

A Tutorial on Calculating and Interpreting Regression Coefficients in Health Behavior Research

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Abstract

Regression analyses are frequently employed by health educators who conduct empirical research examining a variety of health behaviors. Within regression, there are a variety of coefficients produced, which are not always easily understood and/or articulated by health education researchers. It is important to not only understand what these coefficients are, but also understand what each represents and how each is interpreted. By correctly interpreting regression coefficients (Pearson r , Pearson r^2 , Multiple R^2 , a , b , β , r_{gs} , r^2_{gs} , partial correlation and semi-partial correlation), the informed health behavior researcher can better understand the dynamics of his/her data. The purpose of this manuscript is to describe and explain some of the coefficients produced in regression analysis. Specifically, the manuscript will describe (a) why and when each regression coefficient is important, (b) how each coefficient can be calculated and explained, and (c) the uniqueness between and among specific coefficients. A data set originally used by Holzinger and Swineford (1939) will be referenced throughout the manuscript to tangibly illustrate how coefficients should be calculated and interpreted in both simple and multiple regression analyses.

continuous outcome variable and two or more continuous, predictor variables (Thompson, 2006). Within both types of regression, there are a variety of coefficients produced, which are not always easily understood and articulated by health education researchers. The purpose of this manuscript is to describe and explain a variety of regression coefficients used in regression analysis. Specifically, the manuscript will describe (a) why and when each regression coefficient is important, (b) how each coefficient can be calculated and explained, and (c) the uniqueness between and among specific coefficients. A data set originally used by Holzinger and Swineford (1939) will be utilized to demonstrate how to conduct and interpret both simple and multiple regression analyses. This data set reflects scores on 24 psychological tests administered to junior high school students to assess various acuties. It has been used by researchers to explain various analytic techniques used throughout the history of statistics (Hetzl, 1996).

Pearson r

Continuously scaled variables are variables which are measured on a scale of equal units. These are the types of variables that can be examined using regression analytic techniques. When two variables are measured on a continuous scale, we can compute the Pearson product-moment correlation coefficient (r) between the two variables, computed as:

$$r_{xy} = \text{COV}_{xy} / (\text{SD}_x * \text{SD}_y),$$

where COV_{xy} is a description of bivariate relationship called the covariance and SD_x and SD_y are the standard deviations of both the independent (X) and dependent (Y) variables (Thompson, 2006). The covariance is used primarily as an intermediate calculation in obtaining the Pearson product moment correlation, because it does not have a definitive range of possible values (Thompson, 2004). Pearson r addresses the question, "In an ordinary least squares distribution, how well does the line of best possible fit (regression line) capture the data points in a scattergram?" When Pearson r is positive, the relationship between two variables is positive. This means either (a) as scores on one variable become larger, scores on the other variable (on the average) tend to also be larger, or (b) as scores on one variable become smaller, scores on the other variable (on the average) tend to also become smaller. When Pearson r is negative, the relationship between two variables is negative.

Regression analyses are frequently employed within empirical studies examining health behavior to determine correlations between variables of interest. Simple regression analyses can be used to predict or explain a continuously scaled dependent variable by using one continuously scaled independent variable. Multiple regression analyses can be used to investigate relationships between a single,

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This means either (a) as scores on one variable become larger, scores on the other variable (on the average) tend to become smaller, or (b) as scores on one variable become smaller, scores on other variable (on the average) tend to become larger. The Pearson r is a descriptive statistic, quantifying the amount of linear relationship between two continuous variables. Pearson r statistics themselves, however, are ordinally scaled as regards to the variance common to two variables (Thompson, 2006); therefore, you cannot quantify the relationship between two distinct Pearson r values unless each is squared.

Pearson r^2 (also known as the coefficient of determination or the common variance proportion), unlike Pearson r , reflects the percentage of variance common to two variables (Thompson, 2006). This statistic is not ordinally scaled; rather, it is continuously scaled and thus a comparable statistic. It tells us that with knowledge of the scores on one predictive or explanatory, independent variable, we can explain or predict a given percentage, on the average, of the variability or Sum of Squares (SOS) of a dependent variable. One minus the Pearson r^2 yields the coefficient of alienation which describes the proportion of variance in the dependent variable that we cannot predict with knowledge of an independent variable (Thompson, 2006).

The $SOS_{EXPLAINED}$, or the proportion of the SOS of the dependent variable that is linearly explained by the independent variable, divided by the SOS_{TOTAL} , the total amount of explained and unexplained (i.e. not explained by the independent variable) variability in the dependent variable (Y), tells us the proportion of the variability of individual differences that we can explain with an independent variable (X):

$$r^2_{YX} = SOS_{EXPLAINED} / SOS_{TOTAL}$$

In the case of two or more independent variables, the Pearson r^2 computation above becomes referred to as multiple R^2 , to account for the multiple independent variables (X_1, X_2) having the opportunity to explain or predict the variance in the dependent variable (Y):

$$R^2_{YX_1, X_2, \dots} = SOS_{EXPLAINED} / SOS_{TOTAL}$$

Pearson r^2 and multiple R^2 measure the strength of the relationship between the independent variable(s) and dependent variable. Pearson r^2 (and multiple R^2) values have also been explained as indices which quantify the degree to which predicted scores match up with actual scores (Huck, 2004).

Figure 1 provides three SPSS (SPSS, Inc., 2006) syntaxes and outputs reflecting two simple (Simple #1 and Simple #2) and one multiple regression analysis using scores on variables t5 (Paragraph Comprehension Test), t6 (General Information Verbal Test), and t9 (Word Meaning Test).

In the Simple #1 regression analysis, we are calculating the Pearson r^2 correlation between scores on the Word Meaning Test (entered as the independent variable) and General Information Verbal Test scores (entered as the dependent variable). Notice that the correlation between the two variables is $r^2 = .547$. In the Simple #2 regression analysis, we are calculating the Pearson r^2 correlation between scores on the Paragraph Comprehension Test scores (entered as the independent variable) and General Information Verbal Test scores (entered as the dependent variable). Notice that the correlation between the two variables is a bit smaller, as $r^2 = .432$. In the Multiple regression analysis, we are calculating the multiple R^2 correlation to see the effect of Word Meaning Test scores (independent variable) and Paragraph Comprehension Test scores (independent variable) on predicting General Information Verbal Test Scores (dependent variable). Notice that the multiple R^2 (.583) entering both predictors simultaneously is slightly larger than the r^2 (.547) between Word Meaning Test scores and General Information Verbal Test scores.

The Regression Equation

Regression analysis employs two types of weights: an additive constant, a , applied to every individual participant, and a multiplicative constant, b , applied to the entire predictor variable for each individual participant (Thompson, 2006). The weighting system takes the form of a regression equation that serves as the set of weights generated in a given analysis:

$$Y_i \leftarrow Y_i = a + b(X_i)$$

The a weight is the point where the regression line (i. e. line of best fit) crosses the y -axis when x equals 0. This point is also called the y -intercept. To compute the a weight, one must determine an individual's *predicted* dependent variable score (Y) [see Note below] and their corresponding independent variable (X) score. The regression line always pivots on the mean of X (M_X) and the mean of Y (M_Y); therefore, the M_Y is itself a Y score corresponding to M_X , given that this predicted dependent variable score (M_Y) is always perfectly predicted to correspond with M_X . With this knowledge, the M_Y score can be input as the Y score in the regression equation.

When working with standardized scores (i. e. scores which have been standardized by removing or dividing by the standard deviation (SD) units of both the independent and dependent variables, the a weight will always be equal to zero, because the regression line always pivots on the Cartesian Coordinate (M_X, M_Y), which when dealing with

Note: The statistical symbol that is to be a Latin capital letter Y with circumflex (character map: U+0176) is represented as Y in this article.

Simple #1

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT t5
/METHOD=ENTER t9 .

```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.739(a)	.547	.545	8.351

Predictor: WORD MEANING TEST

Simple #2

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT t5
/METHOD=ENTER t6 .

```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.657(a)	.432	.430	9.347

Predictor: PARAGRAPH COMPREHENSION TEST

Multiple

```

REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT t5
/METHOD=ENTER t6 t9 .

```

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.764(a)	.583	.581	8.017

Predictors: WORD MEANING TEST, PARAGRAPH COMPREHENSION TEST

Figure 1. SPSS syntaxes and outputs for simple and multiple regression(s).

standardized scores is (0,0). When the independent variable(s) is useless (i.e. does not predict or explain any of the variation in the dependent variable), the *a* weight will always equal the M_y , because, in this instance, the M_y is the

best we can do in making the best possible prediction (Thompson, 2006).

The *b* weight is the slope (i.e. change in rise/change in run) of the regression line, and is described as the regression

weight. The value of b signifies how many predicted units change (either up or down) in the dependent variable there will be for any one unit increase in the independent variable. In a best case scenario, where the independent variable(s) perfectly predicts the outcome variable, the b weight perfectly matches the dispersions of the Y_i (individual's actual score) and \hat{Y}_i (individual's predicted score). When the predictor variable(s) is useless (i. e. does not predict or explain any of the variation in the outcome variable), the b weight will equal 0 to "kill" the useless independent variable and remove its influence from the regression equation (Thompson, 2006). If the metrics of the variables of interest have been standardized, the regression weight is expressed as beta (β). A positive β (or b) means that the slope of the regression line is positive, tilting from lower left to upper right, whereas a negative β (or b) indicates that the slope of the regression is negative, tilting from upper left to lower right (Huck, 2004). Thus, the sign of b or β indicates the kind of correlation between the variables.

Consider the SPSS outputs and scatterplots contained in Figure 2. These were developed analyzing the Holtzinger and Swineford (1939) data set discussed earlier. Notice the non-statistically significant results ($P = .648$) at for the β weight (.042) describing the correlation between the Memory of Target Numbers test scores and the General Information Verbal test scores (Model 1). Also, notice the flat regression line of best fit, indicating that the relationship between these two variables is neither positive nor negative (i. e., the relationship is non-existent). Conversely, notice the statistically significant ($P = .001$) β weight (.739) describing the positive relationship between the Word Meaning Test scores (utilized earlier) and the General Information Verbal test scores (Model 2). This relationship is evidenced by the line of best fit tilting from lower left to upper right.

The a and b (or β) weights are constants, in that they do not vary from individual score to individual score. Their function in the regression equation is primarily two fold. First, the b or β attempts to make the spreadoutness of the Y scores (predicted dependent variable scores) and Y scores (actual dependent variable scores) the same, which only happens when a predictor variable perfectly predicts a dependent variable. Second, the a weight seeks to make $M_Y = M_{\hat{Y}}$, which it always accomplishes perfectly. Essentially, the multiplicative weight (b , β) begins the process by affecting the dispersion (SOS_Y and central tendency (M_Y) of Y , and then the a weight is turned loose to make $M_Y = M_{\hat{Y}}$.

Interpreting Regression Coefficients with Correlated Predictors

When independent variables have nonzero β s which do not equal the independent variable's respective Pearson r correlation with the dependent variable (Y), the independent variables are said to be collinear with one another. Collinearity refers to the extent which the independent variables have nonzero correlations with each other (Thompson, 2006). If

two or more independent variables are entered in a multiple regression and those variables are correlated with each other to a high degree and correlated with the dependent variable, then the β weights for the independent variables are arbitrarily allocated predictive/explanatory credit among the correlated independent variables. The independent variables with higher β s are arbitrarily allocated credit for both uniquely and commonly explained area of the dependent variable. This allocation of predictive/explanatory credit given to each independent variable can happen only one time, since more than one independent variable can not be given predictive/explanatory credit for the commonly explained area of the dependent variable (Y). Thus, one must determine what is uniquely explained by each independent variable and how predictive/explanatory credit is allocated among the independent variables for the area that is commonly explained. The formulas for the $\hat{\beta}$ s of two correlated predictors adjudicates the arbitrary allocation of shared credit (Thompson, 2006):

$$\hat{\beta}_1 = r_{YX1} - [(r_{YX2})(r_{X1X2})] / [1 - r_{X1X2}^2]$$

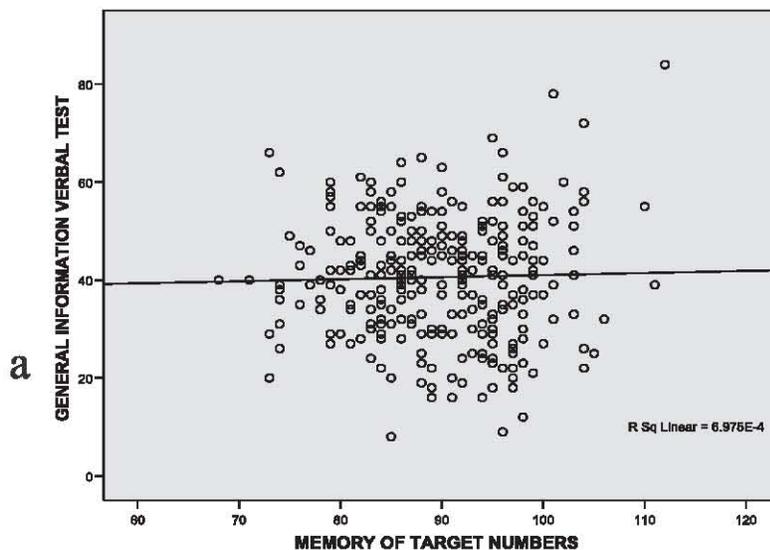
$$\hat{\beta}_2 = r_{YX2} - [(r_{YX1})(r_{X1X2})] / [1 - r_{X1X2}^2]$$

To mentally conceptualize how these formulas allocate credit between two independent variables operationalized in a type III SOS situation, think of horses feeding in a trough. Think of the feed in the trough as the SOS_Y (SOS of the dependent variable) and each horse representing a unique independent variable, thus each possessing a unique SOS_X (assuming the horses are of unequal sizes--i.e. unequal SOS s). The r_{YX1} and r_{YX2} can be thought of as the amount of feed that each horse can eat from the trough. The r_{X1X2} is equivalent to the amount of feed that both horses commonly (yet individually) ate from the trough. The amount of feed that each horse ate from the trough may overlap among both horses, so it may be hard to distinguish which horse ate which proportion of the feed (given that the feed does not stay in a fixed position within the trough). However, as the farm handler, you may be asked to arbitrarily distinguish which horse ate which proportion of the feed. If you were able to view the amount of newly eaten feed present in each horse's stomach, then you would be able to see which horse ate more individually (describing both r_{YX1} and r_{YX2}) and thus give unique credit to each horse. You can not see this, however, so you must arbitrarily give credit to one (and only one) horse for eating a commonly eaten proportion of the feed (represented within r_{X1X2}).

The structure coefficient (r_s) of a predictor variable is the correlation between the independent variable and Y (Thompson & Borrello, 1985). Recall that the collinearity of measured independent variables affects the $\hat{\beta}$ s of these variables; however, collinearity does not effect r_s computations. Thus, r_s s are incredibly useful for interpreting regression results (Thompson, 2006). Unless a researcher is (a) researching a specific set of independent variables which

Model 1	MEMORY OF TARGET NUMBERS	B	Std. Error	Beta	t	Sig.
		.042	.093	.026	.457	.648

Dependent Variable: GENERAL INFORMATION VERBAL TEST



Model 2	WORD MEANING TEST	B	Std. Error	Beta	t	Sig.
		1.193	.063	.739	18.984	.000

Dependent Variable: GENERAL INFORMATION VERBAL TEST

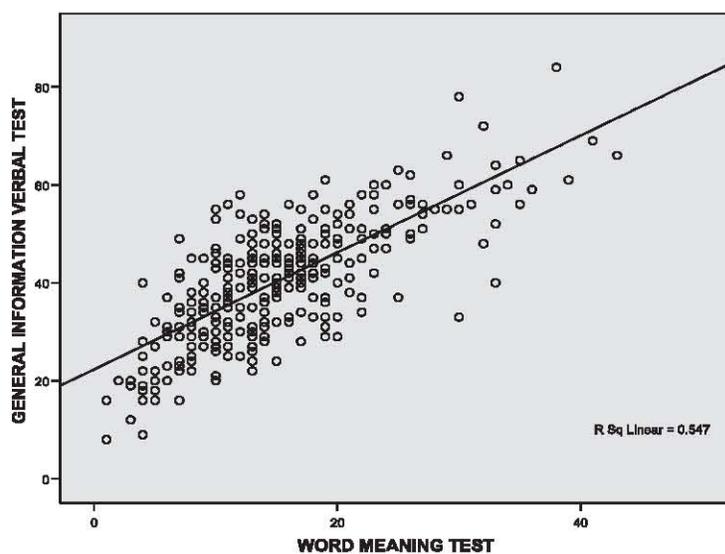


Figure 2. Sample SPSS outputs looking at beta weights and scatterplots.

are not even remotely affected by other independent variables or (b) researching independent variables which are perfectly uncorrelated, then r_{s} s should always be interpreted along with β weights (Courville & Thompson, 2001). Pedhazur (1982) objected to this necessity and noted that r_{s} s are simply correlations of independent variables with dependent variables divided by multiple R. This interpretation is mathematically valid, but neglects the idea that the focus of regression analysis is to understand the makeup of Y (the proportion of Y that is explained by the independent variables), not mathematically divide Pearson product moment correlations by multiple R.

Calculating and Interpreting Structure Coefficients (r_{s} s) Using SPSS

To calculate r_{s} s to explore/confirm the predictive/explanatory value of independent variables, the researcher can ask SPSS, Version 14.0 (2006) to compute and report r_{s} s for each of the independent variables. Before computing r_{s} s for each independent variable, the user must run a regression analysis entering all independent variables together. The SPSS output resulting from this initial step will provide unstandardized weights (a & b) used to calculate Y . These weights are plugged into the equation $Y = a + b(X_1) + b(X_2) + b(X_3)$, to create the synthetic variable Y for each individual participant.

The bivariate correlations between the observed variables and synthetic variable Y are computed to interpret the structure coefficients for each independent variable. The structure coefficients have been circled in Figure 3 to help the reader locate the correlations between the independent variables and synthetic variable Y (i.e. structure coefficients). One way to check whether or not the correlation table has been calculated correctly is to compare the multiple R from the regression model summary generated from the multiple regression to that of the bivariate Pearson r between the dependent variable Y and Y . Notice that these numbers are the same (.764), and are simply two different ways to express the variance proportion of the dependent variable that is explained by the independent variables. In the example depicted in Figure 3, the structure coefficients confirm for us that the beta weights are accurately depicting the explanatory credit given to each independent variable. It is important to remember, however, that when interpreting β weights, common predictive and/or explanatory credit can not be given to individual independent variables more than once. For this reason, certain IVs with sufficiently large r_{s} s may be denied credit for predicting or explaining Y . Because of this, both β and r_{s} must be interpreted, as a predictor may have a near zero β , but have the largest r_{s} and just be denied credit due to the context specific dynamics of β (Thompson, 2006). See Figure 4 for an explanation of how to interpret the worth of an independent variable by examining β s and r_{s} s.

Partial Correlation Coefficients

Partial correlation is the correlation between two variables with the influence of a third variable removed from both. For example, a researcher could investigate the relationship between height and running speed with the influence of age removed from the relationship (Hinkle, Wiersma, and Jurs, 2003). The formula for the partial correlation coefficient (of A and B) controlling for only one variable (C) is:

$$[r_{AB} - (r_{AC})(r_{BC})] / [((1 - r_{AB}^2)^2)((1 - r_{BC}^2)^2)]$$

A partial correlation coefficient accounts for or explains the third variable problem. An extra variable may spuriously inflate or attenuate a correlation coefficient (Thompson, 2006), because the common variance between two variables may be radically different after controlling for the influence of a third variable. Squared partial regression coefficients can be determined in multiple regression between the dependent and one of the multiple predictor variables (controlling for the influence of other predictor variables) using a procedure known as commonality analysis, which is used to decompose R^2 into unique and common explanatory and predictive powers of the predictors in all their possible combinations (Thompson, 2006).

The bivariate correlation and partial correlation matrices for three of the variables discussed earlier (Paragraph Comprehension Test scores, General Information Verbal Test scores, and Word Meaning Test scores) are presented in Figure 5. Notice that the correlation between Paragraph Comprehension Test scores and General Information Verbal Test scores is rather strong ($r = .657$), as is the correlation between Word Meaning Test scores and General Information test scores ($r = .739$). However, when the influence of each is removed from one another, the correlation between Word Meaning test scores and General Information Verbal test scores stays relatively strong ($r = .517$); whereas, the correlation between Paragraph Comprehension scores and General Information Verbal Test scores drops noticeably ($r = .285$). From these partial correlations, we can see that, although both variables are highly correlated with the General Information Verbal test scores, the Word Meaning Test scores remain highly correlated when the influence of Paragraph Comprehension scores is removed from consideration. The same can not be said for Word Meaning test scores, as much of its correlation with General Information Verbal test scores is lost when the influence of Word Meaning Test scores is removed. From this analysis of the partial correlations, we can vest considerable confidence that the correlation between the Word Meaning Test scores and General Information Verbal Test scores is far superior to the correlation between Paragraph Comprehension scores and General Information Verbal Test scores.

A semi-partial correlation or part correlation is the correlation between two variables with the influence of a

SPSS Syntax for computing structure coefficients

```
COMPUTE yhat = 21.205 + t9 * .886 + t6 * .965 + t15 * -.034 .
EXECUTE .
COMPUTE e = t5 - yhat .
EXECUTE .
```

```
list variables = t9 t6 t15 t5 yhat e .
```

```
CORRELATIONS
/VARIABLES = t9 t6 t15 t5 yhat e
/PRINT = TWOTAIL NOSIG
/MISSING = PAIRWISE .
```

SPSS Output

Regression Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.764	.584	.580	8.027

Predictors: MEMORY OF TARGET NUMBERS, WORD MEANING TEST, PARAGRAPH COMPREHENSION TEST;
 Dependent Variable: GENERAL INFORMATION VERBAL TEST

Beta Weights

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	SE	Beta		
(Constant)	21.205 (a)	5.482		3.868	.000
WORD MEANING TEST	.886	.085	.549	10.404	.000
PARAGRAPH COMP TEST	.965	.187	.272	5.154	.000
MEMORY OF NUMBERS	-.034	.060	-.021	-.559	.577

Dependent Variable: GENERAL INFORMATION VERBAL TEST

Structure Coefficients

	WORD MEANING TEST	PARA COMP TEST	MEMOF NUMBERS	GEN INFO VERBAL TEST	yhat
WMEAN TEST	1	.704**	.052	.739**	.967**
PCTEST	.704**	1	.069	.657**	.860**
MEMOF NUM	.052	.069	1	.026	.034
GIVTEST	.739**	.657**	.026	1	.764**
yhat	.967**	.860**	.034	.764**	1

**Correlation is significant at the 0.01 level

Figure 3. Interpreting beta weights and structure coefficients.

If the predictor variable has a...	Then...
r_s equal to 0 β equal to 0	It is a useless predictor. It explains none of the variation in the dependent variable.
r_s not equal to 0 β equal to 0	The predictor variable explains some of the variation in the dependent variable, but other predictor variables are getting explanatory credit for what is being explained by the predictor variable.
r_s equal to 0 β not equal to 0	The predictor variable does not directly explain any of the variation in the dependent variable, but its presence does increase the explanatory credit assigned to other predictor variables.

Figure 4. Interpreting the β s and r_s s of a predictor variable.

third variable taken away from only one of the two variables. For example, you could investigate the relationship between height and running speed with the influence of age removed from only the height variable (Hinkle, Wiersma, and Jurs, 2003). The formula for the semi-partial or part correlation coefficient of Y and Z, removing the effects of X from only Y is:

$$r_{z(y-x)} = (r_{yz} - r_{xy}r_{xz}) / \text{square root of } 1 - r_{xy}^2.$$

This equation actually reflects the correlation between Z and the error of Y (Hinkle, Wiersma, and Jurs, 2003). The sample size necessary for adequate semi-partial correlation estimation accuracy depends strongly on three factors: (a) the population squared multiple correlation coefficient, (b) the population increase in coefficient, and (c) the desired degree of accuracy. The number of predictors has a small effect on the required sample size (Algina, Moulder, & Moser, 2002).

Correlations				
		GENERAL INFO VERBAL TEST	PARAGRAPH COMP TEST	WORD MEANING TEST
GEN INFO VERBAL TEST	Pearson Correlation	1	.657	.739
PARA COMP TEST	Pearson Correlation	.657	1	.704
WORD MEANING TEST	Pearson Correlation	.739	.704	1
Partial Correlations				
Control Variable			PARAGRAPH COMP TEST	GENERAL INFO VERBAL TEST
WORD MEANING TEST	PARA COMP TEST	Partial Correlation	1	.285
	GEN INFO VERBAL TEST	Partial Correlation	.285	1
Control Variable			GENERAL INFO VERBAL TEST	WORD MEANING TEST
PARA COMP TEST	GEN INFO VERBAL TEST	Partial Correlation	1	.517
	WORD MEANING TEST	Partial Correlation	.517	1

Figure 5. Correlation/partial correlation matrices.

As noted by Buhi (2005), there is a paucity of articles related to statistics or measurement in health education. Unlike other fields within the social sciences, health education has been conspicuously absent from the dialogue surrounding the implementation and interpretation of various statistical analyses. While analyses such as regression are frequently employed by health education researchers, scholars in health education should be able to understand and explain the variety of regression coefficients which can be analyzed. The lack of scholarly discussion in the field (regarding the interpretation of statistical coefficients) discourages empirical knowledge generation and encourages simply memorizing procedures to produce numerical indices.

The health education profession must strive to generate, report, and interpret various regression coefficients accurately and adroitly, so that data explication appropriately reflects the reality we wish to purport. There has been discussion regarding the interpretation of effect sizes in health education research (Buhi, 2005; Merrill, Stoddard, and Shields, 2004; Watkins, Rivers, Rowell, Green, & Rivers, 2006), and it is suggested that similar recommendations stress the importance of computing structure coefficients to complement traditional beta weight coefficients. Through this practice, health educators will be able to more accurately distinguish independent variables which are responsible for impacting our dependent health behaviors of interest. For health education to improve its position as a science, it must embrace the practice of these analytic interpretations. Mandating the need to accurately report and interpret regression coefficients in all realms of health education research is essential to advancing result efficacy in the field.

Conclusion

There are a variety of coefficients used in simple and multiple regression analysis. It is important for health education researchers to not only understand what these coefficients are, but also understand what each represents and how each is computed and interpreted. Interpreting coefficients, such as regression coefficients (Pearson r , Pearson r^2 , R^2 , a , b , β , r_s , r_s^2 , partial correlation and semi-partial correlation), allows the informed health education researcher to better understand the dynamics of his/her data. Consulting these types of coefficients can provide health education research with further insight into correlations between variables of interest.

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