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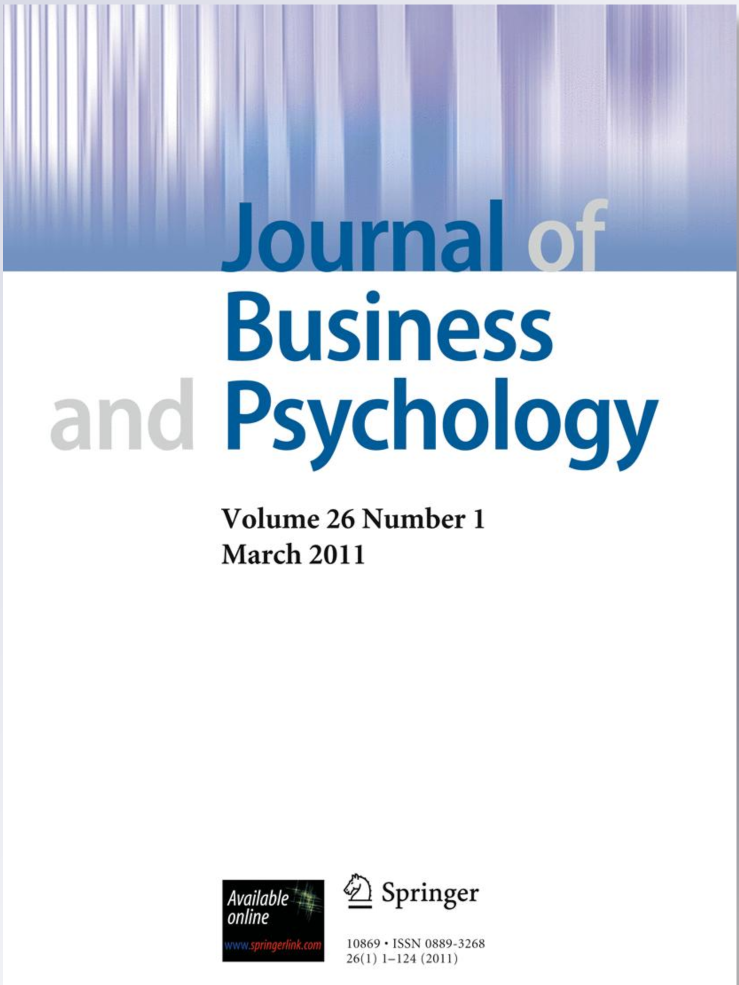

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Relative Importance Analysis: A Useful Supplement to Regression Analysis

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Abstract This article advocates for the wider use of relative importance indices as a supplement to multiple regression analyses. The goal of such analyses is to partition explained variance among multiple predictors to better understand the role played by each predictor in a regression equation. Unfortunately, when predictors are correlated, typically relied upon metrics are flawed indicators of variable importance. To that end, we highlight the key benefits of two relative importance analyses, dominance analysis and relative weight analysis, over estimates produced by multiple regression analysis. We also describe numerous situations where relative importance weights should be used, while simultaneously cautioning readers about the limitations and misconceptions regarding the use of these weights. Finally, we present step-by-step recommendations for researchers interested in incorporating these analyses in their own work and point them to available web resources to assist them in producing these weights.

Keywords Relative importance · Predictor importance · Relative weight analysis · Dominance analysis · Multiple regression

Relative Importance: A Useful Supplement to Regression Analyses

Multiple regression is perhaps the most frequently used statistical tool for the analysis of data in the organizational sciences. The information provided by such analyses is particularly useful for addressing issues related to prediction such as identifying a set of predictors that will maximize the amount of variance explained in the criterion. However, most researchers and practitioners are simultaneously interested in multiple regression for theory testing or explanation purposes. Here, the question of interest becomes understanding the extent to which each variable drives the prediction. Essentially, one wishes to understand the contribution each predictor makes towards explaining variance in the criterion. Past research has documented how indices commonly produced by multiple regression analyses fail to appropriately partition variance to the various predictors when they are correlated (Darlington 1968). In response, two alternative approaches, dominance analysis (Budescu 1993) and relative weight analysis (Fabbris 1980; Johnson 2000), have been developed that allow for more accurate variance partitioning among correlated predictors. The purpose of this article is to call greater attention to these estimates of relative importance by describing how they can be a useful supplement to traditional regression analysis. In what follows, we will discuss the types of information these analyses provide, describe how this information differs from more commonly used indices of importance, present some of the limitations of these analyses, and provide some brief examples of their potential uses. We will not focus on the intricacies of performing dominance analysis or relative weight analysis. Instead, we would refer interested parties to the many papers referenced throughout this article that provide detailed information concerning computing these importance weights. Our goal is to provide a practical, user-friendly guide for those wanting to supplement their regression analysis with relative importance analysis. Information is also provided regarding where one can

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locate the necessary computer programs to perform these computations.

Why Conduct Relative Importance Analysis to Supplement Traditional Regression

Though the term *importance* often has numerous connotations, sometimes referring to statistical significance while at other times referring to practical significance, our use of the term *relative importance* refers to the contribution a variable makes to the prediction of a criterion variable by itself and in combination with other predictor variables (Johnson and LeBreton 2004). This definition considers only the relative contribution of a variable to total predictable variance and makes no assumptions about either the statistical significance or practical significance associated with a particular predictor. Information regarding a variable's contribution to predictable variance is helpful when considering the practical utility of a variable, but aspects of the particular situation must also be considered to fully gauge practical importance (Cortina and Landis 2009). In some situations, a variable may explain only a small proportion of predictable variance and yet be very meaningful (Martell et al. 1996), whereas in other situations, a variable may account for a larger percentage of the variance but may provide little practical utility (Cortina and Landis 2009).

Relative importance weights are a useful supplement to multiple regression because they provide information not readily available from the indices typically produced from a multiple regression analysis. When one is mainly concerned with how much scores on the criterion variable would change based on a unit increase in a predictor while holding the other predictors constant, then regression coefficients are well suited to address such a question. However, we believe researchers' interest in predictor variables extends beyond such simple questions to more fully understand the impact of a particular predictor relative to others in the model. An example of this type of question might be, do certain individual difference variables matter more than others in predicting leader effectiveness? Or, is a particular individual difference variable a meaningful (useful) predictor of leader effectiveness? The central issue in both of these examples concerns how much of the variance explained in leader effectiveness can be attributed to each predictor variable. Such a question is at the heart of what most organizational researchers mean when they talk about predictor importance.

Critics have at times disapproved of relative importance analyses on the grounds that such analyses are atheoretical. On the contrary, relative importance analyses aid in theory building. As already discussed, the strength of relative importance weights is that they help us better understand how various predictors combine in a multiple regression equation. The ability to correctly partition predicted variance to the appropriate variables can only aid in the development of more sound theories. Moreover, as we will discuss later, recent developments now enable researchers to test specific a priori hypotheses they may have regarding the relative importance of variables. Relative importance analyses can also be performed on a latent variable correlation matrix and on meta-analytically derived correlation matrices. Again, such techniques help test predictions, refine current theory, and improve our understanding of our regression models. Theory development is a long-term iterative process of exploring one's data and confirming one's models. Analysis of relative importance leans toward the former in the interest of pursuing the latter.

Problems with Traditional Estimates of Importance

Historically, one of the most common approaches to determining variable importance has been the visual inspection of standardized regression coefficients. Unfortunately, standardized regression weights do not appropriately partition variance when predictors are correlated so these indices are not suitable for addressing questions regarding relative importance. Similarly, simple bivariate correlations are also flawed because they fail to take into account the relationships between the predictors and only address the contribution of a variable by itself, thus not satisfying our definition of relative importance. Change in R^2 also addresses a slightly different question (LeBreton et al. 2007). Any shared explanatory variance is credited to the variable that was entered first in the regression equation, thus leading one to potentially misunderstand a variables true relative contribution.

To illustrate the issues related to the use of traditional regression metrics as estimates of relative importance, Table 1 contains a hypothetical correlation matrix and the corresponding squared standardized regression weight (β^2), perhaps the most commonly used measure of importance. As shown in Table 1, the squared standardized regression weight suggests that predictors X1 and X2 are 26 times more important than predictors three and four despite the small differences in the actual predictive validities for these variables. These small differences in predictive validity become exacerbated because of the colinearity among the predictors. As a result, the standardized regression weights are inappropriately assigning the preponderance of shared variance among the four predictors to X1 and X2 because of their slightly higher bivariate relationship with the criterion.

Table 2 contains another illustration of problem associated with traditional regression metrics as estimates of importance. Again, X1 and X2 appear substantially more important than X3 (314 times more important), despite

Table 1 Problems with squared betas as measures of relative importance when predictors are intercorrelated

	Correlation matrix					Relative importance		
	Y	X1	X2	X3	X4	β^2	General dominance weights	Relative weights
X1	0.30	1				0.026	0.038	0.038
X2	0.30	0.60	1			0.026	0.038	0.038
X3	0.25	0.60	0.60	1		0.001	0.019	0.019
X4	0.25	0.60	0.60	0.60	1	0.001	0.019	0.019

Table 2 Problems with squared betas and product measure weights as measures of relative importance when predictors are intercorrelated

	Correlation matrix					Relative importance			
	Y	XI	X2	X3	X4	β^2	Product measure (r_{xy} β_x)	General dominance weights	Relative weights
XI	0.40	1				0.066	0.103	0.068	0.066
X2	0.40	0.70	1			0.066	0.103	0.068	0.066
X3	0.30	0.60	0.60	1		0.0002	0.004	0.028	0.030
X4	0.30	0.70	0.70	0.40	1	0.004	−0.019	0.027	0.028

more modest differences in the correlation matrix. This example is also useful for illustrating problems with another commonly used measure of relative importance, the product of the standardized regression weight and the correlation coefficient. The importance weight associated with the fourth predictor is negative according to product measure. Such a result is uninterpretable as it suggests that X4 explains negative variance in the criterion variable.

Numerous studies have demonstrated how these traditionally relied upon metrics are flawed indicators of the relative importance of predictors (e.g., Johnson 2000; LeBreton et al. 2004). However, consensus appears to be emerging regarding the use of dominance analysis and relative weight analysis to address questions of variable importance. In what follows, we will provide a brief non-mathematical description of these two analyses and demonstrate their application to the hypothetical data presented in Tables 1 and 2.

Dominance Analysis and Relative Weight Analysis

Dominance analysis (Budescu 1993) approaches the problem of relative importance by examining the change in R^2 resulting from adding a predictor to all possible subset regression models. By averaging across all of the possible models (average squared semipartial correlation), one obtains a predictor's *general dominance weight*, which directly addresses a variable's contribution by itself and in combination with the other predictors, while overcoming the problems associated with correlated predictors.

A second approach for determining variable importance is relative weight analysis. As previously noted, standardized regression weights are flawed measures of importance because of the intercorrelations among the predictors. Relative weight analysis (Fabbris 1980; Johnson 2000) solves this problem by using a variable transformation approach to create a new set of predictors that are orthogonal to one another. One can then regress the criterion on these new orthogonal predictors and make use of the resulting standardized regression coefficients because they no longer suffer from the deleterious effects of multicolinearity. These standardized regression weights are then transformed back to the metric of the original predictors. For example, if a criterion variable is regressed on three variables, the computation of the relative weight for X_1 will involve the following steps (see also Fig. 1).

1. Derive a set of k orthogonal weights Z_{Xk} that are maximally related to the set of j original predictors X_j.

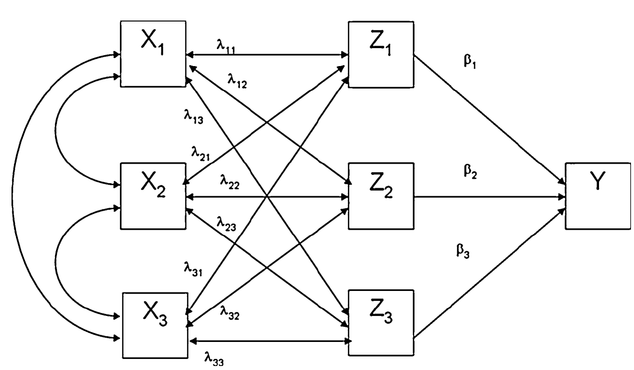

Fig. 1 Calculation of univariate relative weights for a regression model with three predictors

2. Obtain a set of standardized regression coefficients β_k by regressing the criterion variable Y on the set of the newly created orthogonal predictors Z_{Xk}.
3. Obtain a set of standardized regression coefficients λ_{jk} by regressing X_j on the set of the newly created orthogonal predictors Z_{Xk}.
4. Compute relative weights by summing the products of squared standardized regression coefficients β_k^2 and λ_{jk}^2 obtained at steps 2 and 3. Thus, the relative weight for the first predictor (X_1) will be calculated as $\varepsilon_1 = \beta_1^2\lambda_{11}^2 + \beta_2^2\lambda_{12}^2 + \beta_3^2\lambda_{13}^2$. Relative weights for the other predictors in the model are calculated in a similar manner.

One can easily apply both dominance analysis and relative weight analysis to one's own data using a variety of computer programs available to the general public (see Appendix). The results of implementing both of these analyses to the correlation matrix in Tables 1 and 2 can be found in the final two columns of each table. As is apparent, both of these approaches do a much better job of appropriately partitioning the variance among the four predictors despite the colinearity among predictors. Returning to our example in Table 1 we see that X1 and X2 still remain more important than X3 and X4 but the discrepancy between these two sets of predictors according to both dominance weights and relative weights is one-tenth as large as the discrepancy seen for squared regression weights. Returning to our other example in Table 2 we see that dominance weights and relative weights produce more reasonable estimates of importance for the four predictors. These results are consistent with past studies showing superior performance of these two weights for determining relative importance (e.g., LeBreton et al. 2004). General dominance weights and relative weights confer a number of additional advantages over traditional measures of importance. Both metrics were specifically designed to evaluate relative importance in the context of correlated predictor variables, and both indices sum to the model R^2 and thus can be interpreted as measures of relative effect sizes (LeBreton et al. 2007).

It is important to note that the information provided by these two relative importance analyses does not take precedence over standardized regression weights or change in R^2. Instead, relative importance weights provide a *different type of information*, that when used in conjunction with other multiple regression indices, can furnish a more complete understanding of a variable's role in explaining variance in a criterion. LeBreton et al. (2007) provided several examples of how relative importance analyses can be integrated with more traditional analyses to improve our understanding of the role predictors are playing in a regression analysis.

Dominance Analysis Versus Relative Weight Analysis

One question that may arise concerns which relative importance analysis to use, dominance analysis or relative weight analysis. In our view, these two procedures are largely interchangeable with one another mainly because, in our experiences, the differences in the estimates of relative importance produced by these two approaches are miniscule (see Tables 1, 2). Although one might observe some differences in a particular sample, the actual population weights are likely highly similar. Evidence for this comes from some large scale simulation studies were the average difference between the dominance weights and relative weights was often in the third decimal place when collapsing across thousands of simulation runs (LeBreton et al. 2004; LeBreton and Tonidandel 2008; Tonidandel and LeBreton 2010). The similarity in results produced by these two estimates of relative importance is actually an important strength of both procedures. As it is impossible to actually determine the true relative importance of predictors, the fact that both of these analyses arrive at virtually identical answers, while based on different approaches to estimating relative importance, should lend more confidence regarding their ability to accurately partition variance.

Despite these similarities, there may be some instances where a particular relative importance analysis might be preferred. One's choice of importance weight will most likely depend on the number of predictors one has and the type of question one is most likely interested in. Because dominance analysis relies on an all subsets regression approach, obtaining dominance weights becomes more onerous as the number of predictors increases. For example, five predictors require 31 separate regression models to obtain the dominance weights, whereas a model with 15 predictors requires 32,767 separate regressions. While this process can be automated to large extent using computer macros, it is still more cumbersome for dominance analysis when compared to relative weight analysis. The problem becomes significantly worse when one becomes interested in knowing about the sampling distributions for the various importance weights to address questions of statistical significance. The procedures for statistical significance rely on bootstrapping to derive the sampling distribution of both relative weights and dominance weights. For a 10 predictor model, calculating dominance analysis weights across 10,000 bootstrapped samples would require over 10 million separate regressions versus the 20,000 that are required by the relative weight approach.

Despite this computational shortcoming, dominance analysis possesses some advantages over relative weight analysis concerning the type of information provided (Budescu and Azen 2004). One type of information provided by dominance weights concerns whether a predictor outperforms another predictor on average across all subset models. These weights are referred to as general dominance weights and it is these general dominance weights that converge closely to relative weights in past simulation studies. However, dominance analysis can also produce information about what Budescu calls complete dominance and conditional dominance. Complete dominance refers to whether a predictor outperforms another predictor in all of the various subset models whereas conditional dominance refers to situations where a predictor outperforms another predictor on average in each of the family of subset models of the same size. Azen and Budescu (2003) provided an example of how these alternative types of dominance weights can be used in combination with general dominance weights to identify suppressor variables. Thus, one may be able to extract valuable information from these three different sets of dominance weights that would not be available with relative weight analysis alone. In situations where this information is of interest, dominance analysis would be a preferred approach over relative weight analysis. However, in situations where one has a relatively large number of predictors or one is interested in the statistical significance of the relative importance weights, relative weight analysis may be preferred over dominance analysis.

Limitations of Relative Importance Analyses

While we believe that relative importance analyses can provide researchers with valuable information that would not otherwise be available, these analyses are not a cure for the many limitations of multiple regression. Like regression estimates, the importance weights generated on observable manifest variables may differ from the true population values. These differences arise in part due to sampling error, but are also subject to the effects of measurement error (Johnson 2004). However, the potential deleterious effects of measurement error on the observed relative importance indices could be compensated for by using a latent variable correlation matrix as input, rather than the observed correlation matrix.

Also, similar to traditional regression estimates, importance weights are susceptible to model misspecification. One mistakenly held belief is that importance weights should be used to select predictors for a model. In actuality, both dominance analysis and relative weight analysis presuppose that the correct model has already been identified. For those interested in identifying the correct model, we recommend other procedures that may be more appropriate (e.g., procedures that help identify models with maximal R^2; Hocking 1976; Miller 1990; Thall et al. 1997). Once the correct model has been specified, relative importance weights allow for the interpretation of the model and the comparison of predictor variables.

Another myth surrounding the application of relative importance analyses is that these weights solve the problem of multicolinearity among predictors. Although it is true that both dominance analysis and relative weight analysis were developed for use with correlated predictors and do in fact partition variance among correlated predictor variables, high levels of correlation among the predictor variables cannot be ignored. For example, if two or more predictor variables are very highly correlated because they are essentially tapping into the same underlying construct, the resulting importance weights can be misleading. Just like multiple regression, one would need to consider dropping one of the highly multicolinear variables or forming a composite of the variables to obtain accurate estimates of importance. No absolute cut-off exists to indicate too much multicolinearity. Concerns about excessive multicolinearity are more of a theoretical nature than a statistical one. The theoretical question at hand is whether the colinearity is indicative of similarity between two constructs or indicative of construct redundancy. High levels of colinearity between similar yet distinct constructs are not problematic for dominance analysis or relative weight analysis as these methods will perform appropriately and much better than regression weights in terms of correctly partitioning variance despite the correlations among the predictors. However, construct redundancy will have the apparent effect of reducing the overall importance of a particular variable because the overall importance of that variable will be divided up among the redundant predictors thereby possibly producing a misleading result.

Relative importance weights are also not intended to be a replacement for regression or for what regression does well. For example, relative importance weights should not be used as replacements for regression weights when building prediction equations. In addition, importance weights should not be used to select the set of variables that will maximize prediction. Two variables that are highly correlated may have similar importance weights but the second variable may contribute little to overall predictive capability of the model beyond what is explained by the first variable. Finally, relative importance weights are not causal indicators and thus do not necessarily dictate a course of action. Rather these analyses should supplement regression analyses as they provide valuable information about variance partitioning, which is not handled well by regression estimates.

Applications of Relative Importance Analyses

Recently, researchers have made a number of advances concerning the application of these weights to a wider variety of research questions. Applications of dominance analysis to standard multiple regression problems are described by Budescu (1993), while Johnson (2000) presents an introduction to relative weight analysis. More recently, Azen and Budescu (2006) and LeBreton and Tonidandel (2008) extended general dominance weight analysis and relative weight analysis, respectively, to *multivariate* multiple regression designs that model relationships between a set of multiple predictor variables and a set of *multiple* criterion variables. Such analyses may be useful for researchers encountering multidimensional or multifaceted criterion spaces (e.g., job satisfaction, organizational commitment, job performance).

Relative importance analyses are also applicable to situations commonly confronted by organizational scholars where the criteria may not meet the meet the distributional assumptions of ordinary least squares (OLS) regression, such as predicting binary criteria like turnover, promotion decisions, or training success. Although both dominance analysis and relative weight analysis were developed for use with OLS regression, Azen and Traxel (2009) and Tonidandel and LeBreton (2010) presented modifications of these respective analyses to handle categorical criterion variables that would typically be analyzed using logistic regression. Thus, questions of the relative contribution of each of the variables in terms of predicting the categorical criterion can be examined in this context as well.

Another extension of the relative weight approach has been made by LeBreton and Tonidandel (2009) to multiple regression models that contain interactions terms, quadratic terms, or other higher-order terms. Both dominance analysis and relative weight analysis proceed from an assumption that there is no inherent ordering among the predictor variables. However, regression models containing higher-order terms are necessarily hierarchical (ordered) and thus decomposing the predicted variance in such models requires alternative procedures based on the residualization of higher-order terms for lower-order effects.

Relative importance analyses may also be a useful supplement to analyses other than multiple regression such as multivariate analysis of variance (MANOVA) as well. One of the central questions in a MANOVA concerns identifying the dependent variables that are driving the significant multivariate *F*-test. Unfortunately, the correlations among the various dependent variables often make it difficult to accurately identify the role being played by the various dependent variables. Tonidandel et al. (2006) provided an overview of this problem and some potential solutions using relative weight analysis.

As already noted, relative importance weights possess the enviable property of being interpreted as a measure of relative effect size since both dominance weights and relative weights sum to the model R^2. In addition, researchers may also wish to consider whether the observed relative importance weight is statistically significant. Researchers often desire to make claims about whether a particular variable 'matters' in a multiple regression equation. In the past, researchers have inappropriately relied upon the statistical significance of standardized regression coefficients to claim predictors are important or unimportant. Courville and Thompson (2001) reviewed articles published over an 11-year span in the *Journal of Applied Psychology*, and concluded that authors made numerous mistakes where they identified variables as not meaningful when in fact they were because of the mistaken reliance on standardized regression weights. A better metric for making such judgments would be the statistical significance of relative importance weights. Tonidandel et al. (2009) described a bootstrapping procedure for determining the statistical significance of relative weights. This process involves comparing the relative weight produced by the predictors in one's data set to a variable known to be meaningless—a randomly generated variable. If the relative weight of a predictor is statistically significantly different from the relative weight produced by the random variable, that predictor can be appropriately judged to be meaningful. Bootstrapping is used to empirically derive the sampling distribution needed to judge whether the two weights are significantly different from one another. We encourage researchers to use this procedure in the future when they are interested in addressing questions regarding whether particular predictors are meaningful predictors. As with any test of significance, the statistical significance of relative weights will be affected by sample size and, bootstrapping will not overcome the inherent limitations associated with a small sample size.

Numerous other applications of relative importance analysis are also just in their infancy. These applications include applying relative importance analyses to latent correlation matrices to account for sampling error, to partition variance in meta-analytically derived correlation matrices (see O'Boyle et al. 2010), and to multi-level data. Researchers are encouraged to consider other applications where these weights may be useful. A more detailed review of importance analyses and their uses can be found in Krasikova et al. (2011).

Recommendations to Researchers

We recommend that researchers interested in theoretical questions regarding the relative importance of variables should obviously make use of these analyses over other indices. However, even when one's primary interest is not the relative importance of predictors, we encourage users of multiple regression to conduct relative importance analyses as a supplement to their primary analyses.

Relative importance analyses will permit a greater understanding of the particular role played by variables in a multiple regression equation. Importantly, these analyses can reveal the underlying impact of a particular predictor more accurately than standardized regression coefficients or simple correlations. Specifically, we would encourage researchers to do the following:

(1) Decide on the purpose of the relative importance analysis.
If the purpose of the relative importance analysis is to examine patterns of importance, then dominance analysis is the appropriate choice. If, on the other hand, one just wishes to examine the relative importance and corresponding variance attributed to a large number of predictors, then relative weight analysis is a logical choice given its computational efficiencies.

(2) Compute the relative importance weights most appropriate for the situation at hand.
As previously mentioned, relative importance weights are easily obtainable for a variety of regression based problems including multiple regression, logistic regression, multivariate multiple regression, and polynomial regression. These approaches are also a useful supplement to questions related to incremental validity (e.g., LeBreton et al. 2007). References to available computer programs for performing these calculations can be found in the Appendix.

(3) Examine the raw weights and interpret them as a measure of relative effect size.

(4) Determine whether the weights are statistically significant.
In addition to interpreting the sheer size of the weight, one can also evaluate the statistical significance of the importance weights. For relative weight analysis, this can be done using a procedure described in Tonidandel et al. (2009).

(5) Compute confidence intervals around the individual weights.
In the past, researchers have tended to focus on the rank order of predictors identified by the various importance analyses. However, this approach can be misleading, and we urge caution when examining the rank ordering of predictors. Like any statistic, importance weights are subject to sampling variability, and any observed difference in the rank order of variables may not be meaningful. To more fully appreciate the relative importance of individual predictors, one must also have some insight into the sampling distribution of the estimate of relative importance. Thus, we recommend that researchers also compute confidence intervals around the relative importance weight for each individual predictor to get a better idea regarding how these sampling distributions might overlap with one another. A description of this approach for dominance analysis can be found in Azen and Budescu (2003), and a similar approach to confidence intervals for relative weight analysis is discussed in Johnson (2004) with some updated recommendations made in Tonidandel et al. (2009).
It is important to call attention to the fact that the confidence intervals we are recommending here are confidence intervals around the individual relative importance weights. These confidence intervals are meaningfully different from the confidence intervals obtained in step 3 for determining the statistical significance of the relative importance weights. For a detailed discussion of the differences, see Tonidandel et al. (2009).

(6) When appropriate, use relative importance weights to test meaningful hypotheses.
Depending on the particular research question of interest, one may be able to use the relative importance weights to test hypotheses of theoretical interest. For example, one may wish to know if a particular variable is significantly more important than another variable, or one may wish to know if a certain predictor is significantly more important in one sample versus another sample. Both of these questions can be addressed by testing whether two importance weights are significantly different from one another either between or within samples. Procedures for testing such hypotheses using relative weight analysis are described in Johnson (2004).

Answers to Other Common Questions About Relative Importance Analyses

What are the sample size requirements for conducting relative importance analyses and how do these requirements compare with more traditional correlation and regression analyses? The power associated with tests of significance on relative importance weights for different sample sizes is on par with those of other regression based procedures. The significance tests for relative importance weights tend to be slightly less powerful than simple bivariate correlations but more powerful than beta weights, especially as the number of predictors and colinearity among the predictors increases (see Tonidandel et al. 2009, p. 397 for specific information about power rates). Similar to other statistics, Type II errors are most likely when sample sizes are small or when the relative importance weight is small. When small effects are anticipated, one might need to collect data from a slightly larger sample to obtain statistical significance than would usually be required for a simple correlation.

If a relative importance weight is not significant, should it no longer be interpreted (i.e. should one assume its importance is basically zero)? The significance of relative importance weights should be interpreted just like the significance of any other statistic. If you have a correlation that is not statistically significant that does not mean that the population correlation is zero. All it means is that you can not conclude that the population correlation is different from zero. The same is true for relative importance weights. If a relative importance weight is not significant, you can not conclude that the relative importance weight in the population is different from zero, but you should not assume it is zero. That said, just like with the correlation, if one were to have a large sample size and good power, thus producing a small confidence interval around the relative importance weight, and that confidence interval still contains zero, then one can conclude that this predictor is not really contributing (i.e., is zero in the population or at least close enough to zero that we do not really care about it).

Should the magnitudes of the relative importance estimates be interpreted similar to the recommendations made by Cohen for interpreting effect size? Relative importance weights sum to R^2 and thus represent the percentage of variance explained in the criterion that can be attributed to each predictor. However, we urge caution in the unconstrained use of general rules-of-thumb for evaluating effect sizes. Numerous authors (e.g., Aguinis et al. 2010; Cortina and Landis 2009; Martell et al. 1996) continue to stress that the sheer magnitude of an effect is not really meaningful out of context. A large effect in one situation can be pretty meaningless, while a tiny effect in a different situation could be extremely important from a practical standpoint. Any interpretation of a particular effect needs to take the specific context into account. Thus, we discourage the haphazard application of rules-of-thumb for evaluating the magnitude of an effect be they relative importance weights or some other measure of effect size.

If a predictor is significant in the multiple regression equation, but the relative importance weight is not significant, what does that mean? It is highly unlikely that a predictor would be significant in a multiple regression equation and not have a significant relative importance weight. A relative importance weight describes a predictor's contribution by itself and in combination with other predictors. Thus, if a predictor contributes when it is in the multiple regression equation, it will also contribute when it is by itself, unless it is operating as a suppressor. So, when multiple predictors have significant regression weights, the statistical significance of their relative importance weights will not add much to our understanding as they will likely also be significant. Where the relative importance weights contribute to our understanding is in terms of interpreting the importance of those predictors. The regression weights will not perform as well as the relative importance weights for partitioning the variance explained among the predictors. If you are trying to understand what is driving the significant multiple regression equation, and how each variable is contributing, relative importance weights are better suited for this than the regression weights.

Should all theoretically relevant predictors be included in relative importance analysis regardless of their significance in the regression analysis? The regression analysis tells you about the incremental importance/validity of individual predictors. The relative importance analysis provides information about a predictors' relative importance. Though similar, these two analyses provide slightly different pieces of information. As a result, one should include all theoretically relevant variables in the relative importance analysis. In fact, LeBreton et al (2007), provide some specific illustrations of situations where variables with small or even non-significant incremental validity in a regression analysis could actually emerge as the most important predictors in a relative importance analysis.

In conclusion, we believe that researchers should more regularly perform relative importance analyses when conducting multiple regression analyses. Aside from performing the computations described in the steps above using readily available software, no additional steps are needed on the part of the researcher beyond what was already done to execute the primary regression analysis (i.e., no additional data preparation or screening is required). Thus, with minimal effort, a researcher can obtain either dominance weights or relative weights as a supplement to their planned regression analyses. The typical indices produced by regression are useful but do not accurately partition variance among correlated predictors, whereas dominance weights and relative weight analysis are properly suited for this function. Moreover, these two relative importance weights provide valuable information to researchers that can address substantive hypotheses that are not easily addressed by traditional regression results, and because they are scaled in the metric of variance explained, importance weights may be interpreted as estimates of relative effect size. Relative importance analyses are not a replacement for regression analyses, but rather a useful supplement that can only aid in helping us more fully understand the role various predictors are playing.

Appendix

Resources for performing dominance analysis or relative weight analysis can be obtained from the following source. Numerous SAS macros for performing a variety of types of dominance analysis can be found on Razia Azen's macros page located at https://pantherfile.uwm.edu/azen/www/damacro.html. For those that do not use SAS, an Excel file is available on James LeBreton's computer programs page (http://www1.psych.purdue.edu/~jlebreto/relative.htm) that aggregates results across multiple individual regression runs to produce the general dominance weights for as many as six predictors. That same website also contains SPSS macros that can produce relative weights from a data set or a correlation matrix and for calculating relative weights for multivariate multiple regression. SAS programs that perform many of the same function and also compute relative weights for logistic regression and test for statistical significance can be found on Scott Tonidandel's computer programs page (http://www1.davidson.edu/academic/psychology/Tonidandel/TonidandelProgramsMain.htm).

Finally, Jeff Johnson can be contacted via email at Jeff.Johnson@pdri.com, to obtain SPSS syntax for testing the significance of differences between relative weights. The first author has similar programs that can be executed in SAS.

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