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Conceptual Analysis of Moderator and Mediator Variables in Business Research

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Abstract

The major purpose of this article is to expand the domain of the business research by providing conceptual analysis of the moderating and mediating variables and exploring their potent effects in business research. To provide specific implications, Kang et al. (2015) model with respect to Balanced Scorecard technique is conceptually extended. Theoretical foundation of the moderating, mediating, and their major distinctions along with appropriate statistical tests applicable to each situation are also provided. The model is also extended to analyzing interaction effects of Mediated-Moderation and Moderated-Mediation designs and their testing. The article concludes that: 1) the nature of complex business problems will be more transparently captured by considering moderating and mediating variables, 2) without specifying moderating and mediating variables, business models are incomplete and therefore are not able to solve real business obstacles. Lack of inclusion of moderating and mediating effects is one viable reason which indicates why most business models do not function in real practice, 3) moderating and mediating variables are widening the scope of the prevalent business theories, and 4) moderating and moderating variables makes it possible to respond to the inquiries regarding "when" "how" and "why" a particular relationship exists between the independent and dependent variables. Hence, this study posits great impacts in future correlational and experimental studies in business.

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1. Introduction

A famous aphorism in statistics, which is originated by professor Box (1976), the great statistician of the 20 century, is that “all world’s models are wrong”, because they are abstracting the reality so much. On the contrary, it is argued that because of the impossibility of capturing complex realities into a model, some kind of abstraction is mandatory. While this argument stems from the facts, a critical inquiry is: to be useful, how much abstraction should be made in establishing a particular model? Despite a lack of any unambiguous rule in this regard, a general guideline in every disciplines tends to call on scientists to establish a sumptuous model in an attempt to get surrounding to reality as much as possible.

The general motivation of this article is to provide a conceptual analysis for extending the reality into models. This analysis is comprehensive and can be applied to any discipline such as engineering, hard sciences, social sciences, agricultures and medical sciences. However, in order to be specific, merely business models in the context of the Balanced Scorecard (BSC) (Kaplan & Norton, 1992), which is a contemporary universally multidisciplinary technique, will be discussed.In most modern business models,(e. g., Farooq and Hussain, 2011; Karabulut, 2015; and Kang et. al, 2015) when experimental and causal designs are exerted, researchers’ effort is usually focused solely on analyzing the relationship between dependent and independent variables to study designated obstacles. For instance, in the domain of the Balanced Scorecard (BSC), Karabulut (2015) investigates the effect of innovation on the performance of the manufacturing firms based on the BSC and it’s four perspectives. Fig1 shows the study’s design.

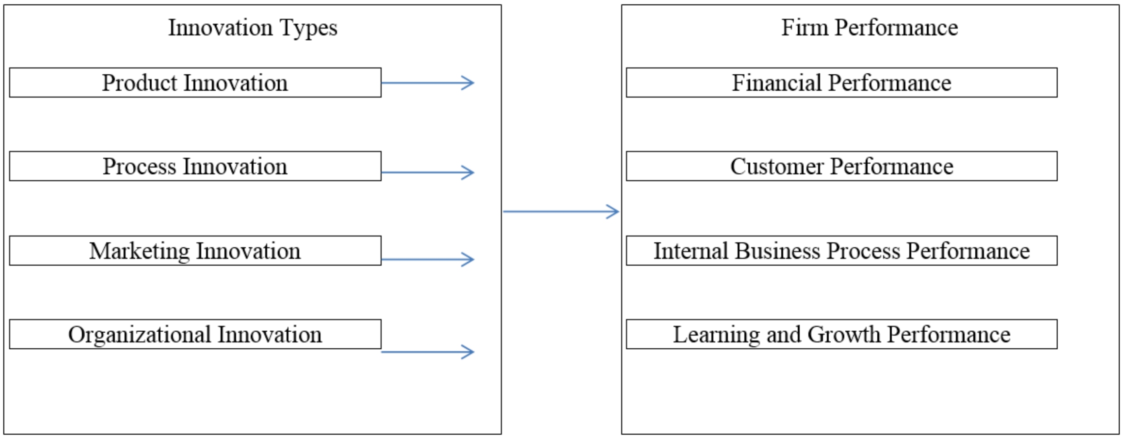

Fig 1. Karabulut (2015: 3159) research model

By applying multiple regression analysis, the author reports that the product, process and organizational innovations show a positive effect on all four BSC perspectives. However, the marketing innovation demonstrates a positive impact only on financial, customer, and internal business processes perspectives and a negative impact on the learning and growth performance.

In a more elaborate study, Kang et al. (2015) study the relationship between Corporate Social Responsibility (CSR) and Family Hotels’ Financial Performance (FHFP) based on the Sustainability Balanced Scorecard (SBSC) – Financial (FIN), Customer (CUS),Internal business (INT), Learning and growth (L & G),Non-market (social and environmental) perspectives, and hotels’ Goals(GOA) and Vision (VIS). Fig 2 shows the research design.

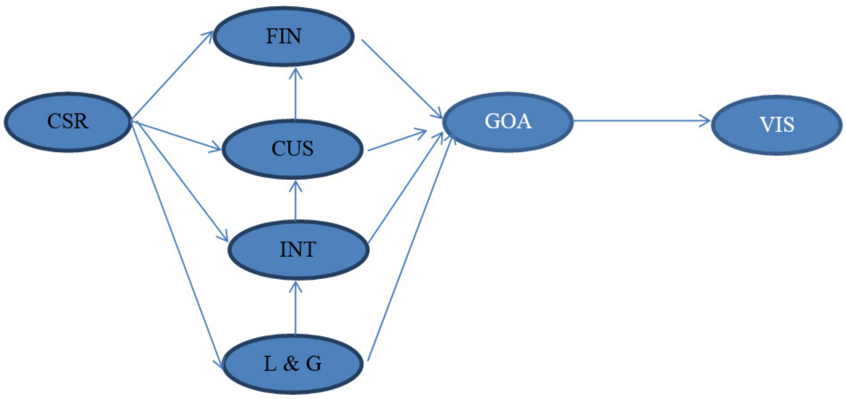

Fig 2. Kang et al. (2015: 127) model

By identifying three groups of stakeholders (managers, employees and customers) and applying Partial Regression, the authors found that: 1) CSR exhibits a significant influence on SBSC for both managers and employees group, 2) CSR shows a significant relation with goals for all stakeholders groups and 3) all stakeholders confirm a causal relation among BSC perspectives.

Although these studies report interesting results, the findings seem somehow spurious and illusory, because reported results are confined to limited research designs which suffer from, at least, three acute shortcomings: parsimony, rationality problems and external validity threats. The first weakness relates to abstracting reality and lacking inclusion of adequate appropriate variables to capture the true nature of the study. The second problem is in regard to the inability of research designs in identifying the true relationship which is dominated between dependent and independent variables as well as with other variables which are ignored by researchers. The third obstacle stems from the potential of generalizability of findings from samples to populations of the studies. Hence, the major inquiry is: what are the effects of these subtle deficiencies on findings of the studies and how can they be solved?

The major purpose of this research is responding to the preceding inquiry by conceptually describing, analyzing and testing the effects of Moderator (MO) and Mediator (ME) variables and their interactions- Mediated-Moderation and Moderated-Mediation effects. In order to be more precise, the design of Kang et al.'s (2015) study, which is more elaborate than many preceding research, will be extended, The importance of this research relates to defining and analyzing potential impacts of MO and ME, their interactions and behaviors in business research. Hence, it provides a potent theoretical basis for conducting more comprehensive empirical studies to analyze complex business problems more truly and accurately. The study also contributes to contemporary knowledge about research designs, and causes refining prevalent business theories, which entails to more insightful, real and valid findings.

The organization of the research is as follows. Sections II and III describe the nature, characteristics and testing of the moderating and mediating variables respectively. Major distinctions of the moderating and mediatizing variables are discussed in section IV, and the effect, testing and extensions of mediated-moderation and moderated-mediation are explored in section V. Section VI provides discussions, conclusions, suggestions and limitations of the study.

2. Moderator Variables

A potent way for enhancing business research designs, and thus providing more realistic and accurate findings, is inserting appropriate MO variables relating to studies. A MO variable is a qualitative (sex, religion, customer satisfaction) or quantitative variable (such as firm's size, financial leverage and price) that affects the strength AND /OR direction of the relationship between the dependent or criterion variable(Y) and the independent or predictor(X) variables (Baron and Kenny, 1986). It may be naturally occurring, measured or determined variables (e. g., age, gender, industry type) or can artificially be created by manipulation of the conditions (e. g., negative/positive service quality) (RO, 2012). A MO variable in fact acts like the second independent variable. When MO is exerted, the following conditions should exist:

- X occurs before Y,
- MO maintains a causal relationship with Y,
- MO plays the same function as X.
- MO does not have any correlation with X.

In correlational studies, a MO variable is a third variable which could affect the amount of the correlation and/or change the direction of the dependent and independent variables. In experimental settings, the effect of a MO variable can be shown via the interaction effect of the X and MO. Hence, a logical extension of the Kang et al. (2015) study is searching and inserting appropriate MO variable(s) based on the theory and pertinent literatures of CSR and FHFP. Kang et al.'s model (2015) is provocatively based on the axiom that the relationship between Corporate Social Responsibility (X) and Family Hotels Financial Performance (Y) is direct, and no other variables are intertwining into this relation. This axiom is, of course, neither realistic nor complete. The true relationship between X and Y is more revealed when critical moderating variables are inserted in the model. Kang et al. (2015), Pivato and Misani (2008), and WU and KO (2013), among others, point out that "size of the hotel" is an influential factor which affects the relationship between X and Y, because small hotels are much more exposed to risks than large franchise hotels. Other researchers (e. g., Namazi et al., 2015, and Niresh and Velnampy, 2014) have also reported the effect of firm size in other contexts. Thus, the real relationship between CSR and FHFP is conditional on the size of the hotels, and conceivably size could be selected as a MO variable. Fig 3 shows the diagram of the size effect. Other exogenous variables -such as promulgation of the laws and regulation relating to CSR, economics, culture and political situation of the country, the existence of a well-organized stock market- and also endogenous variables-like company's (hotel's) exploitation of a more refined financial reporting system, innovation, technology, internal corporate governance, gender, price -could also be chosen as other MO variables.

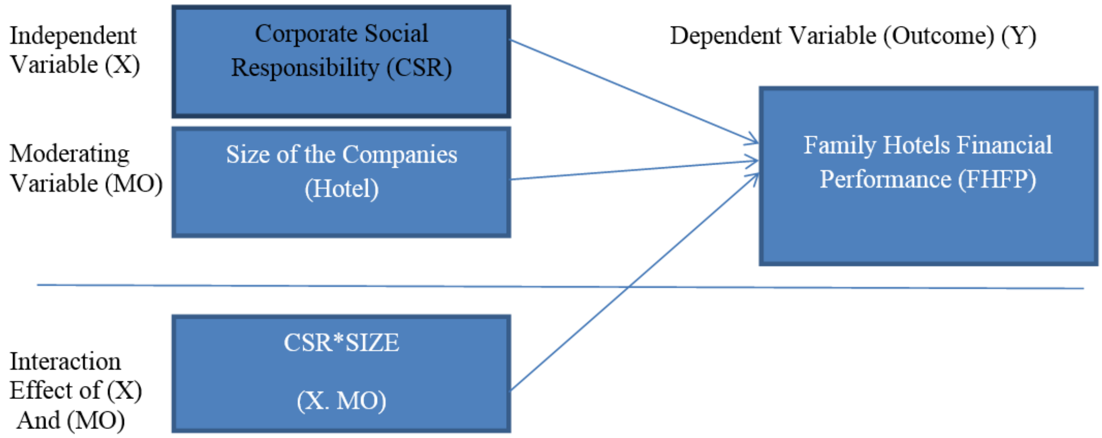

Fig3: Illustration of the moderator effect

To test the size effect of the model statistically, the scale type of the moderator and independent variables should be specified. Alternative cases are as follows (Baron and Kenny, 1986):

- Both MO (size) and X (CSR) are categorical variable- In this case, a 2x2 factorial design exists and ANOVA can be used to statistically test the relationship. If the interaction term is statistically significant, the moderator effect exits. If an interaction between X and MO exists, simple effect of the X is also considered for different levels of MO. Sample means for each condition are also used to visually demonstrate the interaction.

- MO (size) is categorical and X (CSR) is continuous variable- In this case, the first step is to represent the categorical variable with code variables (k-1 coding variables for a moderator with k levels) along with a product term. Then, correlation between X and Y is calculated for each level of MO and their differences are examined statistically. It is preferable that the coefficient of the X on Y is calculated for each group and the difference be examined statistically. If the difference is statistically significant, the reliability of the measurement of X for each level of MO is estimated usually by LISREL. The association of X with Y depends on the value of MO variable.When Mo is categorical (especially dichotomous), the Structural Equation Modeling (SEM) is also appropriate. The Multi-group Approach, which separately determines the relationship between X and Y for each group of MO, can also be exerted. This can be implemented by employing and comparing a “Constrained model (which assumes no interaction effect) with an “Unconstrained model” (which assumes interaction effect). If the unconstrained data fits better, it indicates that moderation exists (Ro, 2012).
- MO (size) is continuous and X (CSR) is categorical variable-In this case, the task is subtle. To measure MO effects, the researcher must know ahead of time how changes in X affect Y as a function of Mo. Generally, the effects of X on Y are not a function of MO because MO contains different levels. Fig 4 shows different cases in which MO could influence X and Y.

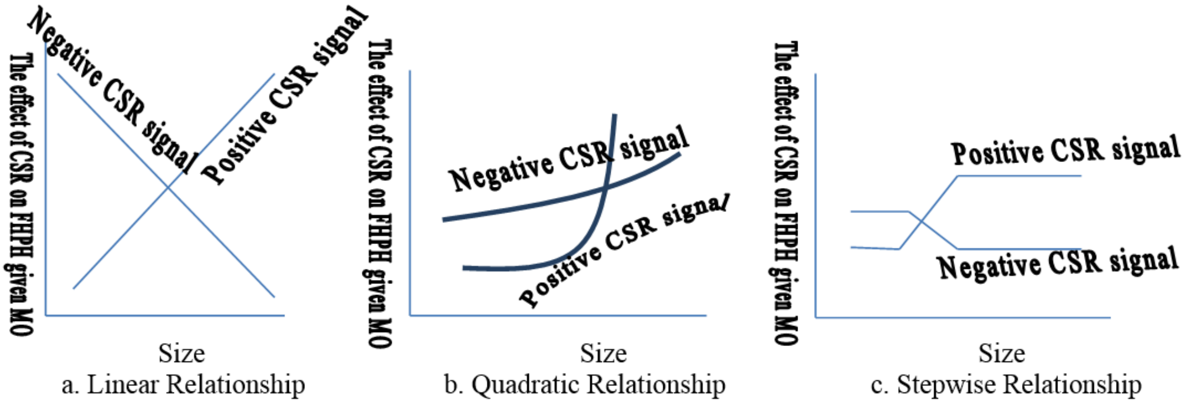

Fig 4: Illustration of the various moderating effect

In Fig 4a, the effect of X on Y given MO is linear. This situation happens when, for example, the researcher’s hypothesis is based on the theory that CSR posits only two signals: positive social and environmental responsibility, and negative social and environmental responsibility, and the effect of size as a MO variable is that positive social and environmental responsibility creates more effects on the performance of the hotels. In these cases to calculate the simple and interaction effect, usually a “Hierarchical Regression Analysis” is used. Consequently, at first, X and Mo are entered into the model as predictors of (Y). At this step, X and/or MO do not have to be significant predictors of the Y in order to test for an interaction. In the next step, an interaction term, the product of X and MO (X*MO), will enter into the model. If the interaction effect is significant, the interaction effect exists. Because the interaction effect is the product of X and MO, muticollinearity problems are likely to incur between the main effects of X and MO and their interaction effects. This multicollinearity results in “bouncing betas”-that is shifting the direction of the beta terms from positive to negative terms and vice versa. To correct this problem, centering (subtracting the sample mean) or standardizing (z scoring) is suggested (Aiken and West, 1991; Frazier et al., 2004).

In Fig 4b, the effects of X on Y given MO are quadratic. This Fig illustrates the situations in which the researcher’s theory is that generally the effects of CSR on the financial performance of the large hotels is greater than small hotels, however, with increasing the size of the hotels, this effects is diminished or lost. In some cases, it is possible that the relationship of one level of X with Y given MO is linear and the relationship of other levels of X on Y is quadratic. In these situations, the adjustment of the quadratic function is made by adding MO2 and X*MO2 and a “Hierarchical

Regression Analysis” is applied. If X*MO is significant, the moderating effect is linear, and if X*MO2 is significant, the moderating effect is quadratic.

In Fig 4c, the effect of X on Y given MO is shown as a “step-wise” relation. This situation might arise when the researcher’s hypothesis is that only at a specific level of size there is a clear difference between the effects of CSR levels. Thus, in a particular level of MO, a distinct difference is seen in the different levels of X. In these situations, MO at this particular level is divided into two levels and the effect of MO is exactly similar to case A above.

D. Both Mo and X are continuous variable-In this situation if the researcher’s hypothesis is based on the premises that the effects of X (CSR) on hotel’s financial performance (Y) given size (MO) can be characterized by ”step-wise ”relation, he/she can divide size (MO) at the step and follows the same approach as discussed in case B above. However, when the preceding relation is assumed to be linear, the situation would be similar to case C above and the interaction effects of X*MO is entered into the regression. If the effect is assumed to be quadratic, the interaction effects of X2* MO is entered into regression. In effect, for case D, a “Hierarchical Multiple Regression” is used. If the interaction term explains a statistically significant amount of variance of Y, and accordingly the change in R2 for the interaction term added model is statistically significant, a moderator effect is present.

SEM can also be employed in this case. By concentrating on the latent interaction effects of MO and X and their products, moderation effects can be explored. However, because the number of interactions may get large, the continuous moderator may be converted into a “categorical variable” and the “multi-group approach” can be used. Adopting this approach, however, may results in the emergence of type I and type II errors (RO, 2012).

In either preceding cases, the following issues should also be considered (Kenny, 2014):

- Power of the model,
- Measurement errors,
- Coarse outcome measures,
- Removing insignificant variables, and
- Artificial grouping.

3. Mediator Variables

In experimental and correlational business research, mediating variables may be identified to explain the kind and effects of the relationship between independent and dependent variables in an attempt to determine the nature of the study more accurately and functionally. A Mediator Variable (ME), also called “intervening or process variable”, is the variable that causes mediation in the relationship between the dependent variable (called outcome) and the independent variable (called causal variable) (Baron & Kenny, 1986, Kenny, 2014,Muller et al.2005). In a mediational model, it is hypothesized that there is no direct relationship between the dependent and independent variables. Instead, the independent variable first influences the mediator variable, and then the mediator influences the dependent variable. Thus, there is a casual chain of effects which characterizes the relationship between the dependent and independent variables. This relation is shown in Fig 5. “One reason for testing mediation is trying to understand the mechanism through which the causal variable affects the outcome. Mediation and moderation analyses are a key part of what has been called “process analysis”, but mediation analyses tend to be more powerful than moderation analyses. Moreover, when most causal or structural models are examined, the mediational part of the model is the most interesting part of that model” (Kenny, 2014).

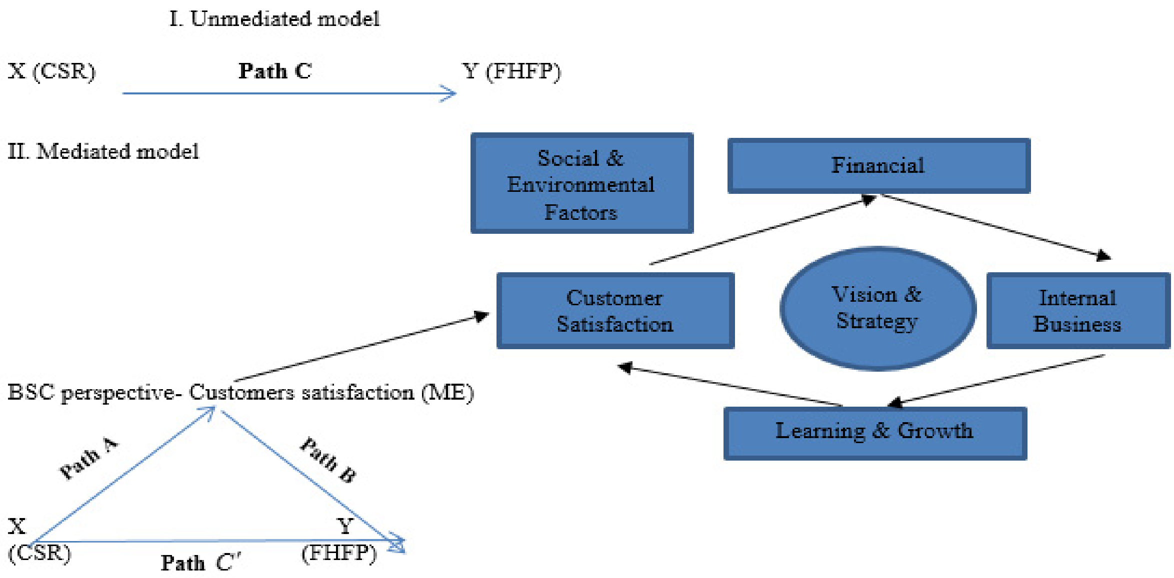

Fig 5: Illustration of the mediator effect

Kang et al. (2015:133) point out that the major limitations of their research is that "this study only tested the direct and indirect effects of CSR on goals and vision, while the mediating effect of BSC dimensions were not examined. Testing the mediating effect of BSC may offer more insight into the holistic effects of CSR and BSC on the strategies of small- and medium-sized hotels". Hence, this article attempts to conceptually extend Katz et al.'s (2015) model to discuss the effects of mediating variables.

Fig 5 illustrates the effect of the mediating variable (ME=stakeholders' perception about CSR) by incorporating BSC- on the relationship between the independent variable (X)- Corporate Social Responsibility (CSR)- and the dependent variable –Family Hotels' Financial Performance (FHFP),as an example of a mediating model. This model is much more accurate and comprehensive than the original Kang et al.'s (2015) model; it hypothesizes that CSR dose not influence FHFP directly, rather CSR affects stakeholders' perception (managers, employees, government and people) about CSR first, and then it is stakeholders 'perception that affects FHFP. In fact, the researchers' interest here might be focused on the main effects of the "stakeholders "perception" on CSR and FHFP, or the interaction effect of the stakeholders' perception and CSR, rather than analyzing the main effect of the CSR on the FHFP. The model is also based on the contemporary theories and literatures on CSR which selects SBSC as a potent performance evaluation technique. SBSC is based on the premises that the chain of cause - effect relationships begins with improvements in the area of "learning and growth" perspective. These improvements would cause positive effects in "business processes", which in turn leads to improvements in "customer satisfaction" and subsequently cause improvements in increasing revenues, profits and "financial performance". The non-market perspective complements all four perspectives by addressing economics, social and environmental issues that are not presented in the BSC model (Kaplan and Norton, 1992;Figge et al., 2002) Hence, it is possible to investigate how and why stakeholders' 'perceptions within each BSC perspectives would affect FHFP. For instance, Fig 5 can be adopted to assess "How and why customers' satisfaction would affect the relationship between CSR and FHFP?"

3.1. Testing Mediation

In Fig 5 the mediating variable (ME) called "intervening or process variable is "stakeholders' perception" – customers' satisfaction. Path C in model I and Path C' in model II are called "direct effect". The direct effect is the coefficient of C, and measures the extent to which Y (financial performance of the hotel) changes when X (CSR) increases by one unit. The indirect effect is the product of path coefficients of A and B, and measures the extent to which Y changes when X holds fixed and ME changes by the amount it would have changed had X increased by one unit. (Robins and Greenland, 1992). In linear systems, the total effect is equal to the sum of the direct and indirect effects (C + AB in the model above). In nonlinear models, the total effect is not generally equal to the sum of the direct and indirect effects, but to a modified combination of the two variables (Pearl, 2001).

In Fig 5, for estimating the effect of paths C, A, B, and C', multiple regression technique (sometimes called Ordinary Least Squares or OLS) can be applied. However, in some instances such other methods as logistic regression, multilevel modeling, and SEM must be used instead of multiple regressions. The steps of testing mediation effects, however, would be the same regardless of the data analysis method. Baron and Kenny (1986) propose the following steps in testing mediation:

Step1) show X is correlated with Y. (Regress Y on X-path C). Baron and Kenny, (1986) contend that mediator tests should only be attempted if this relation is significant.

Step2) show X is correlated with ME (Regress ME on X-path A).

Step3) show ME affects Y, while controlling for X (Regress Y on both X and ME-path B). It is not sufficient just to correlate ME with Y, because they both may be correlated by X.

By controlling the effect of ME, the relationship between X and Y gets weak; the amount of weakening has a direct relation with ME. If the effect of ME is large, ME's control would cause the loss of the relationship between X and Y. If by controlling the effect of ME, the relationship between X and Y does not approach towards zero but gets weak, other ME variables are involved. In business studies, it is possible that several causes be prevalent for each effect.

Step 4) show the effect of X on Y controlling for ME is zero to arrive at this conclusion that ME completely mediates the X-Y relationship (Path c'). The effects of both steps 3 and 4 are estimated in the same equation.

Initially, Baron and Kenny (1986) stated that the preceding steps should be tested in terms of statistical significance. However, Kenny (2014) points out the weaknesses of statistical significance testing and suggests preceding testing via zero and nonzero coefficients. When all four preceding steps are met a "complete or full mediation" is achieved. In this case by including ME, the relationship between X and Y (path C') falls down to zero. Because the probability of the occurrence of this situation is very low, often "partial mediation" is occurred. Partial mediation exists when the first three steps meet but the Step 4 is not. In this case, by controlling ME, the path from X to Y reduces in absolute size but is still different from zero. Most contemporary mediation analysts (e. g., Kenny et al., 1998, Kenny, 2014) assert that essential steps in establishing mediation are just Steps 2 and 3.

In contemporary mediational analysis, however, "The Indirect Effect" of the mediation (path A times path B) is used as a measure of the amount of mediation through the following equations:

$C = C' + AB$; $C-C' = AB$

The equation of $C = C' + AB$ exactly holds when:

1) multiple regression (or SEM without latent variables) is used, 2) the same cases are exerted in all the analyses, and 3) the same covariates are in all equations. However, the models are only approximately equal for multilevel models, logistic analysis and SEM with latent variables. For such models, it is probably inadvisable to compute C from Step 1, but rather C or the = C' + AB (Kenny, 2014). Imai et al. (2010) have defended applying $AB = c - c'$ as the measure of the indirect effect.

Another measure of mediation is the "mediation effect ratio" which is determined by calculating the indirect effect divided by the total effect- or AB/C or equivalently 1 - C'/C. Most often, however, the indirect effect computes directly as the product of A and B. Causal Inference Approach (Pearl, 2011) has also been proposed to measure the indirect effect. SEM can also be applied to test the mediation effects (RO, 2012). The procedure for testing mediator effects in SEM is similar to regression analysis. Thus, for testing the significance of the mediated effects, the fitted mediated models are compared to being with and without the direct path from X and Y constrained to zero. Still the four more widely used tests of the indirect effect of mediation are as follows:

- Joint test of significance- In this test, non-zero effects of mediated relationships are identified by following steps 2 and 3 above (path A and B of Fig5). If these conditions are met, non-zero effects relationships are likely exists. Consequently, to test the null hypothesis that AB = 0, the test of both paths A and B are zero should be attempted (Fritz & MacKinnon, 2007).
- Sobel Test-This test (sometimes called Delta Method) introduced by Sobel (1982). The test compares statistic based on the indirect effect of mediation with its null sampling distribution by estimating the standard error of AB which equals to the square root of (B2*sA2+ A2*sB2). T value is calculated as follows:

$t = (\tau - \tau')/SE$ OR $t = (AB)/SE$

Where SE is the pooled standard error term, $SE = \sqrt{(A^2\sigma^2B + B^2\sigma^2A)}$, and σ^2B and σ^2A are the variance of B and A respectively.

This t statistics is used for significance determination of the mediation effects. The t-test will be significant if the size of the mediated path is greater than the direct path. Alternative methods of calculating Sobel's test have also been proposed (Sobel Z value, Arioan Z value (1944/1947); Goodman Test, 1960) that apply either z or t distribution or each estimates the standard error differently. SPSS and many SEM packages provide solutions to compute Sobel's test. Sobel's test is more accurate than Baron and Kenny (1986); however the test generates a very low power, focuses on the normality assumption, and large sample sizes are required in order to have a sufficient power to detect significant effects. MacKinnon et al., (2002) suggest that a sample size of 1000, 100 and 50 is required to detect small, medium and large effects respectively.

- Bootstrapping Method- This method involves in forming a sample distribution of the indirect mediation effects, as a representation of the population, by selecting a large number (over hundreds or thousands) of replacement resamples to compute the required information regarding each sample (Preacher & Hayes, 2008). Given this distribution, a confidence interval, a p value, or a standard error could be computed. Often A and B are estimated from this resampled data set and the product of the path coefficient is determined. Consequently, point estimates and confidence intervals are determined. This procedure provides a basis to identify the significance or non-significance of the mediation effects. Point estimates determine the mean over the number of bootstrapped samples. If zero does not fall in the interval, then it can be concluded that the indirect effect is different from zero and therefore a significant mediation effect exists to report (Shrout & Bolger, 2002, Hayes, 2013). SPSS, SAS macros and Amos can be employed to bootstrap (Kenny, 2014). Bootstrapping method is superior to Sobel's test because it is a non-parametric test which does not require normality assumption, is applicable to small sample sizes, and increases the power of the test.
- Monte Carlo Method- This test is described by MacKinnon, et al. (2004) and is based on the premises that A and B possess normal distribution. By computing A,B, standard error of A, standard error of B and their associated variances for AB, random normal distribution is generated and the product values is determined. This procedure is simulated a very large number of times and the resulting distribution of the A*B values is expended to estimate a confidence interval around the observed value of A*B. Preacher and Selig (2012) and Selig and Preacher (2008), have provided computer packages to perform this test. These packages are useful when bootstrapping cannot be applied.

4. Distinctions between Moderating and Mediating Variables

The most important differences between MO and ME are as follows:

- A (MO) variable always acts like a new independent variable, and is based upon the condition that: a) MO must be preceding Y, b) MO has no casual relation with X, but posits a casual relation with y, and c) MO maintains a similar role just like X. However, a ME variable is based upon the condition that: a) X always precedes ME and

Y occurs after ME, and b) the role of ME is changing –with respect to X, it acts as a “dependent variable” and in relation to Y, it has a role of the “independent variable”. In either case, a casual relation between ME and X or Y exists.

- MO variables might occur, measured or determined naturally (such as age, sex and gender) or can be created and manipulated artificially (such as the quality of service of the firm). However, ME variables often occur naturally and can only be measured and cannot be manipulated.
- A (MO) variable is really a third variable which is exerted to identify the cause of weak or inconsistent relationship between independent variable and dependent variables more clearly. It specifies “when “or under “what” condition a particular effect is expected, However, a ME variable is used to describe “Why” and “How” such effects are occurred in the relationship between independent and dependent variables.
- MO variables are used when the relationship between independent and dependent variable is “Weak” or non-coherent. But ME variables are exerted when the relation between independent and dependent variables is statistically significant.
- MO variables may increase or decrease the strength of the relationship between independent and dependent variables or they may change their direction; and moderation models are not causal. However, by entering a ME variable into a model, the independent variable may no longer affects the dependent variable (complete mediation) or gets weak(partial mediation),and a causal mediating model exists.
- A researcher who applies MO variables usually is interested in testing unknown relationship between the independent and dependent variables. He/she is more interested in studying the “Independent variable” or “interaction effects” and not MOs, and by entering MOs wants to just test unknown relationships between X and Y, and know ”When” the relationship between independent and dependent variables are established and gets stronger. However, in exerting ME, the issue of “How” and “Why” in the relationship between independent and dependent variable are more important to the researcher than the independent variable. Hence, the researcher’s interest is focused on the ME variable, not the independent variable.
- The statistical tests of the moderating effects are distinctly different from mediating effects (see preceding parts).

5. Mediated-Moderation and Moderated-Mediation

In an attempt to more capture the reality of the business complexities, the effects of MO and Me variables can be studied simultaneously by establishing following models:

5.1. Mediated- Moderation Models

Mediated moderation is a combination of both moderation (MO) and mediation (ME) variables (Muller, et al. 2005; Edwards & Lambert, 2007). Fig 6 illustrates the Mediated-Moderation case based on Kang et al.’s (2015) study. Here, moderation variable (Size effects) must be established first into the model, hence the focus of the research is usually on the prediction of the interaction of X (CSR) and MO (size of the hotels) on Y (financial performance of the hotels). Then a search for injecting a mediated variable should begin, if there is a theoretical reason to believe that there is a fourth variable (BSC-Customers Satisfaction) that acts as the mechanism or process that causes the relationship between CSR and size of the hotels or between size and financial performance of the hotels. Hence, mediated-moderation model assumes that moderation effect is achieved by introducing a ME variable as the fourth variable (X, MO, and Y already exist). In this situation, an interaction between X and MO exists which affects ME (Path D), and then this ME variable affects Y (path E). The model is thus mainly based on a MO variable and ME has a second role; in mediated moderation case, all the Baron and Kenny (1986) and Kenny (2014)’s steps for mediating testing is repeated but here the causal variable or X is really the interaction, and the two main effects would be treated as “covariates”. Consequently, the total effect or the initial moderation effect, the direct effect or how much moderation remains after emergence of the moderator, and the indirect effect of the mediator, can be computed.

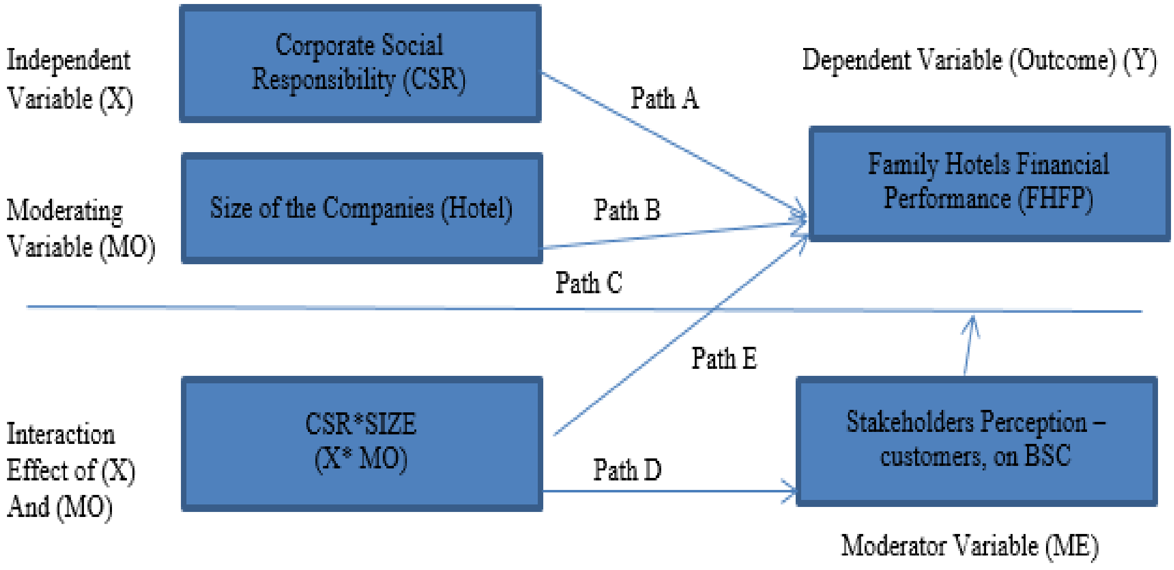

Fig 6: Illustration of the mediated- moderation effect

5.2. *Moderated –Mediation Models*

Moderation- mediation models are established when researchers believe mediated models will get stronger by introducing moderating variables. In these situations, first mediation is performed and then investigation is started to find out whether by adding a moderator variable, mediated effects will be altered (Judd & Yzerbyt, 2005 and Preacher et al. 2007). There are five possible models of moderated- mediation which are shown in Fig7 (Muller et al. 2005):

- In the first model X moderates the relationship between ME and Y.
- Second model inserts a new variable which moderates the relationship between X and the ME (path A).
- Third model exhibits a new moderator variable which moderates the relationship between ME and Y (path B)
- Fourth model illustrates that one MO variable influences both X and ME relationship (Path A) as well as ME and Y relationship (path B).
- Fifth model involves two new moderator variables, one moderating the A path and the other moderating the B path.

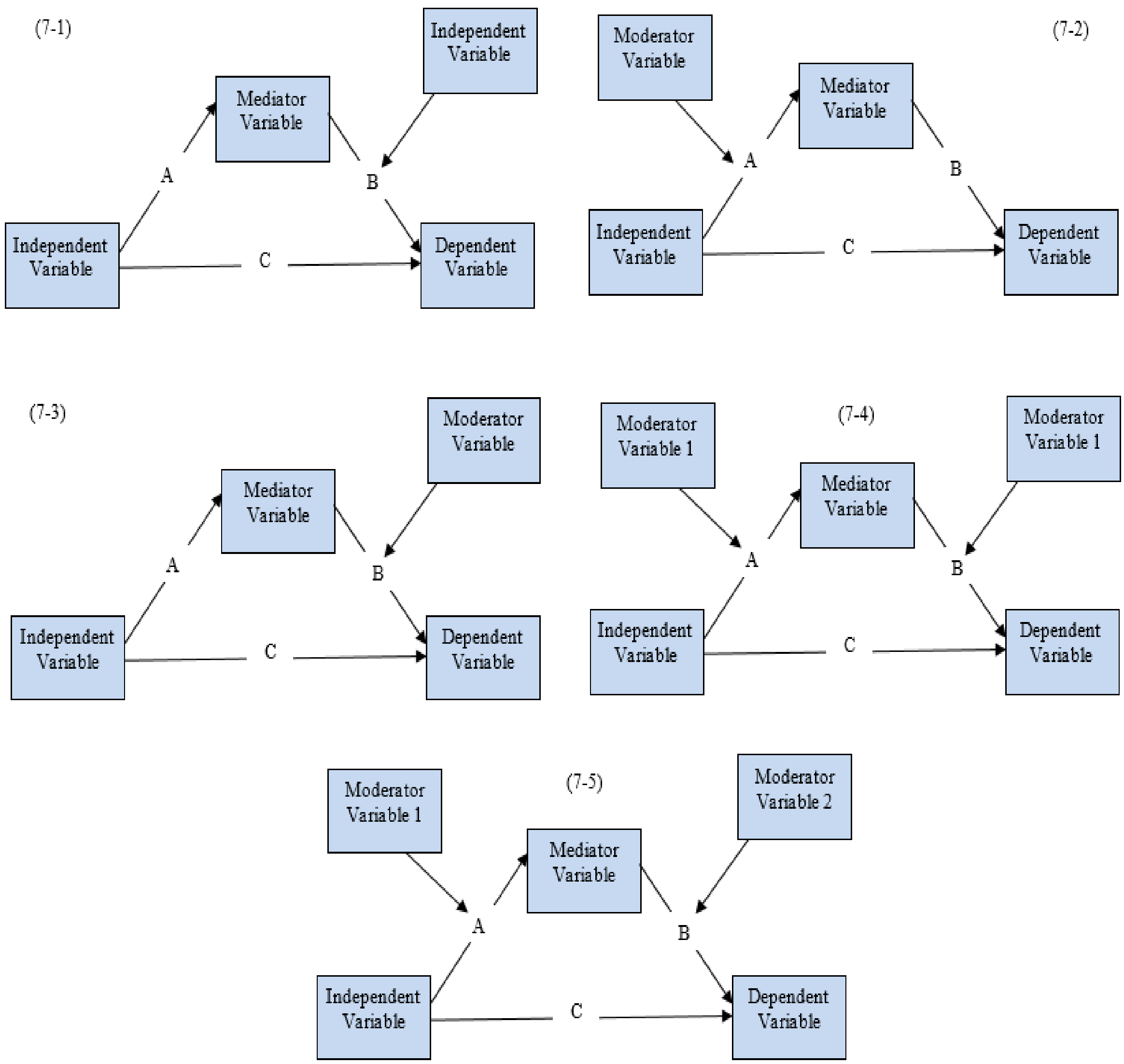

Fig 7-Illustration of the possible models of moderated mediation (Wikipedia, 2015, https://en.wikipedia.org/wiki/Mediation) (statistics)

Fig 8 exhibits the Mediator-Mediation model for Kang et al.'s (2015) study based on the previous designated ME and MO variables. It reflects a situation in which the relationship between Corporate Social Responsibility (CSR), BSC perspective-Customer's Satisfaction (ME) and Family Hotel Financial Performance (FHFP) gets stronger (in comparison with mediated model shown in Fig 5) by considering the size of the company (MO variable). This relationship is stronger for one group (e. g., large hotels) than another group (e. g., small hotels). Thus, the introduction of size as a MO variable changes the theory of the relationship between X, Y and ME relationships. The model, however, is primarily ME oriented and MO plays the second role. Thus ME is preceding MO.

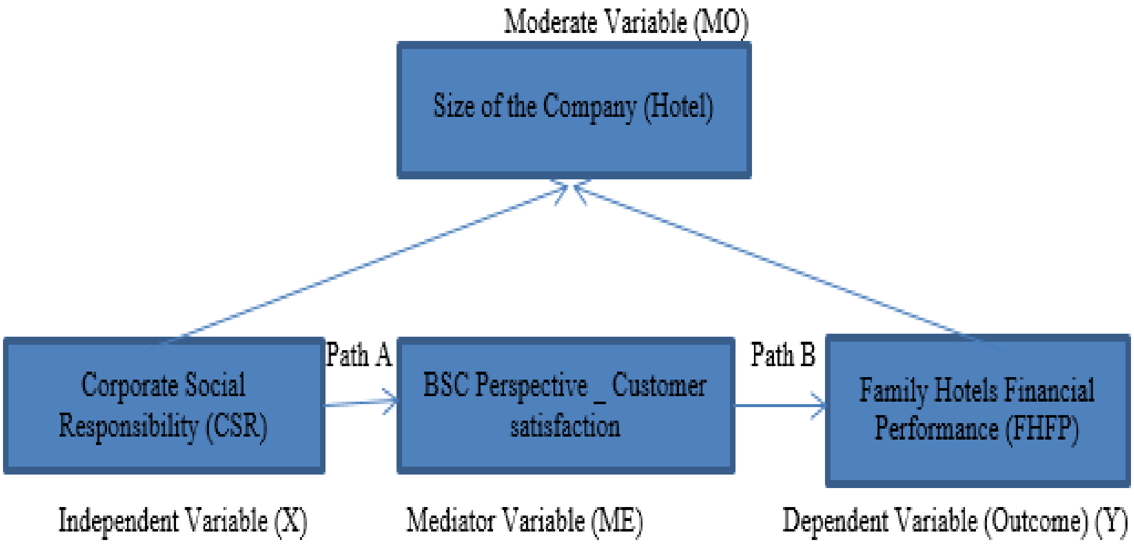

Fig 8. Illustration of the moderated –mediation effect

The major distinction between mediated-moderation and moderated- mediation relates to the issue that in the former, moderation is initially operated and then the related relations are mediated. Whereas for the latter,there is no moderation but the effect of either the treatment on the mediator is moderated or the effect of the mediator on the dependent variable is moderated (Muller et al., 2005).

5.3. Testing Mediated-Moderation and Moderated-Mediation

The effects of the Mediated-Moderation and Moderated-Mediation relationships can be tested statistically through the "multiple regression analysis". Muller et al. (2015), for instance, by utilizing multiple regression analysis, provide three conceptual models that can be applied for both moderated mediation and mediated moderation cases. They distinguish four variations of the effects: Total effect, controlled direct effect, natural direct effect and natural indirect effect. The power of these models lies in their generality; they are applicable to situations with arbitrary nonlinear interactions, arbitrary dependencies among the disturbances, and both continuous and categorical variables.

When some or all of the mediational variables are latent variables, SEM program (e. g., LISREL, Amos, Eqs, or MPlus) can be exerted to estimate the relationship effects. These programs provide measures and tests of indirect effects and are also quite flexible in handling multiple mediators and outcomes. If either ME or Y is dichotomy, the standard method of estimation (e. g., Sobel's test) should not be adopted because of the complication in computation of the indirect effects. Instead Baron and Kenny's (1986) steps and "logistic regression" should be employed. When Y is dichotomous, Mplus program can also be used. With "clustered data", –when data are not just in one level and clustered in groups- "multilevel modeling" should be used (Kenny, 2014). Preacher et al. (2010) have proposed that "Multilevel Structural Equation Methods" or MSEM can also be used to estimate these models.

5.4. Other Extensions of the Model

Kang et al.'s (2015) model can also be extended by several avenues: a) multiple mediators –that is considering other BSC perspectives as mediating variables simultaneously. By formulating this model, it is possible to investigate if the “customer satisfaction” mediation is independent of the effect of other BSC mediators; b) multiple outcomes-that is considering the effect of different performance evaluation criteria (financial, EVA, and non –financial measures). This model makes it possible to consider the effect of each measure and the interaction effects of different measures simultaneously; c) multiple causal variables-in this case, different CSR measures are used which enables researchers to study different effects of each CSR criteria to investigate whether their effects are equal, and the sum of their indirect effects are zero, d) causal mediation analysis-this analysis is based on the logical relationship paradigms of CSR, ME and FHFP which leads to establishing causal diagrams that gives mediation a causal interpretation, and extends analysis from linear to non-linear and nonparametric models; and e) a combination of a, b, c, and d situations.

5.5. Discussion and Conclusion

This article, for first time, explored characteristics, distinctions and significance of the moderating, mediating, mediated-moderation and moderated-mediation effects of business research by extending Katz et al. (2015) model on a Balanced Scorecard perspective. The mechanisms of each preceding variables and appropriate statistical models for testing each condition were also discussed. The contribution of this study is that, the study revealed preceding variables posit a great impact on the design and conceptual theories of the research and create a contemporary theory or change the direction of the prior theories. In addition, the inclusion of these variables and their combination opens new avenues and ample insights into business research and establishes a potent basis to analyze the interaction effects of moderating and mediating variables. This function will also make designated models more comprehensive and pertinent to reality, and enables researchers to solve real business problems and arrive at a more satisfactory and complete solutions. The findings are generally consistent with moderating and mediating literature on business (Baron and Kenny, 1986; Kenny, 2014; Muller et al., 2015; Ro, 2012).

The selection of moderating and/or mediating variables and their combinations, among other things, relates to prevalent business theories and researchers’ interests. Because the effects of moderating variables are distinctly different from mediating variables, care must be exercised in implementing these variables for establishing appropriate business models.

Although recently some contemporary business studies have adopted moderating and/ or mediating variables, the simultaneous implementation of moderating and mediation variables is still scarce. Hence, it is suggested future business researchers expand their models in such a way to encompass both moderating and mediating variables to take advantage of their interaction effects. In addition, some progress could be made with respect to enhancing “Causal Inference Approach to Mediation” and other model buildings as well as providing statistical analysis and packages in this arena.

Finally, this paper solely concentrated in providing a conceptual analysis in this domain; Empirical works in this arena can unambiguously operationalize the effects of the moderating and mediating variables, and reveal the contributions of this article more transparently. In addition, this paper just concentrated on moderating and mediating variables and their interactions. The effects of “control” variables as well as “extraneous variables” can also be studied along with moderating and mediating variables.

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