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IDENTIFICATION AND ANALYSIS OF MODERATOR VARIABLES

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Abstract

Although the concept of moderator variables has been extensively used in marketing-related studies, much confusion exists as to how they are defined and identified. The purpose of this paper is to alleviate this confusion by presenting a typology of moderator variables along with a framework for identifying their presence and type. Simulated data are used to illustrate and validate the proposed framework.

IDENTIFICATION AND ANALYSIS OF MODERATOR VARIABLES

Introduction

The classic validation model in consumer related research attempts to determine the degree of association between a predictor variable or a set of predictor variables and a criterion variable. Although this model has been shown to be useful in many instances, results from a variety of studies as well as various consumer behavior models appear to indicate that there are circumstances under which the classic model is not effective in providing a complete understanding of the phenomenon studied. More specifically, examples exist in which the predictive efficacy of an independent variable and/or the form of the relationship may systematically vary as a function of some other variable(s). For example, exogenous or situational variables posited in many behavioral models (e.g., Engel, Blackwell and Kollat 1978; Howard 1977; Howard and Sheth 1969) are hypothesized to influence classic validation models thereby providing greater insight into the phenomenon examined.

One approach which has been posited as an alternative to the classic validation model by Saunders (1956) in the psychological literature and used increasingly in marketing is the concept of moderator variables. A moderator variable has been defined as one which systematically modifies either the form and/or strength of the relationship between a predictor and criterion variable. As such, the concept of moderator variable holds important implications for understanding and predicting buyer behavior by helping to provide answers to such questions, among others, as (Zaltman, Pinson and Angelmar 1973, p. 165):

1. Are there unrelated independent variables that begin functioning at different points in time?
2. Are there independent variables that are related only at certain times and not at others?

Although most would agree that the concept of moderator variables is an important one, there exists substantial confusion as to what specifically is a moderator variable and how it operates to influence the classic validation model. For example, some researchers have stated that a variable is a moderator if it interacts with a predictor variable (Fry 1971; Horton 1979; Peters and Champoux 1979) irrespective of whether it, the hypothesized moderator variable, is a significant predictor as well. A second conceptual approach argues that a moderator may not be a significant predictor variable nor can it be related to other predictor variables (Cohen and Cohen 1975; Zedeck 1971). Finally, a third approach has ignored the interaction controversy by using an analytic procedure to examine differences between individuals grouped on the basis of some hypothesized moderator variable (e.g., Bennett and Harrell 1975; Ghiselli 1960, 1963; Hobert and Dunnette 1967). This "confusion" has made the comparability of results across studies difficult, at best. More importantly, because different approaches and/or definitions may be appropriate in some situations and not in others, the confusion has obscured the research results or has possibly produced misleading findings (Abrahams and Alf 1972a, 1972b; Dunnette 1972).

The purpose of this paper is to alleviate the confusion surrounding moderator variables by presenting the various types of such variables as well as the relevant methodological and theoretical issues. Basically, there are two types of moderator variables. Onetype influences the classic validation model by impacting the strength of the relationship and the second by modifying the form of the classic validation model. A typology which shows the difference between these two types of moderator variables which influence the strength or form of the classic validation model is presented along with a framework for determining the presence and type of moderator variable. Furthermore, simulated data is used to illustrate the framework.

Types of Moderator Variables

Moderator variables can be considered a subset of a class of variables termed, in the social sciences, "test" or specification variables. A specification variable is one which specifies the form and/or magnitude of the relationship between a predictor and criterion variable (Lazarsfeld 1955; Rosenberg 1968).[1] A typology of specification variables and hence moderator variables can be developed using two dimensions or characteristics. First, they can be classified based on the relationship with the criterion variable. That is, whether they are or are not related to the criterion variable. The second dimension is whether the specification variable interacts with the predictor variable. Such a typology of specification variables is provided in Figure 1.

Figure 1 about here

In the situation where the specification variable is related to the criterion and/or predictor variable but does not interact with the predictor (Quadrant 1), the variable has been referred to as an intervening, exogenous, antecedent, suppressor or additional predictor variable depending on what other characteristics it has. A detailed discussion of how these variables operate and methods for identifying them is provided by Rosenberg (1968). The focus of this paper is on variables in Quadrants 2 through 4. Variables in these quadrants have been referred to as moderator variables.

Conceptually, the variables in the three quadrants in Figure 1, identified generally as moderators, represent two types of moderator variables which differ with respect to whether they influence the strength or the form of the relationship in the classic validation model. The moderator variable shown in Quadrant 2 operates by modifying the strength of the relationship while those in Quadrants 3 and 4 influence the form of the relationship between the predictor and criterion variables.

Homologizer

The type of moderator which falls into Quadrant 2 influences the strength of the relationship, does not interact with the predictor variable and is not significantly related to either the predictor or criterion variable. In such a situation, it is posited that the error term is a function of the moderator variable. Therefore, partitioning the total sample into homogeneous subgroups with respect to the error variance should increase the predictive efficacy of the classic model for specific subgroups. This type of moderator can be more appropriately termed a homologizer variable.[2]

The concept underlying the moderator variable identified as a homologizer variable is that of partial variance (Ghiselli 1964). In order to conceptually illustrate the concept of partial variance assume the case of one predictor variable.[3] Furthermore, assume that the functional relationship between the criterion and the predictor variables for individual i is:

$$y_i = f_i(x_i) + \varepsilon_i \qquad (1)$$

where

y_i is the criterion variable, x_i is the predictor variable, and ε_i is a random error term with a mean of 0 and Var σ_i^2 and f_i is the functional relationship between y_i and x_i.

The strength of the relationship between x and y will depend upon the size of the error term.[4] The greater the error, the smaller the degree of relationship and vice versa. Now, if n_i pairs of repeated measurements for each individual are to be taken, then the total variance, $\sigma_{y_i}{}^2$, of the criterion variable for individual i is given by $\sum_{j=1}^{N}(y_{ij} - \sum_i y_{ij}/n_i)^2/n_i$ and the variance for the criterion variable after the predictor variable is held constant, or the effect of the predictor variable has been partialled out is given by:

$$\sigma^2_{y_i \cdot x_i} = \sum_{j=1}^{n_i}(y_{ij} - \hat{f}_i(x_{ij}))^2/n_i \qquad (2)$$

where $\hat{f}_i$ is an estimate of the function f_i.

The variance, given by Equation (2) can be considered to be an estimate of the variance of ε_i and is often called the partial variance because, as mentioned earlier, it represents the variance in the criterion variable after the effect of the predictor variable has been partialled out. Consequently, the proportion of the criterion variable's variance explained by the predictor variable is given by $(\sigma^2_{y_i} - \sigma^2_{y_i \cdot x_i})/\sigma^2_{y_i}$ OR $1 - \sigma^2_{y_i \cdot x_i}/\sigma^2_{y_i}$ and is referred to as Eta square. Eta square is a generalized measure of the strength of the relationship between the criterion and the predictor variable and the square root of Eta square is a generalized measure of the degree of relationship between the two variables.[5] The aggregate partial variance of all N individuals in the sample can be estimated by using Equation (2) and is expressed by:

$$\sigma^2_{y.x} = [\sum_{i=1}^{N} \sum_{j=1}^{n_i} (y_{ij} - \hat{f}_i(x_{ij}))^2]/N$$

<u>OR</u> $$\sigma^2_{y.x} = \sum_{i=1}^{N} n_i \sigma^2_{y_i.x_i} / \sum_{i=1}^{N} n_i \quad (3)$$

And Eta square is given by:

$$\eta^2 = 1 - \sigma^2_{y.x}/\sigma^2_y \quad (4)$$

where, σ^2_y is the total variance of y for all the individuals.

From Equation (3), it can be seen that the aggregate partial variance is a weighted average of the partial variance of each individual. Consequently, Eta square of the aggregate sample is also a weighted average and hence is a summary measure of the strength of the relationship (Equation (4)). If the function f_i for each individual is assumed to be linear, then the predictive validity (R^2) of the total sample will be a weighted average of the individual R^2s. Therefore, some individuals will have a higher R^2 than the total sample R^2 while others will have a lower one. Thus, if individuals are to be classified into subgroups on the basis of some variable, such that the error variance of each individual in the subgroup will be the same, then some groups will have higher predictive validity than the total sample while others will have a lower predictive validity. The variable used to form homogeneous groups, the homologizer, is deemed to be a moderator variable since it leads to different predictive validity coefficients between subgroups for the predictor variables (Ghiselli 1963; Zedeck 1971).

<u>Pure and Quasi Moderator Variables</u>

The second type of moderator variable is one which basically modifies the <u>form</u> of the relationship between the criterion and predictor variables and is represented by Quadrants 3 and 4 in Figure 1. Consider the following relationship between x and y:[6]

$$y = a + b_1x \qquad (5)$$

Further, assume that the form of the relationship represented by Equation (5) is a function of a third variable, z, expressed mathematically as:

$$y = a + (b_1 + b_2z)x \qquad (6)$$

Equation (6) simply states that the slope of Equation (5) is a function of another variable, z. Alternatively, for different values of z, Equation (6) can be viewed as a family of relationships between y and x (i.e., z is moderating the form of the relationship between y and x), as depicted in Figure 2.

Figure 2 about here

Further insight can be obtained by rewriting Equation (6) as:

$$y = a + b_1x + b_2xz \qquad (7)$$

In Equation (7), z is not related to either the predictor or criterion variable. Rather, it interacts with the predictor variable to modify the form of the relationship between y and x. This type of moderator variable falls in Quadrant 4 of Figure 1 and conforms to the psychometric definition of moderator variable. That is, psychometrically speaking, a moderator variable should "enter into interaction with predictor variables, while having a negligible correlation with the criterion itself" (Cohen and Cohen 1975, p. 314). Hence, it is termed a <u>pure</u> moderator variable.

The moderator variable presented in Quadrant 3 is identical to that in Quadrant 4 except that the moderator variable in Quadrant 3 not only interacts with the predictor variable but is a predictor variable itself. Because it is a predictor, this type of variable is not considered a moderator in the psychometric literature.

Apparently, the reason for restricting the definition of moderator variables to the pure form in the psychometric literature is to obviate the ambiguity in underlying which of its predictor variables is the moderator. In order to examine this ambiguity which can result from identifying a moderator variable as one which not only interacts with another predictor but is also an independent variable, let us modify Equation (6) as follows:

$$y = a + b_1x + b_3z + b_2xz \tag{8}$$

so that z is related to the criterion variable. Equation (8) can then be rewritten as:

$$y = (a + b_3z) + (b_1 + b_2z)x \tag{9}$$

and can be looked upon as a family of relationships between y and x for different values of z--the moderator variable. Since z is related to the criterion variable, however, Equation (8) can also be rewritten as:

$$y = (a + b_1x) + (b_3 + b_2x)z \tag{10}$$

Equation (10) can be viewed, therefore, as a family of relationships between y and z for different values of x (i.e., x moderating z). Thus, if the hypothesized moderator variable turns out to be related to the criterion variable, the moderator effect is not clear because each of the independent variables can, in turn, be interpreted as a moderator.

It is for this reason, that a moderator variable in the psychometric literatur is constrained to be unrelated to the criterion variable. One could argue, however that this ambiguity can be minimized if justification for a particular variable to be a moderator can be provided on theoretical grounds. For example, one would expect knowledge about a product to modify the relationship between price and perceived quality. On the other hand, if knowledge and quality are related then the concept of price modifying the relationship between perceived quality and knowledge will be hard to justify theoretically. Hence, if the search for moderator variables is guided by theory as opposed to strict empiricism, then the definition of moderator variables need not be limited to the psychometric definition. We will call this type of moderator variable a quasi moderator variable in order to differentiate it from the pure moderator variable. In the next sections, we will show how different methods can be used to identify homologizers, pure moderators, and quasi moderators.

Methods for Identifying Moderator Variables

Two basic methods have been used for identifying the presence of moderator variables. They are subgroup analysis and Moderated Regression Analysis (MRA). Although both have been used across a myriad of studies, they cannot be considered as interchangeable or equivalent procedures. Rather, in order to identify the existence of and type of moderator variable, both methods must be used in tandem as shown in the section presenting the framework for identifying moderator variables.

Subgroup Analysis

Of the two methods for identifying moderator variables, subgroup analysis has been used most often. Following this approach, the sample is split into subgroups on the basis of a third variable, the hypothesized moderator. In all but just a few marketing related studies, when the variable treated as a moderator was already in qualitative form such as sex (e.g., Hirschman, Blumenfeld, and Tabor 1977) or discrete situations (Miller and Ginter 1979), the moderator variable was measured in a continuous or quantitative manner such as confidence (e.g., Bennett and Harrell 1975; Day 1970; Fry 1971) or importance (e.g., Bonfield 1974; Peter and Ryan 1976) and then split (e.g., dichotimized, trichotimized). Following the subgrouping of the respondents, regression analysis was typically employed to investigate the relationship between the predictor variable(s) and the criterion variable for each subgroup. Once the regression analysis was performed, some studies (e.g., Bennett and Harrell 1975; Brody and Cunningham 1968, Day 1970; Fry 1971; Sample and Warland 1973; Warland and Sample 1973) emphasized the coefficient of determination, a measure of predictive validity, to determine the existence of a moderator variable while others emphasied the form of the relationship (e.g., Becherer and Richard 1978).

Use of the predictive validity coefficient (R^2) in-and-of-itself to determine the existence of a moderator variable is not satisfactory. The R^2 will vary between segments or subgroups, leading one to conclude that the variable used for subgrouping is a moderator, regardless as to whether it is: (1) a homologizer; (2) related to either the criterion or predictor variable; (3) a pure moderator; or (4) a quasi moderator variable. In the case of homologizers, differential patterns of predictive validity occur because the error term for some segments is reduced (Zedeck, Cranny, Vale, and Smith 1971). That is, the result of subgroup analysis is that for some segments the coefficient will increase markedly over that obtained for the sample as a whole and for other segments, where the error is high, the coefficient will be lower (Ghiselli 1963).

In the second case, the coefficient will vary if the variable is related to either the criterion or predictor variable or both. If z is related to y then the within-subgroup variance of y will vary across subgroups whereas the within-subgroup variance of x will be the same. Hence, R^2 will vary across subgroups. Similarly, R^2 will vary across subgroups if z is related to x (Peters and Champoux 1979).

In the case of pure or quasi moderator variables, subgroup analysis will lead to different R^2s if the individuals across the subgroups are heterogeneous with respect to the form of the relationship. This will occur when the hypothesized moderator variable is continuous and is artificially categorized in order to form subgroups. For example, consider N individuals that are heterogeneous with respect to the form of relationship and homogeneous with respect to the error term. The sum of squares due to regression for each individual i, is given by $b_i \Sigma x_i y_i$ where b_i is the vector of coefficients and $\Sigma x_i y_i$ is the covariance vector.[7] Since the individuals are heterogeneous with respect to b_i, the R^2 will vary across subgroups even though the R^2 of each individual is the same. This is similar to the concept of partial variance, except that in this case, differences in R^2 are due to the heterogenous form of its relationships (Velicer 1972), and are not due to the heterogeneity of the error term. Employing subgroup analysis which uses R^2 as a measure for determining the presence or absence of a moderator variable is, therefore, not appropriate because it is possible that all the variables in Figure 1 can be used to form subgroups which will have varying R^2s.

An alternate approach for identifying the presence of moderator variables is to test whether the form of the relationship of the classic validation model varies across subgroups. Following this approach (e.g., Becherer and Richard 1978; Berkowitz, Ginter and Talarzyk 1977; Tankersley and Lambert 1978), the equality between regression equations is tested using the Chow (1960) or similar test (Johnston 1972). In those instances where the regression coefficients differ across subgroups, the variable is assumed to be a moderator variable. Without additional analysis, however, one cannot identify whether the proposed moderator is a quasi moderator (Quadrant 3, Figure 1), which would be the case if, for example, the proposed moderator was also a predictor variable, or whether it is a pure moderator (Quadrant 4, Figure 1).

Moderated Regression Analysis

Moderated Regression Analysis (MRA) has been differentiated from subgroup analysis because it is an analytic approach which maintains the integrity of a sample yet provides a basis for controlling the effects of a moderator variable. By using this procedure, the loss of information resulting from the artificial transformation of a continuous variable into a qualitative one is avoided. This results in a more complete utilization of the data (Zedeck, et al. 1971). In fact, MRA can be viewed as an extension of subgroup analysis where the number of groups is equal to the number of subjects.

In applying MRA in terms of one predictor variable, three regression equations should be examined for equality of the regression coefficients (Zedeck 1971).

$$y = a + b_1x \tag{11}$$

$$y = a + b_1x + b_2z \tag{12}$$

$$y = a + b_1x + b_2z + b_3xz \tag{13}$$

In the above equations, if Equations (12) and (13) are not significantly different (i.e., $b_3 = 0$; $b_2 \neq 0$) then z is not a moderator variable but simply an independent predictor variable (Quadrant 1, Figure 1). For z to be a pure moderator variable (Quadrant 4, Figure 1), Equations (11) and (12) should not be different but should be different from Equation (13) (i.e., $b_2 = 0$; $b_3 \neq 0$). For z to be classified as a quasi moderator (Quadrant 3, Figure 1), Equations (11), (12), and (13) should be different from each other (i.e., $b_2 \neq 0$; $b_3 \neq 0$).

This procedure, MRA, has been used very little in marketing related studies. Bearden and Mason (1979) used this approach to ascertain if confidence was a significant moderator of the relationship of overall perceived risk and preference. Durand and Gur-Arie (1979) and Gur-Arie, Durand and Sharma (1979) also used the MRA procedure to identify potential variables moderating behavioral intention and the normative and attitudinal dimensions of an attitude model. Although not using the MRA procedure proposed by Zedeck (1971) formally, Bearden and Woodside (1976, 1978), Laroche and Howard (1980) and Horton (1979) used the MRA approach to identify moderator variables through examination of an interaction term in a regression model. It should be noted, however, that except in a few instances (e.g., Durand and Gur-Arie 1979) researchers who have used a regression approach to identify moderator variables have not distinguished between quasi and pure moderators by not reporting the effect of the potential moderator as a predictor variable (e.g., Laroche and Howard 1980).

Comparison of Subgroup Analysis and MRA

Subgroup analysis and MRA identify different types (form and strength) of moderator variables. MRA will identify only moderator variables which modify the form of the relationship. It will not identify homologizers because they operate through the error term. Subgroup analysis, on the other hand, may identify moderator variables depending upon the type of analysis employed. If the subgroups are tested for different R^2s, the presence of moderator variables cannot be detected unambiguously. As discussed earlier, this is due to the fact that all variables in Figure 1 will form subgroups having different R^2s.

When subgroups are tested for equality of regression equations, moderator variables which modify the form of relationship will be detected. Without further analysis, however, such a test will not provide enough information to differentiate between quasi moderator and pure moderator variables.

Identifying the type of moderator variable is important to the researcher in terms of drawing conclusions and implications from the research as well as in the design of additional research studies to examine a particular phenomenon. In the case of a homologizer, since it operates through the error term, the strength of the classic validation model may vary across subgroups for several reasons. If a major portion of the error is due to the measurement scale, the strength of the relationship will vary because the scale is not equally suitable across segments of the population. This implies that the scale must be employed differentially by modifying the scale to suit different segments (Ghiselli 1963, 1972). It is also possible, on the other hand, that the strength of the model will vary between subgroups not because of measurement error but rather due to a lack of correspondence between groups in terms of predictor variable(s). For example, assume that the population is comprised of two groups and that we are concerned with the relationship between y and x. In one group, y is a function of x so that the predictive validity of the model is very high but in the second group, y is a function of x as well as other variables. The strength of the relationship in the second group will be weaker than that of the first.[8] This implies that the measurement scale does not need to be modified across groups but rather in order to explain and understand the phenomenon varying sets of predictor variables may be necessary. In short, the composition of the error term holds major implications for researchers examining homologizers. When the moderator variable operates through an interaction with the predictor variable, on the other hand , emphasis should be placed on specification of the functional relationship rather than the analysis of the error term.

In order to determine the presence and type of moderator variables, a framework which incorporates both MRA and subgroup analysis is presented in the subsequent section along with illustrative examples employing simulated data.

Framework for Identifying Moderator Variables

The proposed framework for identifying moderator variables is provided in Figure 3 and consists of four steps discussed below:

Figure 3 about here

Step 1. Determine if there is a significant interaction between the hypothesized moderator variable,[9] z, and the predictor variable using the MRA procedure (see Equations 11, 12, 13). If there is a significant interaction, then proceed to Step 2. Otherwise, go to Step 3.

Step 2. Determine if z is related to the criterion variable. If it is then z is a quasi moderator variable (Quadrant 3, Figure 1). If not, then z is a pure moderator variable (Quadrant 4, Figure 1). In either case, the moderator influences the form of the relationship in the classic validation model.

Step 3. Determine if z is related to the criterion or predictor variable. If it is related, then z is not a moderator but an exogenous, predictor, intervening, antecedent or a suppressor variable (Quadrant 1, Figure 1). If z is not related to either the predictor or criterion variable proceed to Step 4.

Step 4. Split the total sample into subgroups on the basis of the hypothesized moderator variable. The groups can be formed by a median, quartile or some other type of split. After segmenting the total sample into subgroups, do a test of significance for differences in predictive validity across subgroups. If significant differences exist, then z is a homologizer variable operating through the error term (Quadrant 2, Figure 1). On the other hand, if there are no significant differences, then z is not a moderator variable and the analysis concludes.

Validating the Framework Through Simulation

In this section, the proposed framework will be validated using Monte Carlo simulation. The advantage of using simulated data as opposed to empirical data is that the presence and the type of moderator variables do not have to be inferred but are known. This prior knowledge can then be used to determine if the proposed framework does indeed detect the presence and type of a moderator variable.

Data Generation

Employing the method suggested by Box and Muller (1958) random normal deviates were generated. Then random normal deviates were used to generate a sample of 200 subjects for each of the hypothesized models described below. In all models, y, x, z and ε represent the criterion, predictor, moderator and the error variables respectively, and a, b, c, and d are constants.

Model 1. This model represents the case where there is no moderating effect. The specific relationship between the variables is given by:

$$Y = a + bx + \varepsilon.$$

Model 2. The second model is the case where the moderator variable is affecti the criterion variable through the error term and conforms to the moderator termed homologizer. The relationship used to generate the data is given by:

$$y = a + bx + z\varepsilon.$$

Model 3. In the third model, the hypothesized moderator is both a predictor variable and enters the equation through an interaction term. It represents the quasi moderator variable and can be expressed as:

$$y = a + bx + cz + dxz + \varepsilon.$$

Model 4. In this model, the moderator variable is assumed to affect the criterion variable through an interaction with the predictor variable and represents the pure moderator from. The relationship used to generate the data is given by:

$$y = a + bx + dxz + \varepsilon.$$

Simulated Results

The proposed framework was applied to the data generated by each of the four models. The significance test used for testing the difference between two models is based on the "extra sum of squares" principle (Draper and Smith 1967). The results are summarized in Table 1.

Table 1 about here

Following the procedure set forth in Figure 1, the first step to ascertain whether a moderator variable exists, is to test whether the proposed moderator interacts with the predictor variable. As expected, given the simulated data, the interaction was significant for Models 3 and 4 (i.e., $d \neq 0$) and not significant for Models 1 and 2.

Since the proposed moderator did not interact with the predictor variable for Models 1 and 2, the two models were analyzed to determine if z was a significant predictor variable. The hypothesized moderator, z, was not found to be a significant predictor for both the models (see Table 1). Therefore, subgroup analysis was performed for each model by splitting the sample into quartiles on the basis of the proposed moderator. For Model 2, the predictive validity coefficient varied significantly over the four subgroups as shown in Table 2. This indicates that z is a homologizer. In the case of Model 1, because there

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Table 2 about here
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were no differences across subgroups, z is neither a moderator nor a significant predictor variable.

The significance of the interaction term for Models 3 and 4, indicates that z is a moderator variable in both instances. However, at this point it is not clear whether z is a quasi moderator or a pure moderator. Therefore, Step 2 of the framework was initiated to determine the relationship between z and the criterion variable. As can be seen in Table 1, z was found to be significantly related to the criterion variable for Model 3 and hence is a quasi moderator variable. In Model 4, z is not related to the criterion variable and therefore can be classified as a pure moderator. It should be noted that the R^2s are different across subgroups for Models 3 and 4 (see Table 2) due to the heterogeneity of the form of the relationships.

Summary

The purpose of this paper was threefold. First, a typology of specification variables was presented to alleviate the confusion about the different types of moderator variables and how they operate to influence the strength and/or the form of the relationship between the criterion and predictor variable. Second, a framework which encompasses two different approaches (subgroup and MRA) for identifying moderators was developed for detecting the presence and type of moderator variables. The framework enables one to determine whether the hypothesized moderator variable is: (1) a moderator variable; (2) if it is a moderator variable, then to determine whether it operates through the error term (homologizer) or through an interaction with the predictor variable; and, (3) if it operates through an interaction term whether it is a quasi moderator or pure moderator variable. Finally, the framework was illustrated using simulated data.

Identification of the existence and the type of moderator variable has important implications for marketing research. If a moderator variable is a homologizer, the strength of the relationship varies across subgroups because the size of the error term differs across the subgroups. Subsequent analysis of the error term[10] will be necessary in order to detemine if the strength of the relationship is due to measurement error, requiring the use of differential scales across subgroups, or if it is due to the lack of correspondence of predictor variables across subgroups. If, on the other hand, a moderator variable operates through an interaction with the predictor variable then the form of the relationship between the criterion and the predictor variables is a function of the moderator variable. Therefore, emphasis should be placed on examining the form of the relationship with different values of the moderator.

FOOTNOTES

1. The term, specification variable, should not be confused with the meaning of the term used in the econometric literature.
2. The term "homologizer variable" was coined by Johnson (reported in Zedeck 1971).
3. The assumption of one predictor variable does not limit the concepts to be discussed. However, subsequent discussions will be limited to only one predictor variable.
4. It should be noted that in Equation (1) the error term is added basically for several reasons (Bagozzi 1980; Johnston 1972): First, human or consumer behavior is a function of a multitude of variables. It is not feasible to include all these variables either because they are not known or cannot be quantified or for the sake of parsimony the number of variables in the model is kept at a minimum. Second, there is a certain amount of randomness in consumer responses due to mood, fatigue, etc. Finally, there could be error in measuring variables due to measurement instrument or imperfect correlation between the construct and its operationalization.
5. If the function f_i is assumed to be linear, then the square root of Eta square is the familiar Pearson product moment correlation coefficient.
6. Again, for simplicity, a linear relationship between y and x is assumed. It is important to note that the concept of moderator variables is not affected by the form of relationship assumed between x and y.

7. This assumes that there are repeated measures for each individual.

8. This situation was suggested by one of the reviewers.

9. If the proposed moderator is discrete in nature, dummy variables can be used to ascertain whether it is interacting with the predictor variable.

10. For further details on the analysis of the error term (i.e., residual analysis) the interested reader is referred to Draper and Smith (1967).

Table 1

Partial F-ratios When Different Variable Were Added to the Classic Validation Model

Model	Variable Added z	xz
1	.36	.38
2	.36	.73
3	106.43[a]	193.72[b]
4	.79	193.74[b]

[a]Addition of z is significant at $\alpha = .01$.

[b]Addition of xz is significant at $\alpha = .01$.

Table 2

Predictive Validity Coefficients for Subgroup Analysis[a]

Model	Group 1	Group 2	Group 3	Group 4	Total Sample
1	.937 (49)	.941 (51)	.942 (49)	.948 (51)	.936 (200)
2	.881 (49)	.987 (51)	.823 (49)	.486 (51)	.762 (200)
3	.319 (49)	.648 (51)	.934 (49)	.982 (51)	.356 (200)
4	.540 (49)	.804 (51)	.960 (49)	.991 (51)	.585 (200)

[a]Numbers in parenthesis indicate sample size.

Figure 1

Typology of Specification Variables

	Related to Criterion and/or Predictor	Not Related to Criterion and Predictor
No Interaction With Predictor	1 Intervening, Exogenous, Antecedent, Suppressor, Predictor	2 Moderator (Homologizer)
Interaction With Predictor Variable	3 Moderator ("Quasi" Moderator)	4 Moderator ("Pure" Moderator)

Figure 2

Family of Relationship Between y and x
For Different Values of z

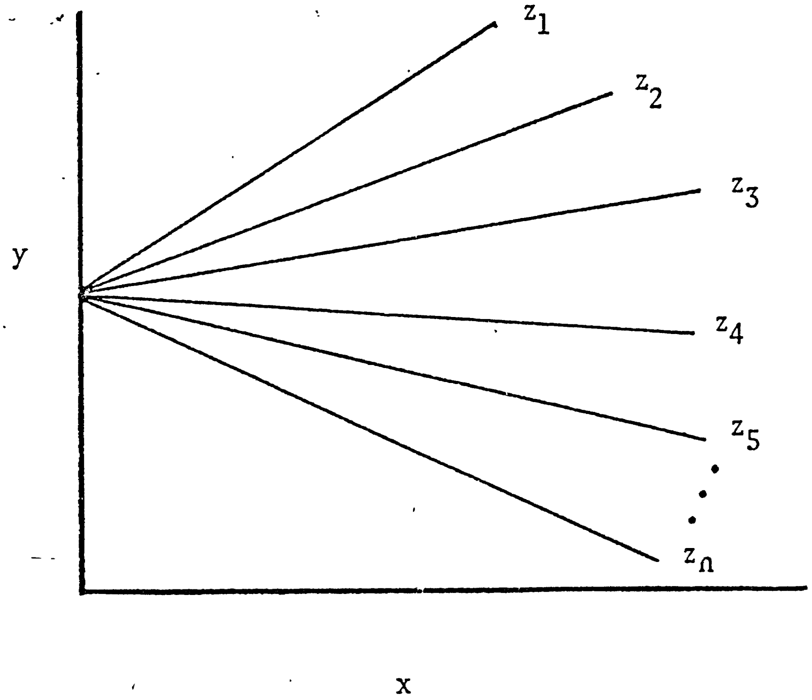
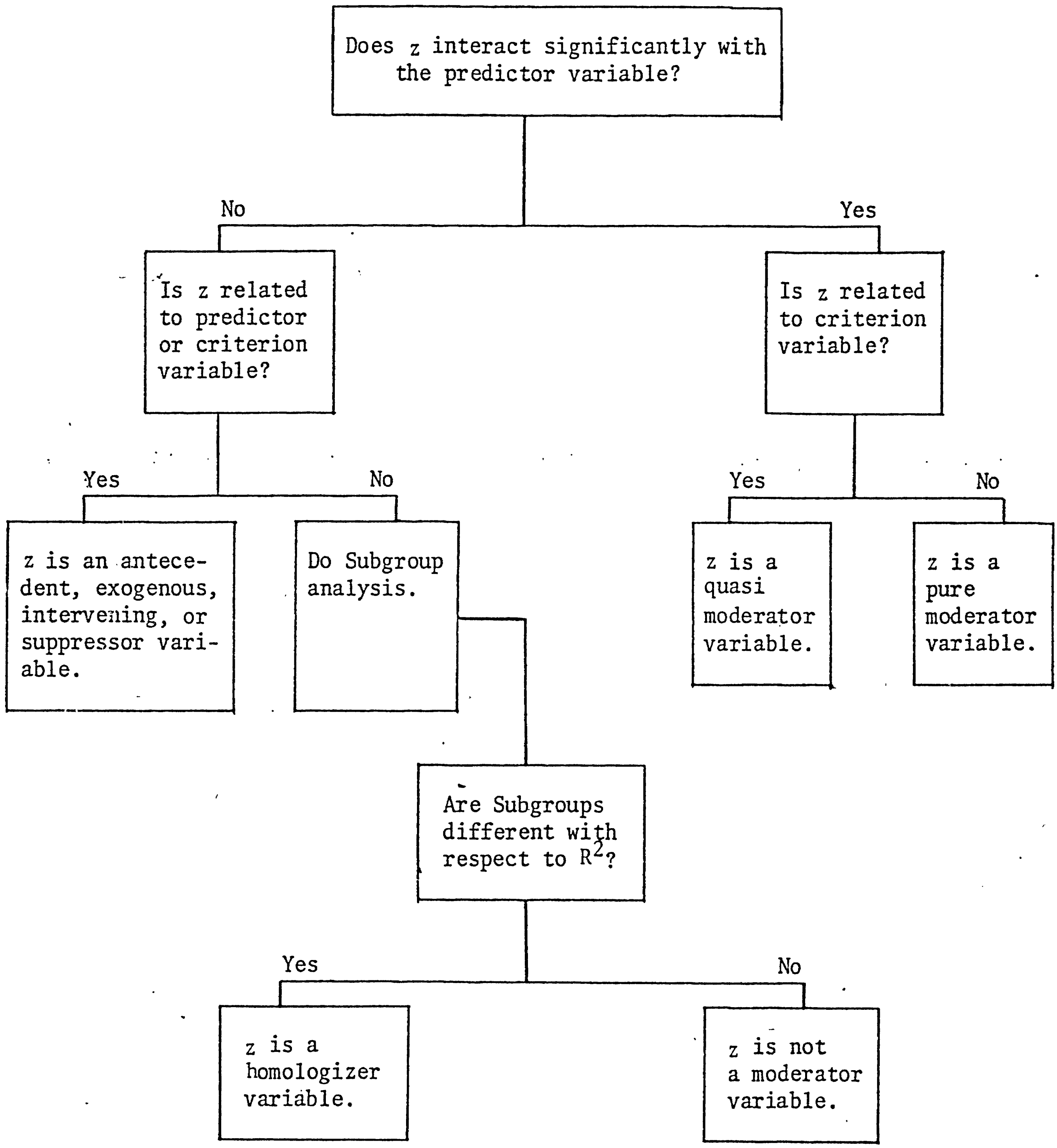


Figure 3

Framework for Identifying Moderator Variables



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