

## MEDIATION, MODERATION AND CONDITIONAL PROCESS ANALYSIS

### ABSTRACT

This paper discusses the main aspects of simple mediation and moderation, as well as the conditional process analysis applied for more complex models, such as mediated moderation and moderated mediation. The recent changes on the way these analysis have been conducted highlights the need to discuss them in order to increase their application in studies conducted in Brazil. The authors provide a discussion about the analysis techniques and the recommendations for the procedures conducted these days. They also present the direct, indirect and total effects and how to read them. Finally, the conditional process analysis, applied for moderated mediation and mediated moderation analysis procedures, is discussed.

**Keywords:** Mediation; Moderation; Mediated Moderation; Moderated Mediation; Conditional Process.

## ANÁLISE DE MEDIAÇÃO, MODERAÇÃO E PROCESSOS CONDICIONAIS

### RESUMO

Este artigo faz uma discussão dos principais aspectos relacionados às análises de mediação e moderação simples, assim como dos processos condicionais utilizados para modelos mais complexos, como os de mediação moderada e de moderação mediada. As recentes mudanças na forma como essas análises têm sido realizadas por pesquisadores traz a necessidade de discuti-las no intuito de estimular a sua utilização em pesquisas brasileiras. Neste artigo, os autores apresentam principalmente uma discussão sobre as técnicas de análise e as principais recomendações para os procedimentos hoje realizados, os tipos de efeitos que devem ser considerados (diretos, indiretos e total) e como interpretá-los. São também discutidos os processos condicionais, amplamente utilizados na condução das análises de moderação mediada e de mediação moderada.

**Palavras-chave:** Mediação; Moderação; Mediação Moderada; Moderação Mediada; Processos Condicionais.

Paulo Henrique Muller Prado<sup>1</sup>  
José Carlos Korelo<sup>2</sup>  
Danielle Mantovani Lucena da Silva<sup>3</sup>

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<sup>1</sup> Doutor em Administração de Empresas pela Fundação Getúlio Vargas – FGV. Professor da Universidade Federal do Paraná – UFPR. Brasil. E-mail: [p Prado@ufpr.br](mailto:p Prado@ufpr.br)

<sup>2</sup> Doutor em Administração pela Universidade Federal do Paraná – UFPR. Professor da Universidade Federal do Paraná – UFPR. Brasil. E-mail: [korelo@yahoo.com](mailto:korelo@yahoo.com)

<sup>3</sup> Doutora em Administração pela Universidade Federal do Paraná – UFPR. Trabalha no BAR. Brazilian Administration Review. Brasil. E-mail: [dm\\_lucena@yahoo.com.br](mailto:dm_lucena@yahoo.com.br)

## 1 INTRODUCTION

In recent years, there has been a growing usage of new techniques of analysis concerning the consumer behavior, mainly in experimental researches the mediation, moderation models and more complex models such as the moderate mediation and moderated mediation started to be used more often in researches. These more complex new techniques of analysis, also called as conditional process analysis, have been widely mentioned in *journals* with a bigger impact factor in the field of marketing and the consumer behavior, such as the *Journal of Consumer Research*, *Journal of Marketing Research* and *Journal of Consumer Psychology*, just to mention some. However, in the Brazilian context there is still the need of disseminating and discussing in a more detailed way the principles which rule the analysis of these models, as well as better justify the steps to be taken when choosing a certain technique of analysis. In this context, this article presents and discusses the principles of mediation, moderation analysis and the convergence of both in conditional process analysis. This article follows the proposal by Baron and Kenny (1986), mainly complemented by the studies of Preacher and Hayes (2004; 2008), Hayes (2009; 2013) and Edwards and Lambert (2007).

Mediation and moderation analysis are used to establish evidences or test hypotheses regarding the mechanisms which explain how certain effects occur or in which conditions they facilitate or inhibit such effects (Hayes, 2013). The moderation effect ( $W$ ) occurs when a variable, categorical or continuous, affects the direction or the intensity of the relation between an independent variable ( $X$ ) and a dependent one ( $Y$ ) (Baron & Kenny, 1986). The moderation is also called conditional effect. The mediation, on the other hand, is the process by which an independent variable ( $X$ ) affects the dependent variable ( $Y$ ) through indirect effect of one or more mediating variables ( $M$ ). The mediation is also called intervenient variable or mechanism (Hoyle & Robinson, 2004).

In a didactic way, Hayes (2013) explains that questions as “How?” are normally assessed by the mediation analysis, while questions as “When?” are almost always responded with moderation analysis. The author defends the relevance of responding to such questions when arguing that it is not only interesting to know whether  $X$  affects  $Y$ , but also to know how such effect occurs, when it happens or when it no longer occurs. How an effect occurs is related to the psychological, cognitive or biological process

which causes the effect of  $X$  on  $Y$ , a characteristic of the mediations. The question regarding when  $X$  affects  $Y$  is related to the conditions of the causal association. Therefore, the moderation has to do with the circumstances or which type of group  $X$  has an effect on  $Y$ .

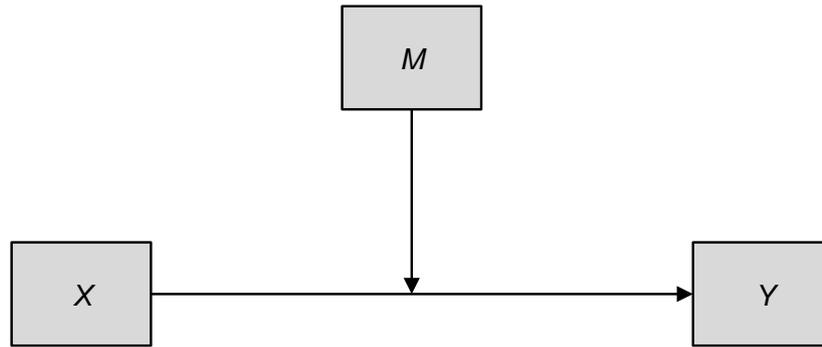
The conditional process analysis is used when the purpose is to describe the boundary conditions of the mechanism by which one variable influences another. Such processes join the usage of mediation and moderation in moderate mediation and mediated moderation models.

In this article, first, there is a discussion on the principles of moderation and mediation, their premises and effects to be analyzed, as well as the main calculus approaches currently used. After this, an explanation is made on the conditional process analyses, which focuses on a discussion regarding the effects to be considered (direct, indirect and total effects), the approaches for calculation as the form of presentation of the analysis results.

## 2 MODERATION

As proposed by Baron and Kenny (1986) the moderation effect corresponds to a variable which affects the direction or intensity of relation of a predictive variable (independent) and another dependent one. Then, the moderation corresponds to individual differences or situational conditions which change the relation initially proposed between two other variables (Edwards & Lambert, 2007).

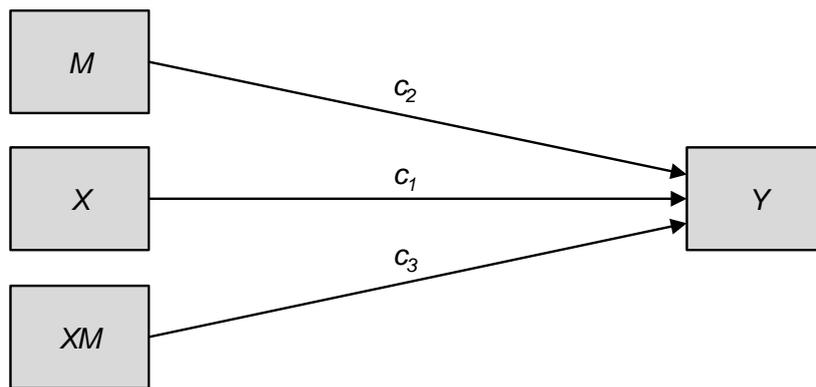
The relation can be specified according to the Figure 1. In this, the variable  $X$  corresponds to the independent variable, normally manipulated through an experimental procedure, and the variable  $Y$  corresponds to the dependent variable. The expectation based on this theory is that changes in  $X$  cause changes in  $Y$ . This then is called main effect of  $X$  in  $Y$  (Baron & Kenny, 1986). The variable  $M$ , on the other hand, corresponds to a moderating variable, which changes the relation between  $X$  and  $Y$ . This relation can be changed in intensity, i.e., in the presence of  $M$ , the relation between  $X$  and  $Y$  becomes stronger or weaker. This relation can also be changed in terms of direction. Thus, in the presence of  $M$ , the relation between  $X$  and  $Y$  is inverted. From these effects it is possible to assess the “validity conditions” of the relation between  $X$  and  $Y$ , as mentioned by Hernandez, Basso, and Brandão (2014).



**Figure 1 - Conceptual Model of Simple Moderation**  
Source: Hayes (2013)

Operationally, in the most common case found in the literature, both the independent variable *X* and the moderating *M* are elements in the experiment manipulated with specific treatments. These treatments are determined by the relation between these components indicated by the tested theory, in which the variables are qualitative. It is possible to find

situations in which the moderator (*M*) is only measured, being considered a continuous quantitative variable (e.g. individual characteristics such as personality traits). The statistical model presented in Figure 2 shows the paths involved in a simple moderation model (which has, at least, one moderator).



**Figure 2 - Statistical Model of Simple Moderation**  
Source: Hayes (2013)

In a formal statistical model of this nature, the relation involves independent variable, moderator and dependent variable, according to the following equation 1:

$$(1) \quad Y = i + c_1X + c_2M + c_3XM + e_Y$$

Where *i* is the regression intercept, *e<sub>Y</sub>* is the error when estimating *Y* and *c<sub>1</sub>*, *c<sub>2</sub>*, and *c<sub>3</sub>* correspond to the main effect of the independent variable *X* on *Y*, main effect of *M* on *Y*, and interaction effect between *X* and *M* on *Y*, respectively. This last one is used to check the moderation effect of *M* on the relation between *X* and *Y*. The proposed model can be used with independent and moderating variables and qualitative and non qualitative variables (Baron & Kenny, 1986).

### 2.1 Approaches for the Moderation Calculation

The first approach to the moderation calculation and the most commonly used is the statistical technique of ANOVA (*n x m*), where *n* is the number of treatments given to the variable *X* and *m* is the number of treatments to the variable *Y*. This technique is the most common due to the manipulated (qualitative) nature of the dependent variable *X* and moderating *M* (Baron & Kenny, 1986).

When the moderating variable *M* is quantitative (e.g. humor measured in a scale ranging from 1 to 7) some types of statistical approaches are possible. The first one is to use the *spotlight* method, in which the variable converted into a qualitative variable using -1 *D.P.* (standard deviation) and + 1 *D.P.* as central elements of the distribution of the two new groups (for example, in the case of humor it is

divided the low and high humor for -1 *D.P.* and +1 *D.P.*, respectively). Although this procedure is common in studies on consumer behavior, Spiller, Fitzsimons, Lynch Jr and McClelland (2013) do not recommend it to be used this way. The authors suggest the usage of alternative techniques depending on the moderator characteristics.

Another way to assess the moderation effect in the condition that it is quantitative, it is to use the assessment of the paths described in Figure 2 through a traditional regression model, which considers the main effect of the variable *X*, the main effect of the variable *M* and the interaction effect *XM* on *Y*. Thus the significance of standardized coefficients of the  $\beta$  regression is assessed, while usually the interest path for a moderation to be considered valid is always the interaction *XM*. This form is, at times, is not favored by the researchers as it does not provides graphic visual information like the ANOVA, and only the regression coefficient is the information to assess the level of inclination of the line represented by the effect in the dependent variable *Y* depending on the independent variable *X* moderated by *M*.

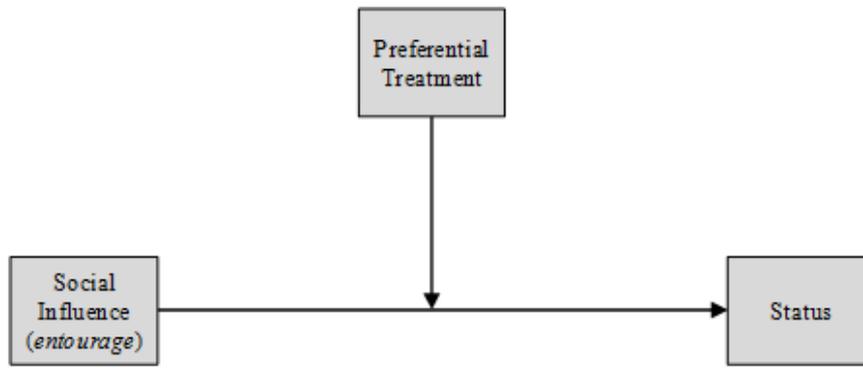
Still, another way to assess the moderation is to use the models proposed by Hayes (2013) in which the *bootstrapping* technique is used (to be later more explored in section 3.2 of the approaches for mediation calculation). The technique is based on the assessment of the paths presented in the Figure 2, however it provides the significance calculus of the effects through the theory test with normal distribution (significant coefficient “*p*”) and non normal distribution (*CI* superior and inferior), for values of -1 *D.P.*, average and +1 *D.P.* of the moderator *M*. Besides this, the model can be calculated with script PROCESS, developed by the author for SPSS and freely available. The procedure used by the author still offers options for testing more than one moderator and provides data for generating the moderation function graphic, which may help in the visualization of the interaction effects.

## 2.2 Moderation Example

Several cases of application of moderation assessment can be found in the main publications in Psychology and in Consumer Behavior. An example

of application was presented by McFerran and Argo (2014). The research focuses on how much the presence of other people may change the perception of status of very important people (*entourage effect*). In an initial study, in a field experiment, the participants of a group of fans of a professional soccer club would have access to a luxurious cabin to attend half of a game from their soccer team, as an award for VIPs. Approached during the game, these fans could choose whether they wanted to see the game there with a friend in that moment (social influence stimulus) or not (control). Afterwards, they filled in a research about the “*fan experience*”. That is, a single factor test was carried out in two levels, with *vs.* without the social influence effect (*entourage effect*). The results presented a main effect, in which the average of status perception of participants with friends ( $M = 5,71$ ) was significantly higher than those who went alone ( $M = 4,51$ ;  $t(52) = 2,21$ ;  $p = 0,03$ ).

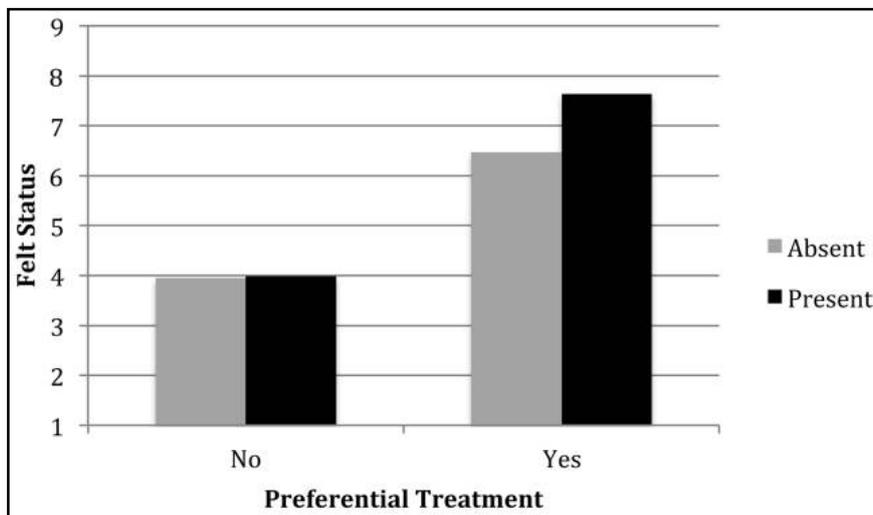
The result of this first experiment could simply show people’s predisposition to getting the award just because they were fans. In a second experiment, the authors suggest that, the additional stimulus of preferential treatment, in the presence of other people, would reinforce the *entourage* effect. In this case, now at a lab study, the participants were stimulated to imagine a situation in which they would go to a game. In the condition of social influence (*entourage effect*), they would have 4 tickets with friends to sit together at the stadium. In the condition without the social influence, they would have only their ticket. In the manipulation of special treatment, these places would be at a fancy room, and in the other situation, that would be at a commonplace at the stadium. The dependent variable in these cases was “how special you felt in this situation”. That is, in this case, the experiment would be a 2 (*entourage*: present *vs.* absent) *vs.* 2 (preferential treatment: yes *vs.* no) between subjects. To conceptually show how a moderation is normally represented, Figure 3 illustrates the focus moderation of McFerran and Argo’s study (2014).



**Figure 3** - Moderation Conceptual Model proposed by McFerran and Argo (2014)  
Source: Developed by the authors

The assessment result of this model can be seen in Figure 4, which presents one of the most traditional ways to illustrate a simple moderation effect for independent variables and qualitative moderators. The main effect found in the first experiment was repeated for the social influence effect (*entourage effect*) ( $F(1, 149) = 4,56; p = 0,03$ ) and the differentiated treatment effect was also found ( $F(1, 149) = 119,60; p < 0,001$ ). Also, an interaction effect

of these treatments on the perception of status was found ( $F(1, 149) = 4,08; p < 0,05$ ), showing the moderation. That is, the participants with differentiated treatment (at luxurious cabins) felt they had more status in the social influence situation ( $M = 7,64$ ) than those who were alone ( $M = 6,47; F(1, 149) = 8,63; p < 0,01$ ). For those who sat at commonplaces, there was no significant difference ( $M_1 = 3,99; M_2 = 3,96$ ).



**Figure 4:** Status as a function of the Preferential Treatment and Social Influence (Entourage)  
Source: McFerran and Argo (2014)

In this example it is possible to check the influence of moderation of presence of the preferential

treatment on the relation between the social influence (*entourage effect*) and the feeling of status.

### 3 MEDIATION

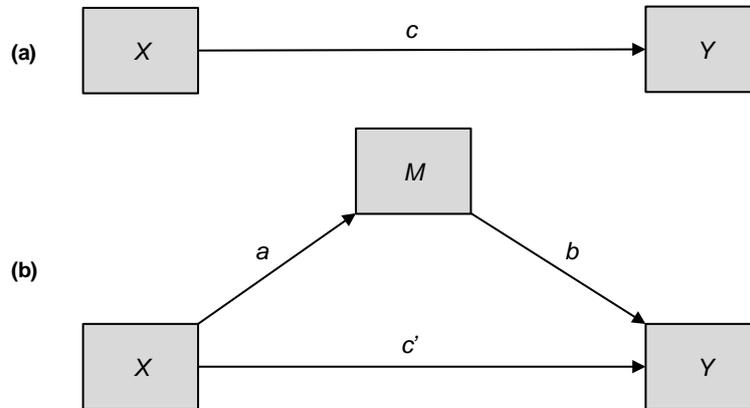
The mediation analysis is a statistical method used to respond questions on how an independent variable  $X$  affects a dependent variable  $Y$ . The

mediation,  $M$ , is the mechanism by which  $X$  influences  $Y$ . This mechanism can be an emotional, cognitive, biological aspect or any other phenomenon.

There are two distinct paths by which the variable  $X$  influences  $Y$ . The letters,  $a$ ,  $b$ ,  $c$  and  $c'$

represent the effect corresponding to each of the relations (Figure 5a and 5b). When the empirical test of a mediation model is carried out, the direct and indirect effects should be taken into consideration, as well as the total effect of the model. In order to derive

such effects it is necessary to estimate the components which constitute the indirect effects, that is, the effect of  $X$  on  $M$ , as well as the effect of  $M$  on  $Y$  (Hayes, 2013).



**Figure 5-** Conceptual and Statistical Model of Simple Mediation  
Source: Hayes (2013)

As there are two consequent variables ( $M$  and  $Y$ ) in this mediation model (Figure 5b), characterized in practical terms by variables in which the arrows of paths reach, two linear models are necessary, one for each consequent variable. The statistical model can be represented by the equations 2 and 3:

(2)

$$M = i_1 + aX + e_M$$

(3)

$$Y = i_2 + c'X + bM + e_Y$$

Where  $i_1$  and  $i_2$  are the regression intercepts,  $e_M$  and  $e_Y$  are the errors when estimating  $M$  and  $Y$ , respectively, and  $a$ ,  $b$ , and  $c'$  are regression coefficients given the previous variables of the model.

### 3.1 Direct, Indirect Effects and Total Effect of the Mediation

The total effect of  $X$  on  $Y$  can be represented in several ways. The total effect is interpreted in how much two groups differ in one unit in  $X$  are likely to differ in  $Y$ . The first Figure 5a illustrates the total effect component. The path  $c$  quantifies the total effect of  $X$  on  $Y$  and is given by  $c = c' + ab$ . In order to estimate this effect other paths should be analyzed which are the direct and indirect effects. In the model of the Figure 5b,  $a$  is the predicting coefficient of the impact of  $X$  on  $M$ , and  $b$  and  $c'$  are the predicting coefficients of the impact of  $M$  and  $X$  on  $Y$ , respectively. The path  $b$  represents the casual effect of the mediator on the dependent variable, without taking into account the impact of the independent variable. The path  $c'$ , on the other hand, represents the direct casual effect of the

independent variable on the dependent controlled by the mediator. In the paths analysis language,  $c'$  quantifies the direct effect of  $X$  on  $Y$ , while the product of  $a$  and  $b$ , quantifies the indirect effect of  $X$  on  $Y$  through the mediator  $M$ . The path  $b$  can also be considered a direct effect, but from the mediator on the dependent variable. The indirect effect ( $ab$  or  $a * b$ ) is the difference between the total effect and the direct effect. The indirect effect is represented by the two paths ( $a$  and  $b$ ) which connect  $X$  to  $Y$  through  $M$ .

Although it is common in the description of the results to present the standardized paths, most of the assessment methods of the mediation are based on unstandardized paths. Authors like Hayes and Scharkow (2013) recommend that the researches follow this premise as the unstandardized coefficients are preferable in the modeling of casual studies in which the independent variables are dichotomous due to their manipulated nature.

### 3.2 Approaches for the Calculation of the Mediation

The mediation models are frequently used in studies in the field of marketing and consumer behavior. Until recently, the most widespread technique for the calculation of the mediation was the *Sobel test* (Sobel, 1982) and the researchers mainly followed the recommendations of Baron and Kenny (1986) in relation to the analysis assumptions and interpretation of results. The approach of these authors proposes that the researcher calculates each of the paths of the model and determines whether the mediating variable reaches statistical significance. For example, if both paths  $a$  and  $b$  from the model of the

Figure 5b are significant and  $c'$  is closer to zero than  $c$ , then the mediator  $M$  is considered significant in the relation between  $X$  and  $Y$ .

However, recently, some studies pointed out limitations in the usage of the *Sobel test*, which presupposes that the distribution of the product between the paths  $a$  and  $b$  is normal. Nonetheless, this normality assumption rarely happens, specially for small samples (Hayes, 2009, 2013). As it is not possible to know for sure if the distribution of  $ab$  is close to a normal distribution, the usage of the *bootstrap* method or *bootstrapping* is suggested to calculate the confidence interval of the value of  $a * b$  (Zhao, Lynch & Chen, 2010; Hernandez, Basso & Brandão, 2014).

The *bootstrapping* technique generates an empirical representation of the sample distribution, by treating the sample size as a representation of the population, but in a smaller scale. Through the repeated sampling procedure, with replacement, and in repeated times, a new sample is formed for each repeated sampling. Once the repeated sampling is made, the paths  $a$  and  $b$  are estimated and the product of both is calculated. This process is repeated  $k$  times, at least 1000 times, although Hayes (2009; 2013) recommends at least 5000 times. After this process, we have  $k$  estimates of the indirect effect whose distribution works as an empirical approach of the sample distribution of the indirect effect, when we have a sample  $n$  of the original population. One inference is made about the size of the indirect effect of the population sampled, using the amount  $k$  of repeated samplings made to generate the confidence interval (CI 95%). This calculation of indirect effect is made the estimates  $a * b$  generated in the repeated samplings from the smallest to the biggest interval are drawn. Thus, to perform the mediation test the simultaneous regressions of the direct effects (independent variables on the dependent ones) indirect effects (independent variables on the dependent ones, through the mediating variable) are conducted, according to Preacher and Hayes' procedure (2004). The procedure assesses the confidence interval (CI) as recommended by Shrout and Bolger (2002), being that, if the values are within the 95% of the confidence interval, the indirect effect is significant and, consequently, the occurrence of mediation can be considered present. This procedure generates these two intervals: lower limit and upper limit of 95%. For the indirect effect to be significant, there can be no change of signal between these two limits. Thus, if the upper and lower limit values are negative, the indirect effect is consequently considered negative. The opposite occurs for positive lower and upper limits. If one of the limits is positive and the other is negative, the effect is considered null or not significant.

Several studies suggest that the *bootstrapping* technique is better than the *Sobel test*

and other forms to test the effect of mediating variables (Williams & MacKinnon, 2008; Preacher & Hayes, 2008; Zhao, Lynch & Chen, 2010). One of the main advantages of the *bootstrapping* is that the inference is based in an estimate of the indirect effect itself, but opposite to the *Sobel test*, this procedure has no normality assumptions of the data distribution (Hayes, 2009). Then, it solves the limitation of the *Sobel test* technique. Thus, the *bootstrapping* technique has been more commonly used, mainly with the usage of the macros elaborated by Hayes, called PROCESS (for details, see Hayes, 2013), which permit the calculation of the mediation models through the *bootstrapping* technique with the usage of the SPSS.

Concerning the analysis of the mediation paths, if one mediating variable,  $M$ , is responsible, at least partially, for the association between  $X$  and  $Y$ , then it can be thought that the impact of  $X$  on  $Y$  should be significant so that the mediator,  $M$ , also has some effect. According to this logic, if there is no evidence that  $X$  influences  $Y$ , so how can the effect of  $X$  on  $Y$  be measured and to what extent is it possible to estimate direct and indirect effects?

Several studies (Biesanz, Falk & Savalei, 2010; Preacher & Hayes, 2008; Hayes, 2013; Hayes & Scharkow, 2013) argue that it is possible to have a significant mediator even if there is no significant effect of  $X$  on  $Y$ . In this case, some authors even avoid using the term mediator and prefer only to state that it is an indirect effect of  $X$  on  $Y$  through  $M$  (Hayes, 2009). For more details about the distinction between mediator and indirect effect, see the study by Mathieu and Taylor (2006). Hayes (2009) argues that even when there is no relation between  $X$  and  $Y$ , that is, when the total effect ( $c$ ) is null, there can be an indirect effect of  $X$  on  $Y$ , through the mediator  $M$ .

### 3.3 Mediation Example

Several mediation examples can also be found in scientific marketing and consumer behavior journals. As an application model, Rucker, Dubois e Galinsky (2011) proposed a research that assesses how much the consumers spend on themselves or with others is affected by the temporary change in their state of power. The initial experiments (1, 2 and 3) present empirical evidences that those individuals experiencing a state of power spend more Money on themselves in relation to the others, while those in a state of lacking power spend more money on others in relation to themselves.

For example, in the experiment 1 the participants received 15 dollars to participate in the study with design 2 (*power*: low vs. high) vs. 3 (*recipient*: own vs. other vs. no specification) vs. 2 (*object*: cup vs. t-shirt) factorial design. The procedures were held at a lab. The power was

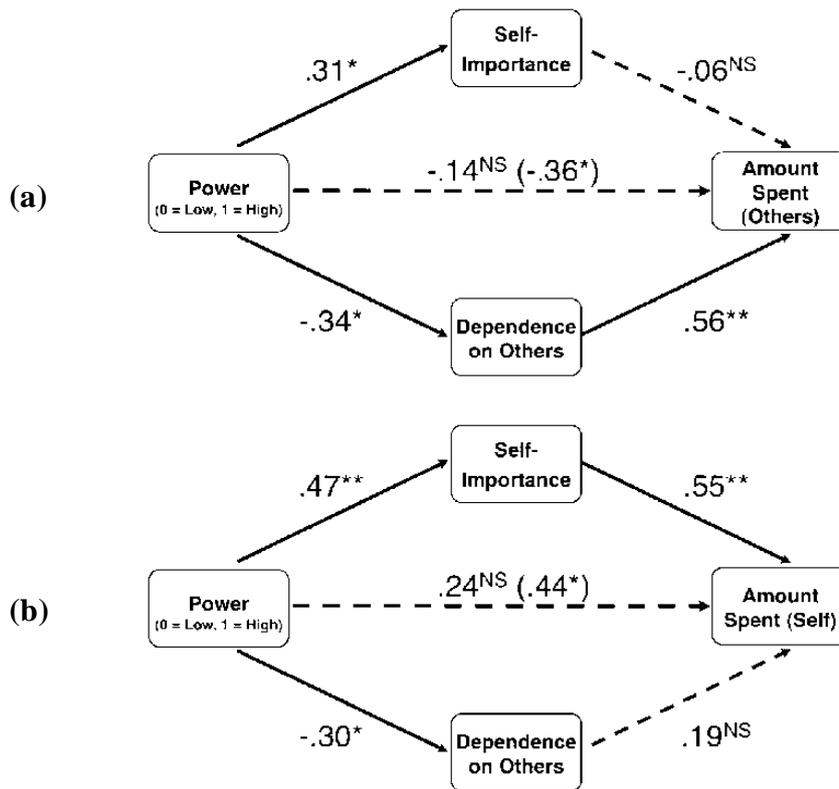
manipulated through an activity in which the participants were supposed to remember an event in which they felt they had power vs. had no power. After that, the participants received instructions to do bids in an auction of products (cup vs. t-shirt) in which the real price of the product was not announced. The participants would only win the auction if the bid given were above the real price of the product, in which the value paid would begin from the value received to participate in the experiment. If the bid were lower than the reserve value of product, the participant would miss the auction but would keep the money for participating. The researchers also manipulated if the sales of the auction would be given to the participants themselves vs. another person vs. no specification.

The results presented main effect of the type of object in which the participants valued more the t-shirt ( $M = \$10,07$ ) than the cup ( $M = \$7,85$ ;  $F(1, 114) = 26,52$ ;  $p < 0,001$ ). There was a significant interaction between the power and the final recipient on how much the participants offered in a bid for the object ( $F(2, 114) = 12,54$ ,  $p < 0,001$ ). Concerning spending on themselves, the participants, when in high power condition, spent more on the bids of the items ( $M = \$12,08$ ) compared to the condition of low power ( $M = \$6,49$ ;  $F(1, 114) = 17,63$ ;  $p < .001$ ). In contrast, in the condition of spending with others, the participants in the low power condition spent more to buy the items ( $M = \$10,81$ ) than the participants in the high power condition ( $M = \$7,10$ ;  $F(1, 114) = 7,77$ ;  $p < .01$ ). When the recipient was not explicitly informed there was no

difference between the bids of the participants either for the low power conditions ( $M = \$8,83$ ) or for the high power ( $M = \$8,44$ ;  $F < 1$ ).

These results describe a moderation effect between the final recipient and the power of the individual on the amount spent on the individual itself vs. others. This study type fits the type of research which involves moderation, such as the one presented in section 2. The final experiments (4 and 5) of Rucker, Dubois and Galinsky (2011) extend this assessment towards a process or mediation, presenting the mechanisms responsible for this type of behavior. For the authors this effect occurs because the power and the lack of it affect the utilitarian psychological assessment of the individual itself vs. others and this affects the assessment of the monetary allocation of own spending vs. in others. This assessment of own importance vs. dependence of others characterizes the two mediating mechanisms proposed by the authors. The Figure 6 shows the double mediation model presented by the authors.

These mediators are tested, for example, in the experiment 4, also carried out at this lab. In this, the participants were instructed to participate in a puzzle activity in a Chinese *tangram* style, constituted by blocks, in which they would take the role of boss vs. employee, being the manipulation of power in a single factor study. The second task (not related) involved the amount the participants would spend in a bowl of sweets for themselves or for other people, as well as the importance given to themselves and dependence of others.



**Figure 6 - Influence of Power on the Amount Spent (own vs. others) mediated by Own Importance and Dependence of Others**  
 Source: Rucker, Dubois and Galinsky (2011)

The results of interaction between the power and the recipient on how much the participants would spend on the bowl of sweets was replicated as well as in the experiment 2. However, more relevant, in the case of the experiment 4 was the mediation test. According to Rucker, Dubois and Galinsky (2011) what was expected was that the differences in spending more on themselves or on others due to power would jointly or in a different way mediated by the importance given to themselves and the dependence of others. As the amount spent on themselves and on others are two distinct dependent variables, two mediation models were necessary for the statistical test.

Firstly, the Figure 6a shows the assessment model for spending on others. The analysis showed that the power predicts the dependence of others ( $\beta = -0,34; t(44) = 2,46; p = 0,02$ ) and own importance ( $\beta = 0,31; t(44) = 2,24; p = 0,03$ ). According to the predictions, only the direct effect of the dependence of others preceded the amount spent with others ( $\beta = 0,56; t(44) = 4,60; p < 0,001$ ), while the own importance did not present significant effect on the amount spent with the others ( $\beta = -0,06; t(44) = -0,47; p = 0,64$ ). The analysis also showed that the power no

longer influenced the spending with others in the presence of the mediators ( $\beta = -0,14; t(44) = 1,16; p = 0,25$ ). The results of the indirect mediation effects via *bootstrapping*, which consider the confidence intervals (CI) at 95% showed that no null effects or zero were found in the intervals for the power on the amount spent with others, via the mediator dependence of others (95% lower CI = -0,371 and upper CI = -0,049), which confirmed the mediation to this path. The indirect effect of power, on one hand, on the amount spent with others, via mediator own importance did not present any significance, with the change of signal and consequent null effect in the confidence intervals CI 95% lower and upper (95% CI = -0,130 to 0,050).

After this, the Figure 6b shows the mediation assessment for the amount spent with the individual itself as a function of the power. again, the power was considered precedent to the dependence of others ( $\beta = -0,30; t(44) = 2,16; p = 0,03$ ) and the own importance ( $\beta = 0,47; t(44) = 3,59; p < .001$ ). Consistent with the supposition of the authors, only the direct effect of own importance on the amount spent for itself was significant ( $\beta = 0,55; t(44) = 4,45; p < 0,001$ ) with the dependence of others on the amount spent with one's

own not being significant ( $\beta = 0,19$ ;  $t(44) = 1,69$ ;  $p = 0,10$ ). Besides this, the analysis showed that the effect of power on the amount spent with its own as non significant ( $\beta = 0,24$ ;  $t(44) = 1,9$ ;  $p = 0,06$ ) in the presence of the mediators. The indirect effect assessment via *bootstrapping* of the power with own spending, via mediator, was seen as significant only for the own importance (95%  $CI = 0,098$  to  $0,467$ ), but not for the dependence of others (95%  $CI = -0,186$  to  $0,001$ ).

The results explored by the authors, show the several ways of application of the mediation models. It is important to reinforce that different from the moderation which uses graphics from the moderation function, the most usual way of presenting the mediation is using Figures which illustrate the process, such as the case of the Figure 6. Besides this, in the case of the example study, the initial experiments showed a moderation effect and later a mediation effect. This is not always the narrative of experimental studies on consumer behavior. Although it is common to find studies which assess moderations and afterwards mediations. Studies only with moderations or only with mediations are also usual in the literature.

There are still some events in which the assessments of moderation and mediation models may become a little obscure for the researchers and some misunderstandings may occur. Na example of this is the contradiction between what the role of a moderator and of a mediator are, specially when they are joined in more complex models of consumption such as in the case of mediated moderations and moderated mediations. The definition and forms of using each of these models will be discussed in more details in the next topic which focuses on the conditional process analysis.

#### 4 CONDITIONAL PROCESS ANALYSIS

To understand what a conditional process is and how theoretical propositions and empirical tests can be made for these types of models, it is necessary to, before that, retrieve the concept of moderation, mediation and after that understand what the mediated moderation and the moderated mediation are. The terms process, mediation and indirect effect will be similarly used with respect to the relation between an independent variable  $X$  and dependent  $Y$  through a mediating variable  $M$ . In the same way the terms moderation or conditional effect will be used with respect to the moderation effect of  $W$  on the relation between the independent variable  $X$  and dependent  $Y$ .

As presented in the section 2 of this article, a moderating variable can be defined as a variable  $M$  which influences the relation between two other variables, the independent  $X$  and dependent  $Y$ . The moderation is also assessed in terms of interaction.

The mediation, on the other hand, approached in section 3, can be defined as a variable  $M$  which accounts indirectly the effect between two variables, the independent  $X$  and dependent  $Y$ . The mediation is also assessed in terms of process.

A conditional process can be defined as the combination between a mediation (unconditional process) and a moderation (conditional), that is, one mediation or process conditioned to a moderation, or one moderation or condition which occurs through a mediator or process (Preacher, Rucker & Hayes, 2007; Preacher & Hayes, 2008). For the authors, a conditional process may occur if the indirect effect on the dependent variable through the mediator ranges according to the values of the moderating variable. In the assessment of the conditional processes it is important to highlight the difference between mediated moderation and moderated mediation. The first refers to an interaction effect of two variables, the independent  $X$  and the moderating  $W$  on a third the dependent  $Y$ , which occurs indirectly through a mediator  $M$  (Preacher & Hayes, 2008). In other words, a simple moderation as described in section 2, presents its effect indirectly through another mediating variable. In contrast, the mediated moderation refers to the moderation  $W$  of an indirect effect of the independent variable  $X$  on the dependent  $Y$  through a mediating variable  $M$  (Preacher & Hayes, 2008). That is to say, a simple mediation as described in section 3 receives the moderation from another variable.

Hayes (2009) states that the difference between the moderated mediation and the mediated moderation is only interpretative and theoretical, and the statistical models are equivalent. The author states that in the moderated mediation, the focus is to estimate the indirect effect of the product of the independent variable and of the moderator on the dependent variable through a mediator, while in the mediated moderation, the interpretation is directed towards the estimates of the indirect conditional effects of the independent variable on the dependent variable through a mediator for the mediator values. In terms of deduction of hypotheses this distinction is relevant as the interpretation of the difference occurs in the theoretical level. Then, it is important to understand that these mechanisms are related to execute the deductive process in a consistent way.

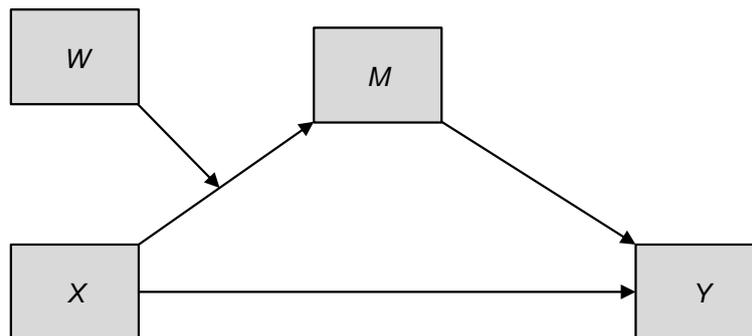
Despite the terms mediated moderation and moderated mediation are commonly found in the literature (*e.g.* Baron & Kenny, 1986; Zhao, Lynch & Chen, 2010; Preacher, Rucker & Hayes, 2007), with the term signed by James and Brett (1984), Preacher, Rucker and Hayes (2007) Hayes (2009) and Hayes (2013) prefer to call these types as modeling techniques of conditional processes. Conditional processes exactly because the models of statistical analysis are the same and the characteristic process of moderation and mediation so traditional in

experiments can be joined in several ways always with a mediation process with at least one mediator and, at least, one moderation.

The idea of joining the moderation and the mediation is not new (e.g. Judd & Kenny, 1981; Kraemer, Kiernan, Essex & Kupfer, 2008). Historically, it was used as an extension of casual strategies (Baron & Kenny, 1986; Edwards & Lambert, 2007). Preacher, Rucker and Hayes (2007) were the first ones to define the concept of indirect conditional effect or conditional process, in which they classify as conditional effect for the values of at least one moderator. Compared with the regression analysis and the analysis of variance, commonly used to test moderation hypothesis, the analysis of how much an indirect effect ranges (mediation) according to a not so recurring moderator, even if intuitively it may be suggested that mediated moderations are probably a quite common phenomenon in the consumer behavior both empirically and theoretically (Zhao, Lynch & Chen, 2010). According to Preacher and Hayes (2008), as more theories are explored in several fields of sciences, in order to include interaction effects, model which incorporate both mediations and moderations tend to increase their frequency.

In consumer behavior, the studies with this type of modeling have increased significantly recently (e.g. study 4 by Di Muro & Noseworthy, 2013 and study 4 by Duclos, Wan & Jiang, 2013), justified by the argument that the phenomena of the discipline are complex due to its interaction with the consumer environment. Contingential factors or boundary conditions may significantly change the traditional models making them more interesting (Preacher & Hayes, 2008; Hayes, 2013). In Brazil examples of studies can also be checked with these modeling types (e.g. Korelo, 2013; Prado, González, Mantovani & Korelo, 2014).

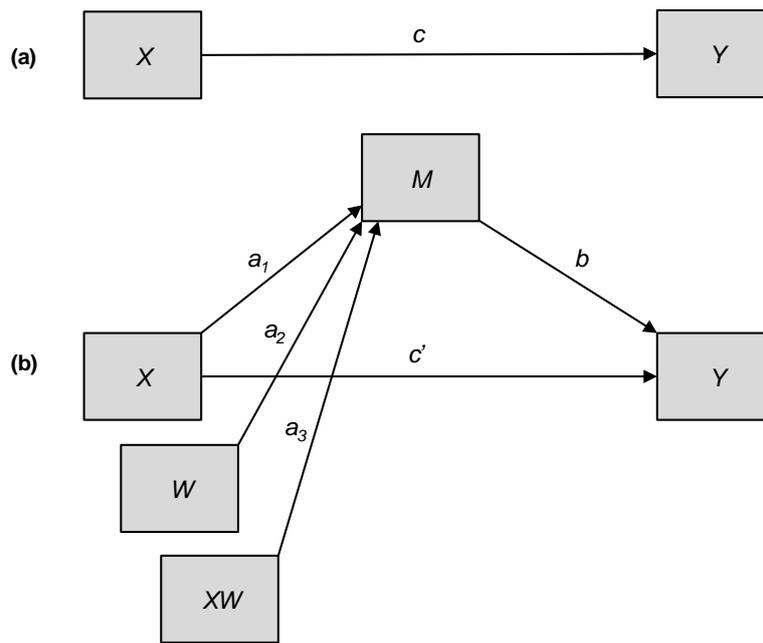
Figure 7 presents one of the forms of conceptual model of conditional process. A basic model is composed by an independent variable ( $X$ ), a dependent variable ( $Y$ ), by at least one mediating variable ( $M$ ) and by at least one moderating variable ( $W$ ). Most of the conditional process models focus on estimating the interactions between the moderator and the paths which define the conditional indirect effects on the dependent variable (Preacher, Rucker & Hayes, 2007; Hayes, 2013) and the moderators can be either continuous as well as categorical variables.



**Figure 7-** Conceptual Model Example of a Conditional Process  
Source: Hayes (2013)

The model of the Figure 7 is called conceptual as it proposes the theoretical relations between the variables to be analyzed. For the understanding and assessment of all the combinations

of paths or relations existing between the variables, the assessment of the statistical model described in Figure 8 is necessary.



**Figure 8 - Statistical Model of Conditional Process**  
Source: Hayes (2013)

Like in the mediation, there are two distinct paths by which the independent variable *X* may influence the dependent variable *Y*. The Figure 8b illustrates such paths, where the letters *a*, *b* and *c* represent the corresponding effect to each of the relations. When the empirical test of the conditional model is carried out, the direct and indirect effects should be considered (Figure 8b), as well as the total effect of the model (Figure 8a). To derive these effects, the components which constitute the indirect effects must be estimated, in other words, the effect of *X*, *W* and *XW* (interaction) in *M*, as well as the effect of *M* on *Y* (Hayes, 2013). Again, two linear models are necessary, being one for each consequent variable. This statistical diagram is presented in the equations 4 and 5:

$$(4) \quad M = i_1 + a_2X + a_1W + a_3XW + e_M$$

$$(5) \quad Y = i_2 + c'X + bM + e_Y$$

Where  $i_1$  and  $i_2$  are the regression intercepts,  $e_M$  and  $e_Y$  are the errors to estimate *M* and *Y*, respectively, and  $a_1$ ,  $a_2$ ,  $a_3$ ,  $b$ , and  $c'$  are the regression coefficients given the preceding variables of the model.

#### 4.1 Direct, Indirect Effect and Total Effect of the Conditional Processes

The total effect of *X* in *Y* given the presence of *W* is represented by  $c = c' + b(a_1 + a_3W)$ , according

to the Figure 8a. This effect is the sum of the direct and indirect effects, decomposed in the Figure 8b. The direct effect can be defined as the effect of *X* in *Y* when the mediator *M* is present in the model for the *W* conditions. This effect is given by  $c'$ . As the indirect effect is the effect of *X* accounted by the mediator *M* for conditional values of the moderator *W*. This effect is given by the value of  $b(a_1 + a_3W)$ . Similar to what happens in the simple mediation, the indirect effect is the difference between the total effect and the direct effect.

#### 4.2 Approaches for the Calculation of Conditional Processes

For the assessment of conditional process models Iacobucci, Saldanha and Deng (2007) suggest the use of assessment of paths through structural equation models (SEM). For the authors this technique is more adequate as it considers the assumptions of multivariate analysis found in the assessments of correlation matrices. However, due to the tradition that experimental studies in consumer behavior have the premise of manipulated variables in which the influence of paths tends to be individually assessed (Baron & Kenny, 1986), the model of conditional process suggested by Preacher, Rucker and Hayes (2007) and Hayes (2013) is more easily adjusted to this tradition and consequently has been more frequently used than the models of structural equations.

As already described in the mediation analysis, the technique uses *bootstrapping* approach and presupposes that the distribution ( $a_i * b$ ) of the

indirect effect is not mandatorily normal. In this sense, the technique uses the calculation of the confidence interval *CI* of upper and lower 95% (Shrout & Bolger, 2002) as an estimate of the indirect effect value (Preacher, Rucker & Hayes, 2007). There can be no presence of the null effect between the negative and positive interval. As described in the mediation section, this technique generates an empirical representation of the sample distribution through sub samplings, generating *k* estimates of the indirect effects. However, for conditional process models these effects are conditioned to specific values of the moderator. These values are -1 *D.P.* (standard deviation), average and +1 *D.P.* when the variable is quantitative (Hayes, 2013). Preacher, Rucker and Hayes (2007) defend this technique in relation to the test of the mediation stage by the theory of normal distribution (e.g. mediation of Baron & Kenny, 1986), because as it occurs in the simple mediation, the conditional models are also mediation models, more specifically submitted to moderation values and similar to the simple mediation models, the distributions of the indirect effect regressions ( $a_i * b$ ) might not be normal.

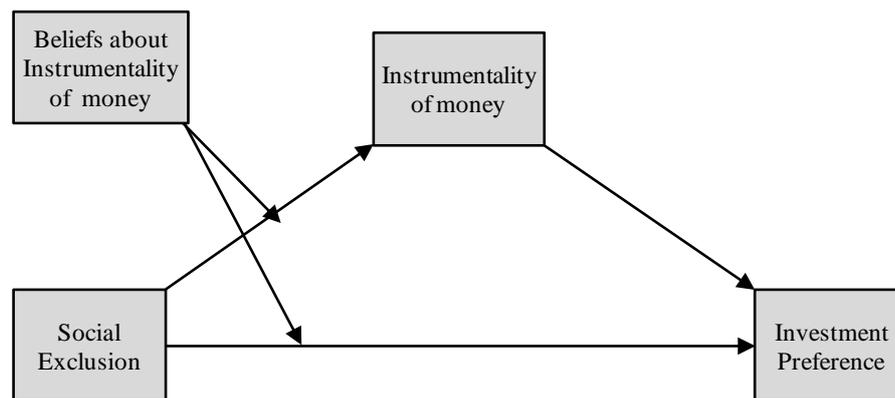
To perform a conditional process test, simultaneous regressions of the direct and indirect effects are conducted for values of at least one moderator. Depending on the complexity of the proposed model and the number of moderators and mediators the regressions may have more variables. For the example of the figure 8b the direct effect is estimated by the effect of the independent variable on the dependent. The indirect effect, on one hand, is estimated by the effect of the independent variable on

the dependent, through the mediating variable considering values or conditions of a moderator (Preacher, Rucker & Hayes, 2007).

In practical terms, the macro PROCESS for SPSS can be used, with at least 5000 sub samples as recommended by (Hayes, 2013). In relation to the analysis of paths of conditional processes, Zhao, Lynch and Chen (2010) and Hayes (2013) argue that because of the complexity of the types of theoretical associations between the variables, a conditional model may present significant total, direct and indirect effect. However, partial models, such as models that only present significant indirect effects, should be also considered valid. To do this, all that is needed is to have technical support for the proposed relation. The authors reinforce that, exactly, the indirect effects for moderator values are the associations of bigger interest when these models are under assessment.

### 4.3 Examples of Conditional Process

An example of conditional process with theoretical proposition of the moderated mediation is the study presented by Duclos, Wan and Jiang (2013) in which the effect of the feeling of social exclusion (independent *X*) increases the Money instrumentality in the everyday life (mediator *M*) which consequently, potentializes the risk and the return on investment financial decisions (dependent *Y*). The authors argue that if the consumers have a decrease in their belief that the money can help (moderator *W*), the indirect effect is reduced. Figure 9 presents the theoretical model proposed by the authors.



**Figure 9** - Model of Influence of Social Exclusion on Investment Preferences mediated by the Instrumentality of money and conditioned to Beliefs about Instrumentality of money.

Source: Duclos, Wan and Jiang (2013)

To assess the conditional process model proposed in the Figure 9, Duclos, Wan and Jiang (2013) performed a number of experiments partially testing the model and later the complete model. In the

experiment 1, for example, there was a test whether the social exclusion leads to more risky investment decisions, but potentially more profitable. To do this the participants were invited to play an *on-line* betting

game called Cyberball, with the purpose to manipulate the social exclusion (inclusion vs. exclusion) in a single factor study. To assess the dependent variable of financial risk (investment preferences), in the sequence the participants were asked to participate in a betting lottery with two options (A:safe vs. B:risky) having to choose in a scale from 1 (strongly prefer option A) to 8 (strongly prefer option B). The results showed a main effect of the social exclusion on the investment option in which the participants in the condition of social exclusion preferred a safer option ( $M = 4,23$ ) in relation to the participants in the social inclusion option ( $M = 2,79$ ;  $F(1,57) = 6,051$ ;  $p < 0,02$ ). For more detailed information check the article.

Advancing in the assessment of the proposed model, in the experiment 3 the authors tested the role of the money instrumentality as mediating mechanisms of the relation between the social exclusion and type of investment. Again the experiment presented 2 experimental conditions (*social*: exclusion vs. inclusion) of single factor. The participants were instructed in an activity in which they had to remember a social experience in which they felt excluded vs. included. To measure the dependent variable the same procedure of the experiment 1 was used. Besides this, the participants were asked to assess their opinion concerning the money instrumentality (mediating variable).

The results of this study replicated the main effect reached in the experiment 1, in which the participants in the social exclusion condition mainly preferred the safe option ( $M = 3,44$ ) in relation to the participants in the social inclusion option ( $M = 2,17$ ;  $F(1,34) = 4,59$ ;  $p < 0,04$ ). To assess if the social exclusion effect concerning the decision of investing in more risky options is accounted by the way the participants think about how much the money can help in their daily lives (mediator: money instrumentality) the authors made a mediation analysis using the procedure of Baron and Kenny (1986) complemented by Preacher, Rucker and Hayes (2007). The groups were codified as 1 = social exclusion and 0 = social inclusion. In this sense any regression value refers to the social exclusion in relation to the social inclusion.

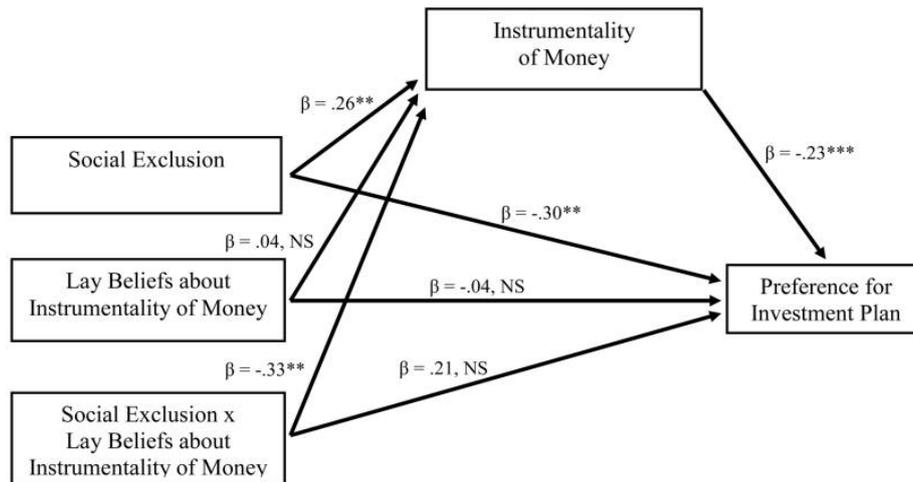
The regression results showed that the social exclusion increases the propensity in investing in more risky options ( $\beta = 0,35$ ;  $t(34) = 2,14$ ;  $p = 0,04$ ), replicating the main effect already shown by the authors. Besides this, the social exclusion also showed the influence of the money instrumentality, in which

the participants in the condition of exclusion see the money as more instrumental than the participants in the condition of social inclusion ( $\beta = 0,34$ ;  $t(34) = 2,13$ ;  $p = 0,04$ ). The money instrumentality also influences the preference of investment in a positive way ( $\beta = 0,46$ ;  $t(34) = 2,98$ ;  $p < 0,01$ ). Finally, the authors showed that the social exclusion started to lose the effect on the preference of investment ( $\beta = 0,21$ ;  $t(33) = 1,32$ ;  $p = 0,19$ ) while the presence of the mediator money instrumentality was significant ( $\beta = 0,39$ ;  $t(33) = 2,36$ ;  $p = 0,03$ ). The assessment of the confidence interval CI of 95% of the indirect effect was significant and different from zero for the lower interval ( $CI = 0,05$ ) and upper interval ( $CI = 0,91$ ). Such results show the mediating role of the money instrumentality in relation to social exclusion and preference of more risky investment.

Finally, in the experiment 4 the authors tested if this same type of rationalization concerning the money instrumentality were changed, the results remained equivalent. The argument of the authors is that if the socially excluded individuals changed their beliefs that the money does not help in terms of better results in life, the preference for higher risk in financial decisions would be inhibited. This rationalization can be visualized in the Figure 9 which shows the study complete model. To test such relations the authors performed an experiment of design 2 (*social*: inclusion vs. exclusion) vs. 2 (*beliefs concerning the money instrumentality*: reference vs. non instrumental) between-subjects.

The manipulation of the social exclusion was carried out using the task of remembering the social situation, similar to the study 3. To manipulate the belief in the money instrumentality the participants were asked to review a report suggesting that learning a foreign language could improve their academic results (condition reference) or that often the money was mistakenly assessed as it proved bigger freedom and life control (non instrumental condition). Concerning the intention of investment (dependent variable) and money instrumentality (mediating variable) the participants assessed conditions similar to previous experiments.

The results of the conditional process model can also be seen in Figure 10. As the focus is to assess the conditional model, these results will be presented in details. For further information of the other statistical results check Duclos, Wan and Jiang (2013).



**Figure 10** - Statistical Model of the Experiment 4 with Conditional Process  
Source: Duclos, Wan and Jiang (2013)

As conceptually described by Preacher, Rucker and Hayes (2007), a conditional process model presents a total effect, a direct effect and an indirect effect. For the assessment of total effects the authors performed the regressions involving the preferences of investment and the three social exclusion predictors (codified as 1 = exclusion and 0 = inclusion), beliefs concerning the money instrumentality (codified as 1 = non instrumental and 0 = reference) and the interaction between both. The techniques of Baron and Kenny (1986) and Preacher, Rucker and Hayes (2007) were joined. Significant main effect of the social exclusion ( $\beta = -0,36$ ;  $t(124) = 3,06$ ;  $p < 0,01$ ) and of interaction ( $\beta = 0,28$ ;  $t(124) = 1,92$ ;  $p = 0,057$ ) were noticed, but no main effect of beliefs on the money instrumentality ( $\beta = -0,05$ ;  $t(124) = -0,41$ ;  $p = 0,68$ ). Such results are consistent with the authors' proposal.

The results of the regressions referring to the indirect effect can be visualized in Figure 10. For this effect to be considered significant, it is expected that the significant interaction effect presented in the total effect ( $\beta = 0,28$ ) is no longer significant and the effect is transferred to the preferences of investment through the mediator money instrumentality. The regressions of the money instrumentality in relation to either predictors and the regression of the preferences of investment in relation to the money instrumentality provide evidences that the indirect effect is significant. Firstly the regressions of the money instrumentality. Significant main effect for exclusion ( $\beta = 0,26$ ;  $t(124) = 2,15$ ;  $p = 0,04$ ) and of interaction ( $\beta = -0,33$ ;  $t(124) = -2,23$ ;  $p = 0,03$ ) were found, but no main effect of beliefs on the money instrumentality ( $\beta = 0,04$ ;  $t(124) = 0,35$ ;  $p = 0,72$ ). Secondly, the regression of the preferences of investment in relation to its predictor money instrumentality. A significant negative effect was noticed ( $\beta = -0,28$ ;  $t(126) = -3,27$ ;  $p < 0,001$ ).

For the assessment of the direct effect the authors tested the regressions of preference of investments in relation to their predictors social exclusion, beliefs concerning the money instrumentality and its interaction, when the mediator is present. The results can also be visualized in Figure 10. The most relevant data show that the effect of the mediator money instrumentality on the dependent variable preferences of investment is significant ( $\beta = -0,23$ ;  $t(123) = -2,64$ ;  $p = 0,009$ ), while the interaction effect of the dependent variable social exclusion and moderator beliefs in money instrumentality is no longer significant ( $\beta = 0,21$ ;  $t(123) = 1,41$ ;  $p = 0,009$ ). The calculation of the indirect effect via confidence interval *CI* 95% showed that this effect is significant and different from zero (*CI* 95% ranging from 0,01 to 0,96).

How is it possible to interpret such results? As a key element of the analysis it should be observed that the interaction total effect (independent and dependent variable) does not present significant effect on the dependent variable in the presence of the mediator. The data from the Figure 10 show that this occurs, in which the interaction indirect effect is significant and the interaction direct effect is not. Limiting the other effects of smaller interest, this shows that the mediated moderation (conditional process) occurs. In the case of the explored example, the mere manipulation of the moderator making the participants believe that the money does not help in the aspects of control of life makes the propensity to invest in a more risky way decrease.

It is important to have in mind that not all research developments involving conditional processes lead to this sequence of development of the experiments. The way the study will develop will depend on the proposition and on the theoretical script

which is expected to be tested. It is possible that more complex models of conditional processes are executed in a first experiment and later the other experiments test more peculiar aspects of the theory.

#### 4.4 Alternative Forms to Present Conditional Processes

As the conditional process models present a reasonable volume of statistical information it is suggested that for its assessment some elements are reported in a way that it does not compromise the interpretation of empirical data in relation to the proposed hypotheses. Using conceptual models such as the one in Figure 10 can always facilitate the reading and the interpretation of the results. However some researchers prefer alternative forms to present their research data, mainly when the moderators are quantitative. Two forms are suggested by Hayes (2013) which are descriptive tables with the regression data of the models and possibly the total, direct and indirect effect of the final assessment and also graphics which show the function of tilting of the indirect effect of the independent variable on the dependent variable through the mediator and in moderating conditions.

Table 1 presents data taken from Hayes (2013), based on the study of Garcia et al. (2010), which mentions an example of conditional process model in which the moderation of *W* occurs both in relation to *X* as well as *M* (Hayes, 2013 - Model 8). The example found in the table concerns the sexual discrimination at the work environment. The

participants read a scenario in which a lawyer was protesting with her workmates for having lost a promotion to another lawyer who was less qualified but who was male. The independent variable *X* called PROTEST refers to the protest of the lawyer in the situation. This variable was manipulated with 1 = protest conducted and 0 = protest not conducted (which implies that the lawyer remained quiet and did not make any protest). The dependent variable *Y* called LIKING refers to how much the participants believe that the workmates assessed the lawyer's attitude. The mediating variable *M* called RESPAPPR refers to the perceived adequacy of the lawyer's attitude. High scores mean a bigger perception that the answer is more appropriate. Finally the variable SEXISM refers to how much the sexual discrimination is spread in the society and it was the moderating variable *W*. For such measuring high values mean that the sexual discrimination is widely spread.

Table 1 presents the coefficients of the paths of the conditional process model. This form of illustrating the effects of the paths may facilitate the reading of these types of models. The letters listed in the table (*a*, *b*, *c* and *i*) represent the regressions paths according to each proposed model (for example the conceptual model of the Figure 8b). The interpretation is done through the assessment of two regression models. One for the mediating variable *M* and other for the dependent variable *Y*, as the model presents both variables as consequent (arrows reaching).

**Table 1 - Model Coefficients for the Conditional Process Model**

Antecedent	CONSEQUENCES									
	Model Mediador <i>M</i> (RESPAPPR)					Model Dependent <i>Y</i> (LIKING)				
		Coef.	S.E.*	<i>p</i>		Coef.	S.E.*	<i>p</i>		
<i>X</i> (PROTEST)	<i>a</i> <sub>1</sub>	-2,687	1.452	0,067		<i>c'</i> <sub>1</sub>	-2,808	1,161	0,139	
<i>M</i> (RESPAPPR)		-	-	-		<i>B</i>	0,359	0,071	< 0,001	
<i>W</i> (SEXISM)	<i>a</i> <sub>2</sub>	-0,529	0,236	0,027		<i>c'</i> <sub>2</sub>	-0,282	0,190	0,139	
<i>X</i> x <i>W</i>	<i>a</i> <sub>3</sub>	0,810	0,282	0,005		<i>c'</i> <sub>3</sub>	0,543	0,230	0,020	
Constant	<i>i</i> <sub>1</sub>	6,567	1,210	< 0,001		<i>i</i> <sub>2</sub>	5,347	1,061	< 0,001	
		<i>R</i> <sup>2</sup> = 0,296					<i>R</i> <sup>2</sup> = 0,283			
		<i>F</i> (3, 125) = 17.534, <i>p</i> < 0,001					<i>F</i> (4, 124) = 12.255, <i>p</i> < 0,001			

\*S.E. = Standard Error

Fonte: Hayes (2013)

In terms of results it is noticed that both models are significant due to the *p*-value in the last line of the table. For the model in which the regressions are considered for RESPAPPR, it can be seen that there is negative main effect of the SEXISM ( $\beta = -0,529$ , *p* =

0,027) and of positive interaction *XW* ( $\beta = 0,810$ , *p* = 0,005). For the regression model LIKING, the table shows that there is positive main effect of RESPAPPR ( $\beta = 0,359$ , *p* = 0,005), and an also positive interaction effect *XW* ( $\beta = 0,543$ , *p* = 0,020). In this sense, the

interaction  $XWA$  of this last model can be reported as the interaction of highest interest of the total effect of the model. Besides this, it is noticeable that the mediator  $RESPAPPR$  presents evidences that it measured the relation between  $X$  and  $Y$  for  $W$  values.

For assessment of the direct and indirect effects of the conditional process models. The example

of the same research illustrated in the table 2, can help researchers to report their results of the effects of these types of models. It is expected that the indirect effect is significant for the moderator ranges and that the direct effect tends to be non significant. This shows that the total effect of interaction significant  $XW$  in table 1, starts to be mediated.

**Table 2 - Model Coefficients for the Conditional Process Model**

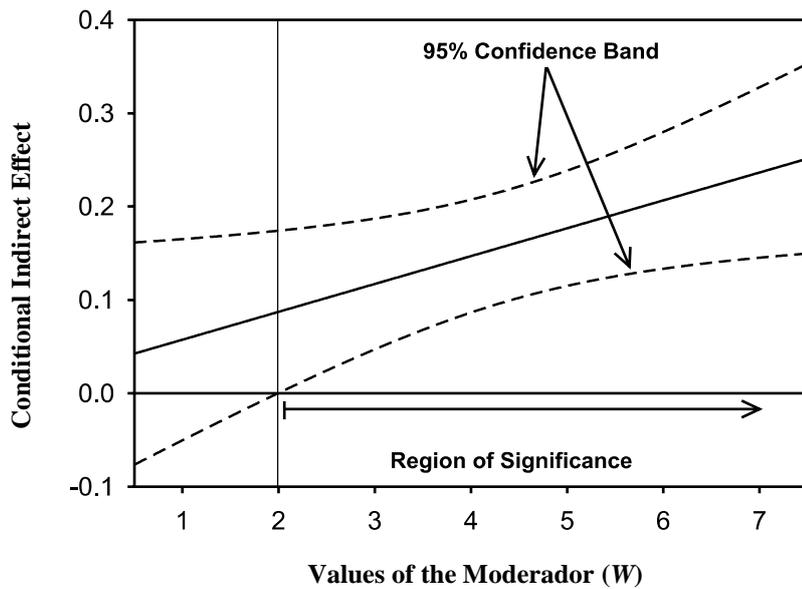
<i>W</i>	INDIRECT EFFECT			<i>W</i>	DIRECT EFFECT	
	<i>Coef.</i>	<i>CI inf.</i>	<i>CI Sup.</i>		<i>Coef.</i>	<i>CI inf.</i>
4,12	0,234	-0,007	0,564	-0,572	0,279	0,043
4,50	0,344	0,147	0,634	-0,366	0,226	0,108
5,12	0,525	0,308	0,828	-0,030	0,200	0,883
5,60	0,670	0,378	1,059	0,242	0,246	0,327
6.12	0,816	0,430	1,318	0,513	0,327	0,120

Source: Hayes (2013)

These tables are more summarized and present the direct and indirect effects of  $X$  on  $Y$  given the moderator values. The macro for SPSS (Model 8) provided by Hayes (2013) permits calculating these effects and provides the values range for the moderator  $W$  and its respective direct and indirect effects which can be reported in these types of tables. As already mentioned, the interpretation is the assessment of the lawyer's behavior, described by  $LIKING$  is due to  $SEXIM$  that is to say, due to how much the discrimination is spread. In this sense, the bigger the discrimination, the better its assessment by the workmates, as this is measured by how adequate her attitude is. It is important to highlight that for an indirect conditional value be considered significant there can be no change of signal or null effect within the lower and upper confidence interval  $CI$ . The only non significant region for the indirect effect described in table 2 is for the moderator  $W$  values = 4,12 in which the confidence intervals range from ( $CI$  95% = -0,007 to 0,0564).

Another form to present and assess the conditional indirect effect is the technique of significance regions Johnson-Neyman, recommended

by Jonshon, Neyman (1936) and Hayes (2013). This strategy does not require the selection of conditional arbitrary values from the moderator to investigate the indirect effect significance. The graphic presentation helps in the analysis of which are the significance regions of the indirect conditional effect. The macro PROCESS which can be used in the SPSS, developed by Hayes (2013), provides the significance values of the indirect effect to be used in the technique of significance region. The Figure 11 explores the indirect effect of the independent variable  $X$  on the dependent variable  $Y$  through the mediator  $M$  for the moderator  $W$  values. In the  $x$  axis ( $x$ ) we have the several levels of the moderator  $W$  and in the  $y$  axis ( $y$ ) there is the indirect effect on the dependent variable  $Y$ . This function must present a tilt different from "0". Besides this, the dotted lines represent the  $CI$  95% *bootstrapping* upper and lower of 95%, but there can be no effect "0" or change of signal in this interval. This effect can be checked in the Figure 11, being represented in the gray region, where the indirect effect of  $X$  on  $Y$  through  $M$  is positive for  $W$  values (values above, close to 2).

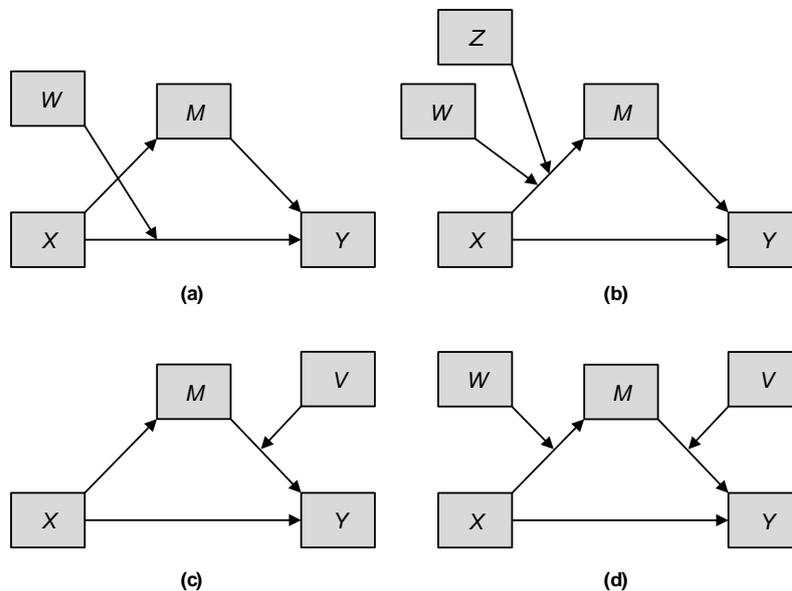


**Figure 11** - Example of the Conditional Process Effect Technique Johnson-Newman  
 Source: Preacher, Rucker and Hayes (2007)

**4.5 Alternative Models of Conditional Process**

The conditional process models presented in the previous sections are more commonly found in the literature. Somehow, simpler models are considered. Preacher, Rucker and Hayes (2007) suggest that there can be several combinations of conditional process

models with  $n$  mediators and/or  $n$  grouped moderators. Figure 12 explores some of these examples. For further details of all possibilities of combinations check Hayes (2013). The author provides a macro for SPSS which assesses the effects of several proposed models.



**Figure 12** - Examples of Conditional Process Models  
 Source: Adapted from Hayes (2013)

The Figure 12a for example, explores an alternative model in which the moderation  $W$  occurs only for the direct effect of  $X$  on  $Y$ , which also occurs in parallel the indirect effect through the mediator  $M$ .

The Figure 12b presents a model in which the indirect effect of  $X$  on  $Y$  through  $M$  is moderated by two variables  $W$  and  $Z$ . In this type of approach the direct effect is conditioned to values of an interaction in pairs

between  $X$  and  $W$ ,  $X$  and  $Z$ ,  $W$  and  $Z$  and also by a higher order group of interaction between  $X$ ,  $W$  and  $Z$ .

The Figure 12c presents a model in which the moderation of  $V$  occurs for the indirect effect of  $X$  on  $Y$  through  $M$ . However, different from the conceptual model expressed in Figure 12b, the moderation of  $V$  occurs after the mediation of  $M$ . This model can be seen as a moderated mediation and in this case the interaction occurs between  $M$  and  $V$  on  $Y$ . Finally, the model of the Figure 12d presents a theoretical proposal in which the indirect effect of  $X$  on  $Y$  mediated by  $M$  is moderated by  $W$  in the relation between  $X$  and  $M$  and moderated by  $V$  in the relation between  $M$  and  $Y$ . In this case it can be said that over time, in terms of processes the model is conditioned to  $W$  and previously to  $V$ .

Besides these models, Hayes (2013) presents a series of possible combinations to be made using the same technique. Instrumentally the application of these models under the statistical and computational point of view is simple. However, the difficulty concerning the usage of these models is in the component of the theoretical development, specially in the construction of the hypothetical relations between the variables. It is important to remember that to include each new variable in a given hypothetical model, the theoretical complexity is quite high, as each relation between the variables should be foreseen by the literature and, besides that, each effect should be strongly reasoned mainly in terms of the values of the conditions of the several moderators to be tested.

## 5 CONCLUSION

The techniques of analysis of mediation, moderation and conditional process characterized by the assessments of mediated moderation and moderated mediation are shown as a group of tools which boosts the academic investigations in relation to the phenomena of consumer behavior. In the last few years the number of researches which include these types of models increased significantly, especially due to the help of the developed computational techniques. However in the Brazilian context these techniques are not yet explored so significantly. Few studies explore hypothesis which consider indirect conditional effects. The purpose of the present article was to clarify some of the basic components of moderation, mediation and conditional process models with the intention to stimulate the development of new researches that consider such models.

It is important to reinforce that for the development of these models the assumptions of each type of the phenomenon to be explored in terms of consumer behavior are clear for the researcher. Especially more complex models as in the case of conditional process, demand a clear understanding of

the theoretical relations between the variables to be studied so that the hypotheses to be empirically tested are covered in the literature. If that does not happen, the use of moderation, mediation and conditional process tools may take a dangerous place in a scientific point of view in which the propositions are explored more empirically than theoretically and the use of the tools is not the theoretical exploration but the end of the research itself. Thus, a deep knowledge of the literature is necessary in order to propose a coherent conceptual model. According to what was pointed out in the introduction of the present work, the researcher needs to know *a priori* which type of effect occurs and how the variables interact.

A deeper study concerning the methodological components and the theoretical relations brings an opportunity of development for the researcher and may arise a good development in the empirical field. In this sense a number of new opportunities involving more complex consumption phenomenon can be explored by assessments of conditional process. It is expected that in the next few years these types of research are more recurrently used in the Brazilian context.

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