Multiple Mediation and Moderation Variables Effect and Review: Statistical Analysis with a Multiple Independent Variables

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Abstract

This study briefly discusses the process of mediating and moderating analysis in a management research process. The modern approaches to statistical mediation and moderation analysis focus on estimation and inference about the indirect effect of independent variables X on dependent variable Y through proposed intervening variable M and moderation variable Z. Mediators and moderators are often overlooked in research designs, or the terms are used incorrectly. To date, virtually all discussions of these approaches have assumed X is either dichotomous or continuous, even though investigators frequently are interested in testing mediation hypotheses involving multiple independent variables. The aim of the research study is to learn from past practice and to use that knowledge to signal to researchers the importance of correctly applying mediation and moderation tests as well as to facilitate the valid testing of mediation and moderation models and the reporting of mediations and moderators results in future management research studies. This research article summarizes the conceptual differences between mediators and moderators. The statistical analysis of mediators and moderators in multiple regressions is briefly described and presented. The authors describe the estimation of indirect effects in statistical mediation analysis with a multi-independent variables and moderation variables. The authors introduce the concept of the relative indirect effects, show how relative indirect effects are estimated in multiple regressions and structural equation modeling and how they are interpreted as functions of how the variables are analyzed. The authors describe inferential tests for the relative indirect effects and provide examples.

Keywords: Mediation, Moderation, Mediated moderation, Multi independent variables.

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Introduction

Mediator and moderator variables provide useful information about how, why, or when a phenomenon occurs. Unfortunately, many management researchers fail to test mediators or moderators in their data or use the terms incorrectly. For example, "mediator" is often used as if it meant "predictor". A mediator or moderator is a third variable that changes the association between an independent variable and dependent variable (Baron & Kenny, 1986). Thus, consideration of a mediator or moderator allows a more precise description of the relationship between independent and outcome variables. If a researcher fails to consider the possibility of a mediator or moderator effect in the data, a more exact explanation for an outcome may be missed.

Statistical mediation analysis is commonplace in the social and behavioral sciences. This may be in part because the concept of mediation gets to the very heart of why scientists become scientists in the first place. Establishing that some independent variable X influences dependent variable Y while also being able to describe and empirically quantify the mechanism of an effect of mediator variable M or moderation variable Z that transmits that effect is a lofty scientific accomplishment. Though not easy to do so convincingly (Bullock; et.al. 2010), establishing the mechanism of an effect is an important scientific goal, and one that certainly gives scientists some professional satisfaction when they succeed at it.

The aim of the study is to learn from past practice and to use that knowledge to signal to researchers the importance of correctly applying mediation and moderation tests as well as to facilitate the valid testing of mediation and moderation models and the reporting of mediations and moderators results in future management research studies. To achieve that purpose, mediators and moderators are defined and differentiated. In addition, statistical methods for analysis of mediator and moderator effects are described and examples presented. In intervention studies, a mediator or moderator can explain why an intervention works in management research. The analysis of mediators and moderators in descriptive studies can elicit information about why or how a direct and indirect association occurs between an independent and dependent variable.

This research paper composed into five sections. Section 2 describes overview of literature, section 3 explains statistical mediation analysis, section 4 illustrates covariates and moderation. In the last section conclusions are given.

Overview of Literature

All the literature in statistical mediation analysis that has taken this perspective has done so in the context of analyses in which the independent variable is dichotomous or continuous, for this is a requirement of the implementation of the methods that have been discussed and studied either analytically or through simulation. Yet in many studies that researchers undertake, especially in experiments where it is easier to meet the conditions of causal inference, the independent variable is neither dichotomous nor continuous but multi-variables. With such a design and absent any methodological guidance to the contrary, researchers have had to resort to alternative but potentially less desirable approaches to assess whether the independent variable's effect on a dependent variable of interest is mediated.

For the last 30 years, the causal steps approach as described by Baron and Kenny (1986) and Judd and Kenny (1981) have dominated the practice of statistical mediation analysis. But for reasons noted below, researchers have recently been advised to steer away from methods that rely on tests of significance of individual paths in a mediation model and, instead, to focus more on the indirect effect of X on Y through M and Z inferential tests thereof (Rucker, et. al., 2011) using approaches that respect the irregularity of the sampling distribution of the indirect effect rather than assuming it is normal. These methods include bootstrapping, the distribution of the product approach, and Monte Carlo confidence intervals (Hayes, 2009; Preacher & Selig 2012; Rucker et. al., 2011; Williams & MacKinnon, 2008).

For instance, some researchers use the causal steps method by assessing whether group differences revealed in an analysis of variance disappear or diminish after accounting for a proposed mediator or mediators (Pandalaere, et. al., 2010; Wirtz & McColl-Kennedy, 2009). Alternatively, investigators modify their data to produce a dichotomous X in order to quantify and test indirect effects, such as conducting separate analyses comparing various groups of interest while discarding the remaining data (Pedersen, et. al., 2011; Werle, et. al., 2011), or collapsing multiple groups into one for the sake of comparison with another group or set of groups (Janssen, et. al., 2010; Ruva, et. al., 2011). Another strategy that has been used in experiments involves substituting a continuous manipulation check for the multi variable X and proceeding with a mediation analysis as if X were observed as a continuum rather than categorically manipulated (Forgas, 2011).

MacKinnon et. al., (2002) have identified and compared four methods of testing for mediation, intervening variables, and indirect effects. They categorized the methods into three general frameworks: (a) the causal steps approach, (b) differences in coefficients, and (c) products of coefficients (Robert Wood et. al., 2008). The following measures used for conducting mediation analysis (Amrita Sidhu, et.al.2021) are Baran and Kenny's mediation analysis (1986), Sobel test (1982), Preacher and Hayes's Bootstrap method (2004) and Structural Equation Modelling (MacKinnon, 2000).

Causal Steps Approach: The causal steps approach includes a series of conditions or rules for inferring mediation, which vary somewhat across developers. This approach has been found to have low Type I error rates and low statistical power for detecting mediation effects for small and moderate effect sizes and for large effect sizes with samples of fewer than 100 (MacKinnon et al., 2002). The two most commonly used causal steps approaches are those of Baron and Kenny (1986) and James and Brett (1984).

James and Brett (1984) specified similar conditions to those stated by Baron and Kenny (1986) for the bivariate relationships between the independent variable and the mediator and mediator and the dependent variable. The most commonly used approach is the causal steps strategy popularized by Baron and Kenny (1986), which requires the investigator to establish using a set of hypothesis tests that a, b, and c are statistically different from zero. If so, then M is deemed a mediator of the effect of X on Y if c' is closer to zero than c. A failure to reject the null hypothesis that c' equals zero brands *M* as a complete mediator, whereas rejection of this null leads to the claim that M is a partial mediator, for it only partially accounts for *X*'s effect on *Y*.

As noted above, the causal steps strategy has fallen out of favor among methodologists who write about mediation analysis, although it still remains quite popular probably because it has become so deeply ingrained in the habits and statistical language of researchers and their academic offspring. Yet recent advice tells us to focus not on a, b, and c in a mediation model and whether they are different from zero as evidenced by a hypothesis test but, rather, on explicitly estimating the indirect effect and making an inference about its size in the population irrespective of the size or significance of the total effect (Hayes, 2009; Rucker et. al., 2011).

Differences in Coefficients Approach: The differences in coefficients tests provide estimates of the standard error and assessment of the statistical significance of the mediation effect (MacKinnon et. al., 2002). The differences in coefficients approach involves statistically comparing coefficients before and after adjustment for the mediator.

Products of Coefficients Approach: The products of coefficients tests provide estimates of the standard error and assessment of the statistical significance of the mediation effect (MacKinnon et. al., 2002). The product of coefficients approach includes the Sobel (1982) test and its variants, among other tests, which involve testing for indirect effects using a path model. The product of coefficients is algebraically equivalent to tests of the change in the regression coefficient following the introduction of the mediator (MacKinnon, et. al., 1995), which, we presume, was the reason Baron and Kenny (1986) suggested the Sobel test as a possible test of the fourth condition in their causal steps approach. Overall, these approaches have been found to have accurate or low Type I error rates and higher power to detect mediation effects compared to the causal steps approach (MacKinnon et. al., 2002).

The Sobel test (Sobel, 1982) was acknowledged by Baron and Kenny (1986) as a hypothesis testing procedure for indirect effects. This test involves the estimation of the standard error of the indirect effect, calculating the ratio of the estimated indirect effect to its estimated standard error, and deriving a p-value for this ratio assuming the indirect effect is zero in the population. However, this test has been found wanting and is rarely recommended these days because of the implausible assumption, at least in small to moderate samples, that the sampling distribution of ab is normal.

Modern Approaches: Modern approaches to mediation analysis rely on inferential tools that do not make this assumption and that are more powerful than the Sobel test and the causal steps approach, such as bootstrapping (MacKinnon, et. al., 2004), the distribution of the product method (MacKinnon, et. al., 2007), and Monte Carlo confidence intervals (Preacher & Selig, 2012; MacKinnon et. al., 2004). Application of these approaches is made easy by freely available computational tools and code for software researchers are already using, such as SPSS, SAS, SPLS and R.

Originators of the causal steps approach recommended that structural equation modeling (SEM) be used as an alternative to regression in tests for mediation when multiple indicators are collected for variables to address measurement unreliability (Baron & Kenny, 1986), when the conditions for confirmatory analysis have been met (James & Brett, 1984), and when a model includes latent constructs (Kenny, et. al., 1998). MacKinnon (2000) addressed the use of SEM for complex models that include multiple mediators and/or dependent variables. SEM enables the tests of more complex mediation models than the simple $X \rightarrow M \rightarrow Y$ model discussed in James and Brett (1984) and Baron and Kenny (1986).

In this paper, Authors describe a method for assessing and testing indirect effects in statistical mediation analysis involving a multi-independent variable. Although Authors are not the first to acknowledge the potential utility of the approach they describe, to date there has been no systematic description of how to parameterize the model depending on the hypotheses one wishes to test and how the various effects (direct and indirect) are interpreted. After reviewing the basic principles of mediation analysis, Authors introduce the concept of the relative indirect effect in statistical mediation analysis with a multi-independent variable and illustrate how relative indirect effects are Multi-independent X in Mediation Analysis estimated and interpreted. Following this, Authors describe some inferential tests of relative effects and illustrate their computation in SPSS and SPLS using tools they have produced for this purpose. Thus, primary goal in this paper is to facilitate the use of the approach Authors describe by illustrating different ways that groups could be represented in a mediation model and the consequences of those choices on how to interpret the indirect and direct effects that result, while also providing the research community with a simple means of implementing this approach using software that they are probably already using day-to-day.

At the outset, it is important to note that what Authors offer in this manuscript is not a means of assessing cause using a statistical model. Mediation is a causal phenomenon, yet no statistical model can prove causality, as causality is established more by research design and logical or theoretical argument. Statistics can be used to ascertain only whether an association between variables likely exists, and of what magnitude. This may aid in establishing the soundness of the causal argument but does not by any means prove it. Yet a statistical model can be used to help rule out certain alternative explanations, and more complex statistical approaches than we discuss here can be used in non-experimental studies when causal inference is less justified due to limitations of the design (Hong, 2012). Causal inference can be strengthened if the researcher can argue or demonstrate that the variables are modeled in the appropriate causal sequence, if key effects in a mediation model are not confounded by omitted variables (Imai, et. al, 2010), and if no important moderation effects go un-modeled (Vander Weele & Vansteelandt, 2010). The first two of these assumptions usually are defensible if X is experimentally manipulated. For the purposes of this paper, Authors assume that the user of the method describe here is comfortable with causal claims researcher is making or at least acknowledges when non causal interpretations exist and couches researcher claims with the appropriate caveats and cautions.

Statistical Mediation Analysis

Working Example: The example Authors use throughout this paper is based on their pilot study data. Authors proposed that Intellectual capital would have a more positive effect toward the Innovation capability, with the effect becoming more positive as the level of organizational motivation increased. Authors also proposed various potential mechanisms to explain this effect. They reasoned that people would feel that a Intellectual capital is more interactive, and this interactivity would translate into a more favorable innovation capability. Thus, we argue that intellectual capital influences innovation capability at least partly indirectly through organizational motivation.

In this study, 70 participants spent time to filling our structured questionnaire by Managers and Executives of the Apparel Industry in Sri Lanka. A single-factor analysis of variance on the innovation measure reveals the expected effect of Intellectual capital on Innovation capability. All possible pairwise comparisons between group means using a pooled error term reveals that those assigned to the highly had a significantly more positive on innovation capability. Whether one of the mechanisms is perceived interactivity as hypothesized will be addressed throughout the rest of this article.

Indirect, Direct and Total Effects

The simple mediation model, which is the focus of this article, is diagramed in Figure 1. If it is assumed that M and Y are treated as continuous, *X* is either dichotomous or treated as continuous, and all effects are modeled as linear, then the various effects in this model (*c, c', a,* and *b*) can be estimated with a set of ordinary least squares regressions or simultaneously using a structural equation modeling (SEM) program. In the regression context, two linear models are required to estimate M and Y, as such:

$$M = i_1 + aX + e_M \quad (1)$$
$$Y = i_2 + c'X + bM + eY \quad (2)$$

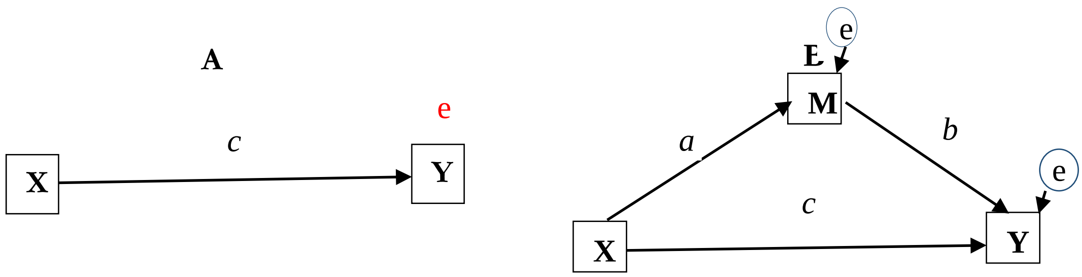

Figure 1: A simple mediator model

In principle Authors like to know the population effects or parameters of the model, but in practice the best Authors can do estimate these parameters given available data. To simplify notation, Authors do not distinguish between population effects and estimates of those quantities here. Our focus in this section is on estimates of population effects derived by mathematically modeling one's data using Equations (1) and (2) and Authors introduce when appropriate.

There are two effects of *X* that are of primary interest in mediation analysis. Most central is the indirect effect of *X*, quantified as the product of coefficients a and b. This product, ab, is interpreted as the amount by which two cases that differ by one unit on *X* are estimated to differ on *Y* as a result of the effect of *X* on *M* which in turn affects *Y*. The indirect effect of *X* serves as a quantitative instantiation of the mechanism through which *X* influences *Y*. But it is not the only path of influence from X to Y. X can also influence Y directly, independent of its indirect effect via M. The direct effect (c') quantifies how much two cases who differ by one unit on X but who are equal on M are estimated to differ on Y.

Though not a focus in modern approaches to mediation analysis, the total effect of X on Y, represented as coefficient c in Figure 1(*A*), is the sum of X's direct effect on Y and its indirect effect on Y through M, i.e., $c = c' + ab$. Thus, the total effect can be estimated by combining estimates derived from Equations (1) and (2). A separate model is not needed to estimate c. However, researchers frequently do begin their mediation analysis by first estimating Y from X in isolation to establish whether there is a total effect to explain prior to deciding whether to proceed with the estimation of the indirect effect. In that case, c can be equivalently estimated from

$$Y = i_3 + cX + e_Y \tag{3}$$

The total effect is interpreted as the amount by which two cases differing by one unit on X are estimated to differ on Y through both the direct and indirect pathways. The one unit difference on X interpretation given above is a general interpretation that applies regardless of whether X is dichotomous or continuous. But when X is dichotomous with the two values or groups with a single unit difference, the indirect and direct effects can be interpreted in terms of mean differences in Y. So, the indirect effect, ab, represents the mean difference between the two groups on Y that results from X's causal influence on M which in turn affects Y. The direct effect is the mean difference in Y independent of X's effect on M. This direct effect can also be called an adjusted mean difference in the lingo of analysis of covariance, for it reflects the expected difference between the means of the two groups on Y if they were equal on the mediator on average. The total effect is simply the difference between the two group means on Y. Thus, the observed difference between the group means on Y can be partitioned entirely into the difference due to the indirect effect and the difference due to the direct effect. That is,

$$c = (\bar{Y}_H - \bar{Y}_L) = c' + ab = \left(\bar{Y}_H^* - \bar{Y}_L^*\right) + (\bar{M}_H - \bar{M}_L)b \tag{4}$$

where Y_H and M_H are the means of Y and M for the group coded one unit higher, YL and ML are the means of Y and M for the group coded lower, and Y_H and Y_L are adjusted means, from the parameter estimates from Equation (2) but substituting M for M:

$$\bar{Y}^* = i_2 + c'X + b\bar{M}. \tag{5}$$

As discussed below, the adjusted means as well as the direct and indirect effects are sensible quantities to calculate and interpret only if one can assume no interaction between X and M in the model of Y (Imae et al., 2010a, VanderWeele & Vansteelandt, 2010). In the analysis of covariance literature, this is known as the assumption of homogeneity of regression (Keppel & Wickens, 2004).

Estimating the Effects of a Multiple Independent Variable

In studies that involve a multi-independent variable *X*, it is not possible to estimate the effects of *X* using Equations (1) and (2) as described above because there is no single *a* or *c′* that represents *X*'s effect on *M* or *Y*. The difficulty stems from the fact that in order to fully represent the effect of a categorical variable with *k* mutually exclusive categories on some dependent variable (whether *M* or *Y* in Figure 1), $k - 1$ parameter estimates are needed (Cohen, et. Al., 2003). As noted above, absent the ability to model *M* and *Y* using Equations (1) and (2), researchers interested in examining mediation of the effect of a multi-independent variable *X* have had no choice but to resort to the causal steps approach without estimating the indirect effect or by aggregating groups or throwing out data so as to produce a dichotomous *X* and then applying modern approaches based on an estimate of the indirect effect.

Authors illustrate the former procedure the causal steps strategy using our pilot study data. First recall that it has already been established above that Intellectual capital (*X*) affected Innovation capability (*Y*), as revealed by a statistically significant single-factor ANOVA. There is also evidence from a single-factor ANOVA that *X* affects *M*—meaning motivation influenced perceptions of interactivity, $F(3, 66) = 50.685$, $p = 0.000$. All possible pairwise comparisons been group means reveals that the Intellectual capital on Innovation capability as significantly more interactive by mediating variable organizational motivation. There is a relationship between Intellectual capital and Innovation capability after controlling for condition, such that the organizational motivation had a significantly more positive on innovation capability about the value, $b = 0.738$, $p < 0.000$. This establishes that *M* is related to *Y*, holding *X* constant.

This application of the causal steps strategy suffers from the same limitations as when used to assess the mediation of the effect of a dichotomous or continuous *X*. This approach does not involve a quantification of the indirect effect, even though it is the indirect effect that is of primary interest in mediation analysis. Rather, the existence of an indirect effect is logically inferred through the rejection of a set of null hypothesis tests, none of which directly test the indirect effect itself. In addition, simulation research has shown that the causal steps approach is among the lowest in power when *X* is dichotomous or quantitative, and there is no reason to believe the same would not be true when *X* is multi categorical. Yet it is hard to fault researchers for using this strategy when no other approaches have been offered to date by methodologists.

Authors take a general linear model approach to estimating the indirect effect in models of this sort. Authors rely on the well-established fact that mean differences can be estimated with a linear model by representing the group to which each case belongs with a set of $k - 1$ variables, where *k* is the number of groups. The method Authors describe is mathematically identical to analysis of variance and covariance in that the model is parameterized so as to exactly reproduce the *k* group means on *M* and *Y* (both unadjusted and adjusted for group differences on *M*). As a consequence, the model, the parameter estimates, and model fit statistics (such as R^2) retain all the information about how the *k* groups differ from each other, unlike when groups are collapsed to form a single dichotomous variable. It also allows for simultaneous hypothesis tests if the groups are represented with a carefully selected set of group codes which represent various comparisons of interest.

There are many different strategies that can be used to represent the groups. In this section, we introduce our approach using indicator coding, also known as dummy coding. Later, Authors describe alternative coding schemes. To dummy code k groups, $k - 1$ dummy variables (X) are constructed, with Xi set to 1 if a case is in group i, and 0 otherwise. One group is not explicitly coded, meaning all $k - 1$ X variables are set to zero for cases in that group. However, this group is implicitly represented in the coding scheme as it functions as the reference category in the analysis, meaning that parameters in the model pertinent to group differences are quantifications relative to this reference group. Using this approach, the simple mediation model is parameterized with two linear models, one for M and one for Y, using the $k - 1$ dummy variables to represent group membership. The linear models are;

$$M = i1 + a1X1 + a2X2 + \ldots + ak\text{-}1Xk\text{-}1 + eM \qquad (6)$$

$$Y = i2 + c'1X1 + c'2X2 + \ldots + c'k\text{-}1Xk\text{-}1 + bM + eY \qquad (7)$$

and are represented in path diagram form in Figure 2 panel B. As in mediation analysis with a continuous or dichotomous X, these linear models can be estimated separately as an OLS regression-based path analysis or simultaneously in an SEM program.

Estimation of these models yields k –1 a coefficient quantifying differences between the groups on M, $k - 1$ c' coefficients quantifying differences between groups on Y holding M constant, and a single b estimating the effect of M on Y while statistically equating the groups on average on X and M. The direct effect of X on Y is captured in the $k - 1$ estimate of $c'i$ from Equation (7) and the indirect effect of X on Y through M is estimated by the $k - 1$ products aib, $i = 1$ to $k - 1$ from Equations (6) and (7).

Authors adopt the terms relative indirect effect and relative direct effect to refer to aib and $c'i$, respectively. In general, their interpretations will depend on how groups or levels of the categorical variables are defined, but they will always quantify the effect of being in one group relative to some reference group or set of groups. In a simple dummy coding system, as in this example, aib is the indirect effect on Y via M of being in group i relative to the reference group. $c'i$ represents the direct effect of being in group i on Y relative to the reference group.

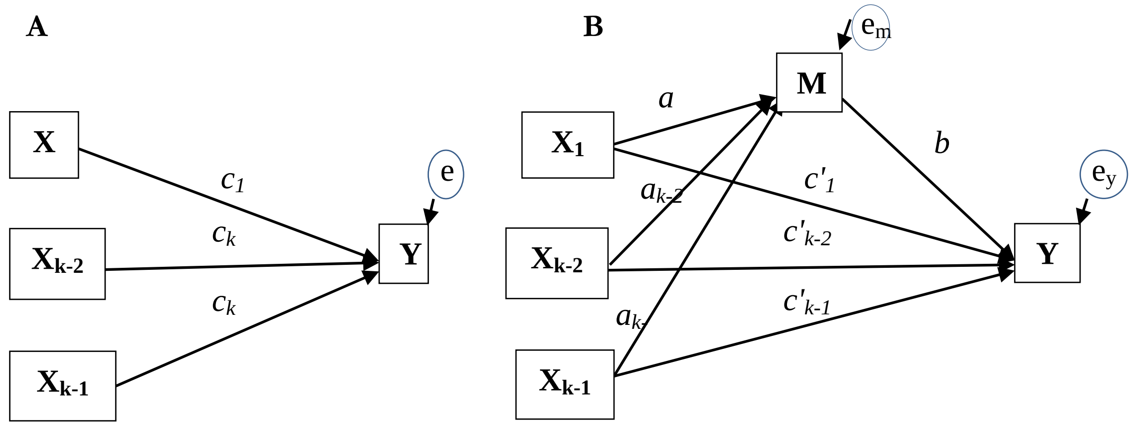

Figure 2: A mediation model with multiple independents variables

When X is multi categorical, there is no single parameter that can be interpreted as the total effect of X, so it is impossible to talk about the total effect using a single number. Rather, the total effect is quantified with a set of $k - 1$ parameter estimates resulting from the estimation of Y from the $k - 1$ X variables coding groups in a linear model (Figure 2):

$$Y = i3 + c1X1 + c2X2 + \ldots + ck\text{-}1Xk\text{-}1 + eY \tag{8}$$

In Equation (8) the $k - 1$ estimates of ci, $i = 1$ to k, quantify mean differences between the groups on Y. Authors refer to this $k - 1$ estimates as relative total effects. In the case of indicator coding, ci quantifies the mean difference in Y between the group coded with Xi and the reference group.

Although formal estimation of the relative total effects is straightforward, it is not actually necessary, for regardless of the system used for coding groups, the relative total effects are equal to the sum of the corresponding relative direct and indirect effects. That is,

$$ci = c'i + aib. \tag{9}$$

Authors illustrate the estimation and computation of the relative indirect, direct, and total effects using our pilot study data. $X1$ codes the Human capital, $X2$ codes the Social capital and X_3 the Organizational capital. Estimating the linear models in Equations (6), (7), and (8) using either an OLS regression program or simultaneously in an SEM program using maximum likelihood estimation yields $i1 = -0.085$, $i2 = 0.745$, $i3 = 0.731$, $a1 = 0.825$, $a2 = 0.695$, $a3 = 0.724$, $b = 0.738$, $c'1 = 0.392$, $c'2 = 0.414$, $c'3 = 0.0.539$, $c1 = 0.758$, $c2 = 0.714$, and $c3 = 0.785$. The resulting models reproduce the group means on M as well as the adjusted and unadjusted group means on Y found in Table 1.

The relative indirect effects of X on Y through M are constructed by multiplying the parameter estimates for the effect of intellectual capital on organizational motivation ($a1$, $a2$ and $a3$) by the effect of organizational motivation on innovation capability independent of intellectual capital (b). $a1$, $a2$ and $a3$ correspond to the mean differences in motivation between the human, social and organizational capital.

Thus, human capital was perceived as 0.825 units more interactive than was the social capital as 0.695, and the organizational capital was perceived as 0.724 units Multi categorical X in Mediation Analysis more interactive than the non-mediation. Furthermore, holding condition constant, those who perceived the intellectual capital as more interactive also had innovation capability that were more favorable Motivation ($b = 0.359$). The relative indirect effects of human capital $a1b = (0.825)(0.738) = 0.609$ and $a2b = (0.695)(0.738) = 0.513$ and also $a3b = (0.724)(0.738) = 0.534$.

Relative to the control condition, those assigned to the human capital condition had innovation capability toward the intellectual capital that were $a1b = 0.609$ units more favorable as a result of the positive effect of human capital on motivation (from the sign of $a1$), which in turn increases the favorability of innovation capability (from the sign of b). Similarly, those assigned to social capital condition had innovation capability that were $a2b = 0.513$ units more favorable than those assigned to the social capital condition (from the sign of $a2$) as a result of the positive effect of organizational capital on motivation, which in turn results in more favorable innovation capability. In Equation (7), $c'1$, $c'2$ and $c'3$ represent the relative direct effects of human, social and organizational capital respectively, relative to the organizational capital condition, and quantify the corresponding differences between adjusted means ($\bar{Y}$) on the innovation capability measure.

Substantively, Authors can say that after adjusting for group differences in organizational motivation, the human capital reported innovation that were 1.001 units more favorable toward the intellectual capital than social capital and organizational capital had innovation capability 1.093 units more favorable than social capital. The relative total effects, $c1$, $c2$ and $c3$, can be found in Table 1 when estimated using Equation (8). These are equivalent to the mean difference in innovation respectively. These relative total effects can also be calculated by adding the corresponding relative direct and indirect effects. That is, $c1 = c'1 + a1b = 0.392 + 0.609 = 1.001$, $c2 = c'2 + a2b$, and $c3 = c'3 + a3b$ respectively 0.927and 1.073.

Investigators usually are interested in generalizing beyond their data to the data generating process or to the population from which the sample was derived. The various effects described above are sample-specific instantiations of their corresponding population effects. Typically, researchers proceed by testing hypotheses about these effects, either ruling out chance as a plausible explanation for an obtained effect or by the construction of interval estimates of their population values. In this section, Authors address statistical inference about relative indirect, direct, and total effects.

Relative Direct and Total Effects

The relative direct and total effects $c'i$ and ci quantify mean differences, either on Y adjusted for group differences in M (in the case of $c'i$ —the relative direct effect) or on Y unadjusted for such group differences (in the case of ci —the relative total effect) between a group or combination of groups relative to some kind of comparison group or set of groups.

Statistical inference about these relative effects is straightforward and fairly noncontroversial. All regression routines programmed into statistical packages that are widely used, as well most SEM programs, provide standard errors for these estimates and p-values for testing the null hypothesis using a level of significance α, and $100(1 - \alpha)\%$ confidence intervals can be constructed in the usual way. All relative direct and total effects is different from zero and positive for all comparisons. So regardless of whether or not organizational motivation is controlled intellectual capital seems to lead to more favorable innovation capability to the organization.

As noted above, users of the causal steps approach to mediation analysis infer the existence of indirect effects through a logical argument based on the successful rejection of null hypotheses about the effect of X on M and the effect of M on Y controlling for X. The Sobel test is analytically superior to the causal steps approach because it is based on an explicit quantification of the indirect effect, but inappropriately assumes normality of the sampling distribution of the product of coefficients and is not as powerful as competing methods. Of the methods available for making inferences about indirect effects in statistical mediation analysis

(MacKinnon et al., 2004), Authors recommend bootstrap confidence intervals because of their superior statistical characteristics and performance as evidenced in numerous simulation studies (Biesanz, et. al., 2010) and their ease of implementation in existing software such as SPSS and SPLS procedures. A bootstrap confidence interval for a relative indirect effect is constructed by repeatedly taking samples of size *n* with replacement from rows in the data file, where *n* is the size of the original sample, and estimating all the coefficients in the mediation model using Equations (6) and (7) in each bootstrap sample. From the estimated coefficients, the relative indirect effects are calculated. Repeated many times, the distribution of the relative indirect effects over multiple bootstrap estimations serves as an empirical approximation of their sampling distributions. These estimates are sorted from low to high, and a $100(1 - \alpha)\%$ confidence interval for each relative indirect effect is constructed by treating as confidence limits the bootstrap estimates that define the lower and upper $100(1-\alpha/2)\%$ of this distribution. If zero is outside this interval, then the relative indirect effect is deemed statistically different from zero. Adjustments to these endpoints can be made to produce, in theory, a —better confidence interval, such as bias correction or bias correction and acceleration. These adjustments defy nonmathematical description. Lunneborg (2000).

The relative indirect effects are estimated as products of coefficients and are interpreted similarly to the direct effects, and the SPSS and SAS macros generate bootstrap confidence intervals for inference. The relative indirect effect for the first contrast comparing any intellectual capital to the control condition is the contrast for organizational motivation multiplied by the effect of interactivity on innovation capability independent of intellectual capital, $b = 0.738$. Thus, $a1b = (0.825)\ (0.738) = 0.609$. Any human capital results in a more favorable innovation capability by 0.758 units as a result of greater perceptions of interactivity in the intellectual capital (from the sign of $a1$), which in turn leads to a more favorable innovation capability (from the sign of b) A 95% bias-corrected bootstrap confidence interval for this relative indirect effect as 0.609. This indirect effect is statistically different from zero, indicating that these intellectual capitals indirectly influence innovation capability through organizational motivation.

The relative indirect effect for the second contrast corresponds to the effect of social capital on innovation capability through organizational motivation and is calculated similarly as the product of coefficients. The contrast for organizational motivation corresponds to the difference in mean motivation between the human and social capital. When multiplied by the effect of motivation on innovation capability, the result is the relative indirect effect of social capital on innovation capability, $a2b = (0.695)\ (0.738) = 0.513$.

Social capital results in innovation capability that is 0.513 units less favorable on average relative to human capital as a result of the greater perceptions of motivation that results from more social capital (from the sign of $a2$), which in turn positively influences innovation capability (from the sign of b). But a 95% bias-corrected bootstrap confidence interval for this relative indirect effect straddles zero. Thus, the evidence is not sufficiently strong to declare the presence of such an indirect effect of high relative to human capital.

The relative direct effect $c'1$ corresponds to the unweight effect of any intellectual capital on innovation capability relative to none, independent of motivation. The relative direct effect $c'2$

is the effect of social capital relative to human capital on innovation capability, again independent of motivation. These relative direct effects correspond to differences between adjusted means, in the former case an unweight combination of the means in the three intellectual capitals.

Thus, independent of the effect of organizational motivation on innovation capability, any intellectual capital yields innovation are 0.738 units more favorable toward the motivation on average relative to no intellectual capital. Furthermore, human capital yields attitudes that are 0.825 units more favorable on average than social capital and organization capital. Tests of significance available in standard regression output can be used for inference about these relative direct effects.

The relative total effects, $c1$, $c2$ and $c3$, in Table 1 are estimated using Equation (8) or by adding the corresponding relative direct and indirect effects. These relative total effects of intellectual capital on innovation capability quantify the mean difference in innovation toward the motivation for intellectual capital relative to human capital, social capital and organizational capital. Observe that these relative total effects partition perfectly into the relative direct and indirect effects: $c1 = c'1 + a1b = 0.392 + 0.609 = 1.001$ and $c2 = c'2 + a2b = 0.414 + 0.513 = 0.927$ and $c3 = c'3 + a3b$=0.539+0.534=1.073. Again, regression output contains inferential tests for these relative total effects.

The relative indirect effects are still estimated as products of coefficients. The $a1$ coefficients quantify the mean differences in motivation between the human capital, social capital and organizational capital. When $a1$, $a2$, and $a3$ are multiplied by the effect of motivation on innovation, holding intellectual capital constant ($b = 0.738$), the result is the relative indirect effects of intellectual capital on innovation capability through organizational motivation.

The relative indirect effect $a1b$ estimates the indirect effect of human capital relative to intellectual capital through motivation on innovation. The human capital were 1.001 units more favorable on average (with a 95%) than the assigned to the social capital as a result of this indirect mechanism linking intellectual capital to innovation through motivation. The relative indirect effect $a2b$ estimates 0.927 the indirect effect of social capital relative to innovation through motivation. Organizational capital resulted in innovation $a3b$ that were 1.073 units more favorable on average than social and human capital as a result of this indirect mechanism linking intellectual capital to innovation through motivation.

As when other coding systems are used, the relative total effects can be estimated by using Equation (8) or by adding the relative direct and indirect effects. With $c1$ estimates the mean difference in innovation between the human capital and, $c2$ and $c3$ estimates the mean difference in innovation respectively the social and organizational capital. As these effects are positive, this suggests innovation increases in favorability as intellectual capital increases. Finally, notice that the relative total effects partition cleanly into the relative direct and relative indirect effects.

Multiple Group Effect of M on Y

An assumption frequently described as necessary for causal inference in mediation analysis is the no-interaction assumption the assumption of homogeneity of regression. If this assumption is violated, then it is not sensible to estimate the relative indirect effect of *Xi* as *aib* because *b* in Equation (7) does not adequately characterize the association between *M* and *Y*. Nor is it meaningful to quantify the relative direct effect of *Xi* as *c'i* because interaction between *X* and *M* implies not only that the effect of *M* on *Y* depends on *X* but also that the effect of *X* on *Y* depends on *M*.

This assumption can be investigated empirically by including the necessary interaction terms in the model of *Y* and determining whether there is a collective effect of these interaction terms on *Y*. This interaction would be tested by re-specifying the model of *Y* in Equation (7) as

$$Y = i2 + c'1X1 + c'2X2 + \ldots + c'k\text{-}1Xk\text{-}1 + b1X1M + b2X2M + \ldots + bk\text{-}1Xk\text{-}1M + bkM + eY \quad (10)$$

and testing the composite null hypothesis that all population *bi*, $i = 1$ to $k - 1$ are equal to zero. Rejection of this null hypothesis implies that the effect of *M* on *Y* depends on *X*. If such an interaction is found, the procedure described in this paper should not be used, in the same way that one should not interpret the results of an analysis of covariance when this assumption is violated.

When using OLS regression, this assumption can be tested using hierarchical variable entry in which R^2 from the model in Equation (7) is subtracted from R^2 from Equation (10) to yield □ R^2. Under the null hypothesis of no interaction and the standard assumptions of ordinary least squares regression, $df\,(\Delta R^2)\ /\ [(1 - R^2)(k - 1)]$ follows the $F(k - 1, df)$ distribution, where *df* and R^2 are the residual degrees of freedom and squared multiple correlation, respectively, from the model in Equation (10). Alternatively, in a structural equation modeling program, the fit of two models can be statistically compared, one in which all *bi*, $i = 1$ to $k - 1$, are constrained to zero versus one in which they are freely estimated. As these are nested models, under the null hypothesis of no interaction, the difference in χ2 for the two models follows the $\chi^2_{(k\ -\ 1)}$ distribution. If the *p*-value for this test is below the nominal α, then the assumption of homogeneity of regression has been violated to some degree. Importantly, the outcome of either test will be invariant to the choice made as to how to code the groups.

The MEDIATE tool for SPSS and SPLS described in Appendix performs this test automatically. As can be seen in the output in Appendix, the difference in R^2 between the two models of attitudes toward the web portal (*Y*) with and without the $k - 1$ products representing the interaction between web customization condition (*X*: *X*1 , X_2 and *X*3) and perceived interactivity (*M*) is $\Delta R^2 = 0.004$ and not statistically significant, $F(2,54) = 0.297$, $p = 0.744$. Thus, the homogeneity of regression assumption is not contradicted by the data, and the relative direct and indirect effects can be interpreted as described above.

This assumption of no interaction between *X* and *M* represents an important special case of the assumption that one's model is properly specified. Because both *X* and *M* are available in the data, it is an assumption that is easy to test, and Authors strongly recommend doing so. Yet it principle any of the paths in a mediation model could be moderated by other variables either available in the data or not, and a failure to include such interactions potentially also represents a misspecification that is equally as important as the assumption that *X* does not interact with *M*. It is routine for researchers to either ignore such possibilities or empirically test them. There is a literature on ―moderated mediation and the estimation of indirect effects that are moderated (Edwards & Lambert, 2007; Preacher, et. al., 2007) and the principles described in that literature could be extended without much difficulty to models with a multi-independent variable.

Our discussion thus far has ignored the potential influence of random measurement error in *X*, *M*, or *Y*. In experiments, and even when *X* is an observed categorical variable, measurement error in *X* is often negligible to nonexistent unless the categories were constructed through some kind of artificial categorization of a continuum or there is some ambiguity or subjectivity in the decision as to which category a particular case in the data belongs. But *M* and/or *Y* may and often do contain some random measurement error. If only *Y* is measured with random error, the consequence is reduced power for hypothesis tests of the indirect and direct effects, and greater sampling variation in those estimates, meaning wider confidence intervals. If *M* is measured with error, the result is likely to be some bias in the estimation of the effects of *X*—both indirect and direct (Darlington, 1990). There are other sources that can produce bias, such as model misspecification, and in practice there is often not much Authors can do to eliminate bias entirely. Furthermore, Ledgerwood and Shrout (2011) have shown that the reduction in bias can sometimes come at the cost of reduced power. Even so, most would agree that, when possible, it is prudent to reduce the influence of random measurement error on the estimation of the coefficients in the model and therefore the indirect effects.

The method Authors have described above can easily be modified to accommodate two approaches that account for random measurement error. The first is to estimate the effects in a SEM program while specifying *M*, *Y*, or both as single-indicator latent variables with observed *M* or *Y* as the sole indicator of the latent variable and constraining the unique variance of each indicator to a function of its reliability. This approach (Coffman & MacCallum, 2005; Stephenson & Holbert, 2003) requires a trustworthy estimate of the reliability of the observed *M* and/or *Y*. Indeed, the proposed method described above and all related treatments of mediation analysis with observed variables is a special case of this approach where reliability of measurement is assumed to be 1. A second alternative, also conducted in SEM, is to model variables measured with error as latent with a measurement model component that links the latent variable causally to its indicators. With this approach, the measurement error that would have permeated the observed measurement of *M* and/or *Y* is instead distributed throughout the errors in the estimation of the indicators of the latent variable(s). This approach requires some preliminary modeling in order to ascertain whether the proposed measurement model for the latent variable(s) satisfies various criteria for claiming ―good fit, for direct and indirect effects linking latent variables that are not modeled well have little substantive meaning.

Multiple Mediators

The approach Authors have described for estimating relative indirect and direct effects can be extended to models with any number (*m*) of intervening variables operating in parallel. Figure 3 depicts a model with *m* proposed mediators and a multi categorical *X* with *k* categories.

The relative total effects, c_i, can be estimated if desired using Equation 8 whereas the relative indirect and direct effects are pieced together from parameter estimates from $m + 1$ linear models, one for each of the m intervening variables and one for Y:

$$Mj = i1j + a1jX1 + a2jX2 + \ldots + a(k\text{-}1)jXk\text{-}1 + eMj \quad (11)$$

$$Y = i2 + c'1X1 + c'2X2 + \ldots + c'k\text{-}1Xk\text{-}1 + b1M1 + b2M2 + \ldots + bmMm + eY \quad (12)$$

The same relationships among relative total, indirect, and direct effects exist in multiple mediator models as in single-mediator models. The relative total effect for Xi can be partitioned into the relative direct effect for Xi plus the sum of the relative specific indirect effects for Xi,

This last term in (13) is the relative total indirect effect of Xi. Each relative specific indirect effect quantifies the component of the relative total indirect effect that is carried uniquely through that intervening variable. Inferential tests of relative specific indirect effects can be undertaken just as described above, and these would typically be the focus of mediation Multi categorical X in Mediation Analysis.

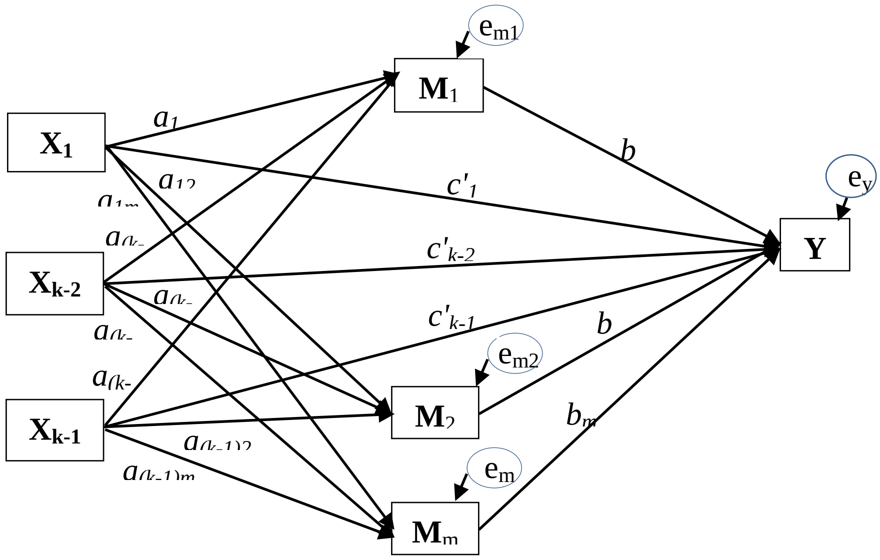

Figure 3: A multiple mediation model with multiple independents variables

Covariates and Moderation

In a mediation model, the interpretation of an indirect effect as a causal one assumes that the intermediary variable M is causally located between X and Y. That is, it is assumed that X causes M and M causes Y. When X is experimentally manipulated and sounds experimental procedures are followed, a causal association between X and M and between X and Y is established by showing that the k groups differ on M and Y on average. Of course, as many others have emphasized before us (Bullock et al., 2010; Mathieu, et. al., 2006; Stone-Romero & Rosopa, 2010), this does not establish that M causes Y. It could be that Y causes M or that M and

Y are spuriously associated (both are caused by some variable Z) or epiphenomenally associated (M is correlated with the ―true intermediary variable Z). If X is not experimentally manipulated, such threats to causal inference also exist in the interpretation of the association between X and M as well.

Spuriousness and epiphenomenally, as alternative explanations at least with respect to a given competing variable Z, can be accounted for in a mediation model by including Z as an additional predictor or ―covariate in the models of M and Y. For example, Equations (1), (2), and (3) with the inclusion of Z as a covariate would be

$$M = i1 + aX + d1Z + eM \tag{13}$$

$$Y = i2 + c'X + bM + d2Z + eY \tag{14}$$

$$Y = i3 + cX + d3Z + eY \tag{15}$$

The addition of covariates is simple in any OLS regression program; covariates can be added to each of the statements in the SPSS and SPLS tool described.

By controlling for Z when estimating the various effects in a mediation model, all effects are adjusted for the shared associations between W and all variables in the model. Such effects could then be called ―partial effects, such as the ―relative partial indirect effect of Xi on M through Y controlling for Z. The mathematics described above still applies. For example, the partial total effect for a given Xi is equal to the sum of the relative partial indirect effect of Xi and the relative partial direct effect of Xi. Mean differences quantified by the $k - 1$ a and c coefficients represent adjusted mean differences, controlling for Z, as do the $k - 1$ estimates of c' (which adjust for Z and M). Of course, several covariates could be included simultaneously when estimating the coefficients in the models, and covariates could be added to models with more than one intervening variable as well. Including Z as a covariate can be beneficial even if Z does not threaten the validity of the causal inference. If Z is correlated with Y, for instance, including Z in the model of Y will tend to decrease the standard errors (i.e., the sampling variance) of the b, c, and c' coefficients if Z is uncorrelated or correlated only weakly with M and X. If Z is correlated with M but not X, this will tend to decrease the standard errors of the a coefficients. The increased precision in estimation of model coefficients will increase the power of tests of the relative direct, indirect, and total effects and narrow the width of confidence intervals.

However, by also examining moderator effects, one is able to investigate whether the experiment differentially affects subgroups of individuals (MacKinnon 2001). Three potential models in which this examination may take place are (a) moderated mediation, (b) mediated moderation, and (c) mediated baseline by treatment moderation models.

The moderated mediation model (Figure 4) is the simplest statistical model with moderator and mediation effects (Judd et al. 2010). In this model, a variable mediates the effect of an independent variable on a dependent variable, and the mediated effect depends on the level of a moderator. Thus, the mediational mechanism differs for subgroups of participants (James & Brett 1984). The single-mediator version of this model consists of estimating the same mediation model for each subgroup and then comparing the mediated effect across subgroups. A statistical test of the equivalence of the mediated effect across groups was described in MacKinnon (2007), and tests of the equality of a , b, and c' can provide information on the invariance-of-action theory (how the program changes mediators) and conceptual theory (how mediators are related to the outcome) across groups.

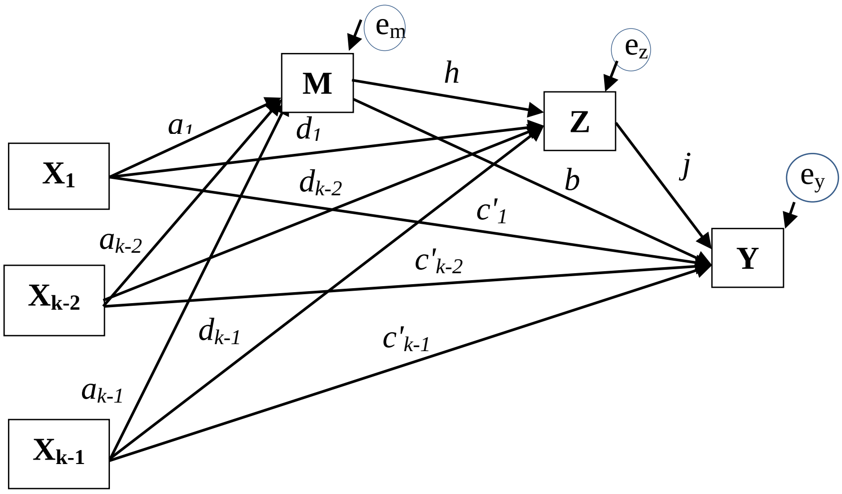

Figure 4. A mediation and moderation model

The moderated mediation model is more complex when the moderator variable is continuous. Although the regression equations required to estimate the continuous moderated mediation model are the same as for the categorical case, the interpretation of results is complicated because of the large number of values of a continuous moderator. In this case, researchers may choose to analyze simple mediation effects.

Mediated moderation (Baron & Kenny 1986, Morgan-Lopez & MacKinnon 2001) occurs when a mediator is intermediate in the causal sequence from an interaction effect to a dependent variable. The purpose of mediated moderation is to determine the mediating variable(s) that explain the interaction effect. This model consists of estimating a series of regression equations where the main effect of a covariate and the interaction of the covariate and program exposure are included in both models. Morgan-Lopez & MacKinnon (2001) describe an estimator of the mediated moderator effect that requires further development and evaluation.

The mediated baseline by treatment moderation model is a special case of the mediated moderation model. The substantive interpretation of the mediated effect in this model is that the mediated effect depends on the baseline level of the mediator. This scenario is a common result in intellectual capital and innovation capability research, where the effects of an intellectual capital are often stronger for performances which are at higher motivation on the mediating variable. These organizational motivations by baseline interactions have been found in numerous areas of research, ranging from intellectual capital with motivation to innovation capability with the organizational characteristics. Information provided in these models may indicate for intellectual capital is ineffective or even counterproductive and may be mediated by motivation into more effective innovation capability based on their organizational characteristics.

Various authors have outlined the equations and rationale for the mediated baseline by treatment moderator model (Baron & Kenny 1986, Morgan-Lopez & MacKinnon 2001). To date, models with moderators and mediators have remained largely independent. This separation in their presentation has contributed to confusion in the understanding of each relative to the others. A critical goal of future research in this area will be to develop and test a general model in which each of the models is a special case. One such model is described in Muller et al. (2005). Another model is in development but has not yet been empirically tested in applied research (MacKinnon 2007):

$$Y = i4 + c'1X + c'2Z + c'3XZ + b1M + b2MZ + hXM + jXMZ + eY \tag{16}$$

In this model, the XM and XMZ interactions are added to the individual mediation and moderation equations to form a general model that includes all effects (including additional c' and b effects). Here the h coefficient represents the test of whether the M to Y relation differs across levels of X, and the j coefficient represents the three-way interaction effect whereby the relations between Z and M and Y differ across levels of X. If a statistically significant j coefficient is found, further simple interaction effects and simple mediated effects are explored.

Conclusions

In this study, Authors have described and illustrated existing approaches to estimating indirect and direct effects in statistical mediation analysis that can be used with a multi categorical independent variable. Relative indirect and direct effects quantify the effects of being in one category on some outcome relative to some other group or set of groups used as a reference for comparison. The outcome of tests of relative indirect and direct effects will, naturally, be dependent to some extent on the choices one makes about groups and which group, or groups are used as the reference for comparison purposes.

There is broad and sustained interest in mediation and moderation analysis from many areas of management and other fields: Tests for mediation differ considerably in type I error rates and statistical power (MacKinnon et al. 2004). The recommended test of mediation assesses the statistical significance of the X to M relation, *a* path, and then the M to Y relation, *b* path. If both are statistically significant, there is evidence of mediation. Because confidence limits are important for understanding effects, confidence limits based on the distribution of the product, or the bootstrap are recommended. This approach also applies to mediated effects in more complicated models. It is also important to consider opposing mediated effects and more complicated models such that overall relations may not be statistically significant, yet mediation may still exist in a research study. These opposing effects or mediated effects that counteract each other resulting in a non-significant X to Y relation may be of substantive interest.

Person-oriented approaches based on trajectory classes (Muth´en & Muth´en 2000) and staged responses across trials (Collins et al. 1998) represent new ways to understand mediational processes consistent with the goal of examining individual-level processes and group-level processes. Longitudinal data provide rich information for the investigation of mediation. In particular, latent growth curve and latent difference score models may be especially suited to the examination of mediation chains across multiple waves of data because of the ability to investigate the effect of prior change on later change. The usefulness of causal inference models and different alternatives to learning more about mediation are an important topic for future research. Additionally, experimental designs to investigate mediation require further development. Similarly, methods to combine qualitative as well as quantitative information about mediational processes should clarify mediation relations. These developments will advance our ability to answer mediation questions in management. Authors hope the computational tools for SPSS and SPLS that Authors provide will facilitate use of the type of analysis Authors describe and enable researchers to apply the advice given recently by methodologists who study mediation and moderation analysis to research designs that include multi categorical independent variables.

Analysis of mediator and moderator effects may supply more in-depth information about a research phenomenon than can be explained by direct effects alone. Important four elements that should be included in this paper of mediator and moderator research are (a) correct definition and use of the terms mediator and moderator, (b) a rationale for the hypothesized mediator and moderator effect and evidence for the hypothesis based on literature and conceptual framework, (c) statistical analysis that is matched to the hypothesized mediator and moderator effect, and (d) interpretation of the mediator and moderator effect in the findings. The Apparel Manufacturing employees who are interested in exploring more than just the direct effects of intellectual capital on innovation capability may want to consider hypotheses about mediator of organizational motivation and moderators of organizational characteristics that could provide additional information about why an observed phenomenon occurs or under what circumstances an intellectual capital has the greatest effect on innovation capability which lead to organizational performance.

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Appendix 1

Table 1. Results of Regression models

Variables/ Models	Model1	Model2	Model3	Model4	Model5	Model6	Model7
HC	0.226		0.632			0.071	0.635
	(0.098)		(0.000)			(0.646)	(0.668)
SC	0.243		0.166			0.203	1.472
	(0.027)		(0.118)			(0.064)	(0.254)
OC	0.426		0.084			0.405	-0.191
	(0.001)		(0.500)			(0.002)	(0.850)
IC		0.822		0.815			
		(0.000)		(0.000)			
OM			a	a	0.738	0.246	0.558
					(0.000)	(0.052)	(0.413)
Och							-0.395
							(0.511)
InC	a	a			a	a	a
HC_Och							0.028
							(0.985)
SC_Och							-0.037
							(0.974)
OC_Och							1.145
							(0.353)
OM_Och							-0.371
							(0.660)
HC_SC							-2.454
							(0.442)
SC_OC							-1.451
							(0.589)
HC_SC_OC							2.038
							(0.430)
β	0.779	0,731	-0.120	-0.084	1.626	0.803	-0.077
R^2	0.679	0.671	0.697	0.665	0.545	0.698	0.712
F	46.598	141.605	50.685	134.769	81.326	37.477	11.728
Sig	0.000	0.000	0.000	0.000	0.000	0.000	0.000

a- Dependent variable

IC- Intellectual Capital, **HC**- Human Capital, **SC**- Social Capital, **OC**- Organizational Capital,**OM**- Organizational Motivation, **Och**- Organizational Characteristics