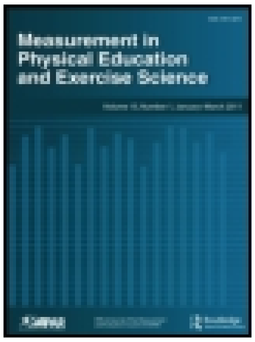

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The Use of Structure Coefficients to Address Multicollinearity in Sport and Exercise Science

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ABSTRACT

A common practice in general linear model (GLM) analyses is to interpret regression coefficients (e.g., standardized β weights) as indicators of variable importance. However, focusing solely on standardized beta weights may provide limited or erroneous information. For example, β weights become increasingly unreliable when predictor variables are correlated, which is often the case in the social sciences. To address this issue, structure coefficients, which are simply the bivariate correlation between a predictor and the synthetic $\hat{Y}$ variable, should also be interpreted. By examining β weights and structure coefficients in conjunction, the predictive worth of each independent variable can be more accurately judged. Despite this benefit, researchers in the field of sport and exercise science have rarely reported structure coefficients when conducting multiple regression analysis. Thus, the purpose of the present article is to discuss problems associated with the sole interpretation of β weights and to demonstrate how structure coefficients can be incorporated to improve accuracy of interpretation. Additionally, a content analysis was conducted to examine current trends in reporting multiple regression results within sport and exercise science research.

KEYWORDS
general linear model; multiple regression; physical fitness; structure coefficient; β weight

As the basis for many statistical analyses in sport and exercise science, multiple regression is a popular method for determining whether an outcome variable (i.e., dependent variable [DV]) can be predicted by, or is related to, a set of predictors (i.e., independent variables [IVs]). If a sufficient relationship exists, then knowledge of one or more IVs is then presumed to provide information about the DV, assuming the relationship is generalizable across samples (Cohen, Cohen, West, & Aiken, 2003). If a noteworthy relationship or prediction is observed, then standardized regression coefficients (i.e., β weights) can be examined to determine the predictive power of individual IVs (Nathans, Oswald, & Nimon, 2012). However, if IVs are interrelated (i.e., multicollinearity exists), then the accuracy of β weights can be seriously compromised, which can misconstrue the relationship between the predictors and outcome (Nathans et al., 2012). While there are other pieces of information that can be consulted in such situations, they are rarely employed in exercise science research. Thus, the purpose of the current article is to describe problems associated with the interpretation of β weights in the presence of multicollinearity and to discuss the benefits of examining structure coefficients in conjunction with β weights in order to positively impact research practice. A real world example will be employed to illustrate this purpose.

As part of the general linear model (GLM), regression follows four basic principles that apply to all GLM analyses (Cohen, 1968; Cohen et al., 2003). First, all GLM analyses are correlational in nature. This is evident in simple (one predictor) linear regression because the β weight for a given predictor is equivalent to the correlation between the predictor and DV. When multiple IVs are used, β weights equal the correlation between each predictor and the DV only if all predictors are perfectly uncorrelated, which of course will likely never occur in a real-world situation. Second, because all GLM analyses are correlational in nature, they all yield r^2-type effect sizes, which provide an estimate of the total variance in the DV that can be explained by the optimally weighted IVs in the regression equation.

Third, a system of weights is applied to observed variables to create synthetic (i.e., latent) variables. In multiple regression, the standard linear equation produces synthetic $\hat{Y}$ (i.e., predicted DV) scores by multiplying each regression coefficient (i.e., b [slope] or β weights, depending on whether the unstandardized or

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standardized equation, respectively, is used) with their corresponding observed scores (i.e., X_i; see Cohen et al., 2003). If observed scores are standardized to Z score form, and β weights are applied, the standardized equation for a two-predictor situation would be

$$\hat{Y} = \beta_1 X_1 + \beta_2 X_2. \tag{1}$$

The computation of the β weights used in this equation must take into account the relationship among the IVs in an effort to minimize the discrepancy between the DV and $\hat{Y}$ scores. This relationship among the IVs can have a strong influence on the magnitude of the weights in the equation and can directly impact how the predictors are interpreted when creating the $\hat{Y}$ scores.

Finally, the synthetic variables are of primary interest when interpreting results. In multiple regression, the synthetic $\hat{Y}$ scores are usually the analytic focus. A key statistic in multiple regression is the multiple R, which reflects the joint correlation between the DV and all of the predictors collectively. However, this multiple R really can be represented as the simple, bivariate correlation between the DV and $\hat{Y}$ scores. Because the synthetic $\hat{Y}$ scores capture the useful part (i.e., the shared variance) of the predictors, the entire multiple regression boils down to this correlation: $r_{\text{DV}-\hat{Y}}$, which makes explicit the fact that the focus of the analysis is really on the synthetic variable scores and their relationship with the DV.

These principles also mirror the two-step approach for interpreting any GLM analysis as proposed by Thompson (1997). To illustrate this process in the field of sport and exercise science, let us assume we wish to determine the predictive relationship of various motor skills (e.g., jumping, kicking, and throwing) and physical fitness (Stodden, Langendorfer, & Roberton, 2009). Thompson's first interpretive question asks whether a result that is noteworthy and worth interpreting has been obtained. The first two principles noted above speak to this step. The strength of the correlation between the predictors and physical fitness can be determined by examining the effect size R^2. Of course, this effect size can also be tested for statistical significance, confidence intervals can be examined, and other factors that might speak to the accuracy of the results can be considered (e.g., bootstrapping or cross-validation).

Only after attaining a noteworthy, meaningful outcome in the first step would the second interpretive question be addressed. In the context of multiple regression, the second question asks which motor skills are important for predicting the physical fitness outcome (Thompson, 1997). It is crucial to follow these steps in order. The second step should only be addressed if a noteworthy relationship was produced in the first step (Henson, 2002). It makes no sense, for example, to explore which predictors are important when there was not a meaningful amount of variance explained in the first place.

The last two GLM principles are especially relevant for this second interpretive step because they speak to the role of the predictors in the regression equation in creating the synthetic $\hat{Y}$ scores. In the current example, this is traditionally accomplished by inspecting the β weight of each motor skill predictor and interpreting the magnitude of each β weight to determine variable importance. It is generally (and incorrectly) assumed that a larger weight means the predictor variable must have a stronger relationship with $\hat{Y}$. However, the sole interpretation of β weights can lead to serious misinterpretation when predictors are interrelated (i.e., multicollinearity; Cohen et al., 2003; Stevens, 2009), and thus additional information is not only useful but generally necessary when interpreting multiple regression analyses (Nathans et al., 2012).

Limitations of β weights

In real world data, predictors typically correlate with one another to some extent and therefore often explain some of the same variance in the DV. For example, it is reasonable to expect that jumping, kicking, and throwing ability would be related to some degree, and potentially each may explain some of the same variance in physical fitness. In these situations, β weights account for the relationships among all variables in the regression equation and divide predictive credit for any shared variance among the relevant IVs (Kraha, Turner, Nimon, Zientek, & Henson, 2012). Because predictors may explain the same variance in the DV, the shared variance is not equally distributed among β weights (Courville & Thompson, 2001), and the sum of the squared bivariate correlations between each IV and the DV will no longer equal the R^2 effect size (Kraha et al., 2012). As a result, how β weights divide credit for any shared variance is heavily impacted by the multicollinearity among the predictors. This is the primary limitation of β weights. The sum of the squared zero-order correlations will equal R^2 only when the predictors are perfectly uncorrelated, and as such, any predictor's β weight would equal its correlation with the DV. In these cases, sole interpretation of β weights would be reasonable, but this is not likely to occur with real data.

Table 1. Frequencies of multiple regression analyses reporting *b* weights, β weights, and structure coefficients from 2012–2014.

	Analysis approach				
Journal	*b* coefficients	β weights	*b* and β	β and r_s	All three coefficients
Research Quarterly for Exercise and Sport	4	9	1	0	0
Psychology of Sport and Exercise	1	13	10	2	0
Journal of Sport and Exercise Psychology	5	12	6	0	1
Journal of Physical Activity & Health	11	33	4	0	0
Total	21	67	21	2	1
Percentage	19%	60%	18%	2%	1%

It is important to understand that β represents a predictor's contribution to the regression equation only in a sample-specific context (Henson, 2002). In fact, a predictor can be highly correlated with the outcome variable but receive a small β weight because another predictor received credit (i.e., a larger β weight) for the variance that it shared with the outcome variable. It is very possible, even common, that a predictor may be labeled as having more predictive power than another when, in reality, both variables have almost the same relationship with the outcome variable (Kraha et al., 2012). More extreme misinterpretations are possible, such that a predictor with a weaker relationship with the DV can even have a larger β than a predictor with a stronger relationship with the DV. As a result, the contribution of both variables is not clearly evident by using only the information provided by β weights (Nathans et al., 2012).

The context-specific nature of β weights is further exemplified by how they can substantially change with the addition or deletion of predictors or across samples (Courville & Thompson, 2001). This lack of reliability is commonly referred to as the "bouncing beta" problem (Henson, 2002). Therefore, if β weights are used as the sole source of information for variable importance in multiple regression, multicollinearity can severely limit the generalizability of the results across different studies (Thompson & Borrello, 1985).

The problem of multicollinearity has led to a call for researchers in the social sciences to use additional pieces of information to interpret their results (Courville & Thompson, 2001; Henson, 2002; Kraha et al., 2012; Nathans et al., 2012). Su (2011) conducted a content analysis in the *Journal of Teaching in Physical Education* to evaluate the journal's use and interpretation of structure coefficients (to be discussed later as an important piece of interpretation information in addition to β weights). After reviewing all 129 articles from Volume 24, Issue 1, to Volume 29, Issue 2, Su reported that of the 19 articles with regression analyses, only one reported structure coefficients, while the rest relied on regression weights only.

To extend these findings, a content analysis of four prominent journals in the field of sport and exercise science was conducted to provide a summary of how regression analyses are interpreted. The four target journals included *Research Quarterly for Exercise and Sport, Psychology of Sport and Exercise, Journal of Sport and Exercise Psychology*, and *Journal of Physical Activity and Health* from 2012 to 2014. In total, there were 112 articles published across the four journals that included a form of multiple regression (i.e., simultaneous, hierarchical, stepwise, or multivariate). As displayed in Table 1, 21 articles reported only *b* (slope, unstandardized) coefficients, 67 reported only β weights, and 21 reported both coefficients. Only three articles included the use of structure coefficients.

The necessity for a primer on how to use structure coefficients is also apparent after reviewing commonly used GLM or regression textbooks. For example, the popular multiple regression textbooks by Keith (2006) and Cohen et al. (2003) do not introduce structure coefficients when discussing multiple regression or multicollinearity. However, it is interesting that structure coefficients are considered to be essential when these authors discuss canonical correlation analysis (CCA; Pedhazur, 1997). This is primarily due to the assumed multicollinearity within the set of IVs and within the set of DVs. Because CCA is the multivariate GLM and structure coefficients are critical for CCA interpretation, it stands to reason that interpreting other GLM analyses would also require structure coefficients. As Huberty (1994) explained,

> if a researcher is convinced that the use of structure coefficients makes since in, say, a canonical correlation context, he or she would also advocate the use of structure coefficients in the contexts of multiple correlation, common factor analysis, and descriptive discriminant analysis. (p. 263)

Thus, while structure coefficients have been discussed in other contexts, their coverage in regression analysis is limited. Without continued argumentation for their use in multiple regression, it is likely that structure coefficients will continue to be neglected.

The overreliance on unstandardized *b* coefficients and β weights is troubling because it can have important consequences for determining variable importance. Furthermore, the results of the current content analysis highlight the need for a primer on best practices when interpreting multiple regression results in the presence of multicollinearity. Thus, the remainder of this article will expand on techniques to evaluate the predictive power of individual IVs. Zero-order, partial, and semipartial correlation coefficients will be discussed, followed by a rationale and user-friendly example for using structure coefficients in conjunction with β weights in the field of sport and exercise science.

Zero-order, partial, and semipartial correlation coefficients

The role of zero-order, partial, and semipartial correlation coefficients in multiple regression analysis is worth considering because each statistic provides some information on how individual IVs may contribute to the overall effect (R^2) and because some readers may be more familiar with these coefficients. First, zero-order correlations represent the simple, bivariate correlation between a single predictor and the DV, ignoring the existence of other predictors (Cohen et al., 2003). When IVs are completely uncorrelated, squared zero-order correlations will add up to R^2, and they can be useful in interpreting predictor contributions to the effect. Though, in the case where correlation exists between predictors, squared zero-order correlations will generally add up to a value greater than the model R^2.

Second, semipartial correlation coefficients (also called part correlations) can be squared to calculate the amount of variance explained by a predictor after having first removed any variance that other predictors might share with that first predictor. Because any shared variance that might be explained has been removed from the first predictor of interest, the variance this predictor can explain in the DV would have to be *unique* variance that only that predictor can explain. As such, squared semipartial correlations help answer the question of "how much would R^2 drop if the predictor of interest were removed from the regression?" Because they only speak to uniquely explained variance, squared semipartial correlations are limited in their ability to inform a predictor's overall contribution to the effect size.

Finally, squared partial correlation coefficients also represent the amount of *unique* variance explained by a predictor, but only after removing the variance explained by all other predictors with *both* the predictor of interest and the DV in the model. Because the variance of the DV is reduced by what the other predictors can explain, partial correlations will be larger than semipartial correlations. Essentially, squared partial correlations help answer the question of "how much variance in the DV that cannot be explained by other predictors can be explained by the predictor of interest?" Unfortunately, squared partial correlation coefficients also become ambiguous in the presence of multicollinearity. For example, when multicollinearity exists, a predictor may have a large zero-order correlation but a relatively small partial correlation coefficient, indicating a strong relationship with the DV, but very little uniquely explained variance after first removing DV variance explained by the other predictors. Thus, accurately judging variable importance remains difficult.

Structure coefficients

Instead of relying exclusively on β weights as an indicator of variable importance, they should be used in conjunction with structure coefficients. While β weights indicate how much predictive credit an IV is granted in a regression equation, structure coefficients provide information about how an IV relates to $\hat{Y}$ scores independent of other predictors (Henson, 2002). More simply, structure coefficients are the bivariate correlation between a single observed variable (e.g., predictor) and a synthetic variable (e.g., $\hat{Y}$). Thus, structure coefficients are not affected by multicollinearity because they are not influenced directly by the relationships among the predictors (Courville & Thompson, 2001). While structure coefficients represent a correlation between just two variables (i.e., X_i and $\hat{Y}$), they do not represent a value that is independent of the *effect* of other predictors. A major difference between zero-order, semipartial, and partial correlations and structure coefficients is that structure coefficients take other predictors into account indirectly because all other predictors in the regression equation are used in calculating $\hat{Y}$ (Nathans et al., 2012).

The primary value of structure coefficients lies with their ability to define and describe the structure of the effect size observed because they are in line with the third and fourth GLM principles noted above. It is the synthetic $\hat{Y}$ variable that is created by the regression equation (third principle), and $\hat{Y}$ is the focus of the interpretation (fourth principle). Squared structure coefficients tell us the amount of variance a predictor can explain in $\hat{Y}$. Because the squared relationship between the DV and $\hat{Y}$ represents the effect size observed, squared structure coefficients inform the nature and *structure* of the effect size from the multiple regression. That is, they help answer the question of "how much variance of $\hat{Y}$ can a predictor explain by itself?" Therefore, when considered together, all squared structure coefficients speak to the makeup, or *structure*, of the effect size obtained.

To improve interpretation of multiple regression results, both β weights and structure coefficients should be examined concurrently. Not doing so can easily lead to misinterpretation of predictor roles in the model. For example, a regression analysis may result in a predictor receiving a high β weight but a near-zero structure coefficient. In this case, the predictor was assigned a large coefficient in the regression equation, but it did not correlate with predicted $\hat{Y}$ values, thus raising the paradoxical question of how a predictor can get a great deal of credit in creating the $\hat{Y}$ scores but not be correlated with them. This is a classic example of suppression (Cohen et al., 2003), and it would never be identified if only β weights were consulted. A full discussion of suppression is beyond the scope of this article, but it occurs when β weights take into account the covariance among all the variables in the regression equation. Upon examining the correlations between predictors, it would be evident that the predictor causing the suppression is accounting for irrelevant variance in another predictor and not the DV, which artificially inflates the assigned β weight.

On the other hand, it is also possible for a predictor to have a near-zero β weight and a large structure coefficient. This could occur when two correlated predictors share variance with the synthetic $\hat{Y}$ variable. It is not uncommon for one predictor to receive a large β weight in the regression equation (thus getting the most credit for explaining the variance in the DV that both IVs share) while the other receives a small β weight, despite the fact that the variables have similar predictive power. As a result, a predictor with a low β weight could be labeled as a "weak" indicator when it actually might be one of the strongest predictors (Courville & Thompson, 2001). These examples illustrate how the existence of multicollinearity can lead to the misinterpretation of β weights when they are considered alone. By examining both β weights and structure coefficients, problems caused by multicollinearity can be avoided, and the predictive relationship between the IVs and $\hat{Y}$ can be examined (Henson, 2002).

Example of structure coefficients' use in sport and exercise psychology

The data set

To further illustrate the importance of structure coefficients, sample data that were collected as part of a different study will be examined. The sample included 151 young adult females (M_{age} = 19.80, SD = 4.30) whose fitness levels were assessed using the FITNESSGRAM® protocol (Plowman & Meredith, 2013). Specifically, participants completed fitness tests that included measures of body composition (i.e., percent body fat [% BF]), muscular strength and endurance (i.e., push-up test and curl-up test), and aerobic capacity (i.e., Progressive Aerobic Cardiovascular Endurance Run [PACER]). Each of the four fitness variables served as predictors of intrinsic motivation (Deci & Ryan, 1985), which was assessed via self-report from the Behavioural Regulation in Exercise Questionnaire (BREQ-2; Markland & Tobin, 2004). The research question for this example was as follows: How well do body composition, muscular strength and endurance, and cardiovascular endurance predict intrinsic motivation in an adult female sample? If a noteworthy relationship is obtained, the role of each IV in predicting intrinsic motivation will be examined. The means, standard deviations, and correlations of all variables are provided in Table 2.

Table 2. Descriptives and Pearson correlations among all variables.

Variables	Mean	*SD*	1	2	3	4
Intrinsic motivation	3.87	1.00	—			
% BF	25.58	6.86	−.30	—		
Push-ups	10.95	6.41	.38	−.36	—	
Curl-ups	30.05	17.00	.38	−.39	.45	—
PACER	29.54	13.21	.39	−.52	.36	.31

Note. N = 151; $p < .01$ for all relationships.

Traditional analytic technique

Based on a traditional application of regression, the four fitness variables were entered into IBM SPSS Version 22 (IBM Corp., 2014) regression analysis as predictors, and intrinsic motivation was entered as the outcome variable. As shown in Table 3, the analysis yielded a statistically significant overall result, $F(4, 146) = 12.56$, $p < .001$, $R^2 = .26$, indicating that the predictor variables accounted for approximately 26% of

Table 3. Predicting intrinsic motivation with four fitness variables.

	R^2	b	SE	β	r_s	r_s^2
	.26**					
% BF		< −.01	.01	−.02	−.59	.35
Push-ups		.03	.01	.19*	.75	.57
Curl-ups		.01	.01	.21*	.76	.57
PACER laps		.02	.01	.25**	.77	.60

Note. b = unstandardized regression coefficients; SE = standard error of the unstandardized regression coefficients; β = standardized regression coefficients; r_s = structure coefficients; r_s^2 = squared structure coefficients.
*$p < .05$.
**$p < .01$.

the variability in the outcome variable. We considered this outcome as noteworthy and deserving of interpretation, and therefore the next step in interpretation was to examine the variable-level coefficients.

Depending on one's purpose, this focus may be on unstandardized b coefficients or β weights and the standard errors (see Table 3). In a traditional approach, these statistics are generally used to evaluate the individual contributions of each predictor. For example, unstandardized b coefficients represent the slope relationship between intrinsic motivation and each predictor while holding constant the other predictors. The results of the current example indicate that a one-unit increase in PACER resulted in a .02 increase in intrinsic motivation, on average, after holding all other predictors constant.

Likewise, because they are based on standardized Z scores, β weights indicate the number of standard deviations that the outcome will change when a predictor changes by one standard deviation. In the current example, the β weight for PACER laps was .25, indicating that an increase of one standard deviation in PACER laps results in an average increase of .25 standard deviations for intrinsic motivation.

However, as previously discussed, considering b or β weights without referring to other pieces of information limits the accuracy of interpretation. For example, the strength and direction of each regression coefficient can be affected by the variances and covariances among the predictors. In the current study, aerobic capacity (i.e., PACER laps) was the most relevant predictor of intrinsic motivation based solely on the magnitude of its β weight. Aerobic capacity was followed by curl-ups, push-ups, and % BF in terms of variable importance based solely on β magnitude. This interpretation would conclude, in particular, that the non-statistically significant, near-zero β weight for % BF indicated that the variable did not play a role in explaining variance in the outcome variable. However, this interpretation is potentially inaccurate given that different measures of fitness naturally relate to one another. The bivariate correlations among predictors in this example ranged from r = .31 to .52, and it is interesting to note that the strongest correlation among the predictors included % BF. Consequently, further analysis with structure coefficients is needed to fully understand the contribution of each individual predictor.

Calculating structure coefficients using SPSS

Calculating structure coefficients is a simple two-step procedure. First, when running a regression analysis, predicted values (i.e., $\hat{Y}$ scores) must be saved. This can be performed in SPSS by using the following syntax:

```
REGRESSION
/DESCRIPTIVES MEAN STDDEV CORR SIG N
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA
/CRITERIA = PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT BREQ_Intrinsic
/METHOD = ENTER BodyFat Pushup Curlup Pacer
/SAVE PRED.
```

The last line of syntax printed above can be added to standard regression syntax to save predicted values. Alternatively, predicted values can be saved using the point-and-click method in SPSS by clicking "Save" in the regression window. Once the pop-up menu appears, checking the "unstandardized" box under the Predicted Values heading will ensure predicted values are saved as a new variable. If preferred, the "standardized" box will save predicted values in z-score form. Second, to calculate structure coefficients, the $\hat{Y}$ scores must then be correlated with each predictor. The default name for the saved predicted values variable in SPSS is PRE_1. Conducting a simple bivariate correlation between PRE_1 and each predictor will produce structure coefficients. Squaring these values will yield the percentage of variance shared between each predictor and the synthetic $\hat{Y}$ scores.

There is an alternative way to compute structure coefficients by way of a simple formula ($r_s = r_{Y-X} / R$), where the bivariate correlation between each predictor and the DV is divided by the multiple R. While the automated process described above is likely easier when analyzing one's own data, this simple formula can be particularly handy to compute structure coefficients post hoc for other studies that did not report them, assuming the authors have reported zero-order correlations and the multiple R.

Interpretation

Structure coefficients (r_s) for the current analysis are presented in Table 3. Based on the r_s values, aerobic capacity (PACER laps), curl-ups, and push-ups shared similar correlations to the predicted $\hat{Y}$ scores, indicating that they can equally contribute to the overall R^2 effect. The squared structure coefficients indicate the amount of variance of $\hat{Y}$ that each predictor can explain, and PACER laps, curl-ups, and push-ups all can account for substantial, and similar, portions of the effect size. It is also important to note that interpretation of the structure coefficients is largely consistent with the β weights, which also are similar in magnitude, although it does appear that the PACER laps β seems to be slightly larger than the other two.

The consistency in interpretation seems to break down, however, when we consider the % BF predictor. Notably, % BF had the largest difference between its β weight (β = –.02) and structure coefficient (r_s = –.59). As noted, consideration of only the near-zero β would clearly indicate that % BF is not a useful predictor and did not receive "credit" for its relationship with the outcome variable. However, the structure coefficient indicates that % BF indeed has a moderate relationship with the $\hat{Y}$ scores, and the squared structure coefficient shows that this predictor can account for just over a third (35%) of the effect size by itself.

These results may initially appear contradictory, but they are not. They simply reflect the different pieces of information that βs and structure coefficients provide. In this case, the β weight for % BF is artificially low because of its shared variance with other predictors. That is, the variance that % BF could explain is being credited in the regression equation to other predictors. Because the largest correlation among the predictors was between % BF and PACER laps (r = .52), it is likely that most of the variance in question was credited to PACER laps, which also helps to explain the slightly larger β weight for this predictor. This example offers an illustration of the usefulness that structure coefficients provide. The interpretation would have been incorrect had only β weights been considered.

Discussion and conclusion

In multiple regression analysis, interpreting structure coefficients along with β weights is important when trying to determine which variables were influential in producing the overall effect. Accordingly, the purpose of this article was, first, to examine current analytic techniques in sport and exercise science literature and, second, to demonstrate how examining only β weights in the presence of multicollinearity can lead to incorrect interpretations. Unlike β weights, structure coefficients are not suppressed or inflated by multicollinearity. When β weights and structure coefficients are examined in tandem, the influence of each predictor can be more accurately understood. This is particularly relevant in complex models because the issue of multicollinearity often becomes more prominent as the number of predictors increases.

Remember, however, that before β weights and structure coefficients are examined, a meaningful overall effect (R^2) must be present. As pointed out by Courville and Thompson (2001), structure coefficients may seem impressive and invite interpretation even when a minimal overall effect exists. Interpreting structure coefficients in this situation can easily lead to additional misinterpretations because the overall effect is not practically meaningful (Henson, 2002). For example, if R^2 = .02, and the squared structure coefficient for one predictor is .60, then the structure coefficient is only explaining 36% of the overall 2% of variance from the full model. Thus, asking the question of whether the overall model is noteworthy and deserving of interpretation is a critical prerequisite before proceeding to inspect the influence of individual predictors (Thompson, 1997).

Although the benefit of calculating structure coefficients has been discussed in previous literature (e.g., Courville & Thompson, 2001), the field of sport and exercise science has largely ignored these recommendations. Researchers have instead focused solely on unstandardized b coefficients or β weights when interpreting the results of multiple regression analysis. Similar to the widespread overreliance on statistical significance tests (Zhu, 2012), it may take continued efforts to stimulate an improvement in traditional regression reporting practices.

To provide an example of how structure coefficients can expand understanding of multiple regression results, an example can be taken from Stoeber, Uphill, and Hotham (2009). As part of the study, researchers used three-step hierarchical regression to predict triathlon race performance with gender, age, and season best performance (step 1); personal standers and concern over mistakes (step 2); and four achievement goals (Elliot & McGregor, 2001; step 3). To determine the importance of each achievement goal, the authors examined b coefficients or β weights. Step 3 of the regression is displayed in Table 4 and includes unstandardized b coefficients or β weights that were reported on p. 222. In addition, structure coefficients were calculated post hoc using the formula presented earlier ($r_s = r_{Y-X}/R$) and added to the regression table. In their interpretation, authors focused on the performance–avoidance predictor (p. 220), presumably due to its large β weight. Interestingly, structure coefficients reveal that performance–avoidance and performance–approach shared the same percentage of variance with $\hat{Y}$ (r_s^2 = .05 for both predictors). In addition, although mastery–approach did not receive a statistically significant β weight, structure coefficients

Table 4. Variables predicting triathlon performance controlling for seasonal best performance.

	R^2	b	SE	β	r_s	r_s^2
	.61**					
Gender		−10.23	7.09	−.12	−.23	.05
Age		0.81	0.44	.16	−.26	.07
Season best: Swimming		9.78	6.80	.12	.63	.40
Season best: Cycling		1.81	0.78	.22*	.83	.69
Season best: Running		5.77	1.74	.31**	.86	.75
Personal standards		0.81	4.00	.02	.70	.49
Concern over mistakes		2.66	3.65	.08	.29	.09
Performance approach		10.00	2.86	.38**	.22	.05
Performance avoidance		−11.10	2.33	−.50**	−.21	.05
Mastery approach		6.03	2.56	.15	.46	.21
Mastery avoidance		−0.84	2.29	−.03	.18	.03

Note. Table adapted from Stoeber et al. (2009, p. 222). b = unstandardized regression coefficients; SE = standard error of the unstandardized regression coefficients; β = standardized regression coefficients; r_s = structure coefficients; r_s^2 = squared structure coefficients.
*$p < .05$.
**$p < .01$.

indicated that it was a good predictor in the model (r_s^2 = .21). Because of the large multicollinear model, performance–approach was arbitrarily assigned a small β weight despite its predictive effectiveness. This ex ample further illustrates the utility provided by structure coefficients.

There may also be situations when researchers need to partition R^2 beyond just structure coefficients. For example, it is possible to determine how much variance is unique to a single variable (e.g., X_1) and how much is shared with other predictors (e.g., X_1 and X_2). While it is beyond the scope of this article, answers to these research questions can be addressed by using commonality analysis to partition each piece of unique and shared variance from the predictors into non-overlapping parts that sum to R^2 (Nathans et al., 2012; Zientek & Thompson, 2006). Alternatively, the variance inflation factor (VIF) can be calculated to further examine the nature of multicollinearity among a group of IVs. The VIF indicates the amount that the variance of each regression coefficient is increased relative to a situation in which predictors are perfectly uncorrelated (Cohen et al., 2003; O'Brien, 2007). While the VIF can be used to indicate when multicollinearity problems exist, structure coefficients provide more substantive information about each IV. Specifically, the VIF highlights the existence of multicollinearity, while structure coefficients relate unique information about the role that each IV plays in the prediction of variance in the DV (i.e., R^2). It is recommended that researchers use as many sources of information possible when conducting multiple regression analyses. The use of multiple sources of information will allow for more informed decision making and improved accuracy of interpretation.

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