMS TO VARIABLE
LEVEL

take categorical variables which currently have integer values and map them
to their corresponding string variables easiest to create new columns in the
data set
'''
#create new sex column with string labels
df['sex_string'] = df.Sex.map({2:'F', 1:'M'})
df.sex_string.value_counts()#verify recode worked
'''
N = 847
M: 561 (66.23%); rounded to 2 decimal places
F: 286 (33.77%); rounded to 2 decimal places
'''
#recode sex to 0 and 1
df['Sex'] = df.Sex.map({1:0, 2:1})
df.Sex.describe() #verify recode worked

#recode race
df['race_string'] = df.Race.map({1:'Hispanic or Latino',
    2:'American Indian or or Alaska Native',
    3:'Asian', 4:'African American',
    5:'Native Hawaiian or Other Pacific Islander', 6:'White', 7:'Other'})

"race_string" in df #check that column was created
df.race_string.value_counts()#verify recode worked
'''
N = 847
White: 530 (62.57%)
Asian: 220 (25.97%)
Hispanic or Latino: 33 (3.90%)
Other: 32 (3.87%)
African American                          28 (3.31%)
Native Hawaiian or Other Pacific Islander      3 (0.35%)
American Indian or or Alaska Native          1 (0.12%)
'''

#recode Education
df['education_string'] = df.Education.map({1:'High School', 2:'Some College',
    3:'Trade, Vocational, or Technical', 4:'Associates', 5:'Bachelors',
    6:'Masters', 7:'Professional', 8:'Doctorate'})
```

```
"education_string" in df # check that column was created
df.education_string.value_counts()
'''
N = 847
Bachelors                          358 (42.27%)
Masters                           165 (19.48%)
Some College                          110 (12.99%)
Doctorate                          60 (7.08%)
Professional                        45 (5.31%)
High School                          42 (4.96%)
Associates                         36 (4.25%)
Trade, Vocational, or Technical     31 (3.66%)
'''

#recode industry
df['industry_string'] = df.Industry.map({1:'Automotive', 2:'Advertising',
    3:'Consulting Services', 4:'Education', 5:'Entertainment',
    6:'Financial Services', 7:'Government Services', 8:'Healthcare',
    9:'Human Resources', 10:'Information Technology', 11:'Marketing Sales',
    12:'Non-Profit', 13:'Pharmaceuticals', 14:'Public Relations',
    15:'Technical Services', 16:'Travel', 17:'Other'})

"industry_string" in df #check that column was created
df.industry_string.value_counts()
'''
N =  847
Information Technology    173 (20.43%)
Other                    143 (16.88%)
Education                  95 (11.22%)
Healthcare                 73 (8.62%)
Marketing Sales            61 (7.20%)
Financial Services         56 (6.61%)
Technical Services         44 (5.19%)
Government Services        36 (4.25%)
Consulting Services        34 (4.01%)
Non-Profit                 23 (2.72%)
Entertainment              21 (2.48%)
Advertising                20 (2.36%)
Automotive                 19 (2.24%)
Pharmaceuticals            17 (2.01%)
Human Resources            15 (1.77%)
Travel                    14 (1.65%)
Public Relations           3 (0.35%)
'''

#recode job role
```

```
df['job_level_string'] = df.Job_Level.map({1:'Intern', 2:'Entry Level',
    3:'Analyst / Associate', 4:'Project or Product Manager', 5:'Manager',
    6:'Senior Manager', 7:'Director', 8:'Director', 9:'Senior Director',
    10:'Vice President', 11:'Senior Vice President', 12:'C Level Executive',
    13:'President / CEO', 14:'Owner'})

"job_level_string" in df #check that column was created
df.job_level_string.value_counts()

'''
N = 847

Analyst / Associate           250 (29.52%)
Entry Level                   201 (23.73%)
Manager                       140 (16.53%)
Project or Product Manager    105 (12.40%)
Senior Manager                 39 (4.60%)
Intern                         36 (4.25%)
Owner                          33 (3.90%)
Director                       30 (3.54)
President / CEO                 4 (0.47%)
Senior Director                 4 (0.47%)
C Level Executive               2 (0.24%)
Vice President                  2 (0.24%)
Senior Vice President           1 (0.12%)
'''

#descriptives for average hours worked
df.Hours_Week.describe() #returns a values_counts() type result, these should be float numbers
type(df.Hours_Week) #check the data type for this column, it's a series object
df['hours'] = pd.to_numeric(df.Hours_Week, errors='coerce')
#convert the object to a float, by creating a new column
#drop the other column
df.drop(['Hours_Week'], axis =1, inplace=True)

#run descriptives on hours
df.hours.describe()
df.hours.median()
df.hours.mode()

'''
count    900.000000
mean      45.213611
std      100.274964
min        0.000000
25%       40.000000
```

```
50%        40.000000
75%        45.000000
max      3000.000000

We can see that there are some values that are not within an expected range
given that participants had been working full time (min of 32 hours), and there
are not 3,000 hours in a week, so we replace out of range values with the
mode/median.

Total cases = 54

'''
df.hours.replace(0, 40, inplace=True)
#since there are multiple let's switch how we use replace
df.replace({'hours': {0:40, 1:40, 2:40, 3:40, 4:40, 5:40, 6:40, 7:40, 8:40, 9:40,
                10:40, 15:40, 16:40, 20:40, 24:40, 25:40, 26:40, 28:40,
                30:40, 3000:40, 480:40, 150:40}}, inplace=True)

#re-run describe to verify that the descriptives look right
df.hours.describe()
'''
count    846.000000
mean      42.662825
std        7.659092
min       32.000000
25%       40.000000
50%       40.000000
75%       45.000000
max      100.000000
'''

#recode salary
df['salary_string'] = df.Salary.map({1:'10-20K', 2:'21-40K', 3:'41-60K',
    4:'61-80K', 5:'81-100K', 6:'101-149K', 7:'150K+'})

"salary_string" in df #check that column was created
df.salary_string.value_counts()

'''
N = 847
10-20K      283 (33.42%)
21-40K      273 (32.23%)
41-60K      148 (17.47%)
61-80K       69 (8.15%)
81-100K      36 (4.25%)
101-149K     22 (2.60%)
```

```
150K+       16 (1.89%)
'''

#recode age
df['age_string'] = df.Age.map({1:'18-24', 2:'25-34', 3:'35-44', 4:'45-55',
    5:'55-64', 6:'65+'})

"age_string" in df
df.age_string.value_counts()

'''
N = 847
25-34   466 (55.02%)
18-24   232 (27.39%)
35-44   103 (12.16%)
45-55    34 (4.01%)
55-64    11 (1.30%)
65+       1 (0.12%)
'''



'''We need to recode all of our Job Performance variables from their current
Likert 1-5 scale to a 0-4 scale, so we can properly create our job performance
variable and run diagnostics on items. To do this, we do vector addition (or
really subtraction) because we are subtracting 1 from every column.

We can either create a list of the columns and then write a for loop or do a
more elegant vector addition
'''
#changing using a loop, create a list of column headers then loop through and
#subtract 1
jp = ['Job_Performance1',
      'Job_Performance2',
      'Job_Performance3',
      'Job_Performance4',
      'Job_Performance5',
      'Job_Performance6',
      'Job_Performance7',
      'Job_Performance8',
      'Job_Performance9',
      'Job_Performance10',
      'Job_Performance11',
      'Job_Performance12',
      'Job_Performance13',
      'Job_Performance14',
      'Job_Performance15',
    'Job_Performance16',
    'Job_Performance17',
    'Job_Performance18']

#subtract 1 using a for loop
#for col in jp:
#    df[col] = df[col] -1

#vector addition
df[jp] = df[jp] -1

#verify that the range is now 0-4
df.Job_Performance1.describe()
'''
count    847.000000
mean       2.870130
std        1.047181
min        0.000000
25%        2.000000
50%        3.000000
75%        4.000000
max        4.000000
Name: Job_Performance1, dtype: float64
'''
df.Job_Performance18.describe()
'''
count    847.000000
mean       1.343566
std        1.208237
min        0.000000
25%        0.000000
50%        1.000000
75%        2.000000
max        4.000000
Name: Job_Performance18, dtype: float64
'''



'''
CREATE JOB PERFORMANCE VARIABLES OF TASK PERFROAMCNE, CONTEXTUAL
PERFORMANCE,
AND COUNTER PRODUCTIVE PERFORMANCE
'''
#create variables for TASK PERFORMANCE and look at descriptives for this variable
df['task_performance'] = ((df.Job_Performance1 + df.Job_Performance2 + df.Job_Performance3
+
                        df.Job_Performance4 + df.Job_Performance5)/5)
df.task_performance.isnull().sum()
df.task_performance.describe()
df.task_performance.median()
'''
count    847.00000
mean       2.91405
median     3.00000
std        0.77379
min        0.40000
25%        2.40000
50%        3.00000
75%        3.40000
max        4.00000
'''
#run cronbach's alpha (note: had to do this in SPSS)
CronbachAlpha(task)
0.87

#create variables for CONTEXTUAL PERFORMANCE and look at descriptives for this
variable
df['contextual_performance'] = ((df.Job_Performance6 + df.Job_Performance7 +
df.Job_Performance8 +
                        df.Job_Performance9 + df.Job_Performance10 + df.Job_Performance11 +
                        df.Job_Performance12 + df.Job_Performance13)/8)
df.contextual_performance.isnull().sum()
df.contextual_performance.describe()
df.contextual_performance.median()
'''
count    847.000000
mean       2.622639
median     2.625000
std        0.760560
min        0.125000
25%        2.125000
50%        2.625000
75%        3.125000
max        4.000000
'''
#run cronbach's alpha
CronbachAlpha(contextual)
0.85

#create variables for COUNTER-PRODUCTIVE PERFORMANCE and look at descriptives for
this variable
df['cwb'] = ((df.Job_Performance14 + df.Job_Performance15 + df.Job_Performance16 +
                         df.Job_Performance17 + df.Job_Performance18)/5)
df.cwb.isnull().sum()
df.cwb.describe()
df.cwb.median()
'''
count    847.000000
mean       1.246753
std        0.949349
min        0.000000
25%        0.600000
50%        1.000000
75%        1.800000
max        4.000000
'''
#run cronbahc's alpha:
CronbachAlpha(cwb)
0.87

'''
CREATE IMPRESSION MANAGEMENT VARIABLE
note: initially I created mean scaled scores, but the original manuscript detailing the creation of
this measure states that scores should be summed. I've checked both variable creation approaches
and
they do not change the relationship with LIWC pronoun categories, it only changes the values of
the
descriptive statistics reported
'''
#df['impression'] = ((df.Impression_Work1 + df.Impression_Work2 + df.Impression_Work3 +
#                     df.Impression_Work4 + df.Impression_Work5 + df.Impression_Work6 +
#                     df.Impression_Work7 + df.Impression_Work8 + df.Impression_Work9 +
#                     df.Impression_Work10)/10)
#
#df.impression.isnull().sum()
#df.impression.describe()
#df.impression.median()
'''
impression management, full variable
count    847.000000
mean       4.292798
median     4.300000
std        1.082532
min        1.000000
25%        3.700000
50%        4.300000
75%        5.000000
max        7.000000
```

```
'''
#run cronbahc's alpha
CronbachAlpha(impression)
0.84

df['impression_other'] = (df.Impression_Work1 + df.Impression_Work2 + df.Impression_Work3
+
                        df.Impression_Work4 + df.Impression_Work5)
df.impression_other.describe()
df.impression_other.median()
'''
count    847.000000
mean      16.345927
median    16.000000
std        7.596475
min        5.000000
25%       10.000000
50%       16.000000
75%       22.000000
max       35.000000
'''
#run cronbahc's alpha
CronbachAlpha(impression_other)
0.87

df['impression_self'] = (df.Impression_Work6 + df.Impression_Work7 + df.Impression_Work8 +
                       df.Impression_Work9 + df.Impression_Work10)
df.impression_self.describe()
df.impression_self.median()
'''
count    847.000000
mean      26.603306
median    28.000000
std        6.114038
min        5.000000
25%       23.000000
50%       28.000000
75%       31.000000
max       35.000000
'''
#run cronbahc's alpha
CronbachAlpha(impression_self)
0.84


'''
```

```
CREATE SPOT-THE-WORD TEST SCORE
'''
df['stw_score'] = df[["Spot_The_Word_Test:chariot", "Spot_The_Word_Test:lentil",
                "Spot_The_Word_Test:stamen", "Spot_The_Word_Test:comet",
                "Spot_The_Word_Test:pylon", "Spot_The_Word_Test:flannel",
                "Spot_The_Word_Test:fender", "Spot_The_Word_Test:joust",
                "Spot_The_Word_Test:mantis", "Spot_The_Word_Test:sterile",
                "Spot_The_Word_Test:monotheism", "Spot_The_Word_Test:stallion",
                "Spot_The_Word_Test:rictus", "Spot_The_Word_Test:byzantine",
                "Spot_The_Word_Test:monologue", "Spot_The_Word_Test:elegy",
                "Spot_The_Word_Test:malign", "Spot_The_Word_Test:gelding",
                "Spot_The_Word_Test:bulliner", "Spot_The_Word_Test:visage",
                "Spot_The_Word_Test:oratory", "Spot_The_Word_Test:meridian",
                "Spot_The_Word_Test:strumpet", "Spot_The_Word_Test:equine",
                "Spot_The_Word_Test:riposte", "Spot_The_Word_Test:valance",
                "Spot_The_Word_Test:introvert", "Spot_The_Word_Test:penumbra",
                "Spot_The_Word_Test:malinger", "Spot_The_Word_Test:gammon",
                "Spot_The_Word_Test:coracle", "Spot_The_Word_Test:paramour",
                "Spot_The_Word_Test:octaroon", "Spot_The_Word_Test:carnation",
                "Spot_The_Word_Test:agnostic", "Spot_The_Word_Test:plinth",
                "Spot_The_Word_Test:thole", "Spot_The_Word_Test:reform",
                "Spot_The_Word_Test:wraith", "Spot_The_Word_Test:pristine",
                "Spot_The_Word_Test:pauper", "Spot_The_Word_Test:baleen",
                "Spot_The_Word_Test:palindrome", "Spot_The_Word_Test:hedgehog",
                "Spot_The_Word_Test:ferret", "Spot_The_Word_Test:drumlin",
                "Spot_The_Word_Test:texture", "Spot_The_Word_Test:isomorphic",
                "Spot_The_Word_Test:vitriol", "Spot_The_Word_Test:farrago",
                "Spot_The_Word_Test:hermeneutic", "Spot_The_Word_Test:chaos",
                "Spot_The_Word_Test:devastate", "Spot_The_Word_Test:peremptory",
                "Spot_The_Word_Test:camera", "Spot_The_Word_Test:roster",
                "Spot_The_Word_Test:accolade", "Spot_The_Word_Test:pleonasm",
                "Spot_The_Word_Test:infiltrate",
"Spot_The_Word_Test:mystical"]].sum(axis=1)
df.stw_score.isnull().sum()
df.stw_score.describe()
df.stw_score.median()
'''
count    847.000000
mean      45.518300
median    49.000000
std       12.008836
min        0.000000
25%       44.000000
50%       49.000000
75%       52.000000
max       59.000000
```

```
alpha      0.951000
'''
#run cronbahc's alpha
0.87

'''
CREATE DUMMY VARIABLES
'''
#AGE
age_dummy = pd.get_dummies(df['age_string'], prefix='age') #create dummy variable dataframe
df1 = pd.concat([df, age_dummy], axis=1) #join dummy dataframe to original dataframe
df1.drop(['age_25-34'], inplace=True, axis=1)
#drop one of the dummy variables since it is redundent (k-1)
#here we drop the largest group, which is 25-34 year olds to make that our reference group

#SEX: already created since it is dichotomous and we recoded to 0 and 1 earlier

#RACE
race_dummy = pd.get_dummies(df1['race_string'], prefix='race') #create dummy variable
dataframe
df2 = pd.concat([df1, race_dummy], axis=1) #join dummy dataframe to original dataframe
df2.drop(['race_White'], inplace=True, axis=1)
#drop one of the dummy variables since it is redundent (k-1)
#here we drop race_white dummary variable, making whites our reference group

#INDUSTRY
industry_dummy = pd.get_dummies(df1['industry_string'], prefix='industry')
#create dummy variable dataframe
df3 = pd.concat([df2, industry_dummy], axis=1) #join dummy dataframe to original dataframe
df3.drop(['industry_Information Technology'], inplace=True, axis=1)
#drop one of the dummy variables since it is redundent (k-1)
#here we drop Information Technology dummary variable, making Information Technology our
reference group

#SALARY
salary_dummy = pd.get_dummies(df1['salary_string'], prefix='salary')
#create dummy variable dataframe
df4 = pd.concat([df3, salary_dummy], axis=1) #join dummy dataframe to original dataframe
df4.drop(['salary_21-40K'], inplace=True, axis=1)
#drop one of the dummy variables since it is redundent (k-1)
#here we drop salary_21-40K dummary variable, making 21-40K our reference group

#JOB ROLE
job_level_dummy = pd.get_dummies(df1['job_level_string'], prefix='job_level')
#create dummy variable dataframe
df5 = pd.concat([df4, job_level_dummy], axis=1) #join dummy dataframe to original dataframe
```

```
df5.drop(['job_level_Analyst / Associate'], inplace=True, axis=1)
#drop one of the dummy variables since it is redundent (k-1)
#here we drop salary_21-40K dummary variable, making 21-40K our reference group

#rename df5 to final
final = df5

'''
Read in both the final survey data and the text analylsis file generated by LIWC
'''
#cleaned up survey data, with dummy variables
df = pd.read_csv('dissertation_complete_847n_dummies.csv''', header=0, encoding='utf-8')

#text analytics file generated by liwc
dft =
pd.read_csv('C:\Users\joshuaw\Documents\PhD_Year_5\Data\liwc_results_all_resumes_1030_fi
les.csv',
                header=0, encoding='utf-8')

#join the two files on the "Response_ID", we do an inner join because we only want cases that
are in
#both the survey data and liwc data sets.
df = pd.merge(df, dft, how='inner', left_on='Response_ID', right_on='Response_ID')

#write the final, analysis ready file to a csv
df.to_csv("dissertation_complete_847n_dummies.csv", sep=',', encoding='utf-8', index=False,
header=True)
```

Appendix G

Various Functions of First-Person Plural Pronouns (e.g. “We”), Adapted from Pennebaker, 2011

The word “we” has at least five different functions.

You-and-I We

This is the inclusive “we.” It is an identification that a specific person and I are part of the same group. In other words, it indicates a shared identity. However, this can be slightly problematic. For example, I might think that you and I are in the same group, but you might not.

My-Friends-and-Not-You We

This form of we often occurs when talking with people about an event or experience that you shared but not with the people with whom you are speaking. For example, you might be relating a story to your coworker about how you and your grad school mates checked out a new whiskey bar in town. The “we” in that conversation is exclusionary; it refers to a different group, which does not include your coworker.

We-as-You We

This usage of “we” is actually cordially asking or telling someone else to do something. For example, during a meeting, I might say, “Can we please stop using buzz words like ‘machine learning’ and ‘big data’ without first establishing a common understanding of these words?”

My-Friends-and-Not-You We and We-as-You We and Power

The two prior functions of “we” are used more often by those higher in social status and power. For example, your boss’s boss is more likely to use these forms of “we” than your direct report. Your boss’s boss is also more likely to talk more loudly than you, interrupt you, stand or sit close to you, and take up more physical space than you.

We-as-I We

This is the royal “we.” It is used to diffuse responsibility and imply support from others who may or may not exist. For example, a reviewer might say, “We felt the theory you presented was absurdly outrageous. You might as well have theorized that unicorns and time travel are possible.” The only person of this opinion was the particular reviewer. (Note: this example sentence was inspired by true events but does not reflect the exact phrasing by any reviewer).