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BEYOND STANDARDIZED REGRESSION COEFFICIENTS BETA WEIGHTS: INTERPRETING AND APPLYING MULTIPLE LINEAR REGRESSION IN EDUCATIONAL RESEARCH

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Abstract
*The purpose of the study was to use multiple linear regression as a model to analyse and interpret results beyond standardized regression coefficients beta weights. Using a driven data, this study used the model to illustrate how predictors could predict dependent variable by estimating the percentages of contribution. Quantitative approach using descriptive survey was espoused for the study. Using G*POWER, a sample size of 248 was selected from a population of 623 basic school teachers in the Cape Coast Metropolis, Ghana. To prove the instrument reliability, an alpha coefficient of .798 and correlation coefficient .897 were obtained. It was established from the results that in reporting MLR data, researchers should report on the change statistics (R^2 change). This helps to describe both the unique and shared variance contributions of all independent variables that contribute to the R-squared (R^2). Also, to know the contribution of each of the factors, researchers should estimate the R^2 Change and convert the values into percentages. This study recommended that in analysing and interpreting MLR, it should focus on and include variance partitioning statistic in addition to beta weights in the presence of correlated predictors. In this way, comparisons can be drawn in text between techniques that partition R 2 if multiple techniques are used*

Keywords: Regression; Linear; Multiple; Statistical; Research; and Estimates

Introduction
Multiple linear regression is one of the most common form of regression analysis. As a predictive analysis, multiple linear regression is used to describe data and to explain the relationship between one dependent variable and two or more independent variables [1]. Beyond the idea of [1] it is asserted by scholars that multiple linear regression is a multivariate technique for determining the correlation between a response variable (Y) and some combination of two or more predictor variables (X). It can be asserted that the technique or method can be used to analyze data from causal-comparative, correlational, or experimental research [2,3,4].

Drawing inferences from the work of [4], it is evident that multiple linear regression is one of the most extensively used statistical techniques in educational research. It is regarded as the "mother of all statistical techniques." For example, many colleges and universities develop regression models for predicting the GPA of incoming freshmen. This technique is mostly adopted and used based on the riding idea that the predicted GPA can then be used to make admission decisions. In addition, many researchers have studied the use of multiple linear regression in the field of educational research. To determine the predictive validity of the California entry level test (CELT), [5] employed multiple linear regression as their statistical tool to predict the entry level test for their students. Similarly, in the work of [6], the use of multiple linear regression was illustrated in a prediction study of the candidate's 2 aggregate performance in the GCE examination.

It can be argued perhaps, that multiple linear regression (MLR) remains a mainstay analysis in educational research. In educational research analysis, MLR is explained as a multivariate technique for finding out and estimating the correlation between a response variable and some combination of two or more predictor variables [2,3,4]. In educational research, multiple regression analysis is the most commonly used method to answer questions regarding relationships between variables and groups. This technique is valuable and fundamental to empirically address many educational research questions. Examples are: How do parents and siblings affect the school outcomes of a child? How does school climate and students' socioeconomic composition impact average school achievement? What are the factors that may affect the probability for a student to choose a school that is located outside his/her residential area? [18, 24].

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In the work of [7 8], the researchers used multiple linear regression to illustrate a partial credit study of students' final examination score in a mathematics class at Florida International University. In another related study, multiple linear regression was utilized in the study of [8] in that study, the researcher used a multiple linear regression model in predicting college Grade Point Average (GPA) of matriculating freshmen based on their college entrance verbal and mathematics test scores. From all these studies, one striking assumption was common among all the datasets the researchers used. One basic and fundamental thing readers should note is that the technique or the model can handle interval, ordinal, or categorical data. In addition, multiple regression provides estimates for both the magnitude and statistical significance of relationships between variables [18, 24].

Most researchers in the field of education have used multiple linear regression in their quest to analyse and interpret their findings. However, it does papers that most of the reviewed studies ends at standardized regression coefficients beta weights. Most of the previous studies drawn their conclusions and implications using only the coefficients of beta weights. Though not wrong, however, it is clearly not informative enough for decision making. This paper therefore sought to expand the understanding of multiple linear regression beyond standardized regression coefficients beta weights.

Determine whether the association between the response and the term is statistically significant

To determine whether the association between the response and each term in the model is statistically significant, compare the p-value for the term to the significance level to assess the null hypothesis. The null hypothesis is that the term's coefficient is equal to zero, which indicates that there is no association between the term and the response [9, 10]. Usually, a significance level (denoted as α or alpha) of 0.05 works well. A significance level of 0.05 indicates a 5% risk of concluding that an association exists when there is no actual association. P-value ≤ α: The association is statistically significant If the p-value is less than or equal to the significance level, the researcher can conclude that there is a statistically significant association between the response variable and the term. P-value > α: The association is not statistically significant. If the p-value is greater than the significance level, the researcher cannot conclude that there is a statistically significant association between the response variable and the term. In this way, the researchers may want to refit the model without the term.

Determine how well the model fits a data

Determinant 1: S

Use *S* to assess how well the model describes the response. Use *S* instead of the R^2 statistics to compare the fit of models that have no constant. *S* is measured in the units of the response variable and represents the how far the data values fall from the fitted values. The lower the value of *S*, the better the model describes the response. However, a low *S* value by itself does not indicate that the model meets the model assumptions. The researcher should check the residual plots to verify the assumptions [11, 12, 13].

Determinant 2: R-square (R^2)

R^2 is the percentage of variation in the response that is explained by the model. The higher the R^2 value, the better the model fits the data. R^2 is always between 0% and 100%. R^2 always increases when the researcher adds additional predictors to a model. For example, the best five-predictor model will always have an R^2 that is at least as high the best four-predictor model. Therefore, R^2 is most useful when the researcher compares models of the same size [11, 13].

Determinant 3: R-sq (adjusted)

Use adjusted R^2 *-adjusted* when the researcher wants to compare models that have different numbers of predictors. R^2- *adjusted* always increases when the researcher adds a predictor to the model, even when there is no real improvement to the model. The *adjusted* R^2 value incorporates the number of predictors in the model to help the researcher chooses the correct model [14,15].

Determinant 3: R-sq (pred)

The *predicted* R^2 is used to determine how well one model predicts the response for new observations. Models that have larger predicted R^2 values have better predictive ability. A *predicted* R^2 that is substantially less than R^2 may indicate that the model is over-fit. An over-fit model occurs when the researcher adds terms for effects that are not important in the population, although they may appear important in the sample data. The model becomes tailored to the sample data and therefore, may not be useful for making predictions about the population. *Predicted* R^2 can also be more useful than *adjusted* R^2 for comparing models because it is calculated

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with observations that are not included in the model calculation. The following measures should be taken into consideration when the researcher wants to interpret the R^2 values: small samples do not provide a precise estimate of the strength of the relationship between the response and predictors. If the researcher needs R^2 to be more precise, he or she should use a larger sample (typically, 40 or more). It must be noted that R^2 is just one measure of how well the model fits the data. Even when a model has a high R^2, the researcher should check the residual plots to verify that the model meets the model assumptions [14,15].

Testable Assumptions in Multiple Linear Regression (MLR)
For researchers to be able to employ MLR in their studies, they should ride on some fundamental or basic assumptions. One of the assumptions to discuss is the linear relationship. In this assumption, the researcher will want the outcome variable to have a roughly linear relationship with each of the explanatory variables, considering the other explanatory variables in the model. Another key assumption is homoscedasticity. In using MLR in interpretation, researchers should take note of homoscedasticity. This implies that the variance of the residuals should be the same at each level of the explanatory variables (independent variables). This can be tested for each separate explanatory variable (independent variable), although it is more common just to check that the variance of the residuals is constant at all levels of the predicted outcome from the full model (i.e. the model including all the explanatory variables).

Another central assumption that researchers should look for is outliers/influential cases. In multiple linear regression, it is important to look out for cases which may have a disproportionate influence over the regression model [16,17]. The last assumption to test when using MLR is Multicollinearity. In MLR, multicollinearity exists when two or more of the explanatory variables are highly correlated. This is a problem as it can be hard to disentangle which of them best explains any shared variance with the outcome. It also suggests that the two variables may actually represent the same underlying factor.

Methodology
To execute the study, quantitative approach using descriptive survey was espoused for the study. Quantitative approach was deemed apt for this study based on the justification that we wanted to quantify social phenomena and collect and analyse numerical data that will reflect the phenomenon under investigation [18, 19]. The total population of the study was made up of 623 basic school teachers in the Cape Coast Metropolis. Sample size for the study was made up 248 basic school teachers. To obtain the sample, the G*POWER software was employed to arrive at sample of 248. The rational for using the software is based on the rationale that it enables researchers to do analyses for many different t-tests, regression test, F tests, chi-square ($\chi2$) tests, z-tests and some exact tests. The G*Power also facilitate researchers to compute effect sizes and to display graphically the results of power analyses.

The instrument used for the data collection was adapted from the work of Senthil and Rajammal (2018). The instrument contained indicators that predictors of teacher competencies (Construction Administration, Scoring and Analysis & Interpretation). The scale has 80 set if items with 20 items in each of the subscales. The instrument was validated and proven reliable and standardized for data collection. To estimate the validity, content and construct validity were employed. To evaluate the reliability evidence for the instrument, internal consistency using alpha coefficient and correlation coefficient were computed. For alpha coefficient, .798 was obtained and .897 was obtained for correlation coefficient. For the validity, two ratters were asked to score the instrument based on content and construct related evidences.

The items on the questionnaire were close ended and were used to measure the predictors (Construction Administration, Scoring and Analysis & Interpretation Competencies). The items on the questionnaire were multiply scored on a four-point Likert type scale. All the items were positively score. The researchers adapted the scale on the justification that it provided a broad capability, which ensures a more accurate sample to gather targeted results which helped us to draw conclusions and make important decisions. The scale was scored ranging from four (4) for Strongly Agreed to one (1) for Strongly Disagree for positive statements. Negative statements that were captured were scaled in the reverse form in the coding process.

The obtained data was collated and edited without altering the responses. After coding, the data was entered into

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the computer and processed using the Statistical Package for Social Sciences (SPSS v.25) and interpreted with the linear multiple regression (LMR) using the stepwise selection. Using the stepwise selection, we combined the predictors variables in a forward and backward selection matter. In the approach, we began with a null model, then we added the single independent variable that makes the greatest contribution toward explaining the dependent variable, and then iterates the process. Additionally, a check was performed after each such step to see whether one of the variables has now become irrelevant because of its relationship to the other variables. In our case, all the predictors were relevant as such were not removed.

The justification for selecting the multiple linear regression (LMR) using the stepwise selection approach was to show the direction and magnitude of the predictive variables (Construction Administration, Scoring and Analysis & Interpretation Competencies) on the dependent variable (test score pollution). The use of the Linear Multiple regression (LMR) allowed us to identify the unique contribution of each predictor to the outcome variable.

Practical Application of MLR in a Study (Data-Driven Example)
The purpose of the study was to find out perceived variables that predict dependent variable (Y). To analyse, multiple linear regression (MLR) was deemed appropriate for the analysis. Multiple regression in this analysis was utilized to show the direction and magnitude of the effect and relationship between the predicted variables in conducting research. This approach allowed the researcher to identify the unique contribution of each of the predictors Construction Administration, Scoring and Analysis & Interpretation Competencies) to the outcome variable (Y). The analysis was performed at *p-value* =0.05 (two-tailed) level of significant. However, prior to conducting regression analysis test, assumptions were checked or tested. These assumptions were normality, linearity and multicolinearity. The normality and linearity test of the study variables (predictor factors-Construction Administration, Scoring and Analysis & Interpretation Competencies) are presented in Figure 1 and 2 and Table 1.

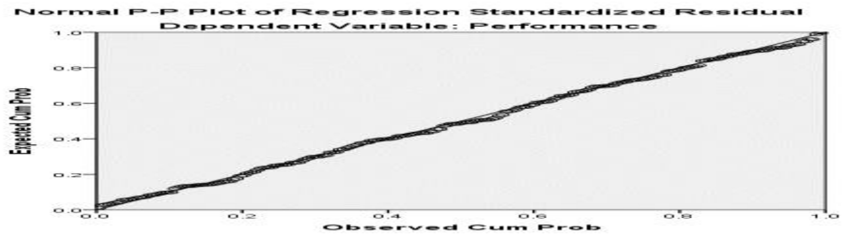

Figure 1: Diagnostic Test of Normality and Linearity

According to [14], a straight normal probability plot is an indication of normality and linearity. Pallant noted that when multiple regression assumptions are met, it produces a reliable result. From Figure 1, a reasonable straight line could be seen from the plot demonstrating normality and linearity of the data. This therefore, means that conducting multiple regression test was justified. Similar interpretation and understanding are recounted and displaced in Figure 2.

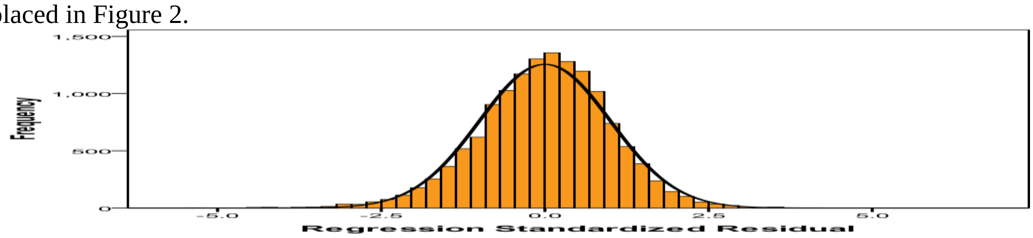

Figure 2: Diagnostic Test of Normality and Linearity
The cluttering of the variables at the centre of the curve shows that the data was normal.

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Table 1: Results of Multicolinearity Diagnostic Test (MDT) of the Study Variables

Predictor Variables (Factors)	Construction	Administration	Scoring	Analysis & Interpretation
Construction (X1)	1.00	.301	.062	.434
Administration (X2)		1.00	.076**	.545
Scoring (X3)			1.00	.615**
Analysis & Interpretation (X4)				1.00

Source: Field survey (2022), $CI_{=95\%}$, $p < 0.05$**

Table 1 indicates the results of multicolinearity diagnostic test of the variables. The problem of multicollinearity is said to exist when independent variables used in the study (Construction Administration, Scoring and Analysis & Interpretation Competencies) are highly correlated with each other. The study followed literature to test this assumption. It is assumed that correlation coefficient of 0.70 or more between independent variables is assumed to demonstrate evidence of multicolinearity problem [20, 21]. From Table 1, the highest correlation coefficient is .615 (Scoring * Analysis & Interpretation) which is less than 0.70. and the least high correlation coefficient is .076 (Administration * Scoring). This gives evidence that there was no problem of multicollinearity in the dataset. Having tested for the assumptions, running multiple regression was deemed appropriate.

Table 2: Descriptive Statistics Results of the Study Variables

Competency Variables	Mean	SD	Sample (n)/Observations
Construction (X1)	24.89	2.342	248
Administration (X2)	22.13	3.034	248
Scoring (X3)	19.92	2.045	248
Analysis & Interpretation (X4)	18.09	2.034	248

Source: Field Survey, (2022) n=248

Results in Table 2 show the descriptive statistics of the study variables. As presented in Table 2, the result implies that descriptively, the factors (Construction Administration, Scoring and Analysis & Interpretation Competencies) differ in terms of their predication level. For example, Construction (X1) recorded the highest mean value (M=24.89, SD=2.342, n=248), Administration (X2) recorded the second highest mean (M=22.13, SD=3.034, n=248). Scoring (X3) followed with a third highest mean (M=19.92, SD=2.045, n=248). Analysis & Interpretation (X4) recorded the least mean value (M=18.09, SD=2.034, n=248). These differences in the mean score do not give enough information on the significance of the predictors. Therefore, multiple linear regression analysis on the coefficients of the factors was performed and the results are depicted in Table 3.

Table 3: Results of Multiple Regression Analysis on the Coefficients of the Factors (Construction Administration, Scoring and Analysis & Interpretation Competencies)

Model	Unstandardized Coefficients		Standardized Coefficients	t-value	*p*-value CI=95%
	B	Std. Error	Beta Weights (β)		
(Constant, Y)	-60.083	11.016		-5.454	.000*
Construction (X1)	1.356	.109	.963	12.378	.000*
Administration (X2)	1.978	.146	.634	13.529	.000*
Scoring (X3)	2.517	.339	.555	7.421	.000*
Analysis & Interpretation (X4)	.1650	.072	.115	2.282	.027*

Dependent Variable[a]: Y *Significant at $p < 0.05$**, CI=95%, n=248
Independent Variable[b]: Predictors (Construction Administration, Scoring and Analysis & Interpretation).
Source: Field Survey, (2022)

Table 3 presents the coefficient model for the perceived factors and how they predicted and contributed to dependent variable (Y). It can be seen from Table 2 that all the four perceived factors (Construction

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Administration, Scoring and Analysis & Interpretation Competencies) serving as the independent variables were statistically significant at 0.05 ($p<0.05$, $CI_{=95\%}$) level of confidence. For example, Construction produced a significant result (*sig-value* = .000**, $p<0.005$, $CI_{=95\%}$), Administration also produced a significant result (*p*-value = .000**). The result on the Scoring was not different (*sig. value* = .000**, $p<0.005$, n=248, $CI_{=95\%}$). Lastly, Analysis & Interpretation also gave a significant result (*p*-value = .027, $CI_{=95\%}$). However, when evaluating the Standardized Coefficients Beta (β) values, among the factors, it was revealed that their contribution was in magnitude. The greatest predictor upon the dependent variable (Competent in test constructing) is in the following order: Construction (β =.962**, $CI_{=95\%}$), Administration (β =.639**, $CI_{=95\%}$), Scoring (β = .558, $CI_{=95\%}$) and Analysis & Interpretation (β = .118**). However, in the quest of assessing the contribution of each of the factors in percentage wise, step wise method in the regression model was conducted. Table 4 presents the findings.

Table 4: Results of Multiple Regression Analysis of Contribution of each the Variables

Model (Predictors)	R	R^2	Adjusted R^2	Change Statistics R^2Change (% Conversion)
Construction (X1)	.614[a]	.377	.365	.377 (37.7%)
Administration (X2)	.839[b]	.705	.693	.328 (32.8%)
Scoring (X3)	.935[c]	.874	.867	.170 (17.0%)
Analysis & Interpretation (X4)	.941[d]	.886	.877	.125 (12.5%)

Dependent Variable[a]: Y *Significant at $p < 0.05$**, CI=95%, n=248
Independent Variables[b]: Predictors (Construction Administration, Scoring and Analysis & Interpretation).
Source: Field Survey, (2022)

Table 4 shows how each of the predictors contributed to the dependent variable (Y). Using the R^2 change statistics, it is evident that Construction contributed more than all the other factors. That is R^2 Change Statistic value of .377 representing 37.7%. Administration contributed R^2 Change Statistic value of .328 ($CI_{=95\%}$) representing 32.8% indicating the second contributor. Scoring contributed R^2 Change Statistic value of .170 ($CI_{=95\%}$) representing 17.0% showing the third contributor. Analysis and Interpretation contributed the least with R^2 Change Statistic value of .125 ($CI_{=95\%}$) representing 12.5%. The implication of this research question is that factor Construction was identified as the best predictor the dependent variable (Y) and as such, to improve the dependent variable of Y, Construction should be given the needed attention and preference.

Discussion

Invariably, many authors who have done extensive works on multiple linear regression (MLR) analyses [4,10, 23, 9], have commonly asserted that multiple regression (MR) are employed in social science fields to establish or determine prediction level of variables. It is also common for interpretation of results to typically reflect overreliance on beta weights (often resulting in very limited interpretations of variable importance. In all these studies, it does appear that few researchers employ other methods to obtain a fuller understanding of what and how independent variables contribute to a regression analysis and interpretation. What this paper has done is to link theoretical framework of multiple linear regression to its real and practical applications.

The paper has also demonstrated the complementary roles they play when interpreting regression findings. Corroborating with the work of [1], we share the idea the idea that multiple linear regression (MLR) remains a mainstay analysis in organizational research, yet intercorrelations between predictors (multicollinearity) undermine the interpretation of MLR weights in terms of predictor contributions to the criterion.

To advance the understanding of reporting and interpreting multiple linear regression (MLR) using a data-driven example, [21] similar work on understanding the results of multiple linear regression beyond standardized regression coefficients recounted similar report but more statistical and advanced. In their study, the they also conducted a secondary data analysis on the correlation matrix reported in [22] to provide an illustrative example of how one might write up the results from regression software. Auspiciously, [23] in their study provided an accessible treatment of the metrics reported by the software presented along with strengths, limitations, and

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recommendations for practice for researchers. This along with other works that also address predictor importance in detail [e.g., 25, 26] and the examples in the current article should provide researchers a general template for their own work in interpreting and reporting MLR models.

Conclusion and Recommendations

This paper has illustrated how educational researchers' conceptualization and assessment of variable importance can be enhanced by viewing MLR results through multiple lenses. The paper clearly demonstrated how MLR is interpreted within the context of educational research beyond standardized regression coefficients beta weights. Researchers' who deem it appropriate to use or apply MLR in their research works should some extend follow the procedure and the interpreting therefore. It should be stressed that MLR findings do not rely solely upon beta weights, except in the case of uncorrelated independent variables.

In conclusion, it must be emphasized that in interpreting MLR, it is imperative to note that beta weights (β) are only informative and revealing with regard to prediction; they do not tell the researcher other important information provided by the other metrics we have precisely outlined in the data driven example. This therefore suggest that researchers should use different tables to help interpret different indices of variable of importance and their prediction level. In doing this, it is worthwhile for researchers to include one table that enables visual comparisons across indices for each independent variable (see Table 4- results of multiple regression analysis of contribution of each the variables**)**. It is useful for researchers to note that joint comparisons across indices can aid in identification of associations between variables and the presence of suppression in a regression equation.

Sequel to the above, it is again significant to know that, in applying MLR in analysis, reporting commonality analysis results in text provide deep information for educational implications. In this regard, researchers should report on the change statistics (*R^2 Change*). This helps to describe both the unique and shared variance contributions of all independent variables and whether each variable contributes more shared or unique variance in its contribution to R^2. To know the contribution of each of the factors (predicator variables or items), always calculate the Change Statistics (R^2 Change) and convert the values to percentages.

Finally, in analysing and interpreting MLR, researchers should focus on an include variance partitioning statistic in addition to beta weights in the presence of correlated predictors (e.g., general dominance weights, relative weights). This way, the researcher must draw comparisons in text between techniques that partition R^2 if multiple techniques are used.

To this end, we hope this paper will guide researchers' on how to interpret and apply MLR in their studies. Furthermore, it is the desire of the researcher that the data-driven example will allow researchers to write their own findings or results in a similar manner that will enable them to better represent the richness of their regression findings and have practical implications on educational theory and policy.

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