DOI: 10.5902/19834659 16968

TWO-WAY AND THREE-WAY MODERATING EFFECS IN REGRESSION ANALYSIS AND INTERACTIVE PLOTS

Received on: 14/02/2015
Approved on: 03/10/2016

Valter da Silva Faia[1]
Valter Afonso Vieira[2]

ABSTRACT

Different studies in the international literature analyze mediating, moderating, moderating-mediating, mediating-moderating, and indirect effects in relationships in the social sciences. Among the modes of interpretation data, understanding the moderating effect using linear regression analysis is one of the possibilities. The paper main goal is to discuss and clarify the concepts of moderation when using multiple regression analysis instead of the traditional Generalized Linear Models (e.g. MANOVA, MANCOVA, ANOVA, ANCOVA, GLM). The second main goal is to apply three estimative, such as (a) two-way moderation with independent continuous variables, (b) two-way moderation with one continuous variable and another dummy variable as independent, and (c) thee-way moderation with independent continuous variables, all using regression analysis . Third, the paper discusses ordinal moderation and the cross over effect. The results showed that the two-way moderation is little used.

1 Bachelor of Accounting from the State University of Maringá, UEM, Master of Business Administration from UEM and PhD in progress in Business Administration by the PPA/UEM. Maringá - PR. Brazil. E-mail: vsfaia@uem.br
2 Bachelor of Business Administration from Universidade Norte do Paraná, UNOPAR, Master of Business Administration from Federal University of Rio Grande do Sul, PPGA/UFRGS, and PhD of Business Administration from University of Brasília, PPGA/UnB. Professor at the State University of Maringá, UEM – PR. Brasil. E-mail: vavieira@uem.br

1 INTRODUCTION

Cortina (1993) comments that there is more and more complexity when examining relations between variables and, thus, some associations are possible, such as: direct relation between *X* and *Y*; indirect relationship between *X* and *Y* via a third mediator variable; spurious effect between *X* and *Y* (when an association occurs but there is no logic); bidirectional relationship between *X* and Y*;* effects not analyzed and moderation effects between X and Y (JACCARDI; TURRISI, 2003).

According to Varadarajan (2003), the relevance of research in the field of marketing lies in the extension of existing knowledge, through the provision of evidence of moderating variables that interferes in the relations between variables already known and that have implications for practitioners. However, national studies showed that in the Brazilian context there is still a lack of studies and, therefore, a need to disseminate the process of analysis of moderating models and the principles that justify this type of analysis (VIEIRA, 2009; PRADO; KORELO; SILVA, 2014). As a result, there is an effort in the literature to understand, explain and apply the use of moderating variables in the field (JAMES; BRETT, 1984; BARON, KENNY, 1986; BATRA, STAYMAN, 1990; CHATTOPADYYAY; BASU, 1990; MACKINNON et al., 2002; HENSELER, FASSOTT, 2010; VIEIRA, 2009). Although Prado, Korelo and Silva, (2014) did a relevant research, we do not know how to present step by step the process of moderation, from the database to the interpretation of the results through graphic representation.

Based on this gap, the paper main goal is to discuss and clarify the concepts of two way and three way moderation (DA-SILVA; DA-SILVA-FAIA; VIEIRA, 2016), demonstrating their use in multiple regression analysis, which can be applied also in logistic regression (ABBADE; DE BEM NORO, 2012). We suggest four major contributions here, complementing some justifications for provoking the debate about these concepts in the literature.

First, we justify this research because there is a discrepancy between moderation, mediation, moderation-mediated and conditional indirect effect in the literature (HAYES, 2013; PRADO; KORELO; SILVA, 2014) that needs clarification. This differentiation is very common in psychology (se use in KIELING; BREI; VIEIRA, 2016), but little used in administration and specifically in marketing. Therefore, the need for differentiation for correcting use is important in the scientific setting.

Second, we justify this paper for examining a significant moderating effect because such a result generates later interpretations that are necessary and should be uncovered in the background. Often a researcher finds a significant moderating effect, but does not present the effect generated at a second step. In this paper, we address this problem in second and third degree. If the results are not uncovered at a second step, then the Type VI error may appear (NEWMAN et al., 1976).

Third, some papers discuss conditional effects (PRADO; KORELO, SILVA, 2014), mediated-moderation, moderation-mediated, moderation, two way moderation, or other effects (MULLER, JERD, YERBYT, 2005; PREACHER; RUCKER; HAYES, 2007). This advance in knowledge with multiple regression models is relevant and should be used in studies in social sciences, but in advance of the basic knowledge of simple, double and triple moderation discussed here.

Fourth, based on Mantovani, Noronha and Gouvêa (2013), there is some difficulty in teaching and learning statistics in the area of Applied Social Sciences, especially in the area of Business and Management. Thus, the paper seeks to provide a learning base for the use of statistics in the area of Business and Management, explaining and applying the equations.

2 MODERATION

The classical model of linear regression analysis is given by Equation 1. The linear model is one of the most used in statistics and suggests that the explained variance of the dependent variable *Y* is given by the variability of another variable, the independent *X*.

(1) $Y = \beta_0 + \beta_1 X$

Based on Vieira (2009) and Whisman and McClelland (2005), a moderating variable, here defined as *Mod*, has moderating (or even interactive for purposes of this article) if the relationship between two or more variables, *X* and *Y*, vary depending on the levels of the *Mod*. This definition is given in Equation 2.

(2) $Y = f(X.Mod)$

The moderator model of Equation 2 is changed by Equation 3 for the purpose of regression analysis (JAMES; BRETT, 1984). There is moderation when the new variable developed by the researcher *X.Mod*, defined as the product of the independent variable *X* and the modifier variable *Mod*, is significant in the regression equation.

(3) $\hat{Y} = \beta_0 + \beta_1 X + \beta_2 Mod + \beta_3 X.Mod + e$

The first order variables that are used in the interaction, as well as all the possible combinations between them, should be included in the regression model so that their direct relations with the dependent variable are tested, besides the moderate relation (WEST, AIKEN, KRULL, 1996). The moderation hypothesis is supported if the interaction (i.e. the multiplicative term *X.Mod*) of Equation 3 is significant.

Moreover, it is desirable, but not necessary, that the effects of the other relations be minimal or insignificant, strengthening the results found for moderation (JAMES; BRETT, 1984). Conventionally, a moderator variable is inserted into the model when there is an inconsistent or weak relationship between an independent variable and a dependent variable (BARON; KENNY, 1986).

One of the major concerns regarding the analysis of the interactive effect is the presence of multicollinearity, making it difficult to distinguish the direct effects of the independent variable, the moderating variable, and the interactive variable on the dependent variable (LITTLE et al., 2007). Several authors recommend standardizing, (centering means to zero), all independent variables that constitute the interactive variable in response to the problem of multicollinearity (ECHAMBADI; HESS, 2007; AIKEN; WEST, 1991). In addition, according to Judd and McClelland (1989), centralization facilitates the interpretation of data.

The standardization solution allows one to better distinguish effects. In another point, Echambadi and Hess (2004) emphasize that the standardization of the variables does not cause changes in the degree of precision of the estimation of the regression coefficients, as well as changes in the coefficient of determination (R^2). Therefore, standardizing variables in the eyes of those authors does not improve the statistical parameters of analysis.

To exemplify the tests with moderation, three different models will be presented. These models are developed using SPSS version 20. The first model describes the interaction between two interval variables. In the second model, the interaction occurs between the same independent interval variable and a nominal dichotomous variable. In the third model, there is a triple interaction between interval variables. The authors created all fictitious data to demonstrate interactions statically; therefore, there is no empirical validity.

3 TWO-WAY MODERATION EFFECT USING CONTINUOUS VARIABLE

In this topic the focus is to discuss the moderation between two interval variables. For this purpose, consider that the relation between the independent variable *X* and the dependent variable *Y* is moderated by the variable *Mod*. All variables are intervals/continuous similar to Likert type, ranging from 0 to 10 points, and the data are arranged in Table 1. They were created (randomly in Excel) for a sample of 20 respondents so that the moderating effect was significant.

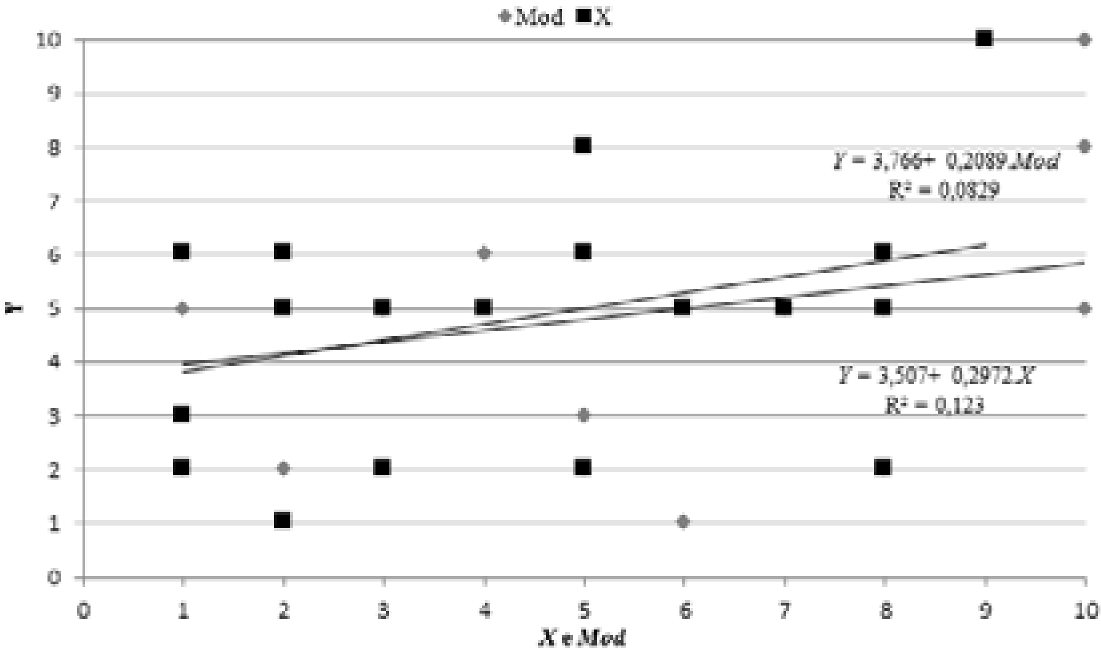
Table 1 – Data for two way moderating effect with interval variables

N	*X*	*Mod*	*Mod ×X*	*Y*
1	5	10	50	8
2	1	5	5	3
3	5	1	5	6
4	2	1	2	6
5	8	10	80	5
6	2	6	12	1
7	8	1	8	2
8	7	3	21	5
9	5	4	20	6
10	9	10	90	10
11	6	7	42	5
12	3	5	15	2
13	3	3	9	5
14	5	2	10	2
15	4	1	4	5
16	1	4	4	6
17	1	8	8	2
18	8	5	40	6
19	2	8	16	5
20	2	5	10	6
Average	4,35	4,95	22,55	4,80
Standard Deviation	2,64	3,09	25,29	2,24

Source: Authors

To test the moderation hypothesis, a simple regression model was first created using Equation 1. This regression tests the degree of prediction of the variable *Y* present in the variables *X* and *Mod*. Therefore, we did two separate regressions, but for presentation purposes both are in the same scatter plot as shown in Figure 1 (elaborated in Excel). The variable *X* had an effect of β = 0.35 and p <0.12. The *Mod* variable had an effect of β = 0.29 and p <0.21.

Figure 1 - Slope of the curve for the independent variables



Source: authors

If the variables are not standardized at the moment of the regression (ECHAMBADI; HESS 2007), then to present the graphs one must use data such as independent variable and moderator variable, standard deviation of both, and non-standardized coefficients (AIKEN; WEST, 1991; FRIEDRICH, 1982). Nevertheless, if the variables are standardized then to present the graphs one can use data such as independent variable means, standard deviation of both = 1, and non-standardized coefficients.

We justify centralizing data by standardizing the values of the multiplication of the two terms, which can vary from 0 * 0 = 0 (minimal) to 10 * 10 = 100 (maximal). Therefore, to meet the standardization suggestion, some steps should be followed: (a) as the variables are continuous, they were standardized in Z score, normalizing them, (b) a multiplicative term was created between the moderator and the independent variable and (c) this new variable together with the moderator and the independent variable were tested.

If the effect of the new variable multiplied is significant, independent of the direct effect of the moderator and the independent variable, it becomes necessary to graphically explore the inclinations of the curve of the independent variable from the conditions of low, medium and high levels of the moderator variable, which are calculated from the descriptive measures of mean and standard deviation. For Preacher, Rucker and Hayes (2007), this procedure of presentation of the findings facilitates the evaluation of more complex models as is the case of indirect conditional committed models.

According to Table 2, both the *Mod* and *X* variables are not significant in explaining the variable Y in the direct effect. The total explained variance was 18% in the first model without multiplication. The results found in the regression analysis showed that the direct relationship between the independent variable X and the dependent variable Y is not significant for any model (β = 0.27, p> 0.16 and β = -0.58; p> 0.16), as well as the relation between the variable *Mod* and the dependent variable Y (β = 0.17, p> 0.28 and β = -0.62, p> 0.08).

The first model shows that *X* and *Mod* do not explain *Y*. Thus, many researchers tend to finalize the research without exploiting additional interactive effects. Therefore, there is a not detailed result.

Table 2 – Regression analysis example 1

Independent Variables	1st model		2nd model	
	B[1]	Sig.	B[1]	Sig.
slope	2,742	0,031	7,108	0,002
X	0,270	0,168	-0,587	0,131
Mod	0,179	0,281	-0,622	0,085
X.Mod			0,147*	0,020*
R^2	0,183		0,424	

[1] Coefficient non standardized * p<0,05.
Source: authors

In the second model, we added the interactive variable *X.Mod*, created by multiplying the response of the independent variable *X* with the response of the moderating variable *Mod*., which generated an increase in the coefficient of determination of 0.241 (ΔR^2 = 0.424 - 0.183), considering this statistically significant discrepancy (F = 6.70, p <0.02). Likewise, the regression coefficient presented for the interaction *X.Mod* also presented statistical significance (β = 0.14, p <0.05), supporting the hypothesis of moderation.

For a better interpretation of the results, we suggest a graph to represent the moderation. To do so, one must estimate the values of *Y*, considering the mean of X and a standard deviation above and below it (+ 1SD and -1SD). Likewise, values based on the *Mod* average and 1 standard deviation above and below are also estimated (WEST; AIKEN; KRULL, 1996; KIM; KAYE; WRIGHT, 2001). The values are estimated according to the equation of the regression model of this example given by Equation 4.

As an example, the equations for the following scenarios are presented: (a) Low X and Low *Mod*; (b) Medium X and Medium *Mod* and (c) High X and High *Mod*, represented by Equations 5, 6 and 7 respectively.

Table 3 presents the values for all possible scenarios (estimation of *Y* from the combinations between low, medium and high values of the independent and moderating variables - 3 by 3).

(4) $\hat{\hat{Y}} = \beta_0 + \beta_1 X + \beta_2 Mod + \beta_3 X.Mod = 7.108 - 0.587.X - 0.622.Mod + 0.147.X.Mod$

(5) $\bar{Y} = 7{,}108 - 0{,}587.(4{,}35 - 2{,}64) - 0{,}622.(4{,}95 - 3{,}09) + 0{,}147.(4{,}35 - 2{,}64).(4{,}95 - 3{,}09) = 5{,}42$

(6) $\hat{\hat{Y}} = 7{,}108 - 0{,}587.4{,}35 - 0{,}622.4{,}95 + 0{,}147.4{,}35.4{,}95 = 4{,}65$

(7) $\hat{\hat{Y}} = 7{,}108 - 0{,}587.(4{,}35 + 2{,}64) - 0{,}622.(4{,}95 + 3{,}09) + 0{,}147.(4{,}35 + 2{,}64).(4{,}95 + 3{,}09) = 6{,}29$

Table 3 – Values for Y to create the plots (example 1)

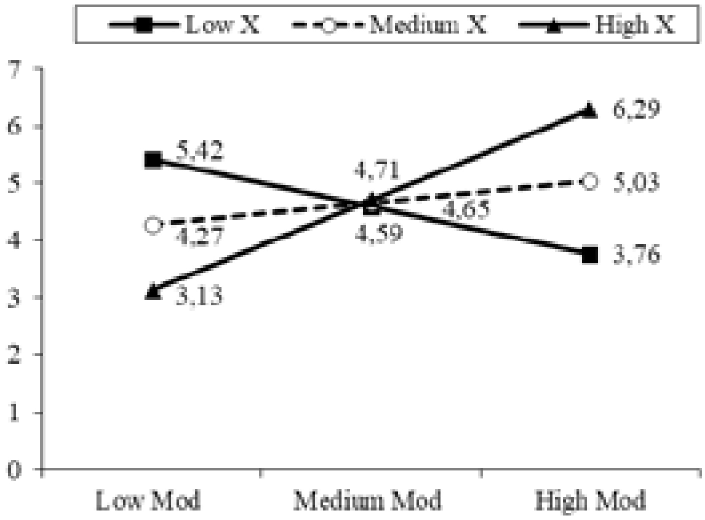
	Low *Mod* (-1 DP)	Medium *Mod* (Average)	High *Mod* (+1 DP)
Low *X* (-1 DP)	5,42	4,59	3,76
Medium *X* (Average)	4,27	4,65	5,03
High *X* (+1 DP)	3,13	4,71	6,29

Source: authors

The results indicated that there is a cross-over effect for Y values due to the interaction between the independent variable *X* and the moderating variable *Mod* (see Figure 2). The greatest results for *Y* occur when there is a combination of high levels (y = 6.29) or low levels (y = 5.42) of *X* and *Mod*. When there is a difference between levels of these variables, the results of and they tend to be smaller.

The combinations of low *X* and high *Mod* (y = 3.76) and high *X* and low *Mod* (y = 3.13) were the ones that presented the lowest values for the dependent variable. Therefore, if the goal is to reach higher values for *Y*, one must seek high indices for both *X* and *Mod*. If it is not possible to achieve this goal for one of these variables, one should choose to maintain low indices for both. These conclusions can be more easily interpreted by analyzing the behavior of the variables depicted in Figure 2.

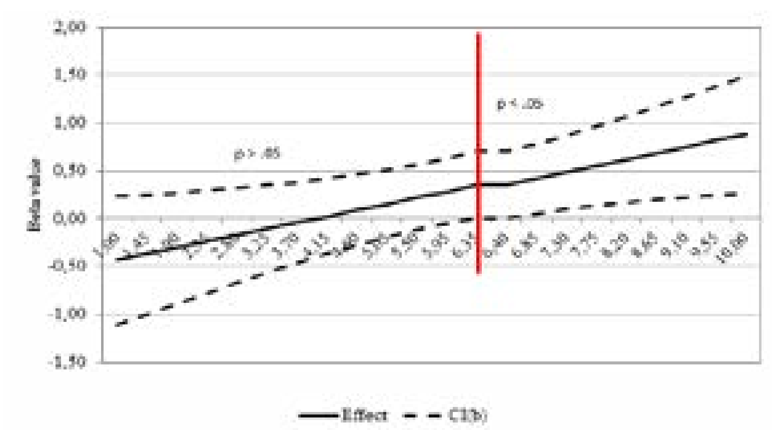
Figure 2 – Plot for the moderation via average (example 1)



The graphical representation of the effects contributes to the interpretation of the moderation hypothesis. Based on the proposals of Hayes and Matthes (2009) and Preacher, Rucker and Hayes (2007), a new moderation chart was developed using non-standard betas, upper and lower limits of confidence intervals and significance region. The graph (see Figure 3) was generated using the Johnson-Neyman technique present in the SPSS macro called Process (HAYES, 2013). The size of the effect (β) of the independent variable on the dependent variable is analyzed from different levels of the moderator variable.

In Figure 3 shows that the effect of the independent variable *X* on the dependent variable *Y*, conditioned by the moderating variable *Mod*, is significant when the value of the moderating variable is greater than 6.35. Therefore, we concluded that the moderating effect occurs when there are high *Mod* values, complementing the neglected results from figure 2.

Figure 3 - Plot of moderation via betas (example 1); upper and lower limits of confidence intervals



4 TWO WAY MODERATION EFFECT USING DUMMY VARIABLE

In our second example, the moderation tests are performed by interacting a 10-point Likert interval variable with a nominal dichotomous moderating variable (and no longer a moderating metric / interval variable). The same relation between the independent variable *X* and the dependent variable *Y* now moderated by the dichotomous variable *Mod* represents two distinct groups, was analyzed. The values for *X* and *Y* were maintained in relation to the previous example and the code used for the Mod variable was 0 and 1. The data are presented in Table 4.

Table 4 – Data for two way interaction between continuous variable and dummy variable

N	*X*	*Mod*	*Mod×X*	*Y*
1	5	1	5	8
2	1	0	0	3
3	5	1	5	6
4	2	0	0	6
5	8	1	8	5
6	2	1	2	1
7	8	0	0	2
8	7	0	0	5
9	5	1	5	6
10	9	1	9	10
11	6	1	6	5
12	3	0	0	2
13	3	0	0	5
14	5	0	0	2
15	4	0	0	5
16	1	0	0	6
17	1	1	1	2
18	8	0	0	6
19	2	1	2	5
20	2	0	0	6
Average	4,35		2,15	4,80
Standard deviation	2,64		3,01	2,24

Source: authors

In the same way as in the previous example, the moderation hypothesis was tested by creating two multiple regression models. In the first one, only the direct relations of the variables *X* and *Mod* with the dependent variable *Y* were tested, while in the second, the product of the two (*X.Mod*) was included. The results are presented in table 5.

Table 5 – Regression analysis example 2

	1st model		2nd model	
Independent variables	B[1]	Sig.	B[1]	Sig.
Slope	3,262	0,005	4,878	0,000
X	0,275	0,169	-0,129	0,573
Mod	0,756	0,456	-3,128	0,082
XMod			0,879*	0,017
R^2	0,152		0,413	

[1] Coefficient non standardized * p<0,05.
Source: authors

The results offered by the regression analysis support the hypothesis of moderation, since the coefficient of regression of the interactive variable obtained a significance level of 95%. Moreover, the addition of this variable to the regression model offered an increase in the adjustment index of 0.261 (ΔR^2 = 0,413 - 0,152), also significant (p<0.02).

To better understand the behavior of the moderating variable over the tested relationship, the values for the dependent variable Y were estimated. Values for the two groups (0 and 1) of the variable Mod and for high values (1 standard deviation above the mean) and low values of the variable X (1 standard deviation below) were estimated. The results are presented in table 6.

Table 6 – Estimating values for y for creating the plots (example 2)

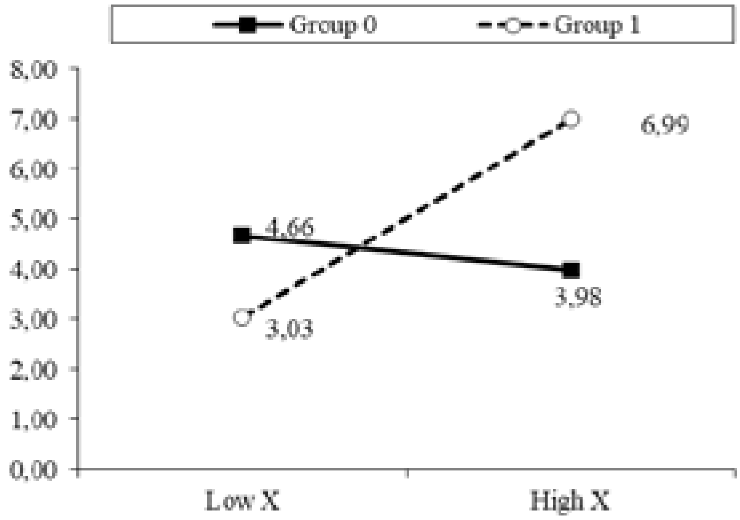
	low X (-1 DP)	high X (+1 DP)
Moderator: Group 0 (low)	4,66	3,98
Moderator: Group 1 (high)	3,03	6,99

Source: authors

The results found indicate the existence of a cross effect for *Y* values resulting from the interaction between the independent variable *X* and the moderating variable *Mod*. If the objective is to obtain the highest values for the dependent variable *Y,* the best combination is given between a high level for the dependent variable *X* and the presence of the element categorized as group 1 (y = 6.99). However, the combination of low level of *X* with group 1 presented the lowest result (y = 3.03). Thus, the greatest *Y* oscillation occurs in group 1 between high and low *X* values.

In group 0, the highest result found of *Y* is when there is a low level of *X* (y = 4.66). When the level of *X* increases, the results for the dependent variable decrease (y = 3.98). This effect is contrary to that of group 1, but with less inclination. This cross-effect can be analyzed in Figure 4.

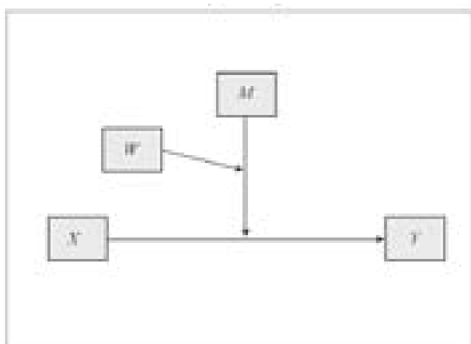
Figure 4 - Cross effect of moderation for dummy variable (example 2)



5 THREE-WAY MODERATING EFFECT

The triple interaction means that the variables, one independent and two moderators, interact in their totality generating at least 8 different effects on the dependent variable. This occurs from the combination of high and low values, in the case of continuous variables, or between groups, for dichotomous variables (2 × 2 × 2). The triple interaction is represented by figure 5.

Figure 5 – Three way moderating effect



In Example 3, the interaction between three 10-point Likert-type interval variables was tested. For this case, besides creating the interactive variable of the three variables (one independent and two moderators), one must also create all possible double interactions. Therefore, considering a direct relationship between X and Y, moderated by *Mod1* and *Mod2*, the following interactions were computed: *X.Mod1, X.Mod2, Mod1.Mod2, X.Mod1.Mod2.* In the same way as in the previous examples, responses were simulated for a sample of 20 people, as described in table 7.

Table 7 – Data for three way moderating effect with continuous variables

N	*X*	*Mod1*	*Mod2*	*X×Mod1*	*X×Mod2*	*Mod1× Mod2*	*X×Mod1 ×Mod2*	*Y*
1	5	10	9	50	45	90	450	8
2	1	5	7	5	7	35	35	3
3	5	1	8	5	40	8	40	6
4	2	1	8	2	16	8	16	6
5	8	10	2	80	16	20	160	5
6	2	6	1	12	2	6	12	1
7	8	1	3	8	24	3	24	2
8	7	3	2	21	14	6	42	5
9	5	4	9	20	45	36	180	6
10	9	10	5	90	45	50	450	10
11	6	7	4	42	24	28	168	5
12	3	5	7	15	21	35	105	2
13	3	3	6	9	18	18	54	5
14	5	2	4	10	20	8	40	2
15	4	1	8	4	32	8	32	5
16	1	4	8	4	8	32	32	6
17	1	8	9	8	9	72	72	2
18	8	5	10	40	80	50	400	6
19	2	8	1	16	2	8	16	5
20	2	5	8	10	16	40	80	6
Average	4,35	4,95	5,95	22,55	24,20	28,05	120,40	4,80
SD	2,64	3,09	2,95	25,29	19,01	23,87	144,42	2,24

Note: source authors; SD = standard deviation

For this example of moderation, three multiple regression models were constructed. In the first model, the direct effects of the variables X, Mod1 and Mod2 were examined in the explanation of Y. In the second, the combinations in pairs (i.e. the double interactions) were added and, finally, in the third, the triple interaction was increased. The results are shown in Table 8.

Table 8 – Regression analysis example 3

Independent Variables	1st model		2nd model		3rd model	
	B[1]	Sig.	B[1]	Sig.	B[1]	Sig.
slope	0,072	0,964	5,292	0,345	-12,695	0,094
X	0,352	0,057	-0,621	0,366	2,179	0,052
Mod1	0,224	0,143	-0,488	0,513	2,177*	0,050
Mod2	0,351*	0,038	0,151	0,796	2,826*	0,011
X.Mod1			0,132	0,098	-0,290	0,066
X.Mod2			0,034	0,563	-0,422*	0,015
Mod1.Mod2			-0,003	0,966	-0,409*	0,011
X.Mod1. Mod2					0,072*	0,008
R^2	0,381		0,570		0,768	

[1] Coefficient non standardized * p<0,05; source: authors.

Observing the results, we can observe that the interactive effect of the three variables obtained a significant regression coefficient ($\beta = 0.07$, $p < 0.01$), showing a positive linear relation with the dependent variable *Y*. Likewise, the third model presented an increase in the index of adjustment in relation to the second one of 0,198 ($\Delta R^2 = 0.768 - 0.570$), significant at the level of 99% ($p < 0.01$). These results support the hypothesis of triple moderation, which will be better interpreted when estimating the values for the dependent variable and from the graphical analysis.

To do so, initially two groups were created: high value (1 standard deviation above average) and low value (1 standard deviation below average) of variable *Mod2*. Then, in each group, 4 values as estimated the following combinations: High X and High *Mod1*; High X and low *Mod1*; Low X and High *Mod1*; and Low X and Low *Mod1*. The results are shown in Table 9.

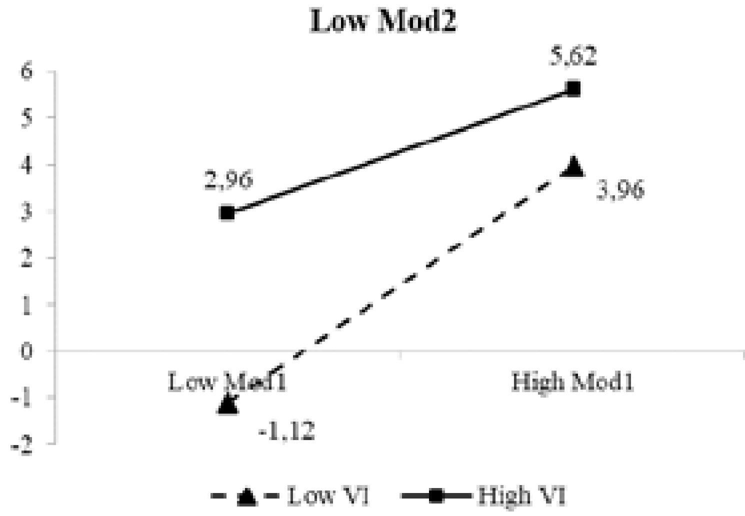
Table 9 – Estimating values for y for creating the plot (example 3)

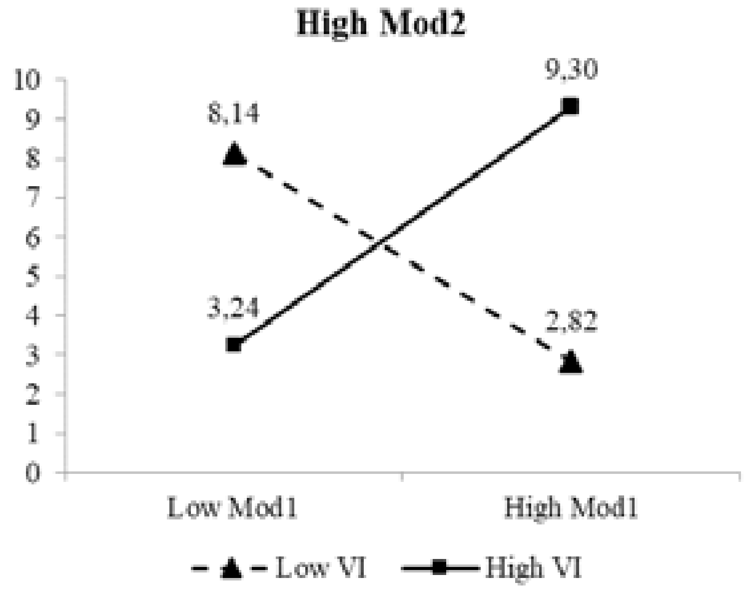
	low Mod_2		high Mod_2	
	low Mod_1	high Mod_1	low Mod_1	high Mod_1
low *X*	-1,12	3,96	8,14	2,82
high *X*	2,96	5,62	3,24	9,30

Fonte: dados do trabalho

The three way interaction is represented in figures 5 and 6. When the level of *Mod2* is low, the relationship between X and *Mod1* is positive (increasing) for both high levels and low levels. In other words, the larger the combination of X and *Mod1*, the greater the tendency of the dependent variable Y will be. This increasing behavior is greater when there is a low level of X. The higher *Y* estimate for the low level scenario Mod2 was found in the combination between high *X* and High *Mod1* (y = 5.62).

Figure 4 and 5 – Three way moderating effect (example 3)





When the level of *Mod2* is high, we see a cross-effect between the combinations between X and *Mod1*. For a low level of *X* the relation is negative (decreasing), whereas for a high level of *X* the relation is positive (increasing). Thus, when *X* is low, the highest result is also for a low level of *Mod1* (y = 8.14). As the level of *Mod1* grows, the estimates for *Y* are decreasing. When X is high, the highest result is also for a high level of Mod1 (y = 9.30). With the fall of the *Mod1* level, the *Y* estimates also decrease.

So if the goal is a higher level of Y, the best scenario will be the combination of high-level *Mod2*, high-level *X,* and high-level *Mod1*. The lowest value, given by the opposite for each variable, low levels of *Mod2*, X and *Mod1*. Table 10 presents the best combinations in pairs for each possible scenario, seeking the highest value for the dependent variable *Y*.

Table 10 – Cenarium for greater values of Y

Cenarium	*X*	Mod_1	Mod_2
High *X*	-	High	High
Low *X*	-	Low	High
High Mod_1	High	-	High
Low Mod_1	Low	-	High
High Mod_2	High	High	-
Low Mod_2	High	High	-

Fonte: dados do trabalho

6 FINAL REMARKS

In social sciences, the search for the explanation of results is sometimes limited to the existence of linear relations, leaving aside curvilinear effects (also known as non-linear, such as cubic, positive quadratic, negative quadratic, etc.), mid-effects or even interactive effects (double, triple, quadruple, cross, ordinal, etc.).

In this article, the interactive effects are highlighted as the possibility of explaining the results. Thus, the interactive effects were analyzed through double and triple moderation with metric variables or dummies. The regression analysis with the interactive effects (FRAAS; NEWMAN, 1977; PEDHAZUR, 1982) aims to show that the variability of the effect of the endogenous variable also depends on a combination of results, being therefore the interactive effect - a combination of multiple results.

The first conclusion is that the effect of one variable on another is conditioned to variations of a third in the existence of moderation, in which the graphical representation should reveal a strange effect. If the results are not uncovered then the type VI error may appear (NEWMAN et al., 1976). Alternative regressions are then estimated with multiplications and, if there is significance of the interactive effects in the result variable, it is necessary to check the combination of multiple results (low vs. high, high vs. high, etc.).

Second, an analysis of variance increment explained must be analyzed. The additional variance created by the moderator in the regression equation is desired. Such evidence shows that a simple linear effect may be non-significant or even weak, but when interacting with the moderator, the relationship becomes clearly strong.

Third, understanding the plot of the curve is critical. Therefore, the effect can be null, positive or negative for each level of the moderator (MULLER; JUDD; YZERBYT, 2005; PREACHER; RUCKER; HAYES, 2007). In fact, all these combinations are plausible to be found and should be clear to the scientist. In this article we elaborate this and advance in the explanations when the result was positive or negative for the levels of the moderator. Obviously, the relationship must be explained with scientific, theoretical and philosophical basis. Indeed, there is a great mistake in seeking regressions and interactive effects without any theory and plausible explanations behind it. Science seeks to explain and predict phenomena in social science, and to do so, to understand the motive, reason, and argument that sustains a result is something extremely necessary.

In sum, cross-interactive effects show that at one level of the moderator variable, the result is negative and when moving to the other level of the moderator variable, the result, conversely, is positive. To explain with convincing arguments and coherent theory this systematic is something necessary for the scientist. Complementarily, ordinal interactive effects show that at one level of the moderator variable, the result is negative and when moving to the other level of the moderator variable, the result, coherently, becomes even more negative, increasing the discrepancy between levels.

REFERÊNCIAS

ABBADE, Eduardo Botti; DE BEM NORO, Greice. Conhecimento, segurança, resistência e utilização de tecnologias de auto-atendimento bancário. **Revista de Administração da UFSM**, v. 5, n. 3, p. 507-524, 2012.

AIKEN, Leona S.; WEST, Stephen G.; RENO, Raymond R. **Multiple regression: Testing and interpreting interactions**. Sage, 1991.

BARON, Reuben M.; KENNY, David A. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. **Journal of personality and social psychology**, v. 51, n. 6, p. 1173, 1986.

BATRA, Rajeev; STAYMAN, Douglas M. The role of mood in advertising effectiveness. **Journal of Consumer research**, v. 17, n. 2, p. 203-214, 1990.

BYRNE, David. **Interpreting quantitative data**. New Delhi: Sage, 2002.

CHATTOPADHYAY, Amitava; BASU, Kunal. Humor in advertising: The moderating role of prior brand evaluation. **Journal of Marketing Research**, v. 27, n. 4, p. 466-476, 1990.

CORTINA, Jose M. Interaction, nonlinearity, and multicollinearity: Implications for multiple regression. **Journal of Management**, v. 19, n. 4, p. 915-922, 1993.

DA SILVA, Juliano Domingues; DA SILVA FAIA, Valter; VIEIRA, Valter Afonso. Os efeitos negativos da experiência e do controle no desempenho do vendedor. **RAE**-**Revista de Administração de Empresas**, v. 56, n. 6, p. 626-640, 2016.

ECHAMBADI, Raj; HESS, James D. Mean-centering does not alleviate collinearity problems in moderated multiple regression models. **Marketing Science**, v. 26, n. 3, p. 438-445, 2007.

FRAAS, John. W.;NEWMAN, Isadore. Malpractice of the interpretation of statistical analysis. In: **Annual Meeting of the Ohio Academy of Science,** Columbus, Ohio, 1997. Disponível em http://eric.ed.gov/?id=ED411256capturado em 17-10-2015.

FRIEDRICH, Robert J. In defense of multiplicative terms in multiple regression equations. **American Journal of Political Science**, v.26, n.4, p. 797-833, 1982.

GONÇALVES, Eric Bacconi; GOUVÊA, Maria Aparecida; MANTOVANI, Daielly Melina Nassif. Análise de risco de crédito com o uso de regressão logística. **Revista Contemporânea de Contabilidade**, v. 10, n. 20, p. 139-160, 2013.

HAYES, Andrew F. **Introduction to mediation, moderation, and conditional process analysis: A regression-based approach**. New York: Guilford Press, 2013.

HAYES, Andrew F.; MATTHES, Jörg. Computational procedures for probing interactions in OLS and logistic regression: SPSS and SAS implementations.**Behavior Research Methods**, v. 41, n. 3, p. 924-936, 2009.

HENSELER, Jörg; FASSOTT, Georg. Testing moderating effects in PLS path models: An illustration of available procedures. In: Esposito Vinzi, V.; Chin, W. W.; Henseler, J. & Wang, H. (eds.). **Handbook**

of Partial Least Squares: concepts, methods and applications. Berlin: Springer, 2010.

IACOBUCCI, Dawn; SALDANHA, Neela; DENG, Xiaoyan. A meditation on mediation: Evidence that structural equations models perform better than regressions. **Journal of Consumer Psychology**, v. 17, n. 2, p. 139-153, 2007.

JACCARDI,James;TURRISI, Robert. **Interaction effects in multiple regression**. 2. ed. Thousand Oaks: Sage, 2003.

JAMES, Lawrence R.; BRETT, Jeanne M. Mediators, moderators, and tests for mediation. **Journal of Applied Psychology**, v. 69, n. 2, p. 307, 1984.

JUDD, Charles M.; MCCLELLAND, Gary H.;RYAN, Carey S. **Data analysis:** A model comparison approach. New York: Routledge, 2011.

KENNY, David A.; JUDD, Charles M. Estimating the nonlinear and interactive effects of latent variables. **Psychological bulletin**, v. 96, n. 1, p. 201, 1984.

KIM, Jin-Sun; KAYE, Judy; WRIGHT, Lore K. Moderating and mediating effects in causal models. **Issues in Mental Health Nursing**, v. 22, n. 1, p. 63-75, 2001.

KIELING, Ana Paula; BREI, Vinícius Andrade; VIEIRA, Valter Afonso. The influence of negative surprise on review. **BBR. Brazilian business review**. Vitória, ES. Vol. 13, n. 3 (maio/jun. 2016), p. 111-132, 2016.

LITTLE, Todd D.; CARD, N. A.; BOVAIRD, J. A.; PREACHER, K. J.; CRANDALL, C. S. Structural equation modeling of mediation and moderation with contextual factors. In: Little, T. D; Bovaird, J. A. & Card, N. A. (eds.). **Modeling Contextual Effects in Longitudinal Studies**. Mahwah: Routledge, 2007.

MACKINNON, David P.;. LOCKWOOD, Chondra. M., HOFFMAN, Jeanne. M., WEST, Stephen. G., SHEETS, Virgil. A comparison of methods to test mediation and other intervening variableeffects. **Psychological Methods**, v. 7, n. 1, p. 83, 2002.

MANTOVANI, Daielly M. N.; GOUVÊA, Maria A.; VIANA, Adriana B. N. Comunicação Síncrona no Ensino de Estatística Aplicada à Administração: Um Estudo em uma Disciplina Semipresencial. **REGE Revista de Gestão**, v. 20, n. 2, p. 165-181, 2013.

MULLER, Dominique; JUDD, Charles M.; YZERBYT, Vincent Y. When moderation is mediated and mediation is moderated. **Journal of Personality and Social Psychology**, v. 89, n. 6, p. 852, 2005.

NEWMAN, I.; DEITCHMAN, R.; BURKHOLDER, J.; SANDERS, R.; ERVIN, L.. Type VI error: Inconsistency between the statistical procedure and the research question. **Multiple Linear Regression Viewpoints**, v.6, n.4, p.1-19, 1976.

PEDHAZUR, E. J. **Multiple regression in behavioral research:** Explanation and prediction. 2. ed. Fort Worth: Harcourt Brace Jovanovich, 1982.

PING Jr., Robert A. Latent variable interaction and quadratic effect estimation: A two-step technique using structural equation analysis. **Psychological Bulletin**, v. 119, n. 1, p. 166-175, 1996.

PRADO, Paulo H. M.; KORELO, José C.; SILVA, Danielle M. L. Análise de Mediação, Moderação e

Processos Condicionais. **Revista Brasileira de Marketing**, v. 13, n. 4, p. 04-24, 2014.

PREACHER, Kristopher J.; RUCKER, Derek D.; HAYES, Andrew F. Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. **Multivariate behavioral research**, v. 42, n. 1, p. 185-227, 2007.

SAUER, Paul L.; DICK, Alan. Using moderator variables in structural equation models. **Advances in consumer research**, v. 20, n. 1, p. 637-640, 1993.

SHARMA, Subhash; DURAND, Richard M.; GUR-ARIE, Oded. Identification and analysis of moderator variables. **Journal of Marketing Research**, v.18, n.3, p. 291-300, 1981.

UDD, Charles M.;MCCLELLAND, Gary H. **Data analysis: A model comparison approach**. New York: Harcourt Brace Jovanovich, 1989.

VARADARAJAN, P. Rajan. Musings on relevance and rigor of scholarly research in marketing. **Journal of the Academy of Marketing Science**, v. 31, n. 4, p. 368-376, 2003.

VIEIRA, Valter A. Moderação, Mediação, Moderadora-Mediadora e Efeitos Indiretos Em Modelagem de Equações Estruturais: Uma Aplicação no Modelo de Desconfirmação de Expectativas. **Revista de Administração (USP)**, v. 44, n. 1, p. 17-33, 2009.

WEST, Stephen G.; AIKEN, Leona S.; KRULL, Jennifer L. Experimental personality designs: Analyzing categorical by continuous variable interactions. **Journal of Personality**, v. 64, n.1, p. 1-48, 1996.

WHISMAN, Mark A.; McCLELLAND, Gary H. Designing, testing, and interpreting interactions and moderator effects in family research. **Journal of Family Psychology**, v. 19, n. 1, p. 111-120, 2005.