METHODOLOGY CORNER

Lilian Wong

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601
Bonnie Long

Efficient research design and well-chosen methods of analysis help immensely in clearing the way for coherent interpretation of study results. The articles published in the "Methodology Corner" are particularly useful for accomplishing this objective. In this issue of Nursing Research, we have again been able to expand this valuable feature into an entire section.

Theoretical and Methodological Differentiation of Moderation and Mediation

PATRICIA LINDLEY • SUSAN NOBLE WALKER

Many of the causal models tested in nursing research involve the presence of one or more third variables, which may be crucial in explaining when, how, and why human phenomena occur. Confusion often arises when the terms *moderating* and *mediating* have been used interchangeably in describing third variables. Moderation and mediation represent different relationships among three or more variables in a proposed theory. Because theoretical clarity is critical to the specification of any causal model, the purpose of this article is to differentiate the moderator and mediator functions in causal models.

For ease in presentation and discussion, the examples of causal models are limited to one predictor variable (X), one third variable (Z), and one outcome or criterion variable (Y). It is recognized that specification of the causal model must be theoretically driven and assumptions necessary for the particular statistical analysis must be met.

The Moderator Function: A moderator is a third variable (Z) that influences the relationship between a predictor variable (X) and an outcome variable (Y). The moderator may be either a categorical or a continuous variable. It may act to reduce the magnitude and/or to reverse the direction of the relationship between the predictor and outcome variables. The moderator effect can be described as an interaction between a predictor variable and a moderator variable, such that the relationship between the predictor and an outcome variable differs depending upon the level of the moderator; the effect of X on Y is *conditional* upon the level of Z.

A causal model involving the moderator function is depicted by the path diagram in Figure 1. Note that, as antecedents of the outcome variable, the moderator and predictor variables are at the same level in the causal model. According to Baron and Kenny (1986), a moder-

Table 1. Mental Health Regressed on Hardiness and Social Network

Predictor Variables	Cumulative R^2	R^2 Change	Significance of Change
Hardiness	.09	.09	.01
Social Network	.10	.01	.46
Hardiness x Social Network	.16	.06	.04

Figure 1. Moderator Model

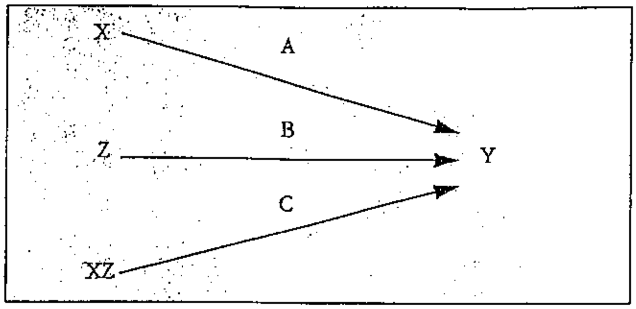


Figure 2. Example of Moderator Model

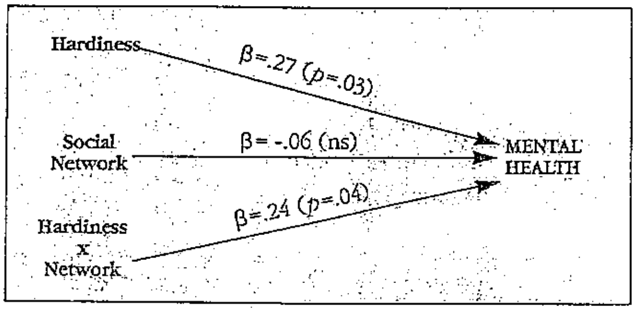


Figure 3. Effect of Hardiness on Mental Health Moderated by Social Network

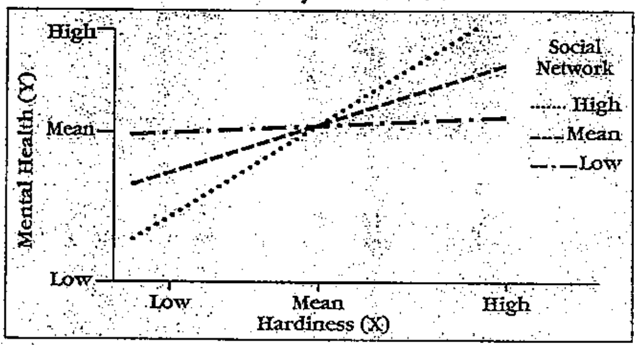
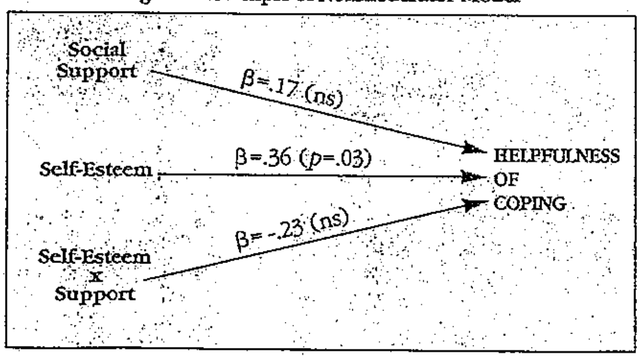


Figure 4. Example of Nonmoderator Model



ator effect is present whenever the interaction (Path C) is significant; main effects (Paths A and/or B) may or may not be significant and are not essential to establishing moderation. However, it is desirable that the moderator variable not be correlated with either the predictor or the outcome variable if the interaction term is to be clearly interpreted.

An example of a moderator model with continuous variables is provided by the relationships among hardiness (X), social network (Z), and mental health (Y) illustrated in Figure 2. Social network is not significantly correlated either with hardiness or with mental health, yet it plays a vital role in the relationship between them. A moderator effect is seen by the significant path from the interaction of hardiness and social network to mental health in the path diagram in Figure 2, and by the significant change in R^2 when the interaction term enters the hierarchical regression (see Table 1).

Figure 3 shows how the effect of hardiness on mental health differs depending upon the size of the social network. The larger the individual's social network, the greater is the relationship between hardiness and mental health. When the social network is small, the relationship is nonsignificant. A significant *positive* relationship of X to Y at either high (as in the example in Figure 3) or low levels of Z is accompanied by a significant *positive* partial regression coefficient for the interaction product term (as in the example in Figure 2). In contrast, a significant *negative* relationship of X to Y at either high or low levels of Z would be accompanied by a significant *negative* partial regression coefficient for the interaction product term.

For comparison, an example of a causal model that does not involve moderation is presented in Figure 4. Note that the path from the interaction of social support and self-esteem to helpfulness of coping is nonsignificant. As shown later, self-esteem actually serves a mediator function when correctly modeled for the given data.

Data analysis procedures for testing moderational hypotheses will vary depending upon the level of measurement of the predictor and the moderator variables. Procedures recommended and discussed in detail in other sources (Aiken & West, 1991; Baron & Kenny, 1986) are summarized in Table 2.

Aiken and West (1991) provide detailed description and discussion concerning the estimation, testing, and probing of interactions in regression models. Of particular value and interest to nursing researchers is their explanation of a procedure for centering continuous predictor and moderator variables in regression analyses. Centering involves subtracting the sample mean of the variable from the variable, thus creating a centered variable in deviation score form with a mean of zero. When uncentered variables are multiplied to form interaction terms, the correlation between the first order terms and the interaction term results in high multicollinearity when entered in regression (Cohen & Cohen, 1983; Pedhazur, 1982). The use of centered variables in regression analyses greatly lessens this problem and yields interpretable regression coefficients for both the first order and the interaction terms.

The Mediator Function: Similar to a moderator, a mediator is a third variable (Z) that influences the relationship between a predictor variable (X) and an outcome variable (Y). More specifically, the mediator represents a process or mechanism, often intrinsic to an individual, that accounts for the relationship between a

Table 2. Statistical Analysis According to Level of Measurement of Predictor and Moderator Variables

	Moderator Variable	
Predictor Variable	Categorical	Continuous
Categorical (Dichotomous)	2 x 2 ANOVA	Hierarchical multiple regression of outcome on predictor, centered moderator and interaction terms (and higher order terms if predictor/outcome relation is curvilinear)
Continuous	Separate regressions for each level of the moderator; *t*-test for differences between groups' unstandardized regression coefficients *OR* Hierarchical multiple regression of outcome on centered predictor, dummy-coded moderator and interaction terms.	Hierarchical multiple regression of outcome on centered predictor, centered moderator and interaction terms (and higher order terms if predictor/outcome relation is curvilinear)

predictor variable and an outcome variable. The mediator specifies how or why the relationship occurs (Baron & Kenny, 1986).

A minimum of three variables are needed to depict a causal model involving mediation, as illustrated in Figure 5. The predictor is an antecedent variable that precedes both the mediator and the outcome variables. The mediator is a consequence of the predictor variable and an antecedent to the outcome variable. The outcome variable is the consequence of both the predictor and the mediator variables.

To test for mediation, three regression equations are necessary. First, the outcome variable is regressed on the predictor variable (Step 1 in Figure 5). If this relationship is significant, then second and third equations are analyzed (Step 2 in Figure 5). In the second equation, the mediator is regressed on the predictor variable (Path A). The third equation involves regressing the outcome variable simultaneously on the predictor (Path C_2) and mediator (Path B) variables. According to Baron and Kenny (1986), the mediator function is substantiated by three findings: (a) Path A is statistically significant; (b) Path B is statistically significant; and (c) after statistically controlling for Paths A and B, a previously significant relationship between the predictor variable and the outcome variable (Path C_1 in Step 1) becomes nonsignificant (Path C_2 in Step 2). The strongest case of mediation occurs when Path C_2 in Step 2 becomes zero, suggesting that one dominant mediator is operating in the causal model.

An example of a mediator model is depicted by the path diagram in Figure 6. Social support (X) influences the helpfulness of coping (Y) through self-esteem (Z). In Step 1, there is a significant path from social support to helpfulness of coping when self-esteem is not included in the model. In Step 2, the mediator function of self-esteem is substantiated first by the reduction of the path coefficient from .32 to .15, and second by the change from a significant *p* of .03 to a nonsignificant *p* in the path from social support to the helpfulness of coping.

Mediator variables may produce either additive or suppressive influences on the relationship between pre-

Table 3. Comparison of Moderator and Mediator Functions

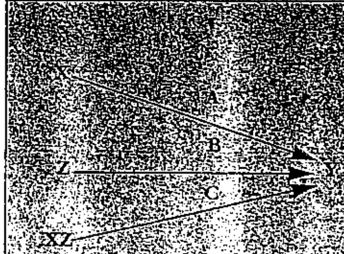
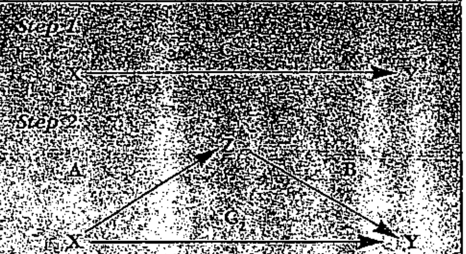
Moderator	Mediator
	
X and Z are antecedents of Y	Z is a consequence of X and an antecedent of Y; Y is a consequence of X and Z
Direction and/or strength of the influence of X on Y is a function of Z	Z is a process or mechanism through which X influences Y
Consider moderation when the relationship of X to Y is strong, weak, or inconsistent	Consider mediation when the relationship of X to Y is strong
Occurs when Path C is significant (and ideally Z is not related to X and to Y)	Occurs when Paths A and B are significant and when Path C_2 becomes nonsignificant
Specifies when or under what conditions X influences Y	Specifies how or why X influences Y

Figure 5. Mediator Model

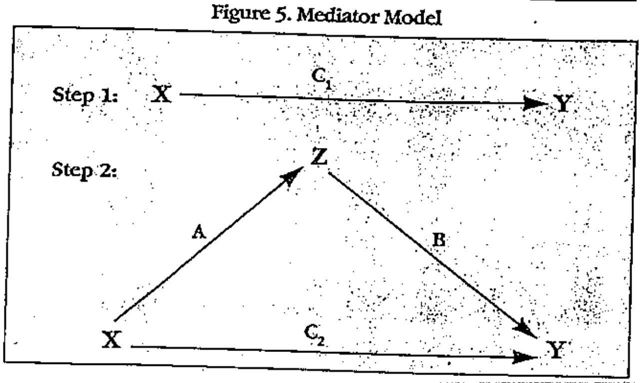


Figure 6. Example of Mediator Model

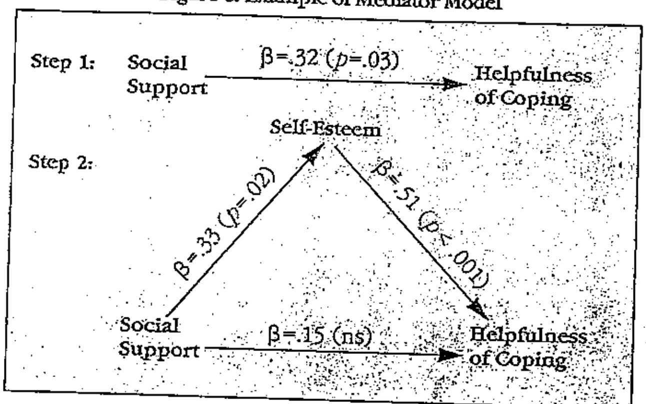
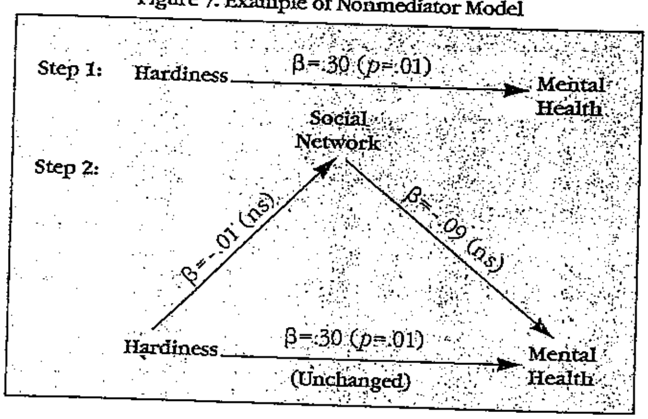


Figure 7. Example of Nonmediator Model



dictor and outcome variables (Wheaton, 1985). To detect which type of influence is occurring, it is necessary to calculate direct, indirect, and total effects within the causal model. Readers unfamiliar with the calculation of effects are referred to Cohen and Cohen (1983) and Pedhazur (1982). An additive influence is evidenced by an increase in the total effect on the outcome variable, while a suppressive influence is evidenced by a decrease in the total effect on the outcome variable.

For comparison, an example of a model that does not involve mediation is presented in Figure 7. Note that the path coefficient from hardiness to mental health is unchanged when social support is entered as a mediator in the model, and that the other two path coefficients are nonsignificant. As shown earlier, social support actually serves a moderator function when correctly modeled for the given data. Table 3 provides a summary of the distinctions between moderator and mediator functions as described above.

Additional Comments: The testing of a causal model becomes more complex when both moderator and mediator functions are influencing the relationship between a predictor variable and an outcome variable. Baron and Kenny (1986) provide a detailed description of analyses testing for mediated moderation and moderated mediation.

One major and often overlooked source of error in testing causal models occurs when there is a reciprocal causal path (i.e., feedback) from the outcome variable to the predictor and/or third variable (Y to X or Y to Z). Such a model cannot be analyzed using the ordinary least squares (OLS) regression techniques described above. This potential problem may be avoided by employing an analysis of nonrecursive models using linear structural equation techniques as described by Bollen (1989).

Clarification of the moderator and mediator functions of third variables in causal models is critical for theoretical and methodological reasons. Failure to substantiate a hypothesized moderator or mediator function, which was originally derived from theoretical literature, may suggest a reanalysis of the theory. Inaccurate specification and/or incomplete testing of a moderator or mediator function may result in erroneous or missed results and inappropriate conclusions about the complex multivariate relationships so often encountered in nursing research.

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Patricia Lindley, PhD, RN,CS, ANP, is an assistant professor, University of Nebraska Medical Center, College of Nursing, Omaha, NE.

Susan Noble Walker, EdD, RN, FAAN, is a professor and chair, Gerontological, Psychosocial and Community Health Nursing, University of Nebraska Medical Center, College of Nursing, Omaha, NE.

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