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Some Common Myths About Centering Predictor Variables in Moderated Multiple Regression and Polynomial Regression

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Abstract

Additive transformations are often offered as a remedy for the common problem of collinearity in moderated regression and polynomial regression analysis. As the authors demonstrate in this article, mean-centering reduces nonessential collinearity but not essential collinearity. Therefore, in most cases, mean-centering of predictors does not accomplish its intended goal. In this article, the authors discuss and explain, through derivation of equations and empirical examples, that mean-centering changes lower order regression coefficients but not the highest order coefficients, does not change the fit of regression models, does not impact the power to detect moderating effects, and does not alter the reliability of product terms. The authors outline the positive effects of mean-centering, namely, the increased interpretability of the results and its importance for moderator analysis in structural equations and multilevel analysis. It is recommended that researchers center their predictor variables when their variables do not have meaningful zero-points within the range of the variables to assist in interpreting the results.

Keywords

moderated regression, polynomial regression, mean-centering, collinearity, multicollinearity

Organizational theories continue to grow in complexity, with more researchers including moderating and nonlinear relationships into their theories of workplace behaviors (Bobko, 2001; Cortina, 1993). To analyze these complex relationships, researchers often use moderated multiple regression analysis (MMRA) and polynomial regression analysis (PRA). Although these techniques are flexible enough to perform many complex analyses using commonly available statistical software, quite often the correlation between components and the product terms used to represent moderating or nonlinear effects are high. This collinearity is often blamed for the lack of statistical support for these

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moderating and nonlinear effects (e.g., Dunlap & Kemery, 1987; Morris, Sherman, & Mansfield, 1986; Sockloff, 1973).

A remedy commonly offered to reduce this collinearity is to transform the variables—usually using mean-centering—before creating the interaction or nonlinear term. Despite the frequency with which predictors are mean-centered, it seems that the original rationales for these additive transformations may be lost. In fact, we believe that in most cases that mean-centering is used, it fails to accomplish the goal intended by the researcher. The purpose of this article, then, is to address some of the myths surrounding mean-centering in MMRA and PRA and to clarify what these additive transformations do and do not accomplish. Throughout the article, we demonstrate our points with derivation of relevant equations as well as illustrative empirical analyses.[1] Before continuing, however, it is prudent to acknowledge that the purpose of this article is educational; the substantive content presented here has been presented elsewhere (e.g., Aiken & West, 1991; Cohen, 1978; Cohen, Cohen, West, & Aiken, 2003; Cronbach, 1987; Echambadi & Hess, 2007; Friedrich, 1982; Jaccard & Turrisi, 2003; Jaccard, Wan, & Turrisi, 1990; Smith & Sasaki, 1979). For example, recent work by Echambadi and Hess (2007) demonstrates some of the results outlined here. However, our treatment of the topic is considerably less technical by not relying on complex matrix algebra (e.g., Kroenecker products). Furthermore, we expand on these works by discussing situations when centering has no impact. In addition, we discuss the role of centering in multilevel models, moderated structural equation modeling, and when analyzing categorical moderator variables. Our intent is to integrate findings across different publications into a single resource to guide organizational researchers in understanding what mean-centering will accomplish in MMRA and PRA and in deciding if and when to center their predictor variables.

Prevalence of MMRA and PRA in Organizational Research

A variable (X_2) is said to moderate the relationship between an antecedent (X_1) and consequence (Y) when the relationship between X_1 and Y varies at different levels of the moderator X_2. Saunders (1955, 1956) credits Gaylord and Carroll's paper at the 1948 American Psychological Association meeting for the first discussion of a moderator variable where they cited examples of moderating relationships from the fields of personnel selection, experimental psychology, and personality dynamics. A nonlinear relationship between an antecedent (X_1) and the outcome (Y) implies that the relationship between X_1 and Y is not constant across the range of X_1. Perhaps the most recognizable nonlinear relationship is the Yerkes-Dodson law—arousal improves performance to a certain point, but then arousal hinders performance (Yerkes & Dodson, 1908).

Additive predictor score transformations in MMRA and PRA were first advocated by Marquardt and Snee (1975), who demonstrated that mean-centering predictor variables reduced ill-conditioning in the data (see also Cohen, 1978; Cronbach, 1987). Loosely, conditioning in the data can be thought of as the stability of the results obtained to fluctuations in said data—the correlations among variables in the data cause ill-conditioning in the data that will then inflate the variances of the coefficients estimated from that data set and cause unstable results. *Nonessential* ill-conditioning results simply from the scaling of the variables, whereas *essential* ill-conditioning results from substantive relationships among the variables (Cohen et al., 2003). As we will detail, mean-centering will remove the nonessential ill-conditioning because mean-centering changes the scaling of the variables in moderator analysis. Bradley and Srivastava (1979) and later Marquardt (1980) extended this work to polynomial regression analysis. Since then, popular regression texts have recommended mean-centering predictor variables prior to conducting MMRA or PRA (e.g., Aiken & West, 1991; Bobko, 2001; Cohen et al., 2003; Jaccard & Turrisi, 2003; Pedhazer, 1997).

As Table 1 shows, an appreciable number of articles, between 2000 and 2010, in three organizational journals have investigated moderating effects; as expected, fewer investigated nonlinear

Table 1. Prevalence of Moderating and Nonlinear Relationships in Organizational Research

Journal	Number of Studies Investigating Moderating Effects	Number of Studies Investigating Nonlinear Effects	Count and Type of Transformations Used	Count and Type of Justification Offered	Count and Sources Cited
Journal of Applied Psychology	118	16	45 mean-centered 7 standardized 3 scale-midpoint centered	18 reduce collinearity 2 improve interpretability 6 both[a]	20 Aiken and West (1991) 9 Cohen, Cohen, West, and Aiken (2003) 2 Cohen and Cohen (1983) 1 Aguinis (1995); Edwards (1994); Jaccard, Turrisi, and Wan (1990); Tabachnick and Fidell (2001)[b]
Academy of Management Journal	56	17	23 mean-centered 5 standardized	6 reduce collinearity 3 improve interpretability 1 reduce nonessential collinearity	9 Aiken and West (1991) 2 Cohen et al. (2003) 2 Cohen and Cohen (1983) 1 Jaccard et al. (1990), Jaccard and Turrisi (2003)[b]
Personnel Psychology	23	4	11 mean-centered 3 standardized	5 reduce collinearity 1 both[a] 1 reduce nonessential collinearity	8 Aiken and West (1991) 1 Cohen and Cohen (1983)

[a]The author(s) centered to both reduce collinearity and improve interpretability.
[b]Each of these authors was cited only once in different articles.

relationships. For those researchers who did transform their variables, mean-centering was by far the most popular, and collinearity reduction was the most cited justification. Interestingly, only two articles noted that their transformation reduced nonessential collinearity—collinearity due simply to the scaling of the variables—even though the source cited most often for these transformations (i.e., Aiken & West, 1991) explicitly states this point (pp. 35-36). In our view, this reliance on centering predictor variables to ‘‘reduce collinearity’’ has become an indoctrinated practice achieving a status of urban legend and has engendered a few myths about what centering does and does not accomplish. Like most urban legends, there is a kernel of truth regarding the capability of additive transformations to reduce collinearity. Throughout this article, we try to caution readers about the inaccuracies regarding centering and collinearity as well as clarifying the kernels of truth.

The Urban Legend and Kernel of Truth

As seen in Table 1, a common justification for additively transforming variables prior to conducting MMRA or PRA is that it reduces collinearity. Furthermore, a common misconception we have heard is that reducing collinearity will then change the results and conclusions of the regression analysis or even make it easier to find significance. Kromrey and Foster-Johnson (1998) had also encountered this misconception with other researchers. They paraphrase the misconception voiced by many that ‘‘The reduction in collinearity afforded by centered data when product terms are included in correlation matrices should ‘logically’ provide better (or at least different) hypothesis test results’’ (pp. 51-52); they go on to correct this misconception. In an example of PRA, Luchak and Gellatly (2007) stated that mean-centering variables before computing the squared term ‘‘had no noticeable impact on our results and did not alter our conclusions’’ (p. 791), implying that there was a possibility that mean-centering *might have* influenced statistical conclusions. In addition, we have had many conversations with researchers, faculty, students, and practitioners who believe that centering is a panacea for the collinearity problem. We believe this thinking is common among organizational researchers.

The kernel of truth to this myth is that mean-centering does reduce collinearity but reduces nonessential collinearity, which is the type of collinearity most researchers do not care about. Indeed, the seminal articles on this topic (e.g., Bradley & Srivastava, 1979; Cohen, 1978; Cronbach, 1987; Friedrich, 1982; Marquardt & Snee, 1975; Smith & Sasaki, 1979) have all noted that the large degree of collinearity would raise computational errors, but mean-centering variables will not alter the substantive conclusions of the analyses (see also Aiken & West, 1991; Jaccard et al., 1990; Jaccard & Turrisi, 2003). Although we demonstrate the following points using mean-centering, the results do generalize to other forms of additive transformations.

Situations Where Additive Transformations Do Not Matter

We begin by outlining results and conclusions that do not change even if predictors in MMRA or PRA are mean-centered.

Mean-centering only reduces nonessential ill-conditioning. Bohrnstedt and Goldberger (1969) derived the equation for the covariance between an interaction term and its constituent part for normally distributed variables. Taking their work, the correlation between an interaction term and its component is:

$$r_{X_1,X_1X_2} = \frac{E(X_2)V(X_1) + E(X_1)C(X_1,X_2)}{\sqrt{V(X_1)\left[E(X_1)^2V(X_2) + E(X_2)^2V(X_1) + 2E(X_1)E(X_2)C(X_1,X_2) + V(X_1)V(X_2) + C(X_1,X_2)^2\right]}} \quad (1)$$

where $E()$, $V()$, and $C()$ are the expected values, variances, and covariances, respectively (see also, Edwards, 2009). This formula generalizes to the case of polynomial regression where X_1^2 is a special form of an interaction term (i.e., X_1X_1). Naturally, the correlation can be high, and these high correlations between the interaction or polynomial term with its component parts were the impetus for the criticisms against the use of MMRA and PRA; indeed, Morris et al. (1986) lamented that "moderating effects that do exist may have a diminished opportunity for detection when [ordinary least squares moderated multiple regression] is used under such conditions [high collinearity among predictors]" (p. 283). Although subsequent work has shown that Morris et al.'s conclusions are misleading (e.g., Cronbach, 1987), we continue to hear this concern today.

Bohrnstedt and Goldberger (1969) demonstrated that the covariance of a product term with its component parts is dependent on the scale of the variables; Equation 1 shows that the correlation is influenced by the means of X_1 and X_2. Marquardt and Snee (1975), Marquardt (1980), and Bradley and Srivastava (1979) showed that a large part of the relationship between a product term and its component parts can be reduced by shifting the origin. This reduction in collinearity is termed *nonessential collinearity*. Nonessential collinearity is collinearity that exists merely due to the scaling of X_1 and X_2 (Cohen et al., 2003); when the scaling of X_1 and X_2 changes, the correlations between an interaction and polynomial term with its components will also change. This can be demonstrated quite effectively by showing that a set of five scores (i.e., 1, 2, 3, 4, 5) correlates 0.98 with their squares (i.e., 1, 4, 9, 16, 25). However, after centering the scores (i.e., –2, –1, 0, 1, 2), the correlation of these centered scores with the squares (i.e., 4, 1, 0, 1, 4) is reduced to 0.00. Here, one can see the large impact scaling has on the correlation between multiplicative terms and their components. Mean-centering reduces the correlation between an interaction and polynomial term with its components by making all expected values 0. If X_1 and X_2 are bivariate normally distributed, mean-centering will reduce r_{X_1,X_1X_2} to 0. Any non-normality in the components will result in $r_{X_1,X_1X_2} \neq 0$; Smith and Sasaki (1979) derived a method for determining constants that will reduce r_{X_1,X_1X_2}, r_{X_2,X_1X_2}, r_{X_1,X_1^2} to 0.

More consequential, however, is that mean-centering will not alter the correlation between X_1 and X_2. The correlation between X_1 and X_2 is all essential collinearity and can have deleterious effects on the estimation of regression models, regardless of mean-centering. In addition, additive transformations will not alter the relationships between X_1 and Y or X_2 and Y. The intercorrelations involving the X_1X_2 term, on the other hand, will be different depending on whether or not X_1 and X_2 are centered; indeed, Cohen (1978) cites these potentially drastic (p. 861) changes in the correlations as the reason that researchers worry about using MMRA and PRA. The differences in these correlations, however, are attributed to the differences in the means of the centered and uncentered X_1X_2 term (see also, Arnold & Evans, 1979; Cronbach, 1987). As demonstrated in the following, the changes in the intercorrelations due to mean-centering will not alter the value of the regression coefficient for the interaction term (i.e., b_3).

Table 2 presents the correlation matrices and descriptive statistics for randomly generated data where X_1, X_2, and Y are normally distributed and to be correlated at $\rho_{X_1,X_2} \approx -.35$, $\rho_{X_1,Y} \approx .40$, and $\rho_{X_2,Y} \approx -.45$. These values were chosen to represent typical, absolute values of correlations in organizational research and to demonstrate the findings with negative as well as positive relationships. As Table 2 shows, the values of r_{X_1,X_1X_2}, r_{X_2,X_1X_2}, and r_{X_1,X_1^2} are lower with centered data; however, r_{X_1,X_2}, $r_{X_1,Y}$, and $r_{X_2,Y}$ remain unchanged. Furthermore, the correlations among centered and uncentered X_1X_2 and Y and X^2 and Y are also different. But some simple algebra will demonstrate that the differences are due to the changes in the means and standard deviations resulting from centering. Indeed, Arnold and Evans (1979) also demonstrated that variances and covariances between a product term and a third variable depend on the means and variances of the variables. Cronbach (1987) presents an equation to calculate the covariance of a centered product term with Y from the means,

Table 2. Descriptive Statistics and Correlations Among Predictors, Outcomes, Interaction, and Polynomial Terms With Centered and Uncentered Data[a]

		M	*SS*	*SD*	X_1	X_2	X_1X_2	X_1^2	X_2^2
Uncentered data	X_1	11.84	7,893.08	6.94	—				
	X_2	4.18	18.85	0.34	−0.38	—			
	X_1X_2	48.55	123,205.85	27.41	0.99	−0.23	—		
	X_1^2	187.94	4,694,664.46	169.19	0.96	−0.42	0.93	—	
	X_2^2	17.55	1,286.32	2.80	−0.37	0.99	−0.23	−0.41	—
	Y^b	3.66	206.21	1.12	0.40	−0.48	0.36	0.41	−0.49
Centered data	X_1	0.00	7,893.08	6.94	—				
	X_2	0.00	18.91	0.34	−0.38	—			
	X_1X_2	−0.88	956.14	2.41	−0.19	0.20	—		
	X_1^2	47.84	335,285.71	45.22	−0.03	−0.21	−0.48	—	
	X_2^2	0.11	5.18	0.18	0.13	−0.20	−0.65	0.14	—
	Y^b	3.66	206.21	1.12	0.40	−0.48	0.02	0.05	−0.08

[a]Data were randomly generated to be normal; however, some non-normality in the data remains.
[b]The scale of *Y* was not altered.

and covariances of the uncentered data where $C()$, X_i, x_i, and μ_i represent covariances, uncentered scores, centered scores, and means, respectively.

$$\begin{aligned} C(x_1x_2, Y) &= C(X_1X_2, Y) - \mu_{x_1}C(X_2, Y) - \mu_{x_2}C(X_1, Y) \\ &= (11.023) - (11.84 \times -0.181) - (4.1754 \times 3.142) = 0.0469. \end{aligned} \tag{2}$$

Dividing this covariance by the product of the standard deviations of x_1x_2 ($SD = 2.41$) and Y ($SD = 1.12$) returns the correlation presented in the bottom panel of Table 2 $r_{x_1x_2,Y} = .02$. A similar relation holds for polynomial terms. As Table 2 shows, the relationships between the lower order term and the outcome is unchanged after centering. The correlation between the higher order terms and Y are different after removing the nonessential ill-condition. However, because the relationship between an interaction term and the outcome is best indexed by a partial regression coefficient, and not a bivariate correlation, substantive conclusions do not change after centering—even though the correlation does. This conclusion is demonstrated in the following.

Mean-centering does change lower order regression coefficients, but not the highest order one. Although the correlations involving the interaction and polynomial terms differ depending on whether they are calculated with centered or raw data, this difference has no effect on the regression coefficient for the interaction or polynomial term. The regression coefficients for the component predictors (e.g., X_1 and X_2) will change, but in a systematic way (Aiken & West, 1991; Cohen, 1978). Note that for multiplicative transformations (i.e., when a constant is multiplied with or divided from the predictors), the highest order terms will change, but the substantive interpretation of the effect represented by the terms will remain unaffected (for a review, see Cohen, 1978).

The form of the multiple regression equation for testing moderation is:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_1X_2 + e. \tag{3}$$

In Equation 3, Y is the outcome variable, X_1 is the predictor variable, and X_2 is the moderator variable. When X_1X_2 is tested with X_1 and X_2 in the model, X_1X_2 is the product variable that captures the moderating effect of X_2 on the X_1-Y relationship after controlling for X_1 and X_2 (i.e., removing the variance attributable to X_1 and X_2; Aiken & West, 1991; Cohen, 1978). Researchers (e.g., Aiken & West, 1991) have demonstrated that the functional form of this relationship does not change as a result of mean-centering. Equation 4.1 represents the functional form of the multiple regression equation after mean-centering X_1 and X_2.

$$Y = b_0 + b_1(X_1 - \bar{X}_1) + b_2(X_2 - \bar{X}_2) + b_3(X_1 - \bar{X}_1)(X_2 - \bar{X}_2) + e. \tag{4.1}$$

In the absence of a significant interaction (i.e., $b_3 = 0$) and after some trivial rearranging, the equation reduces to Equation 4.2:

$$Y = b_1(X_1 - \bar{X}_1) + b_2(X_2 - \bar{X}_2) + b_0. \tag{4.2}$$

After expanding and rearranging Equation 4.2:

$$Y = b_1X_1 + b_2X_2 + (b_0 - b_1\bar{X}_1 - b_2\bar{X}_2). \tag{4.3}$$

Equation 4.3 demonstrates that in the absence of an interaction, mean-centering does not affect the slopes relating X_1 and X_2 to Y and that only the intercept (b_0) changes. However, when an interaction is present (i.e., $b_3 \neq 0$), the slopes relating X_1 and X_2 to Y do change, but not the b_3 coefficient. Equation 4.4 expands and rearranges Equation 4.1 when $b_3 \neq 0$; Equation 4.4 is then rearranged and factored in Equations 4.5 and 4.6, respectively:

$$Y = b_1X_1 - b_1\bar{X}_1 + b_2X_2 - b_2\bar{X}_2 + b_3X_1X_2 - b_3X_1\bar{X}_2 - b_3\bar{X}_1X_2 + b_3\bar{X}_1\bar{X}_2 + b_0, \tag{4.4}$$

$$= b_1X_1 - b_3X_1\bar{X}_2 + b_2X_2 - b_3\bar{X}_1X_2 + b_3X_1X_2 + (b_0 - b_1\bar{X}_1 - b_2\bar{X}_2 + b_3\bar{X}_1\bar{X}_2), \tag{4.5}$$

$$= (b_1 - b_3\bar{X}_2)X_1 + (b_2 - b_3\bar{X}_1)X_2 + b_3X_1X_2 + (b_0 - b_1\bar{X}_1 - b_2\bar{X}_2 + b_3\bar{X}_1\bar{X}_2). \tag{4.6}$$

As can be seen, when there is an interaction, b_0 changes. Furthermore, the slopes for X_1 and X_2 change in a systematic manner. The weights of X_1 and X_2 now contain $\bar{X}_2$ and $\bar{X}_1$, respectively, whereas the means are absent from b_3; b_3 is the same as in Equation 3. Indeed, it is possible to take the regression results from a raw score (i.e., not centered) variables analysis and calculate the b_1, b_2, and b_0 values for a centered variable analysis. Arnold and Evans (1979) demonstrate how centering *predictably* changes the regression weights. Specifically, the slope relating X_1 to Y at a given value of X_2 is $b_1 + b_3X_2$; likewise, the slope relating X_2 to Y at a given value of X_1 is $b_2 + b_3X_1$ (see also Jaccard & Turrisi, 2003).

Given that the b_3 coefficient in MMRA does not differ between centered and uncentered analyses, the standard error and t value also do not change, resulting in the same statistical conclusions. The formula for the t value of a regression coefficient is:

$$t = \frac{b_j}{S_{b_{yj.12\ldots k}}}, \tag{5}$$

where b_j is the regression coefficient and $S_{b_{yj.12\ldots k}}$ is the standard error of the regression coefficient defined as:

$$S_{b_{YX_1X_2.X_1,X_2}} = \sqrt{\frac{MS_{res}}{\sum\left(X_1X_2 - \overline{X_1X_2}\right)^2 \times \left(1 - R^2_{j.12\ldots k}\right)}}. \tag{6}$$

Note that Equation 6 holds for the standard error of $b_{X_1X_2}$. In Equation 6 MS_{res} is the residual mean square from the full regression model, $\overline{X_1X_2}$ is the mean of the interaction variable, and $R^2_{j.12\ldots k}$ is the squared multiple correlation of the jth predictor regressed onto the other predictors. From the aforementioned, b_3 is not different between centered and uncentered analyses. As will be demonstrated in the following, the MS_{res} also does not differ. The denominator of the standard error of the regression

Table 3. Equivalence of Centered and Uncentered Standard Errors for Moderated Multiple Regression Analysis (MMRA)[a]

The equation for the standard error of a regression coefficient MMRA:

$$S_{b_{yX_1X_2.X_1,X_2}} = \sqrt{\frac{MS_{res}}{\sum\left(X_1X_2 - \overline{X_1X_2}\right)^2 \times \left(1 - R^2_{X_1X_2.X_1,X_2}\right)}}$$

Centered analysis

$MS_{res} = .888$

$\sum\left(X_1X_2 - \overline{X_1X_2}\right)^2 = 956.14$

$\left(1 - R^2_{X_1X_2.X_1,X_2}\right) = .946$

$S_{b_{yj.12...k}} = .031$

Uncentered analysis

$MS_{res} = .888$

$\sum\left(X_1X_2 - \overline{X_1X_2}\right)^2 = 123{,}205.85$

$\left(1 - R^2_{X_1X_2.X_1,X_2}\right) = .007$

$S_{b_{yj.12...k}} = .032$

Note: MS_{res} = mean square residual for full regression model; differences are due to rounding error.
[a]Results obtained from data generated for Table 2.

coefficient equation can differ; however, each aspect of the product changes, leaving the value unchanged. That is, when analyzed with uncentered data, the sum of squared deviations is large (see Table 2), but the squared multiple correlation is large, given the large correlation between X_1, X_2, and X_1X_2, making $\left(1 - R^2_{j.12...k}\right)$ small. Alternatively, with centered data, the sum of squared deviations is smaller (because $\overline{X_1X_2}$ is smaller for centered data than uncentered data; see Table 2), but the squared multiple correlation is small, given the reduced correlation between X_1, X_2, and X_1X_2, making $\left(1 - R^2_{j.12...k}\right)$ large. Using the same data generated previously, Table 3 demonstrates these properties for MMRA.

Finally, when an interaction is present (i.e., $b_3 \neq 0$), the lower order terms—b_1 and b_2—do differ between centered and uncentered analyses often in a "dramatic" way (Cohen et al., 2003, p. 264). As described in greater detail in the following, however, when $b_3 \neq 0$ the lower order terms are interpreted conditionally. The interpretation of these simple slopes—the relationship between X_1 (X_2) and Y at specific values of X_2 (X_1)—though is also the same for centered and uncentered analyses (Aiken & West, 1991). Equation 3 can be restructured to:

$$Y = (b_1 + b_3X_2)X_1 + (b_2X_2 + b_0). \tag{7.1}$$

Replacing the raw score variables with the mean-centering formula results in Equation 7.2:

$$Y = (b_1 + b_3[X_2 - \bar{X}_2])[X_1 - \bar{X}_1] + (b_2[X_2 - \bar{X}_2] + b_0). \tag{7.2}$$

And after expanding and collecting terms, Equation 7.3 shows the simple slopes formula for centered variables:

$$Y = (b_1 + b_3X_2 - b_3\bar{X}_2)X_1 + (-b_1\bar{X}_1 - b_3X_2\bar{X}_1 + b_3\bar{X}_1\bar{X}_2 + b_2X_2 - b_2\bar{X}_2 + b_0). \tag{7.3}$$

At first glance, Equation 7.3 seems drastically different from Equation 7.1. However, the differences are merely the result of rescaling—by replacing all X_2 with $(X_2 + \bar{X}_2)$ and collecting terms, Equation 7.3 becomes:

$$Y = (b_1 + b_3X_2)X_1 + (-b_1\bar{X}_1 + b_2X_2 - b_3X_2\bar{X}_1 + b_0). \quad (7.4)$$

As can be seen, the simple regression coefficient in Equation 7.4 matches Equation 7.1, and the only difference between the centered and uncentered simple slopes equation is the regression constant, which is now altered by the inclusions of the relationship between X_1 and Y (i.e., b_1) at the mean of X_1, the relationship between X_2 and Y (i.e., b_2) at the specified value of X_2, and the relationship between the interaction and Y (i.e., b_3) at the mean of X_1 and at the specified value of X_2 (Aiken & West, 1991). Given that the simple slopes do not differ between raw score and centered variables, the interpretation of the interaction as a crossover interaction (i.e., disordinal) or a noncrossover interaction (i.e., ordinal) does not differ either. Table 4 presents the results of the centered and uncentered MMRA of the data generated (see the aforementioned). As Table 4 shows, the b_3 coefficient and the standard error are the same regardless of whether the data were centered or left as raw scores; the simple slopes in Table 4 are identical as well.

Mean-centering does not change the fit of the regression model. Thus far, we have demonstrated that mean-centering does not alter the value of or significance test related to the b_3 regression term in MMRA, and a similar logic holds for the highest order regression term in PRA. When the b_3 term is tested hierarchically, the significance test of the b_3 term is essentially a test of the significance of the change in model fit (i.e., ΔR^2). It follows, then, that neither the ΔR^2 value of the regression model nor its significance differs between centered and uncentered analyses; a similar logic holds for the overall R^2 values as well. Indeed, Table 4 shows that the R^2 and ΔR^2 values are identical for the MMRA with centered and uncentered data—again, the results hold for PRA as well. To demonstrate these points further, we begin with a situation when the interaction (or polynomial) term is not included. In the model without the interaction[2]

$$R^2 = \frac{r^2_{X_1Y} + r^2_{X_2Y} - 2r_{X_1Y}r_{X_2Y}r_{X_1X_2}}{1 - r^2_{X_1X_2}}, \quad (8)$$

where r_{X_1Y} is the correlation between X_1 and Y, r_{X_2Y} is the correlation between X_2 and Y, and $r_{X_1X_2}$ is the correlation between X_1 and X_2. As demonstrated previously, centering of the predictor variables does not alter these three relationships. Therefore, the R^2 value for the model with only the component terms will be the same regardless of whether or not the variables are centered.

In the model containing the higher order term, we can demonstrate that the R^2 value is the same using the sum of squares regression and total:

$$R^2 = \frac{SS_{reg}}{SS_{tot}}. \quad (9)$$

From the aforementioned, we have shown that SS_{tot} and SS_{reg} are the same for the centered and uncentered analyses. In particular, Table 4 shows that MS_{reg} is the same for centered and raw score analyses. Since $MS_{reg} = SS_{reg}/k$, where k is the number of predictors, SS_{reg} is the same regardless of centering (i.e., $[SS_{reg} = MS_{reg} \times k]$, where k is equal in centered and uncentered analyses). SS_{tot} is the sum of squares for Y, which is not altered—centering will not affect the R^2 value. The F value, driven by R^2, N, and k, where N is the sample size, is also the same.

Finally, by combining the previous results, it is evident that the ΔR^2 from the model containing only the lower order terms (Model 1 in Table 4) to the model containing the interaction term (Model 2 in Table 4) are the same for centered and uncentered analyses. Given that $\Delta R^2 = R^2_{Model-2} - R^2_{Model-1}$, it can be seen that ΔR^2 is the same for centered and raw score analyses. Again,

Table 4. Centered and Uncentered Moderated Multiple Regression Analyses

Uncentered Data	Model Summary Results	Model	R^2	ΔR^2	MS_{reg}	MS_{res}	F	df	p
		1	.286	—	29.46	.91	32.40	2,162	< .001
		2	.307	.021	21.09	.89	23.75	3,161	< .001
	Regression Coefficient Results	Coefficient	Value	SE	t	p			
		b_0	12.13	1.989	6.10	< .001			
		b_1	–0.24	0.130	–1.88	.062			
		b_2	–2.14	0.467	–4.59	< .001			
		b_3	0.069	0.031	2.21	.028			
	Covariance Matrix of Regression Coefficients[a]	b_1	b_2	b_3					
		b_1	.218						
		b_2	.218	.017					
		b_3	–.013	–.004	.001				
	Simple Slopes Results	Value of X_2	Equation	b	SE^b	t^c	p		
		High: 4.516	$.069X_1 + 2.452$	.069	0.017	4.06	< .001		
		Medium: 4.176	$.045X_1 + 3.183$	.045	0.012	4.00	< .001		
		Low: 3.837	$.022X_1 + 3.911$	.022	0.015	1.67	0.144		
Centered Data	Model Summary Results	Model	R^2	ΔR^2	MS_{reg}	MS_{res}	F	df	p
		1	.286	—	29.46	.91	32.40	2,162	< .001
		2	.307	.021	21.09	.89	23.75	3,161	< .001
	Regression Coefficient Results	Coefficient	Value	SE	t	p			
		b_0	3.72	0.078	47.50	< .001			
		b_1	0.046	0.012	3.94	< .001			
		b_2	–1.32	0.236	–5.59	< .001			
		b_3	0.069	0.031	2.21	.028			
	Covariance Matrix of Regression Coefficients[a]	b_1	b_2	b_3					
		b_1	.056						
		b_2	.001	.0001					
		b_3	–.001	.0001	.001				
	Simple Slopes Results	Value of X_2	Equation	b	SE^b	t^c	p		
		High: 0.339	$.069X_1 + 3.275$	.069	0.017	4.06	< .001		
		Medium: 0.000	$.045X_1 + 3.722$	.045	0.012	3.83	< .001		
		Low: –0.339	$.022X_1 + 4.170$	.022	0.015	1.53	0.144		

[a]Diagonal elements represent variance.
[b]Formula from Aiken and West, 1991: $s_b = \sqrt{s_{11} + 2X_2 s_{13} + X_2^2 S_{33}}$.
[c]Values are distributed on $(n - k - 1)$ degrees of freedom.

F is driven by the number of predictors in each model, the sample size, and ΔR^2; none of these values are altered due to centering and therefore the F is the same.

Mean-centering does not impact the power to detect moderating or nonlinear effects. The power of a statistical test is the probability that the test will detect an effect when one exists in the population. In the context of MMRA or PRA, the power of the analysis is the probability that the interactive or nonlinear effect will be detected. A myriad of factors affect the power of MMRA and PRA (Aguinis, 1995; Aguinis & Stone-Romero, 1997; Stone-Romero & Liakhovitski, 2002), but many of them are unaffected by mean-centering.

Cohen (1988, 1992) outlines four factors that affect the power of statistical tests familiar to most researchers: the statistical test chosen (i.e., parametric vs. nonparametric), the particular α level selected, the sample size, and the effect size for multiple regression analysis (i.e., f^2, which is driven by R^2). None of these factors change as a result of mean-centering.

McClelland and Judd (1993) demonstrate that range restriction in the component part of an interaction can affect the power of MMRA or PRA. They show that the ability of MMRA and PRA to detect the effect is contingent on the residual variance of the product (i.e., $V[X_1X_2.X_1,X_2]$; $V\left[X_1^2.X_1\right]$). The residual variance of the product is the unique variance in X_1X_2 (X_1^2) that is not shared with X_1 or X_2. These values can be estimated from:

$$V(X_1X_2.X_1,X_2) = \frac{MS_{res}}{n(s_{est}^2),} \tag{10}$$

$$V(X_1^2.X_1) = \frac{MS_{res}}{n(s_{est}^2),} \tag{11}$$

where MS_{res} is the mean square residual from the full moderated and polynomial regression models, n is the same size, and s_{est} is the standard error of the estimate. As described earlier, MS_{res}, n, and s_{est} are the same for centered and uncentered models, suggesting that the effects of range restriction are the same for centered and uncentered analyses.

Shieh (2009) developed an approach to determine both the a priori and post hoc power for a MMRA with two continuous predictors, demonstrating that the power is determined by the distributions of X_1 and X_2 as well as the correlations of X_1 and X_2. As discussed earlier, however, centering does not impact the distributions of X_1 and X_2 or the correlation between X_1 and X_2 (see also Shieh, 2010). Furthermore, the aforementioned discussion was related to the power associated with continuous moderators and predictors. Aguinis and Pierce (1998) and Aguinis, Boik, and Pierce (2001) provide a detailed discussion of the determinants of the power of MMRA with categorical moderators; interested readers are directed to their papers. It is worth noting, however, that again, centering has no impact on the determinants they outline in their papers. A factor affecting the power of MMRA and PRA that appears to change after centering is the reliability of the higher order term.

Mean-centering does not alter the reliability of the product term. Unreliability in predictor variables attenuates the power of a statistical test and has been investigated with less than encouraging results for the power of MMRA (Busemeyer & Jones, 1983; Dunlap & Kemery, 1988; Edwards, 2009; Evans, 1985). Like the effects of range restriction, unreliability in the product or polynomial term is exacerbated when unreliable measures are combined to create the higher order terms. Furthermore, given that constructs in organizational research are almost always measured with error, the effects of predictor unreliability are of great importance to organizational researchers investigating moderating and nonlinear effects. Indeed, Jaccard and Turrisi (2003) showed that the unreliability in the product (or polynomial) term will attenuate the ΔR^2 according to:

$$\Delta R^{2*} = \rho_{X_1X_2} \times \Delta R^2, \tag{12}$$

$$\Delta R^{2*} = \rho_{X_1^2} \times \Delta R^2, \tag{13}$$

where $\rho_{X_1X_2}$ and $\rho_{X_1^2}$ are the reliability of the product and polynomial terms, respectively.

Bohrnstedt and Marwell (1978) derived the equation for the reliability of a product term:

$$\rho_{X_1X_2} = \frac{E(X_1)^2V(X_2)\rho_{X_2} + E(X_2)^2V(X_1)\rho_{X_1} + 2E(X_1)E(X_2)C(X_1,X_2) + C(X_1,X_2)^2 + V(X_1)V(X_2)\rho_{X_1}\rho_{X_2}}{E(X_1)^2V(X_2) + E(X_2)^2V(X_1) + 2E(X_1)E(X_2)C(X_1,X_2) + C(X_1,X_2)^2 + V(X_1)V(X_2)}, \tag{14}$$

where, in Equation 14, $\rho_{X_1X_2}$ is the reliability of the product term, ρ_{X_1} is the reliability of X_1, and ρ_{X_2} is the reliability of X_2. $E()$, $V()$, and $C()$ are expected values, variances, and covariances, respectively. If the predictors are standardized, Equation 14 reduces to:

$$\rho_{X_1X_2} = \frac{r^2_{X_1X_2} + \rho_{X_1}\rho_{X_2}}{r^2_{X_1X_2} + 1}, \tag{15}$$

where $r_{X_1X_2}$ is the correlation between X_1 and X_2. Because reliability is defined as the ratio of the true score variance to total variance, the reliability of the polynomial term is defined as $\rho_{X_1X_1} = (\rho_{X_1})^2$ (Moosbrugger, Schermelleh-Engel, Kelava, & Klein, 2009).

From Equation 15, one can see that the reliability of the product term is a function of the reliability of the components and the correlation of the components. Edwards (2009) provides an example: If X_1 and X_2 are uncorrelated and have reliabilities of .70, the reliability of X_1X_2 is only .49. He goes on to demonstrate that if the correlation between X_1 and X_2 increases to .25 and .50, the reliability of X_1X_2 increases to .52 and .59, respectively. As another example, if the reliability of X_1 and X_2 are both 0.80, the reliability of the product term can vary from as low as 0.64 if the variables are uncorrelated to as large as 0.82 if the variables are perfectly correlated. However, if two variables have a reliability of 0.60, the maximum reliability the product term can have is 0.68. Finally, suppose one variable is measured very reliably (i.e., 0.90), whereas the other is measured poorly (i.e., 0.60); the reliability of the product term can be as low as 0.54 for uncorrelated variables and only as high as 0.77 with perfectly correlated variables. The conclusion from this is that even when the components have reliabilities that meet standard cut-offs (see Lance, Butts, & Michels, 2006), the interaction term may not achieve the same standard (Edwards, 2009, p. 149). Moosbrugger et al. (2009) note the paradox that "While multicollinearity of predictors enhances the reliability of an interaction term, it also causes severe estimation and interpretation problems because of the high correlations between all variables in the nonlinear regression model" (pp. 107-108).

With respect to centering, Bohrnstedt and Marwell (1978) recognize that the reliability of a product term is scale dependent. More specifically, they showed that any transformation that alters the ratios of means to standard deviations of the component terms (i.e., μ_{X_1}/σ_{X_1} and μ_{X_2}/σ_{X_2}) will change the reliability of the product—mean-centering is such a transformation as the ratios become 0 by virtue of the means dropping to 0. One would expect that in general, the reliability of the product term will be lower with centered data than with raw scores and that the power of MMRA and PRA will be severely attenuated by using transformed rather than raw scores. However, Lubinski and Humphreys (1990) concluded that the impact of the scaling of X_1 and X_2 on $\rho_{X_1X_2}$ can be disregarded when lower order terms are included in the model because, as outlined earlier, the ΔR^2 is unaffected by the scaling of X_1 and X_2. Therefore, although centering X_1 and X_2 may change the reliability of the product or polynomial term, controlling for X_1 and X_2 by including them in the analyses—which is typically done in MMRA and PRA—controls for the centering and does not affect the power of MMRA and PRA. However, if the components are measured unreliably, then the power of the MMRA and PRA will be severely attenuated regardless of whether the predictors are centered or not.

What Additive Transformations Do Accomplish

Mean-centering does have some beneficial outcomes that aid researchers. In particular, the traditional reason to center was the reduction in nonessential ill-conditioning, limiting the likelihood of computational errors. However, given the computational capacity of today's computers, it is unlikely that failing to remove nonessential ill-conditioning will lead to computational errors for traditional MMRA. There are other reasons, however, that still justify centering.

Mean-centering improves the interpretability of results. In the past, some debate existed as to whether the lower order terms can be interpreted in MMRA and PRA. One view suggested, as Stone (1988) summarizes, that "Main effects cannot be considered in isolation of the interaction effect" (p. 201). Indeed, Katrichis (1993) notes that the arbitrary nature of scales can complicate the interpretation of the lower order term. Alternatively, others believed that the lower order terms have a meaningful interpretation. This is true when there is and is not a moderating effect (see Aguinis, 2004; Irwin & McClelland, 2001). To outline the meaning of lower order terms, suppose a researcher is interested in the effects of job performance and work stress on intentions to quit. In this example, Y is intentions to quit (ITQ), X_1 is work stress (WS), X_2 is job performance (JP), and X_1X_2 is the multiplicative term capturing the moderating impact of JP on WS and ITQ.

In a typical MMRA, the researcher regresses ITQ on WS and JP in the first model (i.e., Model 1) and in the second model (i.e., Model 2) adds the interaction term. The interpretation of the regression weights for WS and JP depends on which model is being interpreted and whether or not the data are centered. Regardless of centering, however, the regression weights for WS and JP in the first model (i.e., the model excluding the interaction term) are interpreted as *average effects* (Aguinis, 2004; Jaccard & Turrisi, 2003). That is, b_1 is the WS-ITQ relationship averaged across JP; similarly, b_2 is the JP-ITQ relationship averaged across WS. Similarly, b_1 and b_2 can be interpreted as the relationship between X_1 (X_2) and Y holding X_2 (X_1) constant. In the second model (i.e., the model including the interaction term), the first-order effects are interpreted as conditional or simple effects (Aguinis, 2004; Jaccard & Turrisi, 2003). In other words, b_1 is the relationship between WS and ITQ at a specific value of JP—that is, when JP equals 0. When variables are centered, JP $= 0$ at the mean value of JP. Similarly, b_2 is the relationship between JP and ITQ at the mean value of WS. In Model 2, then, the regression weights for lower order terms no longer represent average effects, but are conditional on the value of the other lower order term—more generally, with centered variables b_1 (b_2) is the relationship between X_1 (X_2) and Y at the mean value of X_2 (X_1) (Jaccard & Turrisi, 2003).

When variables are not centered in Model 2, b_1 and b_2 are interpreted the same as in the centered case; however, in this instance, 0 is not the mean value of X_2 or X_1. Often, 0 is not a meaningful point in many psychological scales. Indeed, most operationalizations of the constructs in organizational research, and in psychology in general, are arbitrary (Blanton & Jaccard, 2006). Because of the arbitrary nature of most of the scales used by organizational researchers, zero-points fall outside the range of the raw-score variables; this makes interpreting results more complicated.

As just outlined, the zero-point is important in multiple regression because the interpretation of b_1 and b_2 depends on a meaningful zero-point. Similarly, the intercept b_0 corresponds to the expected value of Y when all predictors have a value of zero (Aguinis, 2004; Jaccard & Turrisi, 2003). Centering assists researchers by making the results interpretable. This is shown in Table 4. Following Aiken and West's (1991) procedures for interpreting an interaction at three levels (i.e., at the mean, one standard deviation above the mean, and one standard deviation below the mean), we computed the simple slopes equations. All that differs is that the value of X_2 for the mean in centered analyses is 0. The relationship between X_1 and Y when $X_2 = 0$ is the relationship at the mean value of X_2.

It should be noted that mean-centering may not be necessary when a meaningful zero-point naturally occurs and zero falls within the range of the data. Ratio scales are an example of scales with a meaningful zero-point that organizational researchers do use in their research; some common variables are: tenure, counts of absences, production counts, and number of job searches. When using scales like these, centering for interpretation is not necessary (as long as zero falls in the range of the data). Other than ratio scales, any interval scale that has a meaningful zero-point can also be used without centering. Examples of this type of measurement are item response theory (IRT) parameter estimates; the zero-point indicates average standing on the latent trait continuum. In this situation, researchers would not necessarily need to transform the θ-estimates to make zero the mean θ-level since a θ score of zero is meaningful. Note, however, that these types of variables may still be mean-centered with no impact on the interpretation of the interactive effect (i.e., b_3).

Furthermore, researchers may wish to center their variables at some other value on that variable when he or she wants zero to represent that value. Any constant subtracted from X_1 and X_2 will not affect the significance or interpretation of b_3, and all of the equivalences between mean-centered and uncentered analyses demonstrated previously will hold for centering on any constant when applying MMRA and PRA. In organizational research, some examples of values other than the mean to center at include: a cut score on a selection test, a minimum level of stress, or a specific level of performance. Although the substantive conclusions will be the same, additive transformations other than mean-centering can result in different effects on collinearity (Jaccard & Turrisi, 2003).

Situations Where Additive Transformations Do Matter

Mean-centering matters when testing moderated structural equation models (MSEM). Structural equation modeling (SEM) is a valuable method because it allows researchers to estimate the relationships among variables while controlling for measurement error (Kenny & Judd, 1984). Kenny and Judd (1984) introduced an approach to modeling interactive and nonlinear effects using SEM to account for the measurement error in MMRA and PRA (Busemeyer & Jones, 1983). Since Kenny and Judd's seminal work, many approaches to testing these effects have been proposed (for reviews, see Cortina, Chen, & Dunlap, 2001; Marsh, Wen, & Hau, 2004; Schumacker & Marcoulides, 1998). In MSEM, a researcher specifies both a structural model (i.e., the relationships among the latent factors of X_1, X_2, X_1X_2, and Y) as well as the measurement model (i.e., the relationships among the observed variables and the latent factors). When specifying the measurement model, the researcher has to decide how to use indicators of the latent factors of X_1 and X_2 (i.e., ξ_{X_1}, ξ_{X_2} in LISREL notation, respectively) to create indicators for the interaction latent factor (i.e., $\xi_{X_1X_2}$). A myriad of methods have been proposed to create these indicators, including using combinations of all the indicators of ξ_{X_1} and ξ_{X_2} (e.g., Kenny & Judd, 1984), using a single indicator (e.g., Joreskog & Yang, 1996), and a matched-pairs system (e.g., Yang, 1998; for a review, see Jackman, Leite, & Cochrane, 2011). Mean-centering these indicator variables can impact two aspects of testing a moderated structural equation model: (a) the convergence of the model and (b) the relationships among latent variables.

Mean-centering and model convergence. Many of the approaches used in MSEM are complicated by the use of nonlinear constraints—that is, parameters within the model are constrained to be nonlinear functions of other parameters in the model (for a review, see Cortina et al., 2001). Because of these complicated constraints, these types of models are prone to nonconvergence and improper solutions (Ping, 1998). Structural equation models are tested using iterative processes (e.g., maximum likelihood estimation); a model converges when the values of the unknown parameters are sufficiently close to the convergence criterion (Bollen, 1989); otherwise, model nonconvergence occurs. A myriad of causes for nonconvergence have been identified. Central to MSEM, nonconvergence can result from ill-conditioning in the data (Moosbrugger et al., 2009) that can cause fluctuations in the observed variance and covariances (Bollen, 1989). Furthermore, large input matrices that need to be inverted can cause convergence issues (Ping, 1995, 1996, 1998; Rigdon, Schumacker, & Wothke, 1998).

Kenny and Judd (1984) specified indicators and latent factors with zero-means, and therefore suggested there was no need to model the means of the latent factors. However, Joreskog and Yang (1996) demonstrated that even with zero-means, the mean-structure still needed to be modeled. With zero-means, only the mean for the latent interaction term is needed (i.e., κ_3 in LISREL notation); however, with non-zero-means, the means for all three latent variables (i.e., κ_1, κ_2, κ_3) need to be modeled. In their demonstrations, Joreskog and Yang simulated data with means of zero meaning κ_1 and κ_2 could be set to zero. Algina and Moulder (2001) later demonstrated that nonconvergence can result when modeling the mean structure with indicator means greater than zero. In particular, they showed that the nonconvergence occurred when trying to estimate the error variances of the observed indicators (in LISREL terms, the Θ_δ matrix). This likely results from the fact that these elements need to be constrained by other parameters in the model, including the mean of the observed variables (Algina & Moulder, 2001; Cortina et al., 2001). Algina and Moulder demonstrate that these convergence problems are reduced greatly by sample-mean-centering the indicator variables, then conducting the analysis. These results generalize to other approaches that require the mean structure to be modeled, including the different constrained approaches (for a review, see Cortina et al., 2001), Marsh et al.'s (2004) unconstrained approach, and Wall and Amemiya's (2001) generalized appended product indicator (GAPI) approach.

Ping (1995, 1996, 1998) also demonstrated that the more indicators used to model the latent interaction, the larger the input matrix will become—this will make it more difficult to invert the matrix (as is necessary in SEM estimation). Similarly, Marsh et al. (2007) and Moosbrugger et al. (2009) showed that multicollinearity can cause nonessential ill-conditioning in the input matrix (see previous), which can cause nonconvergence issues in MSEM. They suggest mean-centering the indicator variables to reduce the nonessential ill-conditioning and nonconvergence issues.

Mean-centering variables in MSEM can reduce convergence issues by reducing the nonessential ill-conditioning in the input matrix that needs to be inverted when running the estimation procedure. Furthermore, centering variables prior to modeling the mean-structure can limit convergence issues related to the estimation of the Θ_δ matrix. As a final note, one can eliminate the need to model mean structure all together by using the double-mean-centering approach; however, this approach still requires mean-centering indicator variables (see Lin, Wen, Marsh, & Lin, 2010).

Mean-centering and relationships among latent factors. Other than alleviating nonconvergence issues, mean-centering the indicators of latent variables can alter the relationships among the latent variables. In particular, assuming multivariate normality and after mean-centering, the relationships between the latent factors for X_1 and X_2 will not be related to the latent factor for X_1X_2. In LISREL terms, the Φ_{31} and Φ_{32} parameters become zero. Indeed, this relationship is a major assumption of all of the constrained models—an assumption that is often violated (Marsh et al., 2004). Relaxing this assumption of multivariate normality is what separates approaches like Marsh et al.'s (2004) unconstrained approach from the constrained approaches. Nevertheless, these alternative approaches to testing MSEMs still rely on mean-centering of the indicator variables to alleviate convergence issues.

It is worth noting, also, that centering the manifest variables will not change the relationship between the latent factors for X_1 and X_2. Stated in LISREL terms, the Φ_{21} parameter will remain unchanged after mean-centering (Bollen, 1989). Moosbrugger et al. (2009) noted that with multivariate normality, centering will remove the nonessential ill-conditioning in the data, resulting in the

Φ_{31} and Φ_{32} parameters being zero. With non-normal data, these parameters will be greater than zero because of essential ill-conditioning. However, if these variables are not centered, then Φ_{31} and Φ_{32} will be much larger. The unconstrained approaches model the essential ill-conditioning due to non-normal data. Alternatively, the constrained approaches assume Φ_{31} and Φ_{32} are zero when indicators have zero-means (see Marsh et al., 2004, for a review).

In all, it is important to center one's manifest variables prior to modeling interactions in SEM to alleviate convergence issues related to (a) nonessential ill-conditioning and (b) complex, nonlinear constraints. If one uses a constrained approach that assumes Φ_{31} and Φ_{32} are zero, mean-centering is necessary if the indicator variables have non-zero means. If one uses an unconstrained approach, mean-centering is still recommended to limit convergence issues. Finally, even with indicator variables with meaningful zero-points, centering is still useful to reduce the nonessential ill-conditioning in MSEM regardless of the approach used.

Mean-centering matters when testing multilevel models (MLM). Researchers interested in investigating multilevel phenomena need to decide how to center their variables. That is, researchers have shown that how variables are centered when testing MLM has implications for interpreting the results. In MLM analyses, which are regression based, the results of the Level 1 analysis (i.e., the intercept and slope) become the outcome variables in the Level 2 analysis—the Level 1 results must have a clear meaning (Raudenbush & Bryk, 2002).

In a simple two-level model, the MLM takes the form of Equations 16, 17.1, and 17.2:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij}) + r_{ij}, \tag{16}$$

where Y_{ij} is the outcome variable score of the ith individual in the jth group, β_{0j} is the intercept of the regression equation for the jth group, β_{1j} is the regression coefficient for the independent variable (X_{ij}) in the jth group, X_{ij} is the predictor score for the ith individual in the jth group, and r_{ij} is the random error for the ith person in the jth group.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(Z_j) + u_{0j}. \tag{17.1}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(Z_j) + u_{1j}. \tag{17.2}$$

Equation 17.1 models the variance in the Level 1 intercept across groups from Level 2 predictors. γ_{00} is the intercept term for this regression equation, γ_{01} is the regression coefficient for the change in β_{0j} for a one-unit change in the Level 2 independent variable (Z_j), Z_j is the score on the Level 2 predictor for the jth group, and u_{0j} is the random component of β_{0j} after controlling for the Level 2 variable. Equation 17.2 similarly models the variance in the Level 1 regression slope across groups from Level 2 predictors. γ_{10} is the intercept term for this regression equation, γ_{11} is the regression coefficient for the change in β_{1j} for a one-unit change in the Level 2 independent variable (Z_j), u_{1j} is the random component of β_{1j} after controlling for the Level 2 variable, and all other terms are defined as previously described. Equations 16, 17.1, and 17.2 can be combined to show the relationship between the first-order terms and a product term:

$$Y_{ij} = \gamma_{00} + [\gamma_{01}(Z_j)] + [\gamma_{10}(X_{ij})] + [\gamma_{11}(Z_jX_{ij})] + u_{0j} + [u_{1j}(X_{ij})] + r_{ij}. \tag{18}$$

As can been seen, a meaningful zero-point for X_{ij} is necessary for the MLM to have a meaningful interpretation. Indeed, as Raudenbush and Bryk (2002) note: "It is always important to consider the meaning of $X_{ij} = 0$ because it determines the interpretation of β_{0j}," (p. 32). To that end, two forms of centering have been proposed: grand mean-centering and group mean-centering. Here, we provide a short overview of the two types of centering; for a more detailed outline of centering decision in MLM, see Enders and Tofighi (2007) and Hofmann and Gavin (1998). Furthermore, it should be

Table 5. Interpretation Multilevel Model Parameters Based on Centering Decision[a,b]

	Interpretation of Model Parameters	
Parameter	Grand Mean-Centering	Group Mean-Centering
β_{0j}	Predicted score of someone with a score at the grand mean	Predicted score of someone with a score at the group mean Unadjusted (for Level 1 relationship) group mean
γ_{00}	Average adjusted (for Level 1 relationship) mean	Average unadjusted mean
γ_{10}	Mixture of within- and between-group association between $\boldsymbol{X_{ij}}$ and $\boldsymbol{Y_{ij}}$	Pooled within-group association between $\boldsymbol{X_{ij}}$ and $\boldsymbol{Y_{ij}}$
τ_{00}	Variation in the adjusted outcome means	Variation in the unadjusted group mean Between-group variation in $\boldsymbol{Y_{ij}}$
τ_{11}	Interpretation is ambiguous related to between and within variation Dependency between the intercepts and slopes introduced by the centering method	Variation in the Level 2 slope.

[a]This table only discusses parameters that have an interpretational difference between the centering types.
[b]Interpretations based on Enders and Tofighi (2007) and Hofmann and Gavin (1998).

noted that centering may not be necessary if a variable is measured with a meaningful zero-point within the range of the data and variables can be centered at values other than the mean (for a discussion of these two points, see Raudenbush & Bryk, 2002, pp. 31-35).

Grand mean-centering. In grand mean-centering, the scores are centered about the grand mean of the predictor variable across groups. Grand mean-centering of variables does not change the rank order of scores on either X_{ij} or Y_{ij}. Because grand mean-centering does not alter the rank ordering of the scores, the multilevel association between X_{ij} and Y_{ij} does not change after grand mean-centering (Enders & Tofighi, 2007). Furthermore, the mean differences and correlations among the variables remain the same.

Finally, grand mean-centering results in scores that are correlated at Level 1 and Level 2. Subsequently, X_{ij} becomes a composite variable that contains both within-group and between-group variation. As a result, the interpretation of the model parameters differs greatly compared to group mean-centering. Table 5 outlines how the different model parameters are interpreted with grand mean-centering.

Group mean-centering. In group mean-centering, scores are centered about the mean of the predictor variable within groups. Unlike grand mean-centering, group mean-centering does change the rank order on both X_{ij} and Y_{ij}. Since scores are now centered about the means of their respective groups, observations are now expressed relative to other cases belonging to the same group. Furthermore, group mean-centering will change the mean differences and correlations among the variables (Enders & Tofighi, 2007).

As a result then, group mean-centering will remove all between-group variation; X_{ij} becomes a variable containing only within-group variation that correlates only with Level 1 variables but not with Level 2 variables (Enders & Tofighi, 2007). Because the Level 2 variation is removed with group mean-centering, variables correlate less strongly with each other (compared to grand mean-centered and raw score variables). The interpretation of the model parameters following group mean-centering is also shown in Table 5.

Research questions and centering decisions. Given the structural differences between group mean- and grand mean-centering, as well as the interpretational differences, different research questions call for different types of centering (see Enders & Tofighi, 2007; Hofmann & Gavin, 1998). Centering decisions should always be determined by the researcher based on the particular research question being addressed. We briefly cover four types of questions here, but interested readers can obtain a more detailed review in Enders and Tofighi (2007) and Raudenbush and Bryk (2002).

When the researcher is interested in the effect of the Level 1 predictor (i.e., X_{ij}) on the outcome variable (i.e., Y_{ij}), group mean-centering is the best option. Because group mean-centering removes all between-group variation, the β_{1j} is a pure estimate of the pooled, within-group relationship between X_{ij} and Y_{ij}. Alternatively, when the researcher is interested in knowing how the Level 2 variable (i.e., Z_j) impacts the outcome variable, grand mean-centering is the best option. With grand mean-centering, γ_{01} is the partial regression coefficient that reflects the influence of Z_j controlling for X_{ij} (Enders & Tofighi, 2007).

When one is interested in the interactive effect across levels of analyses (i.e., cross-level interaction), the researcher should use group mean-centering. Cross-level interactions require an unbiased estimate of the Level 1 association (i.e., β_{1j} must be meaningful). As stated earlier, β_{1j} is an unbiased estimate of the within-group variation with group mean-centering (Enders & Tofighi, 2007; Hofmann & Gavin, 1998).

Finally, if a researcher is interested in the effects of a variable at both levels of analyses, the researcher can use either type of centering. That is, the researcher may be interested in whether the relationship between the predictor and outcome is the same at both levels of analyses. In this situation, the researcher can choose to either group mean- or grand mean-center because this is one of the rare situations where the parameter values will be algebraically equivalent and lead to similar substantive conclusions (for the derivations and discussion, see Enders & Tofighi, 2007).

Additive Transformations With Categorical Moderators

Often, researchers are interested in how a categorical variable moderates a relationship between a predictor and an outcome. Cohen (1968) demonstrated the flexibility of multiple regression analyses to handle categorical variables. Here, we briefly describe how centering continuous variables impacts the interpretation of the model parameters when the moderator is categorical. For a more detailed discussion, interested readers are referred to Aguinis (2004) and Cohen et al. (2003).

The two most typical coding schemes for categorical variables are dummy coding and effect coding (for other coding schemes, see Aguinis, 2004; Cohen, 1968). With each type of coding, the researcher creates (c – 1) variables, where c is the number of categories in the moderator variables that are then multiplied with the predictor variable. Then, the component terms and interaction terms are entered into the model—hierarchically if desired—to control for the component terms. Importantly, centering continuous variables prior to conducting the analyses aids in interpreting the results without altering the results (Aguinis, 2004). One may want to center continuous variables for ease of interpreting the results; categorical variables should be coded based on the research questions and should not be altered.

Table 6 outlines the interpretation of the model parameters for a model containing one continuous predictor and a categorical moderator with two levels. Table 6 assumes the continuous variable has been centered; differences in interpretation of the various regression coefficients for dummy and effect coding are discussed. For an expanded discussion, including interpretations of other coding schemes, see Aguinis (2004) or Cohen et al. (2003).

It is important for researchers to carefully consider how they choose to code their variables (Irwin & McClelland, 2001) and should consider centering continuous variables to help interpret the results

Table 6. Interpretation of Moderated Multiple Regression Analyses Model Parameters With Categorical Moderators[a,b]

Model	$Y = b_0 + b_1X_1 + b_2C_1 + b_3X_1C_1$	
Where	Y is the predicted score on the dependent variable b_0 is the intercept parameter X_1 is the score on continuous predictor (score centered) b_1 is the regression parameter relating changes in X_1 to changes in Y C_1 is the variable used for coding the two-level, categorical moderator b_2 is the regression parameter relating changes in C_1 to changes in Y X_1C_1 is the composite variable that captures the interaction of the centered continuous variable and the code variable for the categorical moderator b_3 is the regression parameter relating changes in the interaction term to changes in Y	
	Interpretation of Model Parameters	
Parameter	Dummy Coding	Effect Coding
Coding	Reference group code: 0 Focal group code: 1	Nonfocal group code: –1 Focal group code: 1
b_0	Predicted Y for individuals in the reference group with the mean level of X_1	Weighted (for sample size) mean of mean Y scores across groups—the grand mean when group sample sizes are equal
b_1	The change in Y for a one unit change in X_1 in the reference group (i.e., $C_1 = 0$)	The unweighted (for sample size) average relationship between X_1 and Y across groups of the moderator
b_2	The difference in predicted Y between the focal and reference group for individuals with the mean level of X_1	The mean difference in Y between the focal group and grand mean (i.e., b_0)
b_3	The difference in the X_1-Y relationship between the focal and reference groups	The difference in the X_1-Y relationship between the focal group and the average X_1-Y relationship across groups (i.e., b_1)

[a]Interpretations adapted from Aguinis (2004) and Cohen, Cohen, West, and Aiken (2003).
[b]Interpretations for a model containing one continuous predictor—centered—and one categorical moderator with two levels; for more detailed treatments, see Aguinis (2004).

(Cohen et al., 2003). Also, researchers need to fully consider the power issues specific to MMRA with categorical variables (see Aguinis, 2004; Aguinis et al., 2001; Aguinis & Pierce, 1998).

Final Conclusions and Recommendations

This article has addressed the myth that mean-centering can alter substantive conclusions in moderated multiple regression analysis and polynomial regression analysis. We looked to integrate findings from different fields into a single article that addresses many of the confusions surrounding additive transformations in MMRA and PRA.

We have shown that mean-centering reduces nonessential collinearity between interaction terms and its components. We further showed that although b_1 and b_2 can change after mean-centering, the b_3 coefficient, its standard error, and significance do not change. In line with this, we have demonstrated that the R^2 and ΔR^2 are also the same. Additionally, the simple slopes interpretation of the interaction does not differ between mean-centered and raw score variables.

We further showed that mean-centering does not change the power of the tests of MMRA or PRA. Indeed, if a study suffers from low power, mean-centering the variables will not increase the power. We also showed that mean-centering variables may appear to reduce the reliability of the product term. However, the inclusion of X_1 and X_2 in the model negates the effects of scaling.

Finally, we note, like most scholars on the topic, that mean-centering reduces nonessential collinearity, reducing ill-conditioning in the data. We demonstrated that centering can help interpret the results of the regression analysis by giving X_1 and X_2 meaningful zero-points. We also showed two areas where additive transformations can make an appreciable impact, including when testing MSEMs and when testing hierarchical linear models (HLMs). It is important to recognize that additive transformations will not improve one's chances of finding significant results, and although not demonstrated here, the conclusions outlined previously extend to higher order interactions and polynomial effects (for a discussion, see Jaccard & Turrisi, 2003).

Before concluding with our recommendations on when to center in MMRA and PRA, we note an interesting finding from Landis and Dunlap (2000) regarding the structure of an MMRA. Specifically, Landis and Dunlap argue that in some cases, specifying the criterion and the predictor variable can be interchangeable. Stated differently, they note, "It is possible to examine the influence of [a moderator] of the $x \rightarrow y$ and $y \rightarrow x$ relationships" (p. 255). Although they do note that in most cases this ordering is clear, there are situations where it is more ambiguous (e.g., performance→satisfaction or satisfaction→performance). In these latter situations, then, it is possible that specifying the criterion and predictor in the opposite order can result in a different conclusion related to the moderating effect. They argue for the need for a clear theoretical reason to specify one variable as a criterion and the other as the predictor—if this does not exist, though, they recommend analyzing the moderating relationship on both the $x \rightarrow y$ and $y \rightarrow x$ relationships.

We conclude with some recommendations on when to center variables prior to conducting MMRA or PRA. If one is testing an MSEM or HLM, we recommend centering according to the recommendations of Cortina et al. (2001) or Marsh et al. (2004) for MSEM and Enders and Tofighi (2007) or Hofmann and Gavin (1998) for HLM. If one is testing relationships according to Equation 3, we recommend centering the variables if the variables do not have meaningful zero-points. If the variables have meaningful zero-points (e.g., tenure) within the range of the variable, the variables do not need to be centered to increase interpretability.

Often moderating and nonlinear relationships are investigated together—some researchers investigate moderators of a curvilinear relationship. At a more general level, researchers have suggested that quadratic terms (i.e., X_1^2 and X_2^2) be included in the analysis of moderating relationships (Cortina, 1993; Lubinski & Humphreys, 1990). The recommendations for transformations for MMRA and PRA can be combined when considering moderating and nonlinear relationships simultaneously.

In general, there are some benefits to centering, though they are often exaggerated and misunderstood, especially when discussing regression. We hope this article clarifies the advantages and disadvantages for centering and helps researchers make more informed decisions.

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Notes

1. Derivations in the article are shown for moderated multiple regression analysis (MMRA). However, the substantive conclusions demonstrated for MMRA extend to polynomial regression analysis (PRA), and derivations for the PRA are available upon request.
2. In the case of one variable PRA, the R^2 value for the case where there is no nonlinear effect (i.e., the highest order regression term is 0) is the same with any simple linear regression analysis: $R^2 = r^2_{X_1Y}$. As demonstrated previously and in Table 2, the relationship between X_1 and Y does not change between centered and uncentered analyses.

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