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RELATIVE IMPORTANCE ANALYSIS FOR THE STUDY OF THE FAMILY: ACCEPTING THE CHALLENGE OF CORRELATED PREDICTORS

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Family researchers are often interested in the importance of variables to be included in the prediction of some outcome, and have traditionally used multiple regression analysis (MR) to study variable importance. However, given the non-independence of family data, multicollinearity can be a pervasive phenomenon in this field of research and MR may produce poor or confusing results in the case of highly correlated predictors. In this article I present two alternative techniques of analysis — relative weight analysis (RWA; Johnson, 2000) and dominance analysis (DA; Budescu, 1993) — both of which address questions pertaining to predictor comparisons and are able to provide a plausible assessment of importance among multiple correlated predictors. Examples of application of RWA and DA to address specific questions about family relationships are discussed.

Key words: Family relationships; Multicollinearity; Relative importance; Relative weight analysis; Dominance analysis.

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The real world can be complex and correlated
(Kraha, Turner, Nimon, Reichwein Zientek, & Henson, 2012, p. 9)

Neither index alone tells the full story of a predictor's importance
(Johnson & LeBreton, 2004, p. 240)

The family is a complex system of individuals interacting with and in relation to one another. Often, many variables are needed to predict an outcome regarding family (members') life, as several variables — related to family members and to family relationships — can be simultaneously and interdependently at play (Peterson & Bush, 2003; Scabini & Cigoli, 2000).

Multiple regression analysis (MR) is a common statistical technique used in family research, and, more in general, within social sciences to predict a criterion variable (i.e., outcome or response) from several predictors (i.e., independent variables): "Regression analysis is perhaps the most frequently used statistical tool for the analysis of data in practice" (Wang, Duverger, & Bansal, 2013, p. 321). A brief search performed on the database PsycInfo (1954-2014) revealed that more than five thousand contributions (4097 articles, 997 dissertations, and 65 books) contain the keywords "regression" and "family relations" in their titles or abstracts. For example, the more recent scientific articles indexed in PsycInfo are entitled: "Socioeconomic status and parent-child relationships *predict* metacognitive questions to preschoolers" (Thompson & Foster, 2014); "Polygamy and poor mental health among Arab Bedouin women: Do socioeconomic position and social support *matter*?" (Daoud, Shoham-Vardi, Urquia, & O'Campo, 2014); "Parental, peer and school experiences as *predictors* of alcohol drinking among first and second generation immigrant adolescents in Israel" (Walsh, Djalovski, Boniel-Nissim, & Harel-Fisch, 2014). Beyond their varied contents, these studies share the common aim of identifying a set of predictors (e.g., socioeconomic status, parent-child relationships, social support, relational experiences) that provide a satisfactory description of the criterion variable (e.g., metacognitive questions, mental health, alcohol drinking), and of predictor comparison (e.g., "Does parental experience matter more than peer and school experiences in predicting adolescents' alcohol drinking?").

When using MR, researchers' primary interest focuses on estimating the overall model R^2 and on interpreting the individual regression coefficients (Equation 1). The overall R^2, which refers to the proportion of variance in the criterion variable that is accounted for by the predictor variables, can be interpreted as a general measure of effect size (Cohen, Cohen, West, & Aiken, 2003). Regression coefficients, on the other hand, inform researchers as to the incremental predictive validity of each predictor variable. In particular, unstandardized regression coefficients represent the mean change in the criterion variable (Y) for one single raw unit of change in the predictor variable (e.g., X_1) while holding the other predictors ($X_2,\ldots X_j$) in the model constant; in contrast, standardized regression coefficients (β) express the change in standard deviation units in order to facilitate the comparison of coefficients. This allows researchers to understand that predictor's unique (i.e., incremental) contribution toward explaining variance in the criterion (LeBreton, Tonidandel, & Krasikova, 2013).

$$Y = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_j + e \tag{1}$$

However, interpretation of standardized regression coefficients can be misleading if researchers fail to recognize that this β weight-focused interpretation is inevitably "context-dependent," that is, that it depends on the specified model and the model order entry (Pedhazur, 1997). In other words, the size of β weights depends on the predictors included in the regression equation; adding or removing a single predictor (i.e., "changing the context") could radically alter the size of β weights (Courville & Thompson, 2001). This is clearly evident in the case of correlated predictors: when pairs of combinations of predictors are highly correlated, a change in one predictor will most likely result in a change in the other predictor, thus making it difficult to separate their individual unique contribution (Mosteller & Tukey, 1977).

Multicollinearity (or collinearity) refers to the non-independence of predictors, usually in a regression-type analysis (Alin, 2010). When predictors are perfectly uncorrelated, each predictor's β weight equals each predictor's correlation with the criterion variable. On the contrary, MR fails to appropriately partition variance to the predictors when they are correlated. It is not uncommon for a variable to have a strong significant bivariate correlation with the criterion but a small β weight, if one or more other correlated predictors are assigned credit for that predictor's shared predictive ability. In this case, the predictor that emerges as contributing more uniquely to the criterion may simply be the one that has the weakest correlations with the other predictors (Tonidandel, LeBreton, & Johnson, 2009).

Multicollinearity of the observed variables permeates family research. As a consequence of interdependence within interpersonal relationships (Donato et al., 2014; Kenny, Kashy, & Cook, 2006), measures of family-related variables (e.g., family relationship quality as reported by the parent and the child; father-child relationship quality and mother-child relationship quality, etc.) are often moderately to highly correlated with each other. In fact, family data can be collected from more than one family member, each asked to report his/her perspective on family relationships; moreover, family members experience more than one family relationship (e.g., father-child, mother-child, couple relationships) and influence each other (Kelley et al., 1983). The fact that family members have reciprocal influences defines the very nature of the family: etymologically, the term "relatives" (i.e., members of the same family) derives from Latin *relativus*, meaning "having reference or relation, depending on the relationship to something/someone else, compared to each other" (http://www.etymonline.com/).

Commonly used methods that deal with multicollinearity force researchers to either select uncorrelated predictors or eliminate those predictors with the highest degree of correlation, even in a situation where they wish to include all variables, or to create separate models. Regrettably, the arbitrary elimination of a variable that had been included in the model for presumably sound reasons reduces the explanatory power of the model, while the use of separate models can yield findings that are not representative of the overlapping predictive ability and interplay between predictors (Kidwell & Harrington Brown, 1982). In this vein, researchers interested in family relationships have frequently created separate regression models (e.g., one for father-child relationship and one for mother-child relationship), then descriptively compared them on the basis of R^2 and β weights (Barber, 2005; Stolz, Barber, & Olsen, 2005). Another common response to multicollinearity concerns is to combine reports of fathers' and mothers' behaviors into a variable called "parenting" (e.g., Ghazarian, Supple, & Plunkett, 2008), thus neglecting possible differences between fathers' and mothers' importance (i.e., possible "specialized effects"; Stolz et al., 2005) in predicting the criterion variable.

In this article I present more sophisticated techniques of analysis which can complement traditional regression analysis in assessing the importance of conceptually and empirically correlated predictors. In particular, I focus on relative importance analysis, a fairly new set of techniques — including relative weight analysis (Johnson, 2000) and dominance analysis (Budescu, 1993) — which can estimate the unique and shared contribution of one predictor *within the context* of the other predictors (LeBreton, Ployhart, & Ladd, 2004).

After the description of relative importance analysis, with particular emphasis on the underlying logic, rather than on the mathematical aspects, I will discuss its usefulness in addressing specific questions in family research, and will provide an illustrative example of application of relative weight analysis and dominance analysis to family data.

RELATIVE IMPORTANCE ANALYSIS: A BRIEF OVERVIEW

The general purpose of relative importance analysis is to uncover the contributions of multiple predictors relative to each other (i.e., in relation with or compared to each other) within a selected model. Imagine that a researcher is interested in how each dimension of the mother-child relationship (e.g., intimacy, promotion of autonomy, admiration) contributes to children's overall satisfaction for the relationship with their mothers. Children do not base their satisfaction judgment merely on the unique contribution of each relational aspect; rather, they consider all the important aspects simultaneously and implicitly weight each aspect relative to the others in determining their overall satisfaction.[1] What is the relative importance children place on intimacy, autonomy, and admiration in their satisfaction judgment?

Johnson (2000) defines relative importance as the contribution each variable makes to the prediction of a criterion by itself and in combination with other predictor variables. Similarly, Azen and Budescu (2003) state that a predictor's relative importance reflects its contribution to the prediction of the criterion in the presence of a specific set of predictors. Technically, the estimation of the relative importance requires the partitioning of variance (R^2) among predictors while including all the variables in the model. In the case of completely uncorrelated predictors, by dividing the squared standardized regression coefficients (β^2) by the squared multiple correlation (R^2), the relative weight of each variable is easily expressed as the proportion of predictable variance for which it accounts. In contrast, when predictors are correlated, the β^2 coefficients no longer sum to the R^2, and predictors that are correlated with each other and similarly with the criterion may have very different regression coefficients (Johnson, 2000). Thus, alternative measures of variable importance, among which are relative weight analysis (Johnson, 2000) and dominance analysis (Budescu, 1993), have been designed to provide a more plausible assessment of importance among multiple correlated predictors and to rank order variables in terms of their relative importance.

Relative weight analysis (RWA). RWA aims at partitioning R^2 while minimizing the impact of associations between predictor variables (Nathans, Oswald, & Nimon, 2012). RWA addresses the issue of multicollinearity by using principle component analysis to create a new set of predictor variables (Z_k) that are closely related to the original predictors (X_j), but are uncorrelated with each other (see Johnson, 2000, for the process of obtaining the best-fitting set of orthogonal variables). Assuming to have an $n \times p$ matrix of predictors, Z_ks are the best-fitting approximations of the columns of X in that they minimize the residual sum of squares between the original variables and the orthogonal variables (Johnson, 1966). The criterion variable is regressed on the new uncorrelated variables, Z_k (Equation 2), just as the original predictors are regressed on Z_k (Equation 3). Because the Z_ks are uncorrelated, each squared β_k and λ_{jk} represents the contribution (i.e., the variance account for) of Z_k to Y and of Z_k to X_j, respectively. Relative weights are estimated by multiplying the squared β_k by the squared λ_{jk} (Equation 4). The term $\lambda^2_{jk}\beta^2_k$ describes the proportion of variance in Y associated with X_j through Z_k. R^2 can be decomposed as the sum of the individual relative importance weights (ε_j), with the possibility to rescale each weight in the metric of relative effect size by dividing it by the model R^2 and multiplying this value by 100. In this way, each rescaled weight reflects the percentage of predictable criterion variance.

$$Y = \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + v \quad (2)$$

$$X_1 = \lambda_{11} Z_1 + \lambda_{12} Z_2 + \lambda_{13} Z_3 + \omega \quad (3)$$

$$\varepsilon_1 = \lambda_{11}^2\beta_1^2 + \lambda_{12}^2\beta_2^2 + \lambda_{13}^2\beta_3^2 \quad (4)$$ [2]

Recent developments. RWA has been extended to cover variable importance for multivariate multiple regression (LeBreton & Tonidandel, 2008), logistic regression with categorical outcomes (Tonidandel & LeBreton, 2010), and regression models containing higher-order terms such as cross-product terms, quadratic terms, or other polynomial terms (LeBreton et al., 2013).

Electronic resources. SAS and SPSS macros for performing relative weight analysis are available on James LeBreton's computer programs page (http://www1.psych.purdue.edu/~jlebreto/relative.htm), while SAS programs that compute relative weights for logistic regression can be found on Scott Tonidandel's computer programs page (http://www1.davidson.edu/academic/psychology/Tonidandel/TonidandelProgramsMain.htm). Moreover, Tonidandel and LeBreton (2014) recently presented a new, free, and comprehensive resource, RWA-Web, which can be used to carry out RWA by *R* statistical package (http://relativeimportance.davidson.edu/).

Dominance analysis (*DA*). DA addresses the issue of multicollinearity by examining the change in R^2 that stems from adding a predictor to all possible subset regression models which provide the context of comparison. In contrast to MR, which parses out the unique contributions beyond any effect shared with another predictor, this technique considers the shared variance by assessing the unique variance and any partial joint variance contributed by an individual predictor. Indeed, DA furnishes an index of relative importance based on a predictor's direct effect (i.e., when considered by itself), unique effect (i.e., conditional on all other predictors in the full model), and partial effect (i.e., conditional on all subsets of predictors). When the simple bivariate correlations of each predictor with the criterion are examined, the level of analysis ignores all other predictors. Assuming a model with three predictor variables, each predictor's contribution is then assessed when it is paired with, first, one other predictor, and, second, with both of the other predictors.

Azen and Budescu (2003) identified three levels of dominance: complete dominance, which occurs when a predictor yields a larger increment in R^2 than the other predictors across all subset regression models; conditional dominance, which occurs when the average additional contribution within each of the same-size models is greater for one predictor; and general dominance, which occurs when the additional contributions to R^2 of a predictor, across all subset models, are on average greater than those of the other predictors. The three levels of dominance are hierarchical in nature, meaning that when X_1 dominates X_2 completely, it also dominates X_2 both conditionally and generally. As an example, imagine that you are interested in estimating the contribution of mother-child intimacy, promotion of autonomy, and admiration to children's overall satisfaction with the relationship with their mothers. Intimacy is said to dominate the other predictors completely if its contribution to R^2 is greater than the contributions of autonomy and admiration in every subset model (i.e., in any condition). Instead, intimacy dominates the other predictors only conditionally if there are some models in which it does not make a significant additional contribution, but contributes more on average to the model of each subset size. Intimacy dominates the other predictors generally when it makes a greater additional contribution than other predictors on average when all the subset regression models are combined. Similarly to RWA, because the sum of the dominance weights equals the total model R^2, it is possible to calculate the percentage of predictable criterion variance attributed to each predictor.

Recent developments. DA, originally developed for linear regression, has been further extended to determine predictor importance in logistic regression models (Azen & Traxel, 2009). Moreover, it has been used with Canonical Correlation Analysis, which is a statistical technique used to investigate the relationship between two sets of variables, usually operationalizing multidimensional constructs (Huo & Budescu, 2009).

Electronic resources. Resources for performing dominance analysis, including SAS macros, can be found on Razia Azen's macros page (https://pantherfile.uwm.edu/azen/www/damacro.html). An excel file for estimating general dominance weights for up to six predictors can be downloaded from http://www1.psych.purdue.edu/~jlebreto/downloads.html

RWA versus DA. LeBreton, Hargis, Griepentrog, Oswald, and Ployhart (2007) suggest that either (or both) relative weights or dominant weights should be estimated when psychologists wish to calculate correlated predictor importance. Although based on different statistical rationale (i.e., variable transformation approach vs. all-subset regression approach), RWA and DA indeed present a great convergent validity, arriving at almost identical results in both Monte Carlo simulation studies (LeBreton et al., 2004) and field studies (Johnson, 2000).

The principle strength of RWA is likely its ease of computation as compared to DA, which instead requires a great effort of computation with a large number of predictors: for example, 10 predictors will yield 1,023 possible regression submodels. Moreover, RWA is the only applicable technique with higher-order models, such as moderation regression models. However, DA offers a more complete assessment of predictor importance because it uses information about a predictor's direct, unique, and partial effects, and establishes different patterns of dominance (i.e., complete, conditional, and general). Thus, DA may be preferred over other techniques when researchers are interested in understanding complete and conditional forms of dominance in addition to general dominance weights (LeBreton et al., 2007). Complete and conditional dominance weights can be also used in combination with general dominance weights to identify suppressor variables (Azen & Budescu, 2003). Additionally, DA is better known than is RWA, and, until now, has been used more often and has received more statistical support than has RWA (for details, see Thomas, Zumbo, Kwan, & Schweitzer, 2014).

RELATIVE IMPORTANCE ANALYSIS: APPLICATIONS AND APPLICABILITY IN FAMILY RESEARCH

Despite the many strengths of these techniques, especially in the face of correlated predictors, to the best of my knowledge, thus far very few family studies have applied DA — and none of them RWA. Historically, relative importance analysis came out of the organizational and management sciences, and it has been often used to predict complex constructs such as customer satisfaction, employee selection, turnover, and performance. Recently Hargis, Kotrba, Zhdanova, and Baltes (2011) used RWA and DA for the first time to analyze several antecedents of work-family conflict simultaneously to "more accurately model real world experiences" (p. 389). Their results indicated that negative affectivity and job stressors drove forces behind experiences of work-family conflict, and were more important predictors than had been evidenced in prior research. Further, when considered in combination with other antecedents, some variables (e.g., hours worked and family support) contributed less to the prediction of work-family conflict than previously reported. Although this study was still focused on the individual's experience (here work-family conflict, defined as a form of role pressure deriving from incompatible experiences in the work and family domains, was treated as an individual construct), it represents one of the first applications of relative importance analysis to the family system, or better, to the family-work mesosystem.

Stolz and colleagues (2005) have explicitly wondered about the use of relative importance analysis, specifically of DA, in the study of family relationships. In particular, the authors were interested in assessing the relative importance of paternal and maternal support, behavioral control, and psychological control in predicting children's psychosocial adjustment. They provided an interesting example of application of DA to distinguish differential, but overlapping, contributions of fathers and mothers to their youth. Friedlmeier and Friedlmeier (2012) also included both parents in their DA to measure the relative importance of parenting styles in predicting parent-child value similarity. Interestingly, both these studies re-evaluate the contribution of fathers (which has been largely overlooked in mother-based research): indeed, fathers' support completely dominated all the other predictors in predicting children's social initiative (Stolz et al., 2005), and fathers' parenting variables dominated the contributions of mothers to children's values (Friedlmeier & Friedlmeier, 2012).

The relative importance techniques have thus been introduced into the field of family research to examine fathers' and mothers' contributions, theorized as interconnected and mutually dependent, to their children's development. Using DA to supplement MR, researchers have moved from the measurement of unique paternal and maternal contributions (i.e., contribution of fathers beyond that of mothers and vice versa) to the study of fathering and mothering dimensions that contribute the most to a particular outcome in the context of other fathering and mothering dimensions (Barber, 2005). The same rationale can easily be extended to a larger network of relationships within the family (e.g., grandparent-grandchild or sibling relationships) as well as outside the family (e.g., teacher-student or peer relationships). For example, by applying DA, Stolz and colleagues (2004) pitted the family (fathering and mothering) and the school contexts against each other to investigate the socialization conditions of closeness, regulation, and respect for autonomy as predictors of adolescent academic achievement. The relationship with teacher turned out to be a powerful predictor of adolescent achievement, stronger even than relationship with parents, as closeness with teacher dominated all the other predictors in the model. Plunkett, Henry, Houltberg, Sands, and Abarca-Mortesen (2008) used DA to examine the relative importance of adolescents' perceptions of academic support from fathers, mothers, teachers, and friends in relation to aspects of academic success. The results once again revealed that teachers' academic support, in this case as perceived by the adolescent, was the most important predictor of adolescents' self-reported academic performance and satisfaction.

In brief, in family research relative importance analysis has been fruitfully applied to research questions such as "Which of the theorized relational dimensions (e.g., paternal support and paternal control) is the most important predictor of the outcome?"; "Which of the family relationships (e.g., paternal support and maternal support) is the most important predictor of the outcome?"; "Which of the relational dimensions and from which relationship (e.g., paternal support, paternal control, maternal support, and maternal control) is the most important predictor of the outcome?" Of course, many other questions in family research could be addressed by relative importance analysis. For instance, this technique can provide an effective approach to examining the effects of reports gathered from multiple family members (e.g., mothers' and children's perceptions of mother-child relationship quality): "Which informant's perspective is the most important predictor of the outcome?" Indeed, although family members' viewpoints of the same relationship are partially shared, they may have very different effects on the same outcome (e.g., Boykin McElhaney, Porter, Wrenn Thompson, & Allen, 2008).

In the following illustrative example, I present an application of the relative importance techniques (both RWA and DA) in a family study that involved multiple relationships (i.e., father-child, mother-child, and grandmother-grandchild) and multiple informants (i.e., adolescent children, fathers, mothers, and grandmothers) to assess the perceptions of both members involved in each dyadic relationship. This study aimed at investigating the association between family relationship quality and adolescents' family obligations, with the hypothesis that family satisfaction is related to the youth's willingness to assume a set of responsibilities and duties toward their parents and elderly relatives. In particular, I was interested in identifying which family relationship (i.e., that between father-child, mother-child, or grandmother-grandchild), as perceived by which family member (i.e., the adolescent, the father, the mother, or the grandmother), was the most useful predictor of adolescents' family obligations. The example will demonstrate the potential of combining traditional regression analysis with the relative importance techniques to better understand the contribution of each predictor within a constellation of interrelated perceptions of interrelated relationships.

THE ILLUSTRATIVE EXAMPLE

Participants

Participants were 257 families in which were present an adolescent, both parents, and one grandmother. All participants, 1028 in total, lived in Northern Italy. Adolescents (43.2% male, 56.8% female) were all high-school students and were between 15 and 19 years of age (M = 16.93, SD = 1.31). Fathers and mothers had a mean age of 48.70 (SD = 4.80) and 45.86 (SD = 4.39), respectively. On average, they had 2.12 children (SD = .77). Grandmothers (39.7% paternal and 60.3% maternal) were between 56 and 94 years of age (M = 74.44, SD = 6.78). On average, they had 2.95 children (SD = 1.35) and 5.13 grandchildren (SD = 3.18).

Measures

Family relationship quality was measured by the three-item satisfaction scale from the Networks of Relationship Inventory (Furman & Buhrmester, 1985), translated into Italian (e.g., "How satisfied are you with your relationship with this person?") and using a 5-point scale (from 1 = *not at all* to 5 = *completely*). The level of satisfaction was calculated by averaging the three items: the higher the score, the higher the level of satisfaction. The scale was administered to adolescents, who were asked to report about the relationships with their fathers, mothers, and grandmothers, and to the other family members (i.e., fathers, mothers, and grandmothers), who were asked to report about the relationship with their (grand)child. Cronbach's alphas ranged from .92 (mother-child relationship satisfaction as reported by the child) to .94 (father-child relationship satisfaction as reported by the child).

Adolescents' family obligations were assessed by using a five-item subscale based on Georgas' (1991) scale, translated into Italian. Adolescents were asked to reply to items such as: "Children should obey their parents" or "Children should take care of their elderly parents and relatives" on a 5-point scale (from 1 = *strongly disagree* to 5 = *strongly agree*). The level of obligations was calculated by averaging the five items: the higher the score, the higher the level of importance given to family and the willingness to assume responsibilities and duties toward elderly relatives. Cronbach's alpha was .60.

Results

Table 1 presents the descriptive statistics (means and standard deviations) for the study variables and their bivariate correlations (Pearson's r). Correlation coefficients between the predictor variables ranged from .07 (p = .293) — between father-child relationship satisfaction as reported by the child and grandmother-grandchild relationship satisfaction as reported by the

TABLE 1
Descriptive statistics and zero-order correlations (N = 257)

	1	2	3	4	5	6	Mean	Range	*SD*
1. Father-child relationship satisfaction (reported by CH)	–						3.50	1-5	.98
2. Mother-child relationship satisfaction (reported by CH)	.64**	–					3.73	1-5	.90
3. Grandmother-grandchild relationship satisfaction (reported by CH)	.27**	.32**	–				3.82	1-5	.94
4. Father-child relationship satisfaction (reported by FA)	.33**	.23**	.09	–			3.54	1-5	.79
5. Mother-child relationship satisfaction (reported by MO)	.21**	.40**	.17**	.23**	–		3.61	1-5	.77
6. Grandmother-grandchild relationship satisfaction (reported by GR)	.07	.10	.25**	.17**	.18**	–	4.11	1.33-5	.79
7. Children's family obligations	.31**	.32**	.30**	.23**	.19**	.21**	4.19	2.67-5	.53

Note. CH = adolescent child; FA = father; MO = mother; GR = grandmother.
** p < .01.

grandmother — to .64 (p = .000) — between father-child and mother-child relationship satisfaction, both as reported by the child. Thus, children's perceptions of the relationship satisfaction with their fathers and mothers turned out to be moderately/highly correlated with each other. All the predictor variables were significantly correlated with adolescents' family obligations, with rs ranging from .19 (p = .002) (mother-child relationship satisfaction as reported by the mother) to .32 (p = .000) (mother-child relationship satisfaction as reported by the child).

I conducted a preliminary MR, with (grand)parent-(grand)child relationship satisfaction (as perceived by family members) as predictors, and adolescents' family obligations as the criterion variable. The collinearity diagnostics excluded severe problems of multicollinearity (variance inflation factor from 1.14 to 2.10) and, overall, the six predictors yielded an R^2 = .19, which was reasonably good. Three predictors were statistically significant: each of them contributed uniquely (i.e., beyond the others) to adolescents' family obligations (Table 2). If we were tempted to compare the magnitude of the β coefficients, we would see that adolescents' satisfaction with their relationships with grandmothers and mothers were the most predictive of adolescents' family obligations, substantially more important than the other predictors (see β^2 in Table 2). On the contrary, father-child relationship satisfaction as reported by the child, and mother-child relationship satisfaction as reported by the mother, were not significantly related to the criterion variable and showed the weakest β coefficients.

On the basis of these results, we would be forced to conclude that adolescents' satisfaction with the relationships with their grandmothers and mothers support their willingness to assume responsibilities and duties toward elderly relatives. From MR, father-child relationship, as reported by the adolescent, matters decidedly less than the relationships with (grand)mothers. Thus, the female/maternal lineage, as experienced by the adolescent, seems to be the most salient in the children's socialization to norms and obligations. This conclusion, which coincides with much of the research on socialization (e.g., Barni, 2009; Barni, Vieno, Rosnati, Roccato, & Scabini, 2014; Ranieri & Barni, 2012), could be more than satisfactory for us. Moreover, as seen in previous studies (see Nuijens, Teglasi, & Hancock, 2009), the adolescents' viewpoint on family relationships is more related to their self-reported criterion (in this case, family obligations) than are the perspectives of other family members. When data reported by parents and grandmothers were considered, the father-child and grandmother-child relationships predicted family obligations slightly more than the mother-child relationship did.

Unfortunately, this conclusion, which relied solely on β inspection and comparison, may be misleading. As discussed earlier, since MR is not able to take appropriately into account the shared contribution of correlated predictors, it allows us to ascertain which predictor gives the largest unique contribution, but not the largest overall contribution. With respect to this, expanding MR by the relative importance indices may provide interesting additional information.

In this study, the results obtained via RWA and DA were consistent among themselves (Table 2). Both these techniques confirmed the great importance of adolescents' satisfaction with the relationship with their grandmothers in predicting adolescents' family obligations, which accounted for the largest percentage of the total predicted criterion variance. That is, adolescents' satisfaction with the relationship with grandmothers is the most important and generally dominant predictor of adolescents' willingness of caring and assisting their parents and elderly relatives. More interestingly, in both RWA and DA, father-child relationship satisfaction (as reported

TABLE 2
Relative importance of family relationship satisfaction for predicting adolescents' family obligations (N = 257)

Variables	Regression analysis			Relative weight analysis		Dominance analysis	
	β_j	p	β^2_j	Raw importance estimates	Rescaled estimates (%)	Raw importance estimates	Rescaled estimates (%)
Father-child relationship satisfaction (reported by CH)	.01	.895	.00	.04	21.1	.04	21.1
Mother-child relationship satisfaction (reported by CH)	.21	.020	.04	.04	21.1	.04	21.1
Grandmother-grandchild relationship satisfaction (reported by CH)	.27	.00	.07	.05	26.3	.06	31.5
Father-child relationship satisfaction (reported by FA)	.15	.026	.02	.03	15.7	.02	10.5
Mother-child relationship satisfaction (reported by MO)	–.03	.606	.00	.01	5.3	.01	5.3
Grandmother-grandchild relationship satisfaction (reported by GR)	.11	.107	.01	.02	10.5	.02	10.5
Total R^2 = .19				.19	100.0	.19	100.0

Note. CH = adolescent child; FA = father; MO = mother; GR = grandmother. For the dominance analysis, general dominance weights are reported (no predictor conditionally or completely dominates other predictors). Rescaled estimates (%) were computed by dividing the relative or dominance weights by the total R^2 and multiplying by 100.

by the child) was among the most important predictors of the criterion variable, accounting for predicted variance less than did grandmother-child satisfaction but as much as including mother-child satisfaction did. Thus, relative importance analysis re-evaluates the contribution of father-child relationship in predicting the criterion variable.

This example demonstrates the problems inherent in examining only a single type of effect in isolation from the other effects and shows that small β coefficients could mask larger relative effects in the presence of moderately to highly correlated predictors. It is very likely that two variables that are correlated have similar correlations with the criterion variable and similar relative/dominant weights, but the second variable does not raise R^2 much beyond what the first variable accounts for (Johnson, 2000). In MR, satisfaction with paternal relationship as perceived by the child did not give a substantial contribution beyond that of the other predictors in the regression model, very likely due to its correlation with adolescents' satisfaction with mothers. These two predictors share a certain amount of predictive ability, which is appropriately partitioned by relative importance analysis. In the real world, the adolescent is simultaneously in relation with the various family members; within the context of the other relationships, the father-child relationship also contributes to determining the level of the adolescent's feelings of family obligations.

The results of relative importance analysis also reinforce the conclusion about the greater importance of the adolescents' viewpoint of family relationships, compared to the other members' views, in driving adolescents' norms of filial obligations and assistance to the family. Indeed, adolescents' perceptions of family relationship satisfaction accounted for approximately 70% of the predicted criterion variance.

CONCLUSIONS

The goal of this article was to describe the characteristics of two relatively new techniques of analysis, RWA (Johnson, 2000) and DA (Budescu, 1993), and to show their potential contribution to studying family relationships. RWA and DA are measures of relative importance; this refers to the proportionate contribution each predictor makes to the total predictable criterion variance. These techniques specifically address questions pertaining to predictor comparisons and allow for an understanding of the impact of a particular predictor within a specified modelling framework. Crucially, both provide meaningful estimates of variable importance in the presence of correlated predictors, which is often the case in family studies. RWA and DA encourage researchers to look beyond MR, a technique which is useful in identifying a set of predictors able to maximize the amount of variance explained in the criterion, but which struggles with correlated predictor comparison. Indeed, unlike MR, which parses out the unique contributions beyond any effect shared with another predictor, RWA and DA explicitly consider share variance by assessing the unique variance and any partial joint variance contributed by each predictor in a multiple regression equation (LeBreton et al., 2004). The example reported in this article illustrates how a study's conclusions could be radically altered by expanding the traditional MR through relative importance analysis, even in the presence of non-severe collinearity.

Relative importance analysis has the potential to become a significant resource in family research. A wide variety of research questions related to the study of the family could be indeed addressed more appropriately by supplementing MR with relative importance analysis: "Is a particular aspect of the family (context) an important/useful predictor of a particular outcome?"; "Which aspect of the family (context) matters more in predicting a particular outcome?"; "Does the family (context) matter more than another social context in predicting a particular outcome?". As shown by the literature review and by the example provided in this article, relative importance analysis can be used to sort the differential, although often overlapping, contribution of family dimensions, relationships, and informants in predicting the criterion. This would help to overcome some traditional criticisms of family research, which relate to the exclusive focus on the effects of only one specific relationship within the family (mostly the parent-adolescent relationship) and to the fact that in most of the research performed previously, only one family member's perspective (often that of children) was assessed (Deković & Buist, 2005).

Every individual considers his/her family relationships as a context, one that is meaningful to his or her interactions and that influences his/her behavior (Tagliabue & Lanz, 2014). Relative importance analysis places a strong emphasis on the concept of "context." Indeed, it reflects the effect of each variable "when considered in the context of the other predictors …" (Johnson, 2000, p. 9), "within the context of any subset of the remaining predictors …" (Azen & Budescu, 2003, p. 130), "within an existing (parenting) [bracket added] framework" (Stolz et al., 2005, p. 1088), and uses the specified set of predictors as the interpretative frame. In the words of the Oxford English Dictionary, context is "the connected whole that gives coherence to its parts," a definition which has strong affinities to the Latin term, *contextere*, or, "to weave together" (http://www.oed.com/). Neither dyadic family relationships nor family members' perceptions of these relationships occur in isolation; rather, they are mutually constitutive. It is, therefore, particularly important to examine how family relationships operate together, that is, each in the context of others. This could provide a perspective from which to study the family with more complete — and, likely, new — results. For instance, despite compelling evidence that aspects of parenting are associated with a wide range of youth outcomes, the examination of both fathers' and mothers' parenting is still, surprisingly, an emerging science (Henry & Hubbs-Tait, 2013). Compared to prior family research using MR, the few studies which have applied DA or RWA (including the example reported in this article) are consistent in giving back importance to fathers (e.g., Friedlmeier & Friedlmeier, 2012; Stolz et al., 2005). It is theoretically, as well as empirically, plausible that fathers and mothers share a certain predictive ability toward their children's developmental outcomes. In light of this re-evaluation of the paternal role, we could hypothesize that fathers' importance in predicting their children's outcomes is strongly related to that predictive ability shared with mothers, which is not appropriately treated by MR. Since the overlapping predictive ability between two variables is likely to be greater in the presence of a high correlation between them, we could even speculate that fathers' impact on their children may be stronger when fathers and mothers engage in some similar parenting behaviors. This is merely speculation, which, however, illustrates the potential of the relative importance techniques and stimulates new challenges for researchers. Speaking of this, a notable methodological challenge for future family studies is to distinguish whether correlations between family members are "true" (e.g., that mothers and fathers actually engage in some similar parenting behaviors) or "spurious" (i.e., correlation exists due to shared-method variance) (Plunkett, Ainsworth, Henry, & Behnke, 2011).

Several further challenges are related to the use of relative importance analysis, which, of course, is not free of criticism (see Nathans et al., 2012). In particular, RWA and DA have been developed by researchers as "practical" tools for interpreting predictor importance (e.g., Krana et al., 2012), whereas their theoretical justifications have as yet remained underdeveloped (Thomas et al., 2014; Wang et al., 2013). The very meaning of importance can have numerous connotations, and is often interpreted differently according to the problem and the application (Retzer, Soofi, & Soyer, 2009). Moreover, it is worthwhile noting that, although RWA and DA were developed for use with correlated predictors, very high levels of multicollinearity could be indicative of variable redundancy (Tonidandel & LeBreton, 2010), thus posing a fairly important theoretical question.

However, in many scientific fields variable importance is an extremely active area of research; indeed, RWA and DA have been the foci of the more recent activity in this regard (Grômping, 2007). Determining the relative importance of predictors can help both researchers and practitioners, by allowing the former to develop more parsimonious models and the latter to intervene and take decisions by focusing on the most important predictors (Retzer et al., 2009; Tonidandel & LeBreton, 2010). Indeed, these techniques would allow researchers to identify a succinct set of predictors, all of which contribute to the understanding of the criterion, by dropping out those predictor variables having substantially lower levels of importance. When researchers set out to analyze correlated predictors in relation to an outcome within a multidimensional context, RWA and DA can provide valid support (and stimulation!) as part of a more complete system of results. Given that correlated predictors are the norm in family research, indexes of importance combining multiple effects should be employed to better understand the relevant dynamics within family data and to capture “the full story of a predictor’s importance.”

NOTES

1. This example was adapted from Johnson and LeBreton, 2004.
2. The Equations 2, 3, and 4 refer to the predictor 1 (X_1) in a hypothetical regression equation with three predictors and one criterion variable (Tonidandel et al., 2009).

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