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A primer on relative importance analysis: illustrations of its utility for psychological research

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Abstract

In this primer we present a hands-on introduction to relative importance analysis as a way of exploring the relative importance of predictors in regression analysis. This method is particularly useful when predictors are correlated since it deals with issues of multicollinearity. We outline the benefits of two major approaches to relative importance, relative weights and dominance analyses, by contrasting these two relative importance analyses with correlations and multiple regressions. Based on two already published examples, we illustrate how relative importance analysis can be used to augment the interpretation of results and when relative weights importance is most appropriate. Finally, we discuss the advantages as well as the limitations of relative importance analysis on a more theoretical level. Our aim throughout is to present these analytical methods in a simple way that makes them accessible to a broad audience.

Key words: relative importance, relative weights, dominance analysis, regression, research methods

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Researchers often have the dual goals of both trying to predict valued criteria and trying to understand the relative importance of the variables used to predict these criteria. The statistical method usually employed for this purpose is multiple regression, and researchers interested in evaluating predictors used in multiple regression analyses mostly rely on straightforward statistical indices, such as standardized regression coefficients, squared correlations, zero-order correlations, and semi-partial correlations (Johnson, 2001; Johnson & LeBreton, 2004). Unfortunately, when multiple predictors are correlated with one another, as is nearly always the case, these simpler measures for evaluating the relative importance of predictors can be problematic because they fail to properly partition variance to the different predictors (Darlington, 1968). Since psychological research often measures constructs consisting of different but correlated facets, a more elaborate research methodology is needed. Recent work on relative importance analyses (Azen & Budescu, 2003, Tonidandel & LeBreton, 2011) offers easily accessible ways of determining the importance of multiple predictors while accounting for the correlations between them.

Our aim in this primer is to demonstrate for psychological researchers the potential that comes with using relative importance analyses in addition to classical regression methods. We do this by using data from two already published papers to illustrate two related methods and their respective benefits. Our criteria were that these needed to be from different fields of research so that our examples were accessible to a broad range of readers, and that they must have multiple, correlated predictors – since this best illustrates the added benefits of relative importance analysis. Hence we re-analysed data from an study conducted by Cooper-Thomas, van Vianen, and Anderson (2004) on the impact of socialization tactics on newcomer adjustment. For our second example, we re-analysed data from an organizational governance investigation conducted by Lui and Ngo (2012) on the drivers and outcomes of long-term orientation in co-operative relationships between organisations.

Throughout this primer, we focussed only on the theoretical aspects of the relative importance approach to the extent that it is useful as a context for highlighting the utility of this approach (for a detailed discussion, see Tonidandel & LeBreton, 2011). We next present an overview on relative importance analyses, their theoretical basis and application, before presenting the two examples in more detail.

Relative importance

Various approaches have been proposed for investigating the relative importance of each of a set of correlated predictors. One of the latest and most useful is relative weights analysis. First we present traditional data analysis approaches of correlations and multiple regression analysis, with associated advantages and shortcomings, before elaborating on the mechanics and additional benefits of relative weights analysis.

Correlation and multiple regression analyses

Correlation analyses compare one pair of variables at a time and provide indicators that reflect the direction (positive or negative) and size (-1 to +1) of that specific linear relationship. While this can be useful, a downside is that it ignores the relations that each variable in the pair has with other variables that may be of interest in predicting the target variable. Multiple regression offers an advantage over correlation analysis, in that multiple predictor variables can be considered in predicting a single criterion variable and yielding a single prediction equation, while considering the predictors' collinearity. An overall R^2 is reported which reflects the amount of variance that these predictors jointly explain.

In multiple regression, ideally each predictor variable contributes substantially and independently to the prediction of the variability in the criterion variable (Tabachnick & Fidell, 2001). However, where correlated predictors are entered in a multiple regression, proper partitioning of the variance to the different predictors is a complex matter (Darlington, 1968). The relative contribution of the weakest correlated predictors may be diminished or even suppressed by other stronger predictors, which can even lead to variables that are positively correlated with the criterion having negative regression coefficients, and vice versa. Hence, the overall picture obtained may not match correlation results. For example a predictor that seemed important in the (bivariate) correlation analyses may no longer feature in the regression analysis (Cohen, Cohen, West, & Aiken, 2003).

Researchers may still want to know how much variance each predictor explains in the criterion both by itself and in combination with other predictors (Johnson & LeBreton, 2004). This is known as relative importance, referring to the amount of variance in the criterion variable that can be attributed to each individual predictor variable. Note that this is only of interest where predictors are correlated; if they are not correlated then the squared beta coefficients from a multiple regression will already provide the relative importance of each predictor.

Various approaches to assessing relative importance have been proposed (see Johnson & LeBreton, 2004, for a review). The two most prominent of these are arguably general dominance analysis (Azen & Budescu, 2003) and relative weights analysis (Johnson, 2000) due to their accessibility and easily interpretable results. Therefore, we focus this primer on introducing, comparing, and demonstrating these two approaches.

Dominance analysis

Dominance analysis stems from initial work by Budescus (1993), in which one predictor was considered more important than another if it was be chosen over its competitor predictor in all possible subset models where only one predictor of the pair was entered. One difficulty with this very strict definition of dominance was that a dominant predictor could not always be established between every pair of predictors (i.e., one predictor might be more important in one subset, but less important in another). Azen and Budescu

(2003) therefore refined dominance analysis towards determining the general dominance of predictors so that dominance can be established in almost every case. The underlying idea remains that the quantification of importance depends on which set of predictors is involved in the analysis. Dominance analysis therefore requires specifying all possible subsets of a regression model. For example, consider the case of a criterion variable Y predicted by two predictor variables X_1 and X_2. This model has three possible subsets with either only X_1, or only X_2, or both X_1 and X_2 as predictors together predicting Y. The general dominance of predictor X_i is then computed as the squared semipartial correlation averaged across all possible subset models including X_i. The resulting dominance weights add up to the model's total explained variance (R^2) and thus provide an easily interpretable decomposition of the total predicted variance in the criterion (Azen & Budescu, 2003; Budescu, 1993).

Johnson (2000) noted however, that it quickly becomes very difficult and time-consuming to compute all possible subsets of a regression model, especially as the number of predictor variables increases. In fact, a model with *p* predictors requires the calculation of $2^p - 1$ submodels. Computational requirements thus increase exponentially and were too high for models with more than 10 predictors when dominance analysis was first introduced. Johnson (2000) therefore suggested relative weights analysis as an alternative to dominance analysis that requires considerably fewer computations and yields very close estimates of predictors' relative importance.

Relative weights analysis

The central idea of relative weights analysis is that the correlated predictors are transformed into new variables that are uncorrelated with each other but maximally correlated to their own respective original predictor variable (Johnson, 2000; see also Lindeman, Merenda, & Gold, 1980 for a similar approach). These are called *maximally related orthogonal variables* and are represented in Figure 1. The key idea to retain from this depiction is that each Z is a maximally rotated orthogonal variable that represents the relationship of each of the X predictor variables with the criterion variable Y.

Consider again the example of two correlated variables predicting a criterion. The relationship between any of the two predictors and the criterion variable can be represented by two separate regression equations (one for each predictor; Tonidandel, LeBreton, & Johnson, 2009). The first one describes the relation between the original predictor (e.g. X_1) and the new, orthogonal variables (Z_{X1} and Z_{X2}). For the first predictor in Figure 1 this would be:

$$X_1 = \lambda_{11}Z_1 + \lambda_{12}Z_2 \quad (1)$$

λ_{jk} represents the standardized slope coefficient linking original predictor *j* with orthogonal predictor *k*. A second regression equation is necessary to represent the relations between the orthogonal variables (Z_1 and Z_2) and the criterion (Y):

$$Y = \beta_1 Z_1 + \beta_2 Z_2 + \nu \quad (2)$$

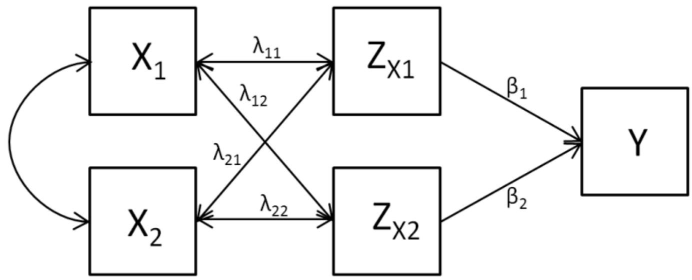

Figure 1:
Graphical representation of relative weights for a regression with two predictors and one criterion (adapted from Johnson & LeBreton, 2004)

In this equation β_k represents the standardized slope coefficient linking orthogonal predictor k with the outcome and ν denotes a disturbance term. Taking these two regression equations into account, the relative weight (ε_k), that is the variance in Y explained by X_1 in Figure 1, can be calculated as the sum of the squared products of the two slope coefficients (λ_{jk}; β_k):

$$\varepsilon_1 = \lambda_{11}^2\beta_1^2 + \lambda_{12}^2\beta_2^2 \tag{3}$$

The squared coefficients λ_{jk}^2 and β_k^2 represent the relative contribution of Z_k to X_j and of Z_k to Y. The combined term (λ_{jk}^2 β_k^2) describes the proportion of variance in Y associated with X_j through Z_k. Summing across all Z_ks finally produces the total proportion of variance attributed to X_j. In other words, the relative weight ε_1 describes how much variance in the criterion Y is explained by predictor X_1 independent of X_2. Consequently, the relative weights of all predictors in a model add up to the model's total squared multiple correlation as illustrated in Equation 4:

$$R^2 = \Sigma\varepsilon_j \tag{4}$$

Several extensions of this basic approach to calculate relative weights have been developed. While this primer will only focus on basic linear regression and regression models with higher-order terms, relative weights can also be applied to a variety of other analytic situations such as multivariate models (LeBreton & Tonidandel, 2008) or logistic regression models (Tonidandel & LeBreton, 2010).

Relative weights, like any statistic, are influenced to some extent by error. Thus comparing two relative weights from the same sample requires estimating the confidence interval of the relative weights. Johnson (2004) suggested a bootstrapping approach in which the standard error is estimated on the basis of a large number (e.g., 10,000) of repeated random subsamples (with replacement) from a sample. The standard deviation across these subsamples represents the standard error of the relative weights. To indicate a statistically significant difference, the confidence intervals of two relative weights should not overlap.

This approach can be extended to estimate the statistical significance of relative weights. Just like R^2, relative weights are hardly ever exactly zero and never below (see also Johnson, 2004). Hence the confidence interval of relative weights will never include zero, thus always indicating statistical significance. In line with the approach suggested by Horn (1965), where the number of factors to retain in a factor analysis is determined by comparing the factors' eigenvalues to the eigenvalues of random variables, Tonidandel and colleagues (2009) suggest comparing the relative weight of a theoretically meaningful predictor to the relative weight of a random variable. Even though a random variable is by definition not related to the criterion variable, its relative weight in a finite sample will almost always be non-zero due to sampling error. If the relative weight of a variable is significantly greater than the relative weight of a randomly generated variable, it is then assumed to be significantly different from zero (see Tonidandel et al., 2009, for more details).

The relation between dominance weights and relative weights

As described above, relative weights analysis was introduced as an elegant alternative to dominance analysis, which was at that time considered inapplicable due to the large computational effort involved (Johnson, 2000). LeBreton, Polyhart and Ladd (2004) demonstrated the adequacy of the assumed convergence between the two rather different approaches by conducting multiple Monte Carlo comparisons of dominance weights and relative weights in relation to each other and to beta coefficients and correlations. The authors concluded that relative weights demonstrated the greatest convergence, and beta weights and correlation coefficients the greatest divergence, with dominance weights. In addition, Johnson (2000) demonstrated a close relation between relative weights and dominance weights based on 31 independent data sets.

However, the Monte Carlo comparisons conducted by LeBreton and colleagues (2004) also revealed several conditions under which relative weights diverged from dominance weights. Specifically, high validity of the predictors, a large collinearity among the predictors, and a large number of predictors reduced the validity of relative weights as alternative to dominance weights. Moreover, Thomas, Zumbo, Kwan, and Schweitzer (2014) substantially criticized the mathematical approach used to obtain the relative weights as theoretically flawed. The authors argue that the method can result in distorted inferences when it is compared with dominance analysis. They warn against using relative weights as indicators of relative importance in regressions yet they also note that the two approaches result in very similar results for most applications and are geometrically identical when using only two predictors.

Since Budescu (1993) first suggested dominance analysis, the computational capabilities of standard computers and software packages increased vastly. This might have rendered relative weights unnecessary as an alternative approach. However, the substantial amount of research on relative weights analysis resulting in advances such as the bootstrapping approach to estimate the significance of relative weights (Johnson, 2004) as well as the extension to more advanced applications such as multivariate models (LeBreton & Tonidandel, 2008) and logistic regression models (Tonidandel & LeBreton, 2010) is not fully paralleled by research on dominance analysis. Therefore, we suggest calculating dominance weights wherever possible and using relative weights in specific cases such as multivariate analyses. When relative weights analysis is used, the validity and number of predictors as well as their intercorrelation should be considered with care.

Limitations of relative importance analyses

Relative importance analyses provides researchers with valuable additional information that would otherwise not be available. However, these analyses do not provide a cure for all limitations of multiple regression. Moreover, there are several limitations that apply equally to both multiple regression and relative importance analyses (see Johnson, 2000 for a more extensive discussion of the limitations of relative weights).

Just like beta weights, both relative weights and dominance weights are based on observable manifest variables and may thus 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). Using a latent variable correlation matrix as input, rather than the observed correlation matrix, could potentially compensate for the potential deleterious effects of measurement error on the observed relative importance indices (Tonidandel & LeBreton, 2011).

It is also important to keep in mind that relative importance analysis does not solve the problem of multicollinearity among predictors. Whereas relative importance analysis was in fact developed for use with correlated predictors and partitions variance among correlated predictor variables, high correlations among the predictor variables must not be ignored. If two or more predictor variables are very highly correlated they might be assessing the same underlying construct. In such a case, the resulting importance weights can be misleading and it would be necessary to consider dropping one of the highly multicollinear variables. No absolute cut-off exists to indicate too much multicollinearity (for a discussion of cut-off values see Craney & Surles, 2002). Concerns about excessive multicollinearity are therefore more of a theoretical nature than a statistical one. High levels of collinearity between similar and yet distinct constructs are not problematic for relative importance analysis, as both methods presented here 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, and this could yield a misleading result.

Most importantly, relative importance weights are also not intended to replace regression, which is the best approach for building prediction equations. Neither relative weights nor dominance weights should be used for this. Neither should relative importance analyses be used to select the set of variables that will maximize prediction.

Two highly correlated variables may have similar importance weights but the second variable may contribute little to overall predictive capability of the model over and above the first variable. Rather these relative importance analyses should be used in addition to regression analyses as they provide valuable information about variance partitioning, which is not handled well by traditional regression estimates (Tonidandel & LeBreton, 2011).

Empirical examples

In the following section, we demonstrate the application, utility, and limitations of both dominance weights and relative weights analysis in comparison to multiple regression using two empirical examples. In each case, we first provide a short overview of the theoretical background of the study as well as selected hypotheses and the study design. We then present and discuss the results based on multiple regression models and the two indicators of relative importance. The first example shows the advantages of relative importance analysis when predictors are correlated and the model explains a large amount of variance in the criterion. The second example shows the benefits of relative importance analysis when the predictors and interaction terms are correlated and there are a large number of predictors. All analyses are based on the original data, kindly provided by the studies' authors.

Empirical example 1 (Cooper-Thomas et al., 2004)

Theoretical background and hypotheses. For our first empirical example, we chose a study by Cooper-Thomas and her colleagues (2004), who investigated the relative importance of three socialisation tactics for newcomer adjustment using multiple regressions. Of the three categories of socialization tactics, that is context, content and social (Jones, 1986), Cooper-Thomas et al. (2004) focus on social aspects since research shows these to have stronger effects relative to the other two types of tactics (Saks, Uggerslev, & Fassina, 2007). These tactics are enacted by experienced organizational members who, in turn, act as role models for newcomers (serial tactic), provide positive social support to newcomers (investiture tactic), and offer mentoring (mentoring tactic). It seems plausible that the use of these tactics might be correlated, that is that experienced colleagues who are role models may concurrently provide greater social support and mentoring. Thus the relative importance of any single tactic may not be fully interpretable using multiple regression analyses alone.

As the socialisation criteria, the study distinguishes between two different forms of person-organization (PO) fit, perceived and actual. Perceived PO fit describes subjective fit as assessed by the newcomer against the perceived environmental characteristics of the organisation. Actual PO fit refers to an independent assessment of individuals' own values and those of the organization and describes the congruence of these two assessments. The contribution of Cooper-Thomas and her colleagues' (2004) study is incorporating both fit measures (i.e., actual and perceived) in a longitudinal design, allowing a comprehensive examination of the influence of different socialization tactics on changes in perceived PO fit after the first stage of socialization (controlling for actual and perceived fit at entry) as well as job satisfaction and organisational commitment. This is represented in their Hypothesis 1: Newcomers who experience mentoring, investiture, and serial organizational socialization tactics should show higher levels of perceived fit, actual fit, job satisfaction, and organisational commitment after controlling for perceived and actual fit at organizational entry. Cooper-Thomas and her colleagues' (2004) study investigates additional hypotheses using other analyses; we focus only on their first hypothesis tested with multiple regression.

Methods. Participants were recruited from newcomers entering the London office of a global professional services firm over a 6-month period. Data were collected during newcomers' first week and again 4 months later (T1 and T2 respectively). All measures were administered by survey, with the exception of the value measure, the Organizational Culture Profile (OCP; Chatman, 1991), which was administered face-to-face due to the complexity of the assessment.

In total, complete survey data at both T1 and T2 was available for 80 newcomers. Complete responses for the OCP at T1 and T2 were obtained for 45 and 44 newcomers, respectively. All subsamples were comparable to the full sample regarding relevant demographic variables (cf. Goodman & Blum, 1996) without finding any significant differences. All scales displayed satisfactory internal consistency and factor analysed as expected.

All analyses were conducted using R 3.1.1. To compute the relative weights as well as the significance levels, for relative weights analysis we adapted the R code provided by Tonidandel and LeBreton on RWA web (see Tonidandel & LeBreton, 2015); to calculate the dominance weights we used the yhat package (Nimon & Roberts, 2009).

Results. Table 1 depicts the correlations between all variables employed in the study. There were moderate to strong correlations between the different socialisation tactics. Investiture tactics correlated strongly with serial tactics (r = .63) and moderately with mentoring tactics (r = .32). There was also a moderate correlation between serial tactics and mentoring tactics (r = .27). These moderate to strong correlations, especially between investiture and serial tactics, are likely to distort the beta weights in the multiple regression analysis but, since relative weights analysis uses maximally orthogonally rotated variables (Z_k), relative weights are not as affected. Any differences would be reflected in a mismatch between beta weights, relative weights, and dominance weights.

From this first inspection of the correlations, we move to the regression results. In total, Cooper-Thomas and her colleagues' (2004) computed 4 different regression models to test Hypothesis 1. Both the beta weights and the relative weights for each model are depicted in Table 2. Perceived fit and actual fit (both at T1) followed by the three socialisation tactics (mentoring, investiture, and serial) were used to predict perceived fit, job satisfaction, and organizational commitment at T2. In order to make the analysis more easily comprehensible, we have identified the respective blocks and provided only the results necessary for the comparison between multiple regression and relative weights (For the full regression analysis see the original publication, Cooper-Thomas et al., 2004).

Table 1:
Mean, standard deviation and correlations of the study variables as reported in Cooper-Thomas et al. (2004)

	Mean	SD	1	2	3	4	5	6	7	8
1 Investiture	4.46	1.05	-							
2 Serial	4.09	1.13	.63**	-						
3 Mentor	3.44	0.76	.32**	.27*	-					
4 Perceived fit (t1)	5.08	1.10	.26*	.18	.03	-				
5 Perceived fit (t2)	4.74	1.37	.67**	.47**	.09	.42**	-			
6 Actual fit (t1)	0.26	0.17	.18	.29	.30	.03	.31*	-		
7 Actual fit (t2)	0.21	0.22	.08	.06	.19	.10	.36*	.74**	-	
8 Job Satisfaction	3.51	1.01	.50**	.52**	.02	.16	.48**	.37*	.35*	-
9 Organisational Commitment	4.86	1.16	.58**	.53**	.17	.40**	.71**	.55**	.50**	.62**

Note. SD = standard deviation; *$p < .05$; **$p < .01$.

Table 2:
Regression Results for Empirical Example 1

	Perceived fit (T2)			Job satisfaction (T2)			Organisational commitment (T2)				Actual fit (T2)		
	Model 1			Model 2			Model 3				Model 4		
Variable	β	RW	DW	β	RW	DW	β	RW	DW	Variable	β	RW	DW
Block 1: Fit T1										Block 1: Actual fit (T1)	.75**	.51*	.50
Perceived fit (T1)	.25*	.11*	.25	.04	.01	.01	.28*	.11*	.14				
Actual fit (T1)	.06	.05	.03	.26*	.08	.09	.38**	.21*	.19	Block 2: Perceived fit (T1)	.11	.01	.00
Block 2: Socialization tactics										Block 3: Socialization tactics			
Investiture	.57*	.25*	.19	.21*	.12*	.19	.28*	.15*	.24	Investiture	.02	.01	.01
Serial	.06	.11*	.18	.31*	.15*	.16	.21	.14*	.13	Serial	-.23	.02	.02
Mentor	.12	.01	.01	-.05	.00	.01	.12	.02	.02	Mentor	-.07	.06	.02
Total R^2		.53**			.38*			.62**				.56**	

Note. RW = relative weights; DW = dominance weights; *p =< .05; **p =< .01.

In Model 1, perceived fit at T1 significantly predicts perceived fit at T2 (β = .25) and explains meaningful amounts of variance (RW = .11; DW = .25). Actual fit at T1 is not significant (β = .06; RW = .05; DW = .05). The socialisation tactics are entered in Block 2 of Model 1. Here, the beta weights and the relative weights provide different pictures on the value of the predictors. In the regression results, contrary to their Hypothesis 1, only investiture significantly predicted perceived fit (β = .57). However, according to the relative weights analysis, investiture (RW = .25; DW = .19) and serial tactics (β = .06; RW = .11; DW = .18) explained meaningful amounts of variance, providing more support for their Hypothesis 1. The relative weights did not match the dominance weights well though with investiture being the most important predictor according to relative weights but perceived fit having the highest dominance weights.

Looking next at the criterion of job satisfaction (Model 2), in the multiple regression this was predicted by actual fit at T1 (β = .26) but not perceived fit at T1 (β = .04). The relative weights analysis shows that neither fit type explained meaningful amounts of variance (RW = .08; DW = .09 and RW = .01; DW = .01, respectively). Regarding the socialisation tactics, investiture (β = .21; RW = .12; DW = .19) and serial (β = .31; RW = .15; DW = .16) tactics both significantly predicted job satisfaction and explained meaningful amounts of variance, whereas mentoring did not (β = -.05; RW = .00; DW = .01). Again, the results differed slightly between relative and dominance weights although, in this case, there were similar results for the hypothesised predictors.

For organisational commitment (Model 3), both perceived fit (β = .28; RW = .11; DW = .14) and actual fit (β = .38; RW = .21; DW = .19) at T1 predicted organisational commitment and explained meaningful amounts of variance. These results are similar across the two analyses. For the socialisation tactics analysed using multiple regression, only investiture significantly predicted organisational commitment (β = .28). However, according to the relative weights analysis, both investiture (RW = .15; DW = .24) and serial (β = .21; RW = .14; DW = .13) explained meaningful amounts of variance. Dominance analysis confirmed this result.

Finally, actual fit at T2 was predicted exclusively by actual fit at T1 (β = .75), which explained 51% of the variance (RW = .51; DW = .50). None of the other predictors was significant or added meaningful amounts of explained variance across any of the three.

Discussion. Our discussion of Example 1 focuses exclusively on the additional information gained from relative importance analyses over and above multiple regression analysis.

Example 1 contrasts the use of beta weights, relative weights, and dominance weights to determine the relative importance of predictors. Given the low correlation between perceived and actual fit at T1 (r = .03) it is not surprising that beta weights and relative importance mostly agree regarding the relative importance of these two predictors. That is, relative importance adds little useful additional information when predictors are (almost) uncorrelated. Only in predicting job satisfaction, the beta weight of actual fit (T1) was significant (β = .26), whereas the relative weight did not significantly differ from a random variable, which was confirmed by the dominance weight.

For the socialisation tactics on the other hand, we found moderate to strong intercorrelations among the predictors. Especially investiture tactics correlated strongly (r = .63) with serial tactics, and subsequently overshadowed serial tactics in the regression analyses. Thus, when using regression analysis, investiture tactics seemed to be the sole significant predictor of perceived fit (T2) and organisational commitment (T2) among the three socialisation tactics, whereas using relative importance, serial tactics were also found to explain meaningful amounts of variance within both criteria. In other words, in the regression analysis, the relationship of serial tactics with each criterion was "hidden" due to the shared variance of serial and investiture tactics. That is, the relationship of one predictor (e.g., serial tactics) may be overshadowed by another, stronger predictor (e.g., investiture tactics). In this case, the regression analysis provides less support for the hypothesised relationships compared to the relative importance analyses because of the latter taking account of intercorrelations among predictors. This is important because it shows that serial tactics are also important alongside investiture tactics in predicting newcomer adjustment, instead of the regression analysis interpretation which suggests that the role of serial tactics is supplanted by investiture tactics.

Further, it demonstrates the value of applying dominance analysis when interested in the relative importance of correlated predictors that explain substantial variance in the criterion. The higher the explained variance in the criterion was, the stronger beta weights and relative weights diverged from the dominance weights. Please also note that computing multivariate relative weights (LeBreton & Tonidandel, 2008) could also have approached the correlated outcomes. We refrained from this analysis to keep this primer as closely linked to the analyses in the original papers as possible.

Empirical example 2: Lui & Ngo, 2012

Theoretical background and hypotheses. Our second example is theoretically grounded in relational exchange theory, and contains main effects as in the previous example, and also a range of moderator and mediator effects that allow us to further display the potential of a relative weights approach.

Relational exchange theory suggests that relationships among firms are not one time economic transactions but instead are embedded in a rich social context of norms and trust (Das & Teng, 2002). Based on this proposition, Lui and Ngo (2012) analysed the relative importance of different social and contextual predictors on buyers' long-term orientation and suppliers' opportunistic behaviour.

Regarding a buyer's long-term orientation, Lui and Ngo (2012) hypothesised that a buyer will have a stronger inclination to continue the collaboration when the relationship with suppliers is found to be satisfactory over a longer period of time (Ryu, Park, & Min, 2007). Therefore, satisfactory prior history should be related positively to a buyer's long-term orientation (their Hypothesis 1). At the same time exchange hazards, such as asset specificity and market uncertainty, are particularly relevant to the development of a buyer's long-term orientation. When a buyer invests in specific assets for a partnership, the assets will be of less value for other uses (Skarmeas & Robson, 2008). In response to this threat, the buyer requires more safeguards before committing to such an investment (Katsikeas, Skarmeas, & Bello, 2009). These safeguards are provided through a buyer's long-term orientation reducing the frequency and extent of re-negotiation, thus safeguarding specific assets. Therefore a buyer's asset specificity should be positively related to the buyer's long-term orientation (Hypothesis 2). Finally, under uncertain market conditions that require being adaptable to various situations (Poppo, Zhou, & Ryu, 2008), a buyer may enhance the flexibility and adaptability of a partnership by adopting long-term orientation towards its supplier. Therefore market uncertainty should be positively related to a buyer's long-term orientation (Hypothesis 3).

In addition to these main effects, Lui and Ngo (2012) also postulate moderator effects for satisfactory prior history on the effects of exchange hazards. Specifically, they hypothesize that satisfactory prior history reduces the relation between a buyer's asset specificity and a buyer's long-term orientation (Hypothesis 4) and strengthens the relation between market uncertainty and a buyer's long-term orientation (Hypothesis 5).

Regarding a supplier's opportunistic behaviour, Lui and Ngo (2012) propose that a buyer's long-term orientation promotes a socialization process where norms and goals of a supplier and a buyer are aligned. This results in the supplier refraining from opportunistic behaviour (Wathne & Heide, 2000), therefore a buyer's long-term orientation should be negatively related to a supplier's opportunistic behaviour (Hypothesis 6). Building on the previous hypotheses, Lui and Ngo (2012) finally propose that a buyer's long-term orientation mediates the relation between satisfactory prior history and a supplier's opportunistic behaviour (Hypothesis 7).

Methods. The sample for this study consisted of a total of 221 trading companies from the garment and toy industries in Hong Kong. Surveys were mailed to contact personnel asking them to answer certain questions with respect to 'a supplier that you have recently dealt with'. All scales used displayed satisfactory internal consistency and factor analysed as expected. Please refer to the original article for full details on the method.

In addition to the variables of interest, Lui and Ngo (2012) included four control variables that could potentially affect a buyer's long-term orientation or a supplier's opportunistic behaviour: Type of industry, firm size, supplier on-time delivery, and the rate of rejected deliveries by the supplier.

All analyses were conducted using R 3.1.1. To compute the relative weights as well as the significance levels, we adapted the R code provided by Tonidandel and LeBreton on RWA web (see Tonidandel & LeBreton, 2015), while to calculate the dominance weights we used the yhat package (Nimon & Roberts, 2009).

Results. Table 3 depicts the correlations between all variables. As can be seen, all of the assumed predictors were significantly correlated to the respective criteria. There were also several significant correlations between the predictors such as between satisfactory prior history and both buyer's asset specificity ($r = .12$) and market uncertainty ($r = .18$). These statistically significant but weak correlations might limit the interpretability of beta weights as direct indicators of the predictors' relative importance but are unlikely to have a big impact. However, this study includes models with a large number of predictors (up to 9), which is likely to have an impact on the utility of beta weights as indicators of relative importance.

Table 3:
Mean, standard deviation and correlations of the study variables as reported in Lui & Ngo (2012)

Variables	Mean	SD	1	2	3	4	5	6	7	8
1 Buyer’s long-term orientation	3.66	0.63								
2 Buyer’s asset specificity	3.71	0.67	.35***							
3 Market uncertainty	3.21	0.98	.25***	.06						
4 Satisfactory prior history	6.53	3.17	.32***	.12*	.18**					
5 Supplier’s opportunistic behaviour	2.80	0.72	-.36***	-.04	-.05	-.21**				
6 Industry (garment = 0)	0.50	0.50	.01	.05	.14*	-.14*	.02			
7 Buyer firm size (ln)	1.99	1.10	.17**	.03	.05	.22***	-.10	-.10		
8 Supplier on time delivery (percentage)	79.25	16.57	.42***	.13*	.10	.18**	-.37***	.03	.10	
9 Supplier rejected delivery (percentage)	5.57	7.50	-.27***	-.12*	.03	-.19**	.31***	.09	-.11	-.53***

Note. SD = standard deviation; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

For the regression results, Lui and Ngo (2012) computed five different regression models to test the seven hypotheses. The beta weights, relative weights, and dominance weights for each model are depicted in Table 4. In Model 1, buyer's long-term orientation was predicted by the control variables alone. Based on the beta weights, both buyer's firm size (β = .15) and supplier on-time delivery (β = .37) significantly predicted buyer's long-term orientation. However, looking at the relative weights, these reveal that only supplier on-time delivery explained a meaningful amount of variance (RW = .13; DW = .13) whereas the amount of variance explained by buyer's firm size (RW = .02) was not above the relative weight of a random variable and similarly dominance analysis showed minimum effects of buyer's firm size (DW = .03). Thus, as expected, relative weights and dominance weights were essentially identical in this model.

In Model 2, the three hypothesised main effects were added as predictors after the control variables. In line with Lui and Ngo's (2012) Hypotheses 1 to 3, buyer's asset specificity (β = .27; RW = .09; DW = .09), market uncertainty (β = .17; RW = .05; DW = .04), and satisfactory prior history (β = .19; RW = .05; DW = .05) all significantly predicted buyer's long-term orientation with positive beta weights. As was to be expected from the small correlations between the predictors, the relative weights supported this result in that all three predictors explained meaningful amounts of variance. Again, relative weights and dominance weights were essentially identical in this model.

Model 3 shows the results for Hypotheses 4 and 5, that is, satisfactory prior history moderating the relation between exchange hazards (buyer's asset specificity and market uncertainty) on buyer's long-term orientation (Model 3). Here the beta weights and relative weights differ. First, it needs to be noted that LeBreton, Tonidandel, and Krasikova (2013) suggest residualizing interaction terms before using them in a relative weights analysis to properly determine their relative weights, as otherwise no clear decomposition of the explained variance is possible. The underlying idea is that the standard interaction term contains information about both the lower order effects (original predictors) and the higher order effects (interaction terms). The residualization process removes the lower order effects from the higher order term; by creating a new residualized variable, one can now proceed with a relative importance analysis. This leads to several important differences between the regression analysis and the relative importance analysis. In the regression analysis the interaction term of satisfactory prior history and buyer's asset specificity correlated moderately to strongly with the two underlying predictors of satisfactory prior history (r = .38) and buyer's asset specificity (r = .65). Similarly, the interaction term of satisfactory prior history and market uncertainty correlate moderately to strongly with the two underlying predictors of satisfactory prior history (r = .32) and market uncertainty (r = .70). In contrast, these correlations were all zero in the relative weights analysis due to the residualization of the interaction terms. This allows the relative weights analysis to show the incremental importance (LeBreton, Hargis, Griepentrog, Oswald, & Ployhart, 2007) of each predictor, including each interaction term, with the criterion, and accounts for the discrepancy evident in the resulting estimates. In line with our hypotheses, the bivariate correlations between the interaction terms with the criterion of buyer's long-term orientation dropped from r = .23 and r = .26 to non-significant values (r = .07 and r = -.10).

Table 4:
Regression Results for Empirical Example 2

	Buyer's long-term orientation									Supplier's opportunistic behaviour					
	Model 1			Model 2			Model 3			Model 4			Model 5		
Variables	β	RW	DW	β	RW	DW	β	RW	DW	β	RW	DW	β	RW	DW
Controls															
Industry	.03	.00	.00	.01	.00	.00	.00	.00	.00	-.00	.00	.00	.00	.00	.00
Buyer firm size (ln)	$.15^{*}$	.02	.03	.08	.01	.02	.09	.01	.02	-.02	.01	.01	-.01	.01	.01
Supplier on-time delivery	$.37^{***}$	$.13^{*}$	.13	$.29^{*}$	$.10^{*}$	.11	$.29^{***}$	$.10^{*}$	.10	$-.27^{***}$	.08*	.08	$-.19^{**}$	$.06^{*}$	.06
Supplier rejected delivery	-.06	.03	.03	-.04	$.03^{*}$	.02	-.02	$.03^{*}$	.02	$.14^{*}$	.03	.04	.13	.03	.03
Main effects															
Buyer's asset specificity (BAS)				$.27^{***}$	$.09^{*}$	.09	$.25^{***}$	$.09^{*}$	.09	.03	.00	.00	.10	.00	.01
Market uncertainty (MUC)				$.17^{**}$	$.05^{*}$	.04	$.18^{***}$	$.03^{*}$	.03	-.03	.00	.00	.03	.00	.00
Satisfactory prior history				$.19^{***}$	$.05^{*}$	.05	$.19^{***}$	$.05^{*}$	.04	$-.13^{*}$	.01	.01	-.07	.01	.01
Mediator															
Buyer's long-term orientation													$-.26^{***}$	$.11^{*}$	.10
Interactions															
BAS x Satisfactory prior history							$-.12^{*}$	.01	.02						
MUC x Satisfactory prior history							$.11^{*}$	.01	.03						
Adjusted R^2		$.19^{***}$			$.35^{***}$			$.37^{***}$			$.15^{***}$			$.20^{***}$	
ΔR^2					$.16^{***}$			$.02^{**}$						$.05^{***}$	

Note. RW = relative weights; DW = dominance weights; *$p < .05$; **$p < .01$; ***$p < .001$.

Turning to the results, for Model 3 they differ across the three analyses. The beta weights support Lui and Ngo's (2012) Hypotheses 4 and 5. That is, satisfactory prior history moderates the impact of buyer's asset specificity on buyer's long-term orientation (β = -.12; Hypothesis 4), and satisfactory prior history moderates the impact of market uncertainty on buyer's long-term orientation (β = .11; Hypothesis 5). Contrary to the multiple regression analyses, where the interaction terms were added as a separate block, for the relative weights analyses, the control variables were entered first, followed by all main effects and interaction terms in a subsequent step (LeBreton et al., 2013). The relative weights showed that the relative importance of the two interaction terms was very low (RW < .01 for both), which was confirmed by the dominance weights. Thus, the relative importance analyses provided different results to regression, according to which Hypotheses 4 and 5 were not supported. Also of note is that relative weights and dominance weights were essentially identical in this model.

To test Hypotheses 6 and 7, a negative relation between satisfactory prior history and supplier's opportunistic behaviour, which was mediated by buyer's long-term orientation, two more models (Models 4 and 5) were computed. Model 5 showed that the beta weight of buyer's long-term orientation on supplier's opportunistic behaviour (β = – .26) was negative and significant, supporting Hypothesis 6. In line with this, Buyer's long-term orientation explained meaningful amounts of variance (RW = .11; DW = .10).

For the mediation (Hypothesis 7), Lui and Ngo (2012) adopted the procedures suggested by Baron and Kenny (1986). The mediator (buyer's long-term orientation) had already been regressed on the predictor (satisfactory prior history) in Model 2 showing a significant relation that explained meaningful amounts of variance (β = .19; RW = .05). The criterion variable (supplier's opportunistic behaviour) was then regressed on satisfactory prior history in Model 4, which also yielded a significant beta weight (β = - .13) but did not explain meaningful amounts of variance (RW = .01; DW = .01). Again, relative weights and dominance weights were similar in this model.

Finally, in Model 5, the criterion variable (supplier's opportunistic behaviour) was regressed on both the predictor (satisfactory prior history) and the mediator (buyer's long-term orientation). In a combined model, the beta weight of satisfactory prior history was no longer significant but (as already reported for Hypothesis 6) buyer's long-term orientation remained a significant and meaningful predictor across all three analyses. Please note that, though indicating mediation, the relative weight of the mediator (buyer's long-term orientation) does not equal the indirect effect. This effect can be computed using a Sobel-test or bootstrapping analysis (Preacher & Hayes, 2004), which was done in the original publication (Lui & Ngo, 2012). Again, relative weights and dominance weights showed similar results in this model.

Discussion. Our discussion focuses exclusively on the additional information gained from relative importance analyses over that yielded by multiple regression analysis. The results' theoretical and practical implications can be found in the original publication (Lui & Ngo, 2012).

The correlations between most predictors in this example were small so that beta weights and relative weights did not differ much in terms of the predictors' relative importance and both indicators could be interpreted properly. Equally, the explained variance of the models was not big enough to influence the utility of the beta weights substantially. Since Lui and Ngo (2012) had very clear hypotheses about the direction of the relations between the predictors and the outcomes, beta weights were important to test these assumptions. Relative weights and dominance weights indicate the relative importance of a predictor variable but do not give any information about the direction of a relationship. The added value of relative importance, thus, lies in estimating the incremental importance of each predictor, which cannot be deduced from the beta weights.

To test mediation (Hypothesis 7), Lui and Ngo (2012) adopted Baron and Kenny's (1986) approach of several successive regressions followed by a Sobel test and bootstrapping. The key relation of satisfactory prior history (independent variable) with supplier's opportunistic behaviour (dependent variable) exhibited a significant beta weight in the regression but not in the relative importance analyses, whereas the other two relations that involved the mediating variable were significant in all analyses. Lui and Ngo (2012) relied on the significant mediation result using Baron and Kenny's approach within multiple regression as a basis to further assess the indirect (mediation) effect, using both a Sobel test and bootstrapping. A relative importance approach on the other hand would have provided no basis for further testing this specific mediation as the direct effect did not explain significant amounts of variance. Kenny (2015) thus argues that, next to statistical significance of regression results, other information such as the collinearity between predictor and mediator should be taken into account. This supports the complementary value of both multiple regressions and relative importance in mediation analyses.

For the moderation hypotheses (Hypotheses 4 and 5), there were strong correlations between the interaction terms and the respective predictors. These correlations limit the interpretability of the beta weights for all predictors in the model and may lead to erroneous estimates (Darlington, 1968). In the current example, the beta weights suggest that the relations between both exchange hazards (buyer's asset specificity and market uncertainty) and buyer's long-term orientation are moderated by a satisfactory prior history. As outlined above, these effects may just be due to the strong correlations between the interaction terms and the original predictors. This is supported by the relative importance analyses, which take these correlations into account and show the interaction terms did not explain meaningful amounts of variance in buyer's long-term orientation. Specifically, the relative importance analysis indicated that satisfactory prior history did not reduce the relation of either buyer's asset specificity with buyer's long-term orientation, nor increase the relation of market uncertainty with buyer's long-term orientation. Hence, the conclusions that can be drawn from the analyses change quite substantially using the more conservative relative importance analyses (Tonidandel et al., 2009). For instance, in their section on managerial implications, Lui and Ngo (2012) caution buyer managers to consider the risks from exchange hazards (buyer's asset specificity and market uncertainty) because (supplier) satisfactory prior history may interact with these, and influence buyer long-term orientation. Given that they frame buyer long-term orientation as a governance mechanism whereby buyers can reduce supplier's opportunistic behaviour, they note the importance of buyers being aware of factors influencing this orientation.

Since the relative importance analyses showed no interaction, this caution to buyer managers is limited to main effects: Buyer managers should be aware that the two exchange hazards and supplier satisfactory prior history may directly influence buyer long-term orientation, with the potential to affect, in turn, how they use this for governance.

To summarise, our second empirical example therefore also illustrates the value of taking intercorrelations between predictors into account by adding relative importance analyses to multiple regressions. As in the first example, note that we could also have computed multivariate relative weights (LeBreton & Tonidandel, 2008) to analyse the correlated outcomes but refrained from such analyses to keep this primer as closely linked to the analyses in the original paper as possible.

General discussion

In this primer we demonstrated using two empirical examples how relative importance analyses could be used as a supplement to multiple regression. The two examples stem from very different areas of research but used similar methodology to answer their respective research questions. In both cases, the researchers were interested in the importance of specific variables for the prediction of relevant real-world outcomes and used multiple regressions to investigate their hypotheses. Even though neither of the two papers explicitly specified any hypotheses about the relative importance of their predictors, relative importance analyses added valuable information by taking the predictors' intercorrelations into account (Tonidandel & LeBreton, 2011). In this way a seemingly difficult to explain dominance of one predictor over the others can potentially be understood as the result of strong correlations among the predictors (see Example 1). In addition, relative importance analyses offer easily interpretable measures of effect sizes for regressions, which, unlike beta weights, control for the correlations between predictors. For instance, a statistically significant interaction term can be revealed as not being meaningfully different from the relative importance of a random variable (see Example 2).

Conclusion

Our aim in this primer was to illustrate how the use of relative weights can add valuable information beyond the indices usually obtained from correlation and regression analyses, and how this information can be interpreted. Using relative weights analyses allowed us to gain additional information regarding the research questions in two examples and to explore the data at a finer level of detail. In conclusion, relative weights should be used to extend on other indices in order to answer theoretical questions regarding the relative importance of variables (Tonidandel & LeBreton, 2011). Nonetheless, even when the primary aim of a study is not to discover the relative importance of predictors, users of multiple regressions should consider conducting relative importance analyses as a valuable supplement to their primary analyses.

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