Identification and analysis of moderator variables
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Identification and Analysis of Moderator Variables

The classic validation model is used in consumer-related research 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 suggest that in some circumstances the classic model does not provide a complete understanding of the phenomenon studied. More specifically, in some cases the predictive efficacy of an independent variable and/or the form of the relationship may vary systematically 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 alternative to the classic validation model, proposed 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 a criterion variable. As such, the moderator variable concept holds important implications for understanding and predicting buyer behavior by helping to answer such questions (Zaltman, Pinson, and Angelmar 1973, p. 165) as:

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

Although most researchers agree that the concept of moderator variables is important, substantial confusion persists as to what specifically a moderator variable is 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 the hypothesized moderator variable is a significant predictor as well. A second concept is that a moderator cannot be a significant predictor variable nor can it be related to other predictor variables (Cohen and Cohen 1975; Zedeck 1971). Finally, a third approach is to ignore 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; Hubert and Donnute 1967). The "confusion" has made the comparability of results across studies difficult at best. More important, because the 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, b; Dunnette 1972).

The purpose of our article is to alleviate the confusion surrounding moderator variables by describing the various types of such variables as well as the
relevant methodological and theoretical issues. Basically, moderator variables are of two types. One type influences the classic validation model by affecting the strength of the relationship and the second modifies the form of the classic validation model. A typology showing the difference between these two types of moderator variables is provided with a framework for determining the presence and type of moderator variable. Simulated data are 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 a criterion variable (Lazarsfeld 1955; Rosenberg 1968). A typology of specification variables and hence moderator variables can be developed by using two dimensions or characteristics. First, classification can be based on the relationship with the criterion variable, that is, whether the specification variables 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 depicted in Figure 1.

If the specification variable is related to the criterion and/or predictor variable but does not interact with the predictor (Quadrant 1), the variable is referred to as an intervening, exogenous, antecedent, suppressor, or additional predictor variable depending on its other characteristics. Rosenberg (1968) discusses in detail how these variables operate and methods for identifying them. We concentrate on variables in Quadrants 2 through 4. Variables in these quadrants are 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 in Quadrant 2 operates by modifying the strength of the relationship whereas those in Quadrants 3 and 4 influence the form of the relationship between the predictor and criterion variables.

**Homologizer**

The type of moderator in 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, the error term is posited to be 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.

The concept underlying the moderator variable identified as a homologizer variable is partial variance (Ghiselli 1964). To illustrate partial variance conceptually, let us assume the case of one predictor variable. Furthermore, let us assume that the functional relationship between the criterion and the predictor variables for individual $i$ is

$$y_i = f_i(x_i) + e_i$$

where $y_i$ is the criterion variable, $x_i$ is the predictor variable, $e_i$ is a random error term with a mean of 0 and $\text{Var} \sigma^2_i$, and $f_i$ is the functional relationship between $y_i$ and $x_i$.

The strength of the relationship between $x$ and $y$ will depend on the size of the error term. 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, the total variance,
\( \sigma_{y_i}^2 \) of the criterion variable for individual \( i \) is given by

\[
\sum_{j=1}^{n_i} \left( y_i - \sum_j y_{ij} / n_i \right)^2 / n_i
\]

and the variance for the criterion variable after the predictor variable has been partialled out, is given by

\[
\sigma_{y_i-x_i}^2 = \sum_{j=1}^{n_i} (y_{ij} - \bar{f}_i(x_{ij}))^2 / n_i,
\]

where \( \bar{f}_i \) is an estimate of the function \( f_i \).

The variance given by equation 2 can be considered an estimate of the variance of \( \varepsilon \), and is often called the partial variance because 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 \( (\sigma_{y^2} - \sigma_{y_i-x_i}^2) / \sigma_{y^2} \) or \( 1 - \sigma_{y_i-x_i}^2 / \sigma_{y^2} \) 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. The aggregate partial variance of all \( N \) individuals in the sample can be estimated by using equation 2 and is expressed by

\[
\sigma_{y-x}^2 = \left( \sum_{i=1}^{N} \sum_{j=1}^{n_i} (y_{ij} - \bar{f}_i(x_{ij}))^2 \right) / N
\]

or

\[
\sigma_{y-x}^2 = \sum_{i=1}^{N} n_i \sigma_{y_i-x_i}^2 / \sum_{i=1}^{N} n_i
\]

Eta square is given by

\[
\eta^2 = 1 - \sigma_{y-x}^2 / \sigma_{y}^2
\]

where \( \sigma_{y}^2 \) is the total variance of \( y \) for all the individuals.

From equation 3, we see 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, the predictive validity (\( R^2 \)) of the total sample will be a weighted average of the individual \( R^2 \)'s. Therefore, some individuals will have an \( R^2 \) higher than the total sample \( R^2 \) and others will have a lower one. If individuals are to be classified into subgroups on the basis of some variable, such that the error variances of the individuals in the subgroup will be the same, some groups will have higher predictive validity than the total sample and others will have a lower predictive validity. The variable used to form homogeneous groups, the homologizer, is deemed to be a moderator variable because it leads to different predictive validity coefficients between subgroups for the predictor variables (Ghiselli 1963; Zedeck 1971).

**Pure and Quasi Moderator Variables**

The second type of moderator variable is one which basically modifies the form 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 \( y \).\(^6\)

\[
y = a + b_1 x
\]

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

\[
y = a + (b_1 + b_2 z) x
\]

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.

Further insight can be obtained by rewriting equation 6 as

\[
y = a + b_1 x + b_2 x z
\]

In equation 7, \( z \) is not related to either the predictor or the 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 fits in Quadrant 4 of Figure 1 and conforms to the psychometric definition of a moderator variable. That is, psychometrically, 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 pure moderator variable.

The moderator variable in Quadrant 3 is identical to that in Quadrant 4 except that the former 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 psy-

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\(^6\)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 \( y \).
Figur 2
FAMILY OF RELATIONSHIPS BETWEEN y AND x FOR DIFFERENT VALUES OF z

\[ y = a + b_1 x + b_3 z + b_2 x z \]

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

\[ y = (a + b_3 z) + (b_1 + b_2 x) x \]

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

\[ y = (a + b_1 x) + (b_3 + b_2 x) z \]

Equation 10 can be viewed, therefore, as a family of relationships between \( y \) and \( z \) for different values of \( x \) (i.e., \( x \) moderating \( z \)). 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.

Consequently, a moderator variable in the psychometric literature 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 being 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. In contrast, if knowledge and quality are related, the concept of price modifying the relationship between perceived quality and knowledge will be difficult to justify theoretically. Hence, if the search for moderator variables is guided by theory rather than strict empiricism, the definition of moderator variables need not be limited to the psychometric definition. We call this type of moderator variable a quasi moderator variable to differentiate it from the pure moderator variable. In the next sections, we 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, subgroup analysis and moderated regression analysis (MRA). Although both have been used in a myriad of studies, they cannot be considered interchangeable or equivalent procedures. Rather, to identify the presence and type of moderator variable, one must use both methods in tandem as shown in the section describing the framework for identifying moderator variables.

**Subgroup Analysis**

Of the two methods for identifying moderator variables, subgroup analysis has been used most often. By 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, if the variable treated as a moderator was already in qualitative form such as sex (e.g., Hirschman, Blumenfeld, and Tabor 1977) or in 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., dichotomized, trichotomized). After the subgrouping of the respondents, regression analysis typically was used to investigate the relationship between the predictor variable(s) and the criterion variable for each subgroup. Once the regression analysis was performed, some researchers (e.g., Bennett and Harrell 1975; Brody and Cunningham 1968; Day 1970; Fry 1971; Sample and Warland 1979; Warland and Sample 1973) emphasized the coefficient of determination, a measure of predictive validity, to determine the presence of a moderator variable whereas others emphasized 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 presence 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 of 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 et al. 1971). That is, the result of subgroup analysis is that for some segments the coefficient increases markedly over that obtained for the sample as a whole and for other segments, where the error is high, the coefficient is 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 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 $R^2$'s if the individuals across the subgroups are heterogeneous with respect to the form of the relationship. This situation will occur when the hypothesized moderator variable is continuous and is categorized artificially 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 $b_i'\Sigma_{x_iy_i}$ where $b_i$ is the vector of coefficients and $\Sigma_{x_iy_i}$ is the covariance vector. Because the individuals are heterogeneous with respect to $b_i$, the $R^2$ will vary across subgroups even though the $R^2$'s of the individuals are the same. This is similar to the concept of partial variance, except that in this case differences in $R^2$ are due to the heterogeneous form of relationships (Velicer 1972) and are not due to the heterogeneity of the error term. Employing subgroup analysis in which $R^2$ is a measure for determining the presence or absence of a moderator variable therefore is not appropriate because it is possible that all the variables in Figure 1 can be used to form subgroups which will have varying $R^2$'s.

An alternate approach for identifying the presence of moderator variables is to test whether the form of the relationship of the classic validation model differs across subgroups. By this approach (e.g., Becherer and Richard 1978; Berkowitz, Ginter, and Talarzyk 1977; Tankersley and Lambert 1978), the equality between regression equations is tested by using the Chow (1960) or similar test (Johnston 1972). In those instances in which 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 were also a predictor variable, or whether it is a pure moderator (Quadrant 4, Figure 1).

**Moderated Regression Analysis**

Moderated regression analysis (MRA) is 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 this procedure, the loss of information resulting from the artificial transformation of a continuous variable into a qualitative one is avoided. Utilization of the data is more nearly complete (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, one should examine three regression equations for equality of the regression coefficients (Zedeck 1971).

\[
(11) \quad y = a + b_1x \\
(12) \quad y = a + b_1x + b_2z \\
(13) \quad y = a + b_1x + b_2z + b_3xz
\]

If equations 12 and 13 are not significantly different (i.e., $b_2 = 0$; $b_3 \neq 0$), $z$ 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., $b_2 = 0$; $b_3 = 0$). 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., $b_2 \neq b_3 \neq 0$).

MRA has been used very little in marketing-related studies. Bearden and Mason (1979) used this approach to ascertain whether 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 they did not use 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. One should note, however, that except in a few instances (e.g., Durand and Gur-Arie 1979) researchers who have used a regression approach to identify moderators or variables have not distinguished between quasi and pure moderators by 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

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7Repeated measures for each individual are assumed.
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, in contrast, may identify moderator variables, depending on the type of analysis used. If the subgroups are tested for different \( R^2 \)'s, the presence of moderator variables cannot be detected unambiguously. As discussed before, this is due to the fact that all variables in Figure 1 will form subgroups having different \( R^2 \)'s.

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 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, because 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. The implication is that one must employ the scale differentially by modifying it to suit different segments (Ghiselli 1963, 1972). Possibly, however, the strength of the model will vary between subgroups not because of measurement error but because of a lack of correspondence between groups in terms of predictor variable(s). For example, assume that the population comprises 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 in the first.\(^6\) The implication is that one need not modify the measurement scale across groups but, to explain and understand the phenomenon, one may need to vary sets of predictor variables. 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, however, emphasis should be placed on specification of the functional relationship rather than the analysis of the error term.

In the following section, we present a framework which incorporates both MRA and subgroup analysis to determine the presence and type of moderator variables. Illustrative examples are based on simulated data.

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\(^6\)This situation was suggested by one of the reviewers.

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**FRAMEWORK FOR IDENTIFYING MODERATOR VARIABLES**

The proposed framework for identifying moderator variables, depicted in Figure 3, consists of four steps.

**Step 1.** Determine whether a significant interaction is present between the hypothesized moderator variable, \( z \), and the predictor variable by the MRA procedure (see equations 11, 12, 13). If a significant interaction is found, proceed to Step 2. Otherwise, go to Step 3.

**Step 2.** Determine whether \( z \) is related to the criterion variable. If it is, \( z \) is a quasi moderator variable (Quadrant 3, Figure 1). If not, \( z \) 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 whether \( z \) is related to the criterion or predictor variable. If it is related, \( z \) 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 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 are found, \( z \) is a homologizer variable operating through the error term (Quadrant 2, Figure 1). If no significant differences are found, \( z \) is not a moderator variable and the analysis concludes.

**VALIDATING THE FRAMEWORK THROUGH SIMULATION**

In this section, the proposed framework is validated by Monté Carlo simulation. The advantage of using simulated rather than empirical data is that the presence and the type of moderator variables need not be inferred but are known. This prior knowledge can be used to determine whether the proposed framework does indeed detect the presence and type of a moderator variable.

**Data Generation**

By 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 hereafter. In all models, \( y, x, z, \) and \( e \) represent the criterion, predictor, moderator, and error variables, respectively, and \( a, b, c, \) and \( d \) are constants.

---

\(^6\)If the proposed moderator is discrete, dummy variables can be used to ascertain whether it is interacting with the predictor variable.
Figure 3
FRAMEWORK FOR IDENTIFYING MODERATOR VARIABLES

Does z interact significantly with the predictor variable?

Yes

Is z related to predictor or criterion variable?

Yes

Do Subgroup analysis.

No

z is an antecedent, exogenous, intervening, or suppressor variable.

No

Are Subgroups different with respect to \(R^2\)?

Yes

z is a homologizer variable.

No

z is not a Moderator variable.

Yes

Is z related to criterion variable?

Yes

z is a quasi moderator variable.

No

z is a pure moderator variable.

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

\[ Y = a + bx + e. \]

Model 2. The second model is the case in which the moderator variable is affecting the criterion variable through the error term and conforms to the moderator termed "homologizer." The relationship used to generate the data is given by

\[ y = a + bx + ze. \]

Model 3. In the third model, the hypothesized moderator is 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 form. 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 for 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.

By the procedure set forth in Figure 1, the first step to ascertain the presence of a moderator variable 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.

Because the proposed moderator did not interact with the predictor variable for Models 1 and 2, the two models were analyzed to determine whether \( z \) was a significant predictor variable. For both models, the hypothesized moderator, \( z \), was found not to be a significant predictor (see Table 1). Therefore, sub-group 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 finding indicates that \( z \) is a homologizer. In the case of Model 1, because there 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, \( z \) is 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. One should note that the \( R^2 \)'s are different across subgroups for Models 3 and 4 (see Table 2) because of the heterogeneity of the form of the relationships.

**SUMMARY**

The purpose of our article is threefold. First, a typology of specification variables is provided 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 encompassing two different approaches (subgroup and MRA) for identifying moderators is developed for detecting the presence and type of moderator variables. The framework enables one (1) to determine whether the hypothesized moderator variable is a moderator variable, (2) if it is a moderator variable, 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 is illustrated with simulated data.

**Table 1**

| Partial F-ratios when different variables are added to the classic validation model |
|----------------------------------|------------------|
| **Model** | **Variable added** | **xx** |
| 1       | .36   | .38 |
| 2       | .36   | .73 |
| 3       | 106.43* | 193.72* |
| 4       | .79   | 193.74* |

*Addition of \( z \) is significant at \( \alpha = .01. \)

*Addition of \( xz \) is significant at \( \alpha = .01. \)

**Table 2**

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<th>Predictive validity coefficients for subgroup analysis*</th>
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*Numbers in parentheses indicate sample size.
Identification of the presence and type of moderator variables 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 will be necessary to determine whether the strength of the relationship is due to measurement error, requiring the use of differential scales across subgroups, or due to the lack of correspondence of predictor variables across subgroups. If, however, a moderator variable operates through an interaction with the predictor variable, 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.

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\(^n^{10}\)For additional details on the analysis of the error term (i.e., residual analysis), see Draper and Smith (1967).


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