Toward the prediction of narcissistic behavior at work

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ABSTRACT

Evidence suggests that employees’ narcissistic behaviors have a variety of negative implications, such as increased counterproductive work behaviors. Unfortunately, the most common measure of narcissism, the Narcissistic Personality Inventory, has a variety of limitations in work contexts. In this study, we discuss the development and validation of a situational judgment test (SJT) to predict employee narcissism. Results using various machine learning procedures suggest that the SJT predicts scores on the narcissism dimension of the PDQ-4, a clinical assessment of narcissism.

**Toward the prediction of narcissistic behavior at work**

Narcissism, which is characterized by feelings of self-importance, self-entitlement, lack of empathy and concern for others, and resistance to criticism (e.g., Tamborski & Brown, 2011), has a variety of negative impacts in the workplace. Though narcissism can be conceptualized as a personality disorder, individuals can also have subclinical narcissistic tendencies. Individuals with these tendencies have behaviors, beliefs, and attitudes that are similar to those with the personality disorder of narcissism, but their tendencies are less severe and perhaps less frequently displayed. In this paper, we focus on individuals displaying subclinical levels of narcissism and, occasionally, refer to these individuals as *narcissists*.

Narcissists have elevated self-esteem and seek affirmation of their self-perceived status from others. To maintain their perceptions of superiority, they often engage in attention-seeking behavior and seek dominance in social situations. These characteristics combined with deficits in empathy, make displaying these narcissistic tendencies problematic at work. Indeed, narcissistic behavior may be particularly destructive when they are assigned to work teams and undermine collaboration (Grijalva, et al., 2020). Unfortunately, narcissists often do well in job interviews in part because they appear charming and willing to talk about themselves (Back et al., 2010; Paulhus, et al., 2013). In addition, they often assume positions of leadership (Nevicka, et al., 2011), where they can have a variety of negative effects on their direct reports (Wang et al., 2021 Xiao et al., 2018).

Given the effect of individuals’ displaying narcissistic tendencies at work, it may be desirable to identify individuals who are likely to display these tendencies and screen them out during the selection process or place them into roles where the effect of displaying narcissistic tendencies is less likely to have negative effect on the work environment. Indeed, evidence suggests that narcissism levels are higher now than they have been in the past (Twenge et al., 2008), which highlights the need to identify individuals with these tendencies.

The most common measure of narcissism used in work settings is the Narcissistic Personality Inventory (NPI; Raskin & Hall, 1979; Raskin & Terry, 1988). The NPI was originally developed (and is usually administered) as a forced choice assessment. In forced choice assessments, individuals are presented with a series of statement pairs and must select the statement that most clearly characterizes themselves. Although evidence suggests that forced choice assessments of personality are less susceptible to faking than traditional personality assessments using Likert-type scales (Cao & Drasgow, 2019), there is little evidence specifically related to the NPI that examines its susceptibility to faking. Indeed, Cao and Drasgow’s (2019) discussion largely focuses on personality traits related to the Big 5. Yet, individuals with narcissistic tendencies may be more likely engage in socially desirable responding (e.g., Maaß & Ziegler, 2017).

Faking is problematic in selection contexts, as many applicants are highly motivated to engage in self-presentation to make themselves look more appealing to potential employers (Jeong et al., 2017). Faking, by rating response options according to how one believes the organization wants one to respond rather than honestly, may influence the accuracy of hiring decisions made on the basis of fakeable assessments (e.g., Berry & Sacket, 2009; Komar et al., 2008). Therefore, if an organization wants to use a measure of narcissism as part of a selection battery, it would be desirable to have a measure that is less susceptive to faking.

Even if the forced choice NPI is as resistant to faking as forced choice assessments of the Big 5 appear to be, its use in a selection context faces other challenges. Namely, that personality measures, especially forced choice ones, tend to elicit negative reactions from applicants (Converse et al., 2008). This isn’t particularly surprising, as many of the items on these assessments do not appear on their face to measure work-relevant behavioral tendencies. For instance, one item on the NPI asks respondents to choose which of the two following statements most closely matches their feelings about themselves:

“I wish somebody would someday writing my biography.

I don’t like people to pry into my life for any reason” (Raskin & Terry, 1988).

Though I/O psychologists understand that this item may predict work relevant behaviors, many applicants may question whether this item has anything to do with their fitness for a job. Compounding this issue is that some applicants may react negatively to having to choose one of these options if they feel that both, or neither, adequately characterize their feelings about themselves. Meta-analytic evidence suggests that if applicants feel that the selection process is not job related or does not provide them with the chance to show off their fitness for the job, they will be less likely to accept the job should it be offered (Chapman et al., 2005). Furthermore, if applicants perceive that an assessment is unfair (for instance, if they feel forced to choose an option that they feel does not adequately characterize themselves), they may be less likely to recommend the organization to others, and, if they do accept the job, are likely to have poorer job performance than if they had perceived the selection process as fair (McCarthy et al., 2017). Thus, it is important for organizations to consider not just how predictive an assessment is of important work outcomes and how susceptible an assessment is to faking, but also how applicants are likely to react to the assessment.

We propose that situational judgment tests (SJTs) are particularly well-suited for assessing narcissism and addressing both of the aforementioned issues. SJTs can take a variety of forms, but, generally, respondents are presented with a scenario and then several potential responses one may have to that scenario. Respondents are then asked to either indicate how likely they are to engage in the potential options listed (behavioral tendency instructions) or how effective each of the potential options would be to address the issue in the scenario (knowledge instructions) (e.g., McDaniel et al., 2007; Nguyen et al., 2005). Figure 1 is an example of an SJT scenario with response options using knowledge instructions.

SJTs are often used to assess interpersonal and other ‘softskills,’ which make them particularly well-suited to assess narcissism as issues related to narcissistic tendencies in the workplace primarily affect interpersonal interactions at work. Furthermore, evidence suggests that SJTs with knowledge instructions are largely resilient to faking (Nguyen et al., 2005; Weekley et al., 2004). Furthermore, as can be seen in Figure 1, SJTs are inherently ‘situational’ meaning that they can be written with a particular context in mind. This means that applicants are more likely to feel that the assessment is fair, given that scenarios can be written that are highly realistic and relevant to the workplace. Furthermore, evidence from past context-specific personality assessments suggest that these assessments are more predictive of work outcomes than context-free personality assessments (Shaffer & Postlethwaite, 2012).

Given this, the goal of this study is to develop an SJT that can be used to assess narcissistic tendencies in the workplace. As the first step in validating this measure, we attempt to demonstrate the extent that SJT items can predict a clinical self-report measure of narcissism in a non-clinical setting. We also evaluate whether the predictive capacity of the SJT is stable across time by evaluating it in two different samples, collected several years apart. As part of these assessments, we utilize ten different machine learning methods to evaluate how well the SJT predicts scores on the clinical assessment of narcissism and compare their results.

**Method**

**Sample**

Data were collected from two samples. Sample 1 consisted of 1,651 respondents, some of whom were undergraduates in a southeastern university and who completed the measures as part of a psychology department course requirement. The remaining respondents were drawn from adult U.S. residents through the Amazon Mechanical Turk Platform and were paid for their participation. These data were collected in the years 2015-2016. Respondents from this sample were mostly white (58.3%) and female (68.7%). The mean age was 26.9 (*SD* = 10.7).

Sample 2 was collected in 2020-2021 and consisted of 325 respondents from two universities in the southeast who were paid for their participation. The majority of these respondents were graduate students. The remaining respondents were non-graduate student staff members, primarily administrative assistants. This sample was less diverse than Sample 1 (78% white; 73% female), but was, on average, older (*M* = 31.5, *SD* = 9.3) and currently employed (71.1%).

**Measures**

 **Situational Judgment Test.** A 23-scenario SJT with 163 scorable response options was developed and administered in 2015 and 2016. To reduce the likelihood of faking, knowledge response options were used (see Figure 1 for an example). A second version of the SJT was developed, based on an analysis of the 163 item SJT. SJT response options with little predictive value were dropped. New items were written in hopes of improving prediction for some personality disorder scales. The second version had 20 scenarios with 100 scorable response options. The study is based on the 45 scorable response options common to both versions of the SJT.

 **Personality Disturbance Questionnaire-4 (PDQ-4).** To establish the construct validity of the SJT, respondents were also asked to complete the PDQ-4 (Hyler, 1994). The PDQ-4 is a clinical assessment of 12 different personality disorders, including narcissism. Due to IRB restrictions, one of the 12 disorders (antisocial personality disorder) was not assessed. The focus of this study was on whether scores on the SJT predict scores on the narcissism dimension of the PDQ-4.

**Analyses**

To determine how well scores on the SJT predict scores on the narcissism dimension of the PDQ-4, we used 10 different machine learning procedures. Table 1 includes these procedures, as well as links to resources that provide overviews of each procedure. For additional information about machine learning, we recommend Kuhn and Johnson (2013, 6th printing or later, which fixed errors in the original book manuscript), which appears to be the most comprehensible book, and which provides R code for many machine learning models.

 All the machine learning methods applied in our analysis use one sample to develop a scoring algorithm. This sample is referred to as a *training sample*. The newly developed algorithm is then applied to a different dataset, termed a *test sample*, to evaluate the degree of prediction. In I/O psychology, such a test sample is often called a *cross-validation sample*. The 1,651 respondents from Sample 1 were randomly assigned to either the training sample (N = 1,000) or the test sample (N = 651). All 325 respondents in Sample 2 were assigned to a second test sample. The training sample of the 2015-2016 data collection was used to create scoring algorithms for each of the 10 machine learning procedures. The resulting 10 algorithms were then used to generate predictions of narcissism for the two test samples, one collected in 2015-2016 and one collected in 2021-2022.

**Results**

Table 2 shows the results of training sample predictions for the 2015-2016 test sample and for the 2021-2022 test sample. They are expressed as correlation coefficients (i.e., validity coefficients) for each of the 10 machine learning procedures. A comparison of the two samples shows very similar magnitude validity coefficients. The *difference in r* (Δ*r*) variable was calculated by subtracting the 2021-2022 test validity from 2015-2016 test validity. There were no differences in validity for two machine learning approaches (i.e., Random Forest, Forward Stepwise Regression). The 2021-2022 test validities were higher for two machine learning approaches (i.e., LASSO Regression and Stochastic Gradient Boosted Regression Trees). In the remaining six machine learning approaches, the 2015-2016 test validities were slightly higher than 2021-2022 test validities with differences ranging from .01 to .04. Random sampling error is likely one cause of the small differences. It is also possible that differences in the composition of the samples may have contributed to the small differences.

Interestingly, the two test samples differed in their scores on the narcissism dimension of the PDQ. Specifically, Sample 1 (comprised of Mturkers and undergraduate students), displayed higher narcissism scores (*M* = 2.73, *SD* = 1.83) than Sample 2 (consisting of mostly graduate students; *M* = 2.01, *SD* = 1.49; Cohen’s *d* = .42). Regardless of the potential reason for this difference, the cross-validities are substantially similar. Thus, overall, results indicated that the SJT predicted narcissism well in both samples, regardless of the specific machine learning procedure used, and despite differing amounts of narcissism between the samples.

In addition to examining the machine learning predictions individually, we also examined combinations of these procedures through two different stepwise regressions[[1]](#footnote-1). The two methods yielded identical results. For the 2015-2016 data, the two stepwise regressions yielded adjusted multiple *R* of .36. For the 2020-2021 data the statistic was .35. In sum, the machine learning scoring of the 45 SJT responses in predicting narcissism are relatively high for uncorrected validity coefficients. The internal consistency reliability of the criterion of narcissism (i.e., the PDQ-4 scale) was .57 for test sample 1 (2015-2016) and .46 in test sample 2 (2021-2022). The low values are likely due in part to the application of this clinical scale in non-clinical samples, which should reduce the variance of scores and the internal consistency reliability. If one corrected the observed correlation for the measurement error in the clinical narcissism scale, the validity coefficient for the adjusted multiple *R* becomes .47 for the test sample 1and .52 for test sample 2. Thus, the validity coefficients in the prediction of narcissism from the 45 SJT response options is larger than anticipated. Taken together, our results suggest that the work oriented SJT predicts narcissism well.

**Discussion**

 The percent of the population of working adults who have narcissistic tendencies is not precisely known. What is known is that such tendencies are not uncommon. Indeed, the frequency of sub-clinical narcissism appears to be increasing over time (Twenge et al., 2008). Furthermore, these tendencies cause a variety of problems in the workplace. Though there is a measure of narcissism, the NPI, that has been used extensively in work-related research settings, its usefulness in a selection context presents challenges. For example, individuals with narcissistic tendencies may be more likely than individuals with fewer of these tendencies to attempt to ‘fake good’ on selection assessments (Maaß & Ziegler, 2017). Although forced choice assessments may generally be more resilient to faking than traditional Likert-type scale personality assessments, evidence related to faking specifically on the NPI is lacking. Furthermore, forced choice assessments, like the NPI, are more likely to elicit negative reactions from applicant test takers than other types of assessments that are more clearly work-related.

In contrast, Weekley et al. (2004) found SJTs have higher means for incumbents than applicants suggesting the faking resilience of SJTs. The opposite was true of the personality measures. SJTs are particularly resilient to faking when they are developed using knowledge instructions. Furthermore, as SJTs are inherently situational, they are likely to elicit more positive reactions from applicants compared to a forced choice personality assessment. Therefore, the goal of this study was to develop an SJT that could predict narcissism. Results suggested that, across two separate samples collected several years apart, scores on the SJT predict scores on the narcissism dimension of the PDQ-4 reasonably well. This supports the notion that SJTs predicting narcissism may be helpful in a selection context.

That being said, at this point, we were unable to assess whether the SJT predicts important undesirable workplace outcomes. If the SJT is going to be used as part of a selection battery (or, indeed in any workplace setting), additional data would need to be collected. For instance, an employer could administer the items to applicants, allow for a passage of time for applicants to become employees beyond their “honeymoon period”, and choose a criterion that, in part, assesses that extent to which employees, tested as applicants with the SJT, engage in narcissism-related behaviors at work. Collecting additional data in a workplace setting would also potentially result in a more diverse sample, which would help with the generalizability of our results.

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**Table 1.** Machine learning methods employed

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| **Method** | **References to helpful introductions to the machine learning method** |
| eXtreme Gradient Boosting (xgboost) | <https://towardsdatascience.com/a-beginners-guide-to-xgboost-87f5d4c30ed7> |
| Elastic Net Regression | <https://machinelearningcompass.com/machine_learning_models/elastic_net_regression/> |
| Random Forest | <https://careerfoundry.com/en/blog/data-analytics/what-is-random-forest/> |
| OLS regression | <https://medium.com/analytics-vidhya/machine-learning-101-linear-regression-using-the-ols-method-299808eab233> |
| Forward Stepwise Regression | <https://deepai.org/publication/stepwise-regression-for-unsupervised-learning> |
| LASSO regression Least Angle Regression (LARS) | <https://machinelearningcompass.com/machine_learning_models/lasso_regression/> |
| Principal Components Regression | <https://towardsdatascience.com/using-principal-component-analysis-pca-for-machine-learning-b6e803f5bf1e> |
| Partial Least Squares Regression | <https://towardsdatascience.com/partial-least-squares-f4e6714452a> |
| Stochastic Gradient Boosted Regression Tree | <https://www.machinelearningplus.com/machine-learning/an-introduction-to-gradient-boosting-decision-trees/> |
| Support Vector Machine - Radial Basis Function | <https://www.geeksforgeeks.org/introduction-to-support-vector-machines-svm/> |

*Note.* In our analyses, all methods used 5-fold cross-validation, conducted 10 times. Also, to reduce the possibility of overfitting, we used the *oneSE* rule which selects simpler models based on one standard error away from the optimal model.

**Table 2.** Validity of various machine learning predictions of a clinical narcissism measure

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| **Machine learning method** | **2015-2016** | **2021-2022** | **Δ*r*** |
| eXtreme Gradient Boosting (xgboost) | .31 | .29 | .02 |
| Elastic Net Regression | .34 | .32 | .02 |
| Random Forest | .32 | .32 | .00 |
| OLS regression | .31 | .26 | .05 |
| Forward Stepwise Regression | .34 | .34 | .00 |
| LASSO regression Least Angle Regression (LARS) | .33 | .34 | -.01 |
| Principal Components Regression | .35 | .31 | .04 |
| Partial Least Squares Regression | .35 | .31 | .04 |
| Stochastic Gradient Boosted Regression Tree | .33 | .33 | -.01 |
| Support Vector Machine - Radial Basis Function | .34 | .31 | .03 |
| *Note*. Δ*r* = Difference in *r*. The calculation of the difference in *r* used all available decimal places. The values in this table were then rounded to two decimal places.  |

**Figure 1.** Sample SJT scenario with responses



1. One stepwise regression procedure was from the R MASS package and used AIC comparisons to determine the best set of predictors. The second stepwise procedure was from the R caret package and selected the optimal set of predictors use cross-validity in 10 subsets of the data. Both stepwise regression procedures permitted the removal of predictors added in an earlier step. [↑](#footnote-ref-1)