Weight No More!

Strategies for Estimating and Communicating Relative Weights

Weight No More: Symposium Info

- **Comparison of Dominance and Relative Weights: An Applied Examination**
  - Ori Shewach, Matthew Reeder, Michael Ingerick (HumRRO)

- **Dominance Analysis: An Open-Source, Interactive, Web-Based R Shiny Tool**
  - Leo Alexander (Rice University), Michael Braun (DePaul University), Frederick Oswald (Rice University), Patrick Converse (Florida Institute of Technology)

- **Dominance Analysis as a Tool to Communicate Predictor Importance**
  - Charlene Zhang (University of Minnesota – Twin Cities), Sean Robson & Maria Lytell (RAND Corporation)

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Introduction

- This symposium demonstrates when and how relative importance methods can be advantageous for interpreting and communicating variable importance

- Relative importance analysis is a common method of assessing relative strength of predictors on criteria in organizational settings

- Relative importance = proportionate contribution that each individual predictor makes to the regression model R^2 (Hoffman, 1962)

- When predictors are correlated, interpretation of regression weights as indices of predictor importance may lead to incorrect conclusions
  - Regression weights were not designed to quantify predictor importance

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Introduction

- Shewach, Reeder, and Ingerick systematically compare two main methods of conducting relative importance analysis – dominance analysis (DA) and relative weights analysis (RWA)

- Alexander, Braun, Oswald, and Converse examine effects of sampling error and measurement error on DA estimates. They introduce a user-friendly, interactive, web-based tool that estimates effects of sampling error and unreliability on DA estimates

- Zhang, Robson, and Lytell demonstrate the value of relative importance analysis, specifically in communicating and visualizing results to non-technical audiences (e.g., policy makers, organizational management)

Comparison of Dominance and Relative Weights:
An Applied Examination

SIOP VIRTUAL 2020

Presenters: Ori Shewach, HumRRO
Matt Reeder, HumRRO
Michael Ingerick, HumRRO

June 2020

Introduction

- Relative weights analysis (RWA; Hoffman, 1960; Johnson, 2000) and dominance analysis (DA; Budescu, 1993) are prominent methods used to conduct relative importance analysis

- Conceptually similar methods – both quantify proportion contribution towards R^2 for individual predictors

- DA estimates incremental R^2 contribution for each predictor across all possible submodels involving that predictor

- RWA transforms correlated predictor variables into orthogonal variables, which are then used to calculate relative importance

Relative Weights Analysis

- Thomas et al. (2014) critique Johnson's (2000) relative weights derivation
  - Authors note use of squared simple correlations during one step, which they argue prevents interpretation of relative weights as a variable importance metric
- However, RWA remains a popular technique in organizational research
- One reason for RWA's popularity is because it is less computationally demanding than DA
  - Modern computing power makes DA feasible in most datasets
  - Yet, there are cases involving large data or many predictors where RWA is more feasible than DA

Present Study

- Research finds small differences (<2%) when comparing RWA and DA
  - Greater predictor intercorrelations produce greater RWA – DA discrepancies (Johnson, 2000; LeBreton, Ployhart, & Ladd, 2004)
- However, most past RWA-DA comparisons used clean, simulated data, under experimentally manipulated conditions
- Research Question: How closely does RWA approximate DA with “data in the wild,” collected from real-world, organizational settings and using conventional validation study designs?
- Military training data containing aptitude, biodata, and motivation predictors with training performance criteria
- This study compares RWA and DA on two features not examined in previous research: (1) regression model type (logistic versus linear) and (2) sample size

Method: Sample

- **Sample**: *N* = 1,360 foreign language trainees from courses in nine languages
  - Within-language sample size ranged from *N* = 92 – 282
- **Criteria:** training course GPA, language proficiency test scores, two binary outcomes indicating if trainee met course standards (i.e., passed)
- **Predictors:** self-reported motivation, prior language exposure, Defense Language Aptitude Battery scores, and seven ASVAB subtest scores
- **Predictive design:** predictor data collected pre-training, criterion data collected during or near completion of training
- Data collected 2011 - 2018

Method: Analytic Approach

- Simulation was used to increase generalizability
  - Simulated 900 datasets → 100 per language, each consisting of original data's sample size ("sample data")
  - Simulations sought to reproduce observed data's structure (*M*, *SD*, skew, intercorrelations)
  - Each dataset represents one "draw" from the observed data
  - Also simulated nine large *N* datasets drawn from the original nine, with *N* = 10,000 ("population data")

- All analyses conducted in *R* using *dominanceanalysis* (Navarette & Soares, 2019) and *SimMultiCorrData* (Fialkowski, 2019) R packages

- Used R code downloaded from Tonidandel and LeBreton's (2015) online application for RWA

Dominance vs. Relative Weight Comparison

	Population Data (9 Samples, *N* per sample = 10,000)					
Criterion	**Mean Abs. Weight Difference**	***SD* Weight Difference**	**% Perfect Rank-Order Agreement**	**Mean Kendall's Tau**	***SD* Kendall's Tau**	**Mean R^2**
Course GPA	.39	.60	88.8%	.98	.02	.24
Training Prof. – Listening	.50	.70	84.4%	.96	.05	.19
Training Prof. – Reading	.46	.62	82.2%	.95	.06	.24
Training Prof. – Speaking	.34	.48	84.4%	.96	.05	.14
Met Course Standards – 1*	.73	1.08	80.0%	.94	.05	.15
Met Course Standards – 2*	.84	1.28	75.6%	.94	.04	.15

* = dichotomous criterion, logistic regression used

Dominance vs. Relative Weight Comparison

	Sample Data (900 Samples, *N* = 92 - 282)					
Criterion	**Mean Abs. Weight Difference**	***SD* Weight Difference**	**% Perfect Rank-Order Agreement**	**Mean Kendall's Tau**	***SD* Kendall's Tau**	**Mean R^2**
Course GPA	.40	.61	81.1%	.95	.05	.23
Training Prof. – Listening	.50	.71	79.4%	.94	.05	.18
Training Prof. – Reading	.46	.63	81.3%	.95	.04	.23
Training Prof. – Speaking	.36	.52	82.6%	.96	.05	.14
Met Course Standards – 1*	1.05	1.80	68.8%	.91	.08	.16
Met Course Standards – 2*	1.10	1.85	67.0%	.91	.08	.17

* = dichotomous criterion, logistic regression used

Table Metric Details

- Mean Abs. Weight Difference = dominance weight – relative weight (both in percent metric), absolute value, averaged across all predictors and samples

- *SD* Weight Difference = standard deviation of the DA-RWA weight difference, averaged across all predictors and samples

- % Perfect Rank-Order Agreement = the percentage of samples where the rank-order of the predictors' relative and dominance weights matched perfectly, across all samples

- Mean/*SD* Kendall's Tau = mean and standard deviation of the DA-RWA rank-order correlation across all samples

- Mean R^2 = mean multiple R^2 value from regression model, corrected for multivariate range restriction

Results

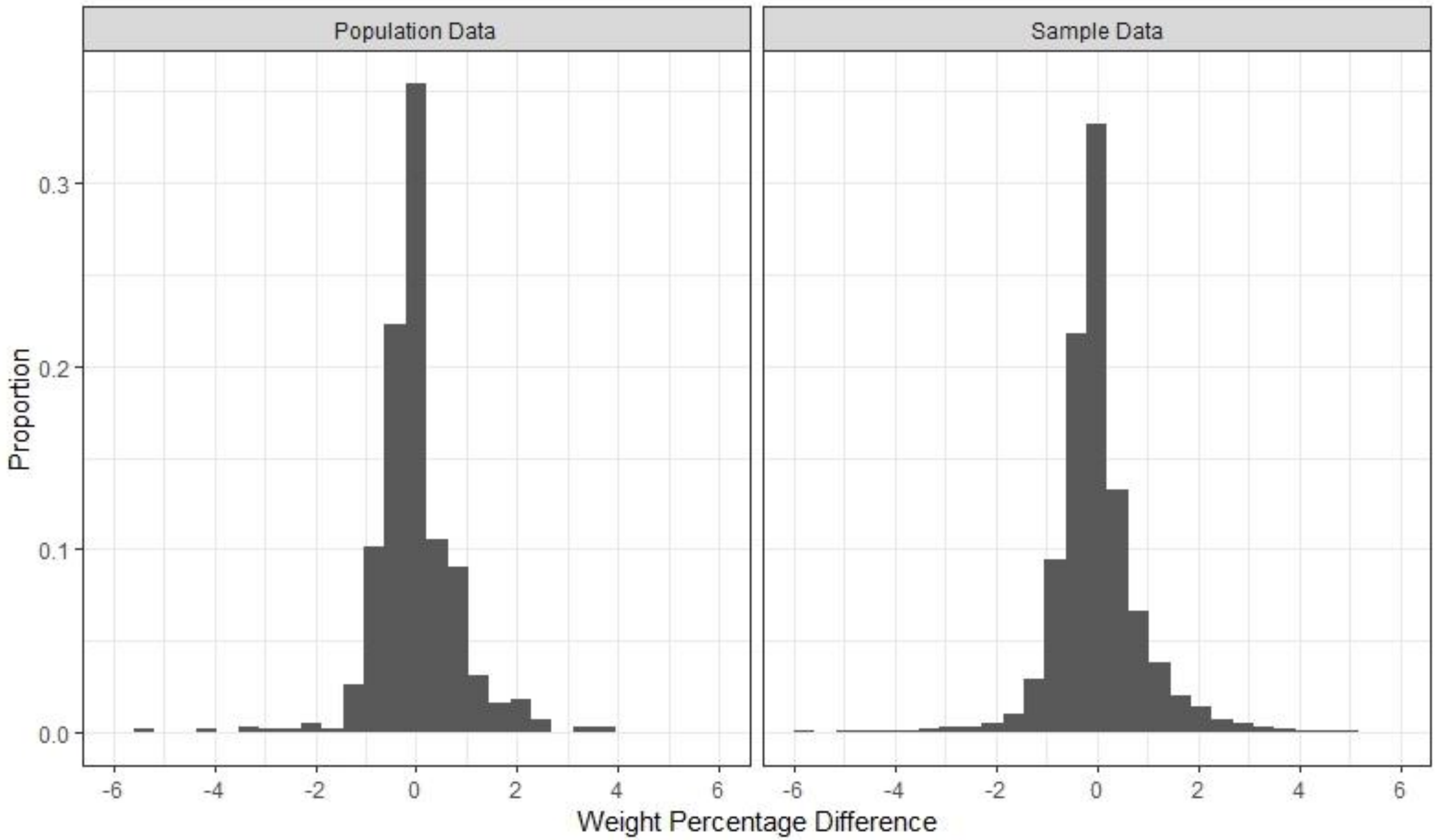
- Vast majority of cases show dominance and relative weights only differ trivially

- Weight difference distributions almost entirely < 2%
  - In line with Johnson's (2000) comparative findings

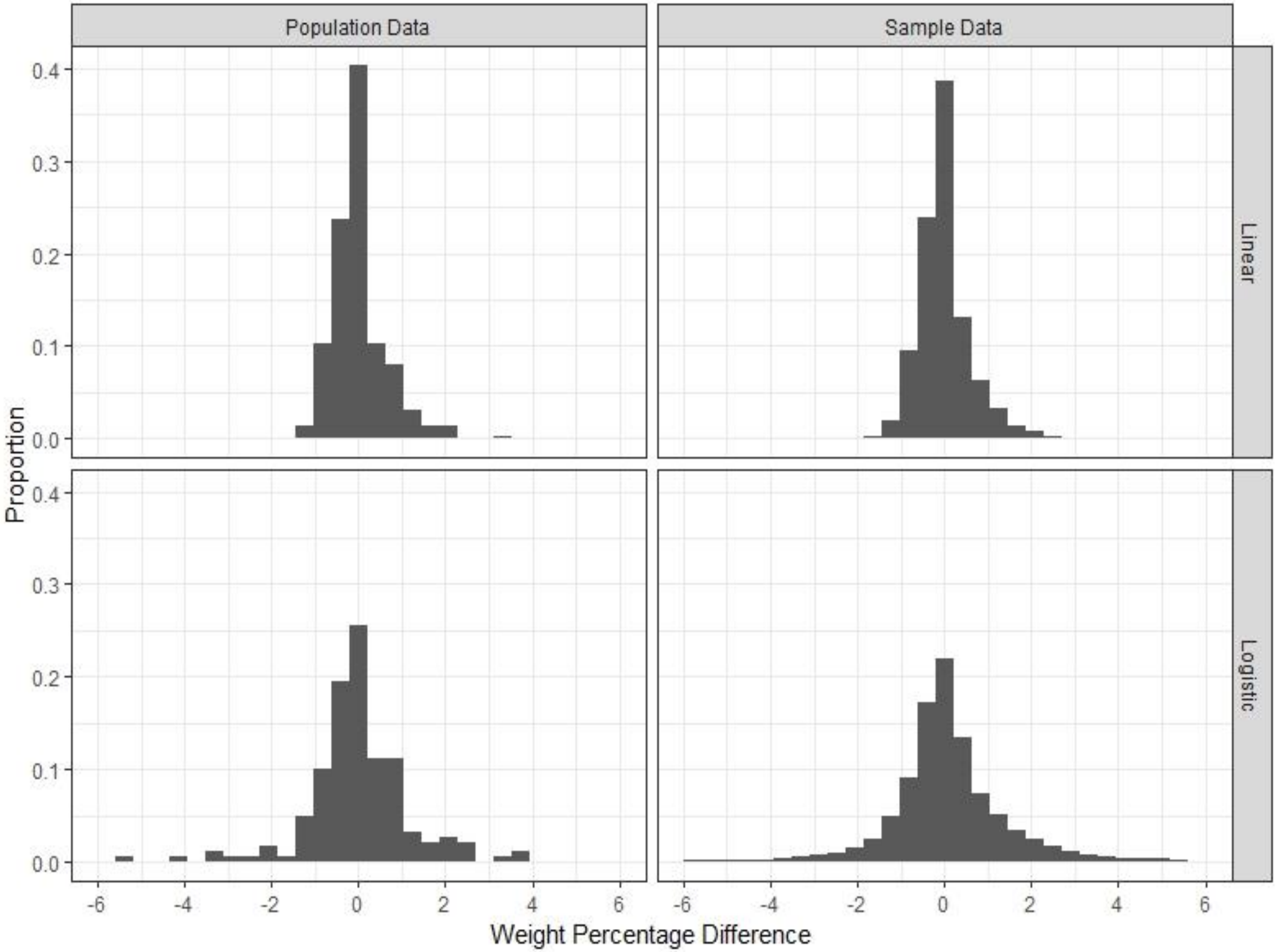
- High agreement between rank-orders of predictors
  - High Kendall's Tau values
  - Perfect rank-order agreement > 80% of the time

- Figures further illustrate small differences in weight difference distributions

Results


Population Data
Sample Data
Proportion
0.0
0.1
0.2
0.3
-6
-4
-2
0
2
4
6
Weight Percentage Difference

Results



Population Data
Sample Data
Linear
Logistic
Proportion
0.0
0.1
0.2
0.3
0.4
-6
-4
-2
0
2
4
6
Weight Percentage Difference

Results

- Logistic regression models showed greater RWA - DA differences than linear models
  - The two logistic criteria had substantially different base rates but were highly correlated. Yet, two showed similar weight differences

- Examined cases with lower RWA – DA agreement
  - In many lower agreement cases, 1 – 2 predictors accounted for most of the weight %’s, while the two weighting schemes only reordered predictors with very small weights
  - Further inspection revealed that when rank-order differs, differentially-ranked predictors almost always displayed low absolute magnitude differences

Conclusions

- Overall, differences between RWA and DA were small and not consequential

- Logistic regression models showed lower RWA – DA convergence than linear regression models
  - However, differences were typically quite small in absolute magnitude
  - More importantly, differences did not change substantive conclusions about relative importance

- Accordingly, continued use of RWA in practical contexts should consider the magnitude of weights in addition to purely rank-ordering of predictors

Manuscript available upon request, contact Ori (oshewach@humrro.org)

Questions?

Email oshewach@humrro.org

Dominance Analysis

An Open-Source, Interactive, Web-Based R Shiny Tool

Leo Alexander III
Rice University

Michael T. Braun
DePaul University

Frederick L. Oswald
Rice University

Patrick D. Converse
Florida Institute of Technology

Overview

In this presentation, I will:

- Describe relative importance analysis, and briefly compare the two most common relative importance analyses

- Discuss the accuracy of relative importance weights

- Explore how relative importance statistics are commonly reported

- Provide a brief demonstration of our Dominance Weights Tool

Relative Importance Analysis

- *Relative importance analysis* encompasses a group of statistical techniques used to determine which predictors in a multiple linear regression explain the most variance in a criterion.

- Currently, *dominance analysis* (DA: Budescu, 1993) and *relative weight analysis* (RWA: Johnson, 2000) are the most popular relative importance analysis methods found in published organizational research.

RWA vs DA

- RWA and DA typically produce very similar results (e.g., Budescu & Azen, 2004; LeBreton, Ployhart, & Ladd, 2004; LeBreton & Tonidandel, 2008).
- DA is currently the recommended method, because RWA has been found to be fundamentally flawed mathematically (Thomas, Zumbo, Kwan, & Schweitzer, 2014).
- DA provides a more statistically well-grounded method for partitioning the total variance in a criterion explained by a regression model into portions explained by each predictor.

Accuracy of Relative Weights

- *Sampling error variance* and *measurement error variance* add noise and bias, respectively, to regression parameter estimates (e.g., Cohen, Cohen, West, & Aiken, 2003).
- Both decrease the interpretability and generalizability of regression coefficients (e.g., Bonett & Wright, 2011; Schmidt, 1971) and the relative importance weights based on them.
- In examining RWA results, Johnson (2004) demonstrated the negative effects of sampling error variance, and then of measurement error variance, in two separate simulations.
- Thus, omitting confidence intervals in the reporting of relative importance analysis results may negatively affect their accuracy and interpretation (Azen & Budescu, 2003; Braun, Converse, & Oswald, 2019; Johnson, 2004).

Reporting Relative Weight Statistics

- A PsycINFO search for articles published in 2018, using the terms "dominance analysis," "dominance analyses," "relative weight," and "relative weights" resulted in 13 articles across a wide variety of research domains.

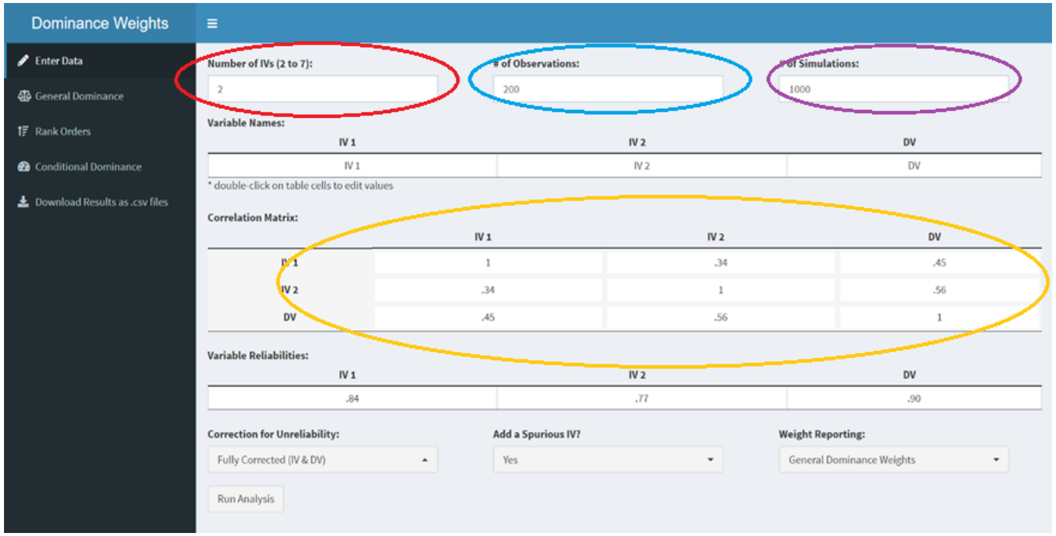
- Of these articles, all reported the magnitude and ranking of the relative importance weights; however, most of these articles did not report confidence intervals or any other indication of inaccuracy of the relative importance weights and their ranks.

An R Shiny Dominance Weights Tool

- We created the *Dominance Weights Tool* to aid researchers and practitioners in better reporting and interpreting relative importance statistics.
- The *Dominance Weights Tool* is an open-source, interactive, web-based application using R (R Core Team, 2018) and R Shiny (Chang, Cheng, Allaire, Xie & McPherson, 2019).
- The tool helps users generate and interpret output from either DA or RWA.
- We recommend the use of DA, but the inclusion of RWA may aid in the interpretation of results previously reported in the literature.
- Assuming a multivariate normal distribution, the tool takes a correlation matrix as input and returns bootstrap estimates of the magnitude of predictor weights and their accuracy to help understand the distinctiveness and statistical significance of those weights.

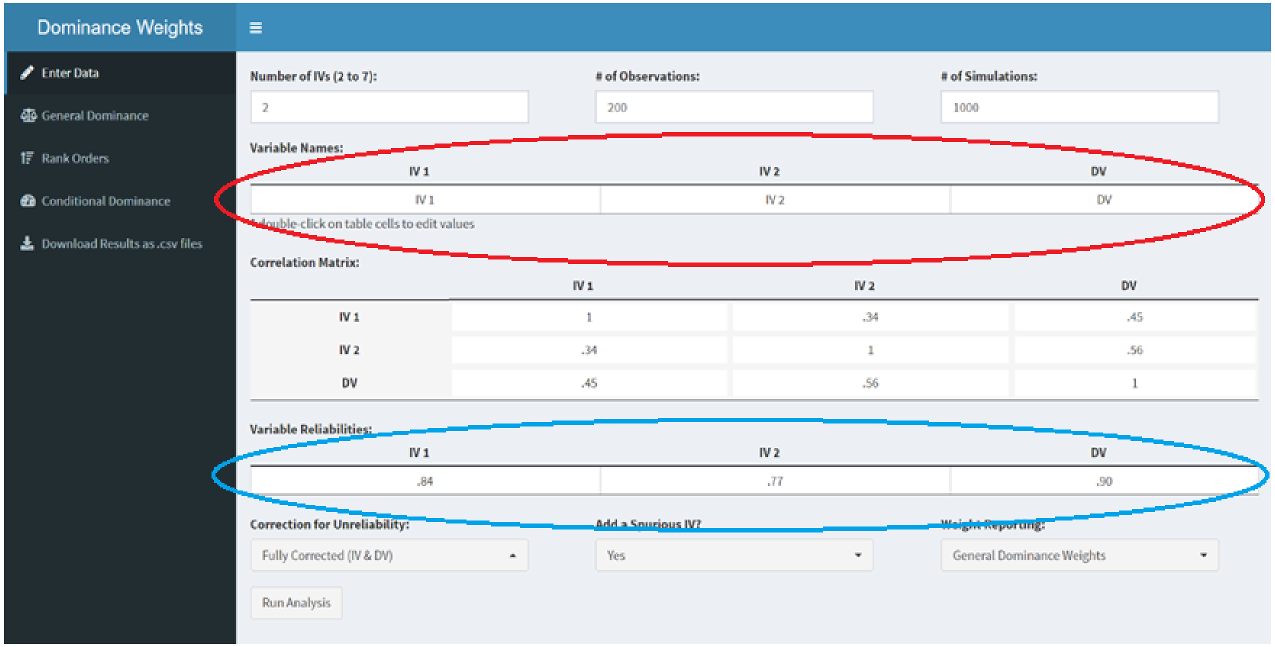
Dominance Weights Tool Demo

First, on the “Enter Data” screen, select the number of IVs to include in the correlation matrix, the number of observations on each variable, and the number of simulations to conduct. Then, enter the correlation matrix.



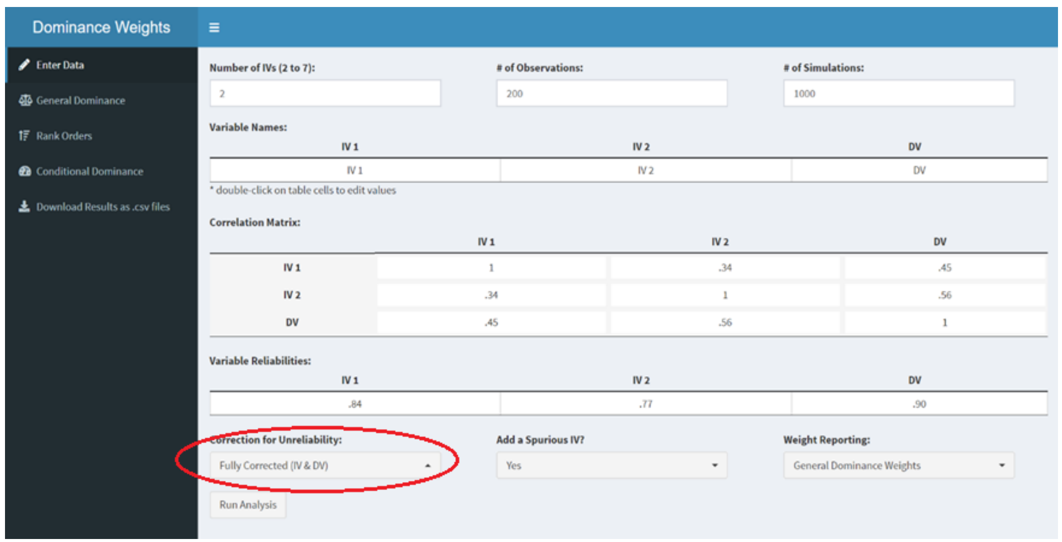
Dominance Weights Tool Demo

Optionally, you can enter variable names and the variable reliabilities.



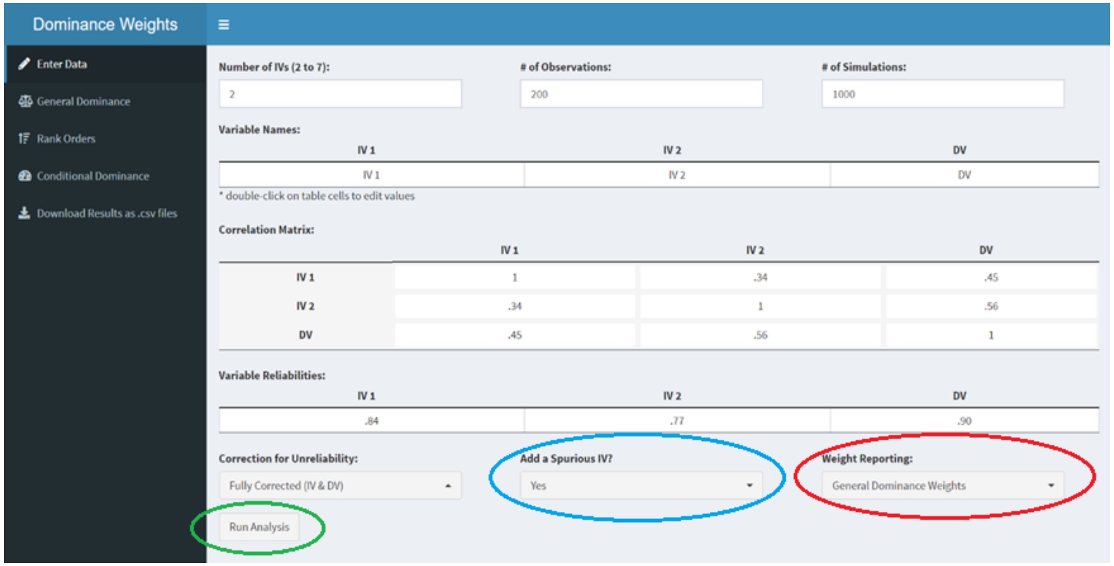
Dominance Weights Tool Demo

In the “Correct for unreliability” pull-down menu, you can choose not to correct for reliability of the variables, to correct for the reliability of the IVs (operational validity), or to fully correct for the reliabilities of the IVs and the DV.



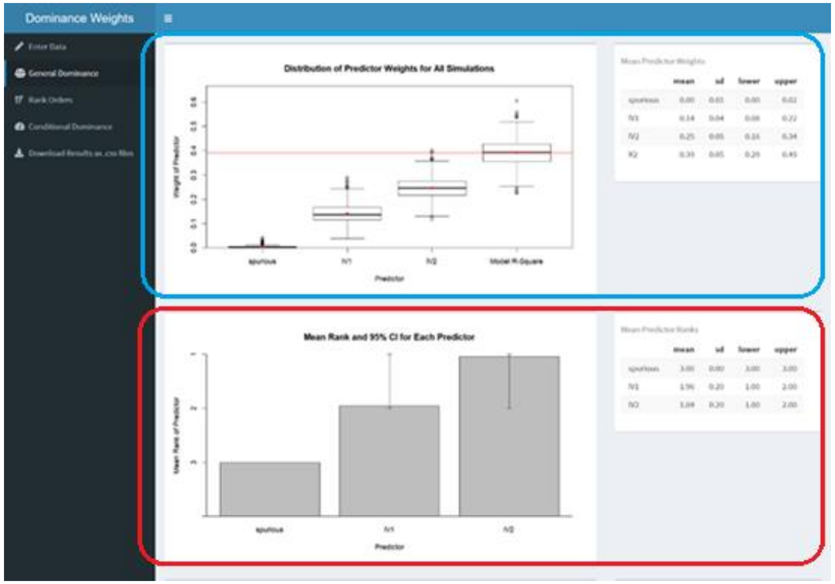
Dominance Weights Tool Demo

Next, you can choose whether or not to add a spurious predictor (which helps avoid the inflation of predictor weights due to error variance). Then, you select the type of weights to report (i.e., DW or RWA). To start the simulations, click “Run Analysis.”



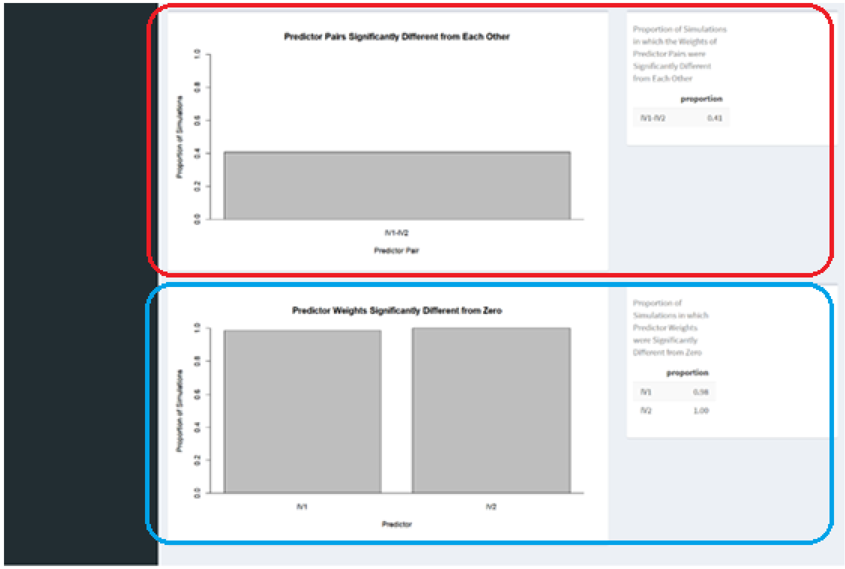
Dominance Weights Tool Demo

After the simulations have completed, the "general dominance" tab is displayed, which tables and graphs the descriptive statistics for the distribution of the simulated sets of predictor weights and the mean rank order of each predictor across simulations.



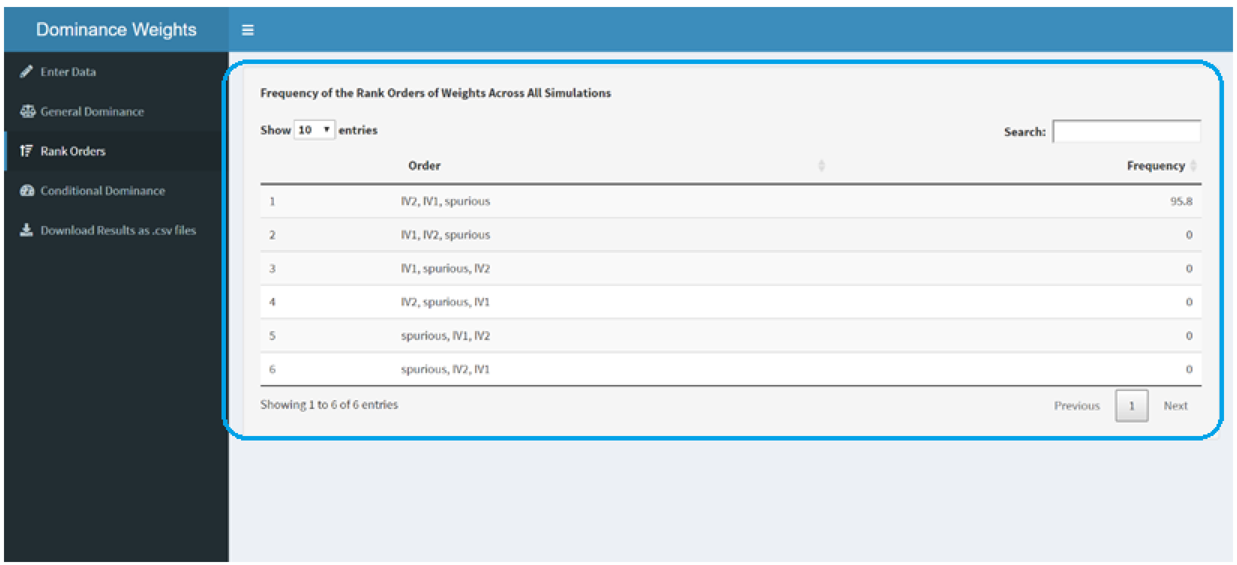
Dominance Weights Tool Demo

The “general dominance” tab also contains tables and graphs of the proportion of simulations where all possible predictor pairs were statistically significantly different from each other and the proportion of simulations where each predictor was statistically significantly different from zero.



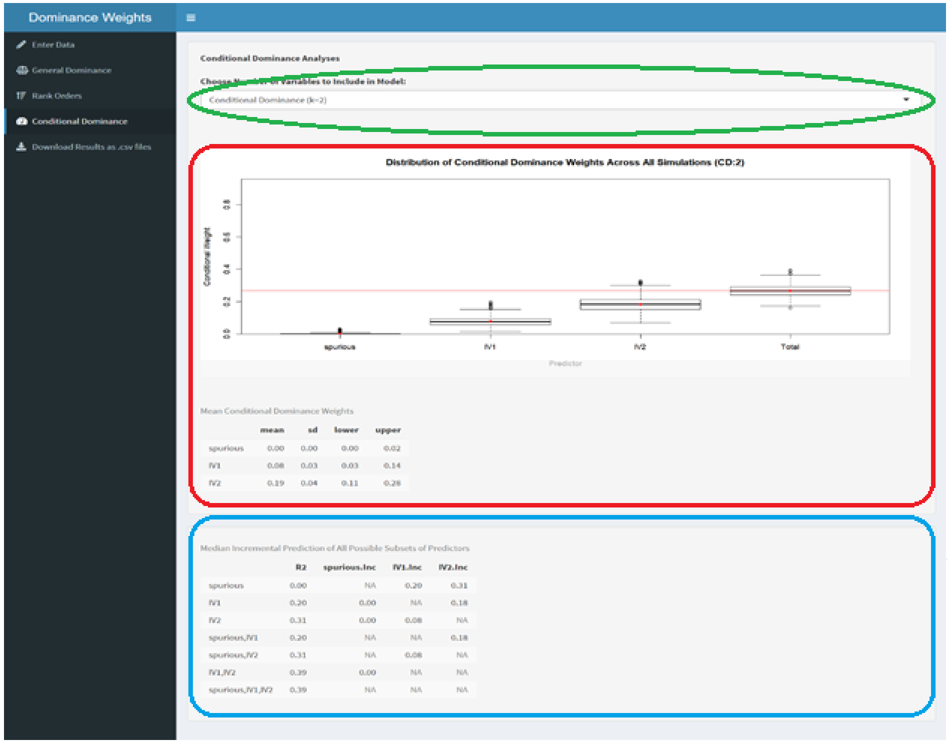
Dominance Weights Tool Demo

If you click on the "rank orders" tab, a table with all possible predictor rank orders and their respective frequencies across all simulations is displayed.



Dominance Weights Tool Demo

If you click on the "conditional dominance" tab, the tool will display the descriptive statistics for the distribution of the conditional dominance weights and the median incremental prediction (R^2) of all possible subsets of predictors. The number of variables to include in the model can be changed in the pull-down menu.



Dominance Weights Tool Demo

Lastly, on the “download results” tab, you can download a .csv file of any table available in the application by selecting the desired table in pull-down menu and clicking the download button.

Conclusion

- It is our hope that this tool will allow users to report the accuracy of DA weights in addition to the magnitude and/or rank order of DA weights.
- This more nuanced approach to the reporting of DA results can increase the credibility and utility of relative importance analysis, by allowing researchers and practitioners to report and qualify their results, so that decisions based on DA are more cautiously and usefully justified.

Questions, Comments, and Suggestions

Please feel free to contact me with any feedback you have at:
leo.alexander@rice.edu.

Thank You

Thank you for viewing this presentation!

And special thanks to all my colleagues who contributed to this project!

Dominance Analysis (DA)
for Communicating Prediction Results

Charlene Zhang
University of Minnesota—Twin Cities

Sean Robson & Maria Lytell
RAND Corporation

June, 2020

Background and Study Objectives

Importance of Effective Selection

Consequences of bad hires (Deering, 2015)

- High turnover rate
- Dampened morale
- Reduced productivity and profitability
- Toxic and unstable organizational culture

Financial cost of bad hires (US Department of Labor, 2013)

- 30% of employees' first year earnings

Employee Selection

Predictors

- General Mental Ability (GMA)
- Education
- Personality
  - Emotional Stability
  - Extraversion
  - Openness
  - Agreeableness
  - Conscientiousness
  - Narcissism
  - Emotional Intelligence
- Vocational interest
- Integrity

Criteria

- Behavioral
  - Training performance
  - Job performance
  - Organizational Citizenship Behavior (OCB)
  - Counterproductive Work Behavior (CWB)
  - Turnover
- Attitudinal
  - Turnover intention
  - Job satisfaction
  - Organizational Commitment
- Leadership
  - Leadership emergence
  - Leadership effectiveness

Study Objectives

1. Integrate meta-analytic information about relationships between work-related predictors and criteria using **multiple regression**

"Every standard deviation increase in an individual's level of agreeableness is associated with .2 times lower likelihood of turnover, given constant levels of general mental ability, education, extraversion, openness to experience, emotional stability, conscientiousness, integrity, and vocational interest."

For non-technical audiences

- Difficult to understand and interpret
- Not readily applicable

Study Objectives

1. Integrate meta-analytic information about relationships between work-related predictors and criteria using **multiple regression**

2. Explain results of prediction models using **dominance analysis** to aid interpretation and communication

DA As a Complement to Multiple Regression (MR)

Multiple Regression

- R^2: overall fit (variance explained) of the model
- β: predictive ability of each predictor holding all other predictors constant

Prediction!

Dominance Analysis

- Assumes the correct model
- General dominance: determine relative variable importance of predictors in a regression model (Azen & Budescu, 2003)

Interpretation!

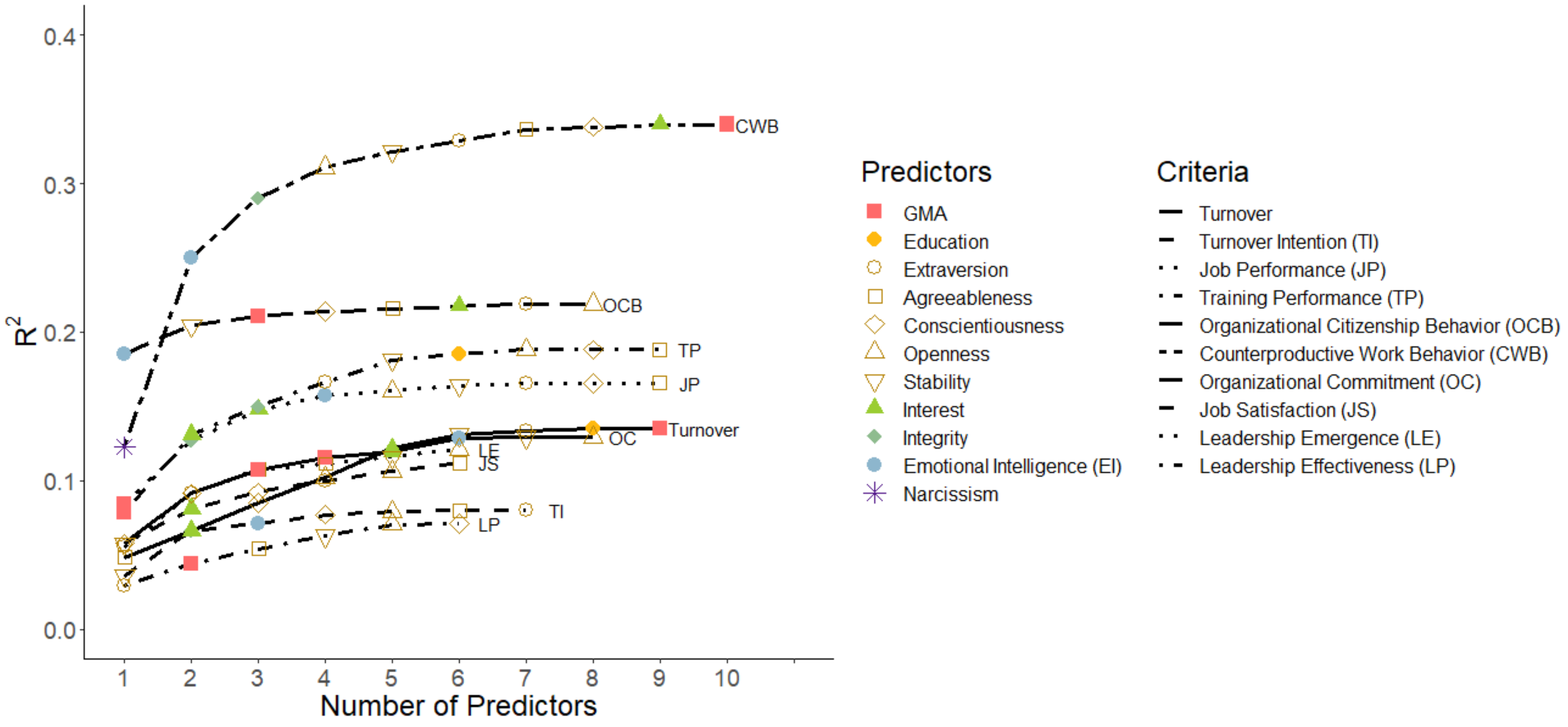
Methods

Methods

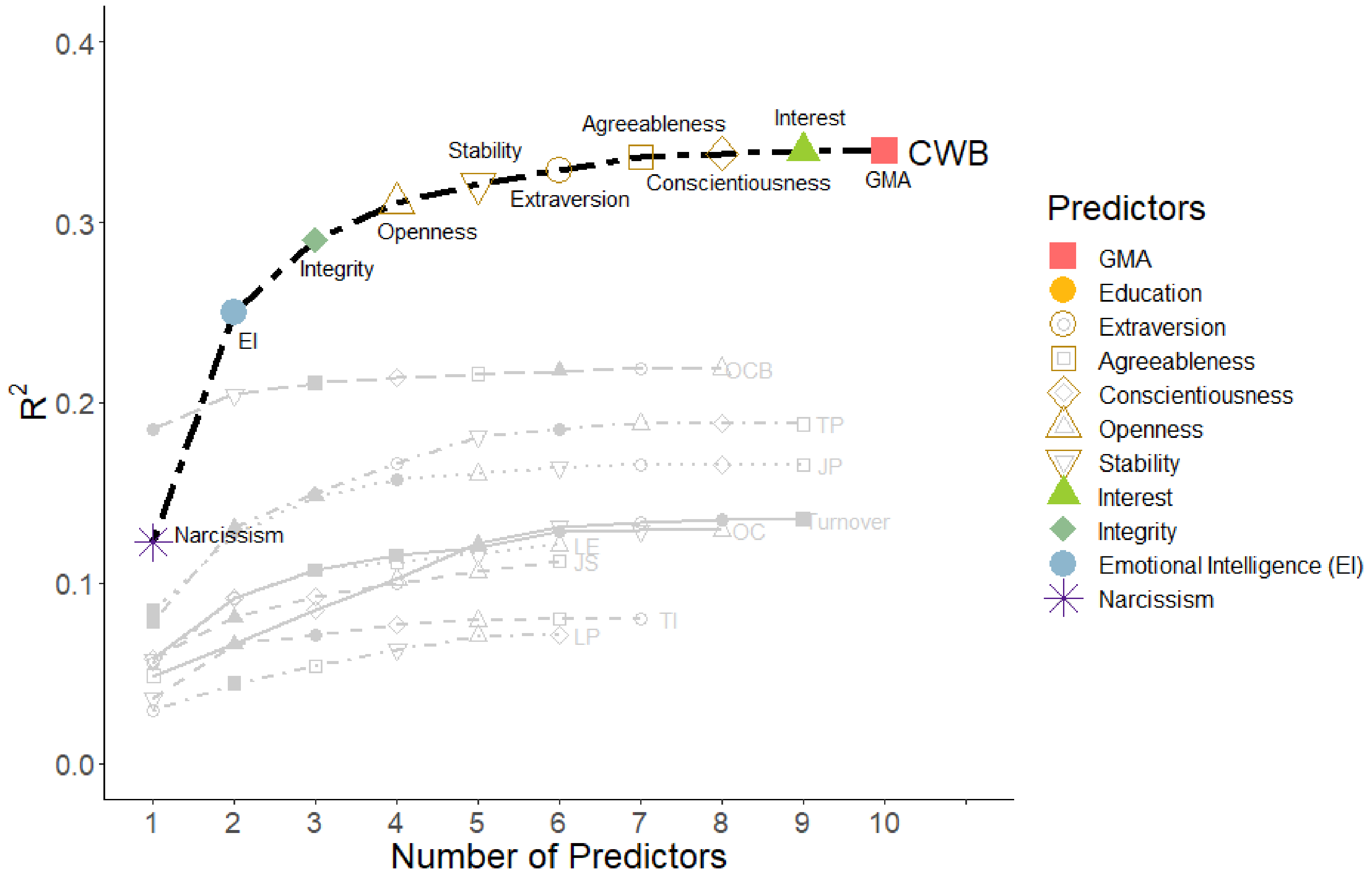
- Meta-analytic estimates of predictor intercorrelations and validities
  - 111 published estimates
  - 21 MetaBUS estimates (Bosko, Uggerslev, & Steel, 2017)
- Multiple regression and dominance analysis using the compiled correlation matrices as input

Results

Regression and Incremental Validity Analyses for All Criteria



Example: Incremental R^2 for Predicting CWB



General Dominance to Communicate Variable Importance

Counterproductive Work Behavior

Predictors	**β**
GMA	.003
Emotional stability	.126
Extraversion	-.107
Openness	.157
Agreeableness	.109
Conscientiousness	-.050
Interest	.042
Integrity	-.256
Emotional intelligence	-.400
Narcissism	.387
R^2	**33.98%**

RAND

General Dominance to Communicate Variable Importance

Counterproductive Work Behavior

Predictors	β	
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Emotional stability	.126	
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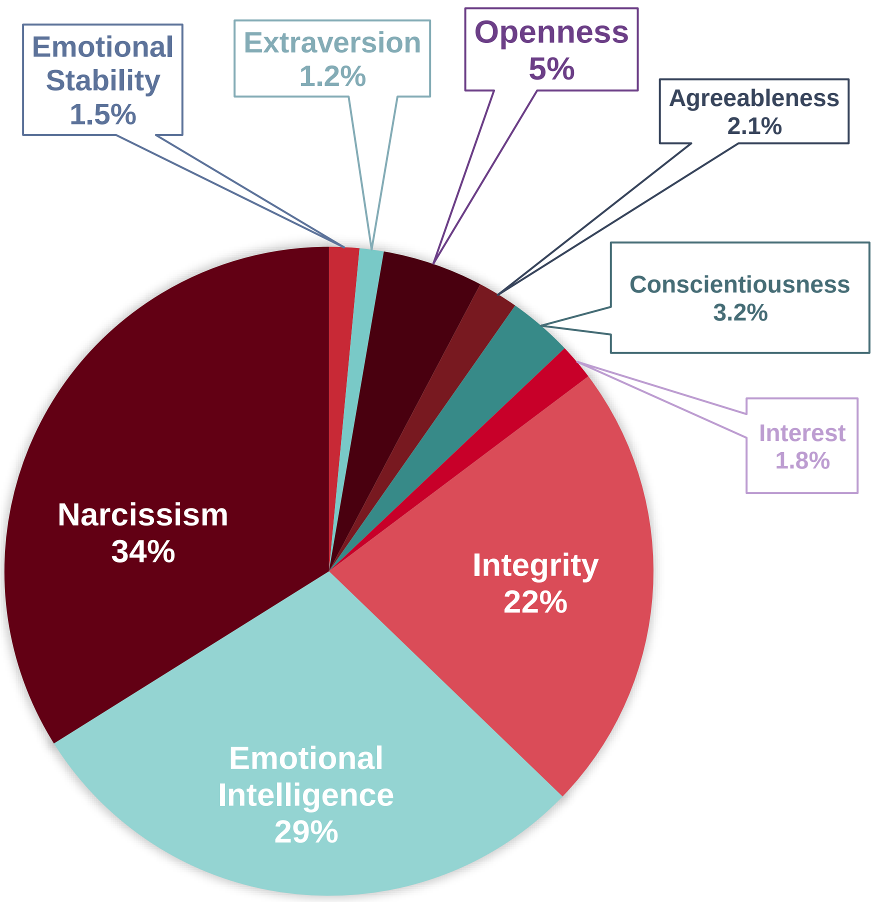
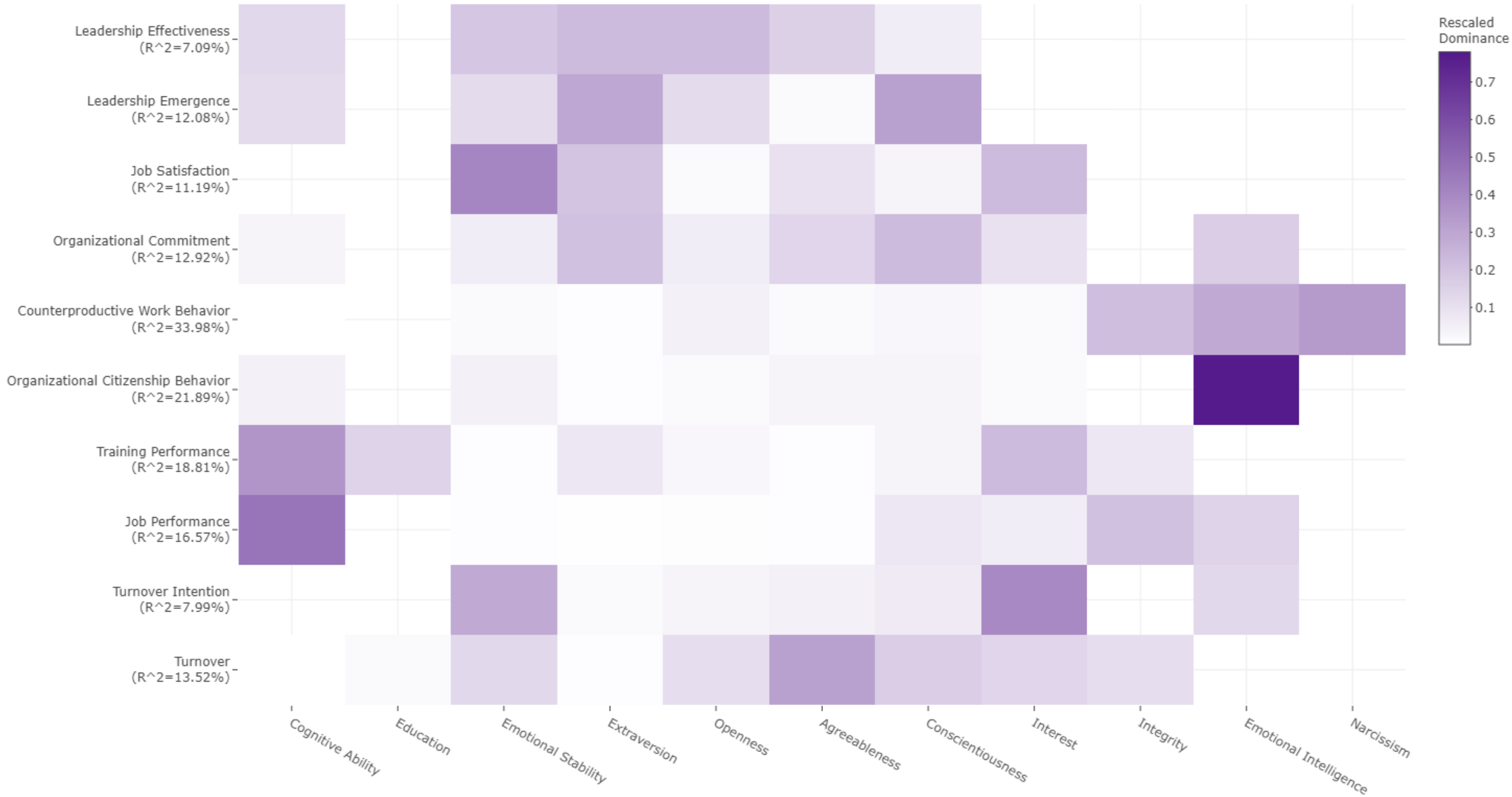


RAND

Dominance Weights for All Criteria



Conclusions
and Recommendations

Conclusions and Recommendations

- For prediction
  - Diminishing returns of adding additional predictors
  - Different predictors are more useful for different criteria
- For interpretation
  - General dominance values are more appropriate indices of variable importance than regression weights when predictors are intercorrelated
  - Dominance analysis provides a tool for communicating prediction model results

Questions:

zhan5449@umn.edu

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