Published in final edited form as:

J Soc Work (Lond). 2011 October 16; 11(4): 387–401. doi:10.1177/1468017310379930.

Moderators and Mediators in Social Work Research: Toward a More Ecologically Valid Evidence Base for Practice

Molly Magill, Ph.D.

Brown University, Center for Alcohol and Addiction Studies, Providence, RI 02912

Abstract

Summary—Evidence-based practice involves the consistent and critical consumption of the social work research literature. As methodologies advance, primers to guide such efforts are often needed. In the present work, common statistical methods for testing moderation and mediation are identified, summarized, and corresponding examples, drawn from the substance abuse, domestic violence, and mental health literature, are provided.

Findings—While methodologically complex, analyses of these third variable effects can provide an optimal fit for the complexity involved in the provision of evidence-based social work services. While a moderator may identify the trait or state requirement for a causal relationship to occur, a mediator is concerned with the transmission of that relationship. In social work practice, these are questions of “under what conditions and for whom?” and of the “how?” of behavior change.

Implications—Implications include a need for greater attention to these methods among practitioners and evaluation researchers. With knowledge gained through the present review, social workers can benefit from a more ecologically valid evidence base for practice.

Keywords

Evidence-Based Practice; Mediation; Mechanisms of Behavior Change; Moderation; Social Work Research; Statistical Methods

Introduction

Social work research, and the intervention practices it informs, addresses multidimensional individual and social problems. This complexity has led many scholars to voice concerns about Evidence-Based Practice (EBP), and particularly about the limited usefulness of clinical knowledge derived from the *gold standard* of the evidential hierarchy - the randomized controlled trial (RCT). Some argue scientific foundations, specifically, the inherent limitations in the pursuit of certainty and universality in practice knowledge (Smith, 1987/2002). Others emphasize that findings derived from RCT designs are specific to the methods that created them. In other words, results may not hold *true* when client characteristics or targeted outcomes even somewhat differ from those within the original research trial (Witkin and Harrison, 2001). Still others identify a level of regimen that may arise out of clinician attempts to replicate the manualized and time-limited treatments validated as evidence-based (Silverman, 1996). Social work practitioners may ask similar questions, that is, do the clients, contexts, or questions of efficacy trials represent the realities of frontline clinical practice? Social work decision-making is therefore conditionally situated within complex service environments (Webb, 2001). In 1969, Paul

asked: “What treatment, by whom, is most effective for this individual with that specific problem, under which set of circumstances, and how does it come about?” The question answered by the efficacy trial is: “What treatment is most effective for this specific problem?” Paul’s question may better capture the needs of practitioners when seeking guidance from the available social work literature.

Evidence-based practice involves the consistent and critical consumption of social work research to inform decision-making. This places a burden on both practitioners and researchers. Practitioners must make use of available knowledge to guide social work practice and researchers must produce the kind of knowledge that practitioners find useful. This article provides a primer to guide such efforts by describing the interpretation, critique, and application of statistical moderators and mediators in social work evaluation research. While methodologically complex, analyses of these *third variable effects* may help to characterize the complexity involved in the provision of social work services. Internationally, social work continues to move toward EBP (see e.g., Campbell Collaboration; National Association of Social Workers; Social Care Institute for Excellence). Analysis of third variable effects represents one type of integration needed to facilitate this movement. That is, the EBP framework is best informed by an integration of science and practice, of the range of social work research methods, and as addressed in the current work – of context, process, and outcome when asking questions of intervention efficacy.

Moderating and mediating variables serve two conceptually distinct third variable functions that may enhance knowledge derived from RCT research. *Moderators* are categorical (e.g., gender, race) or continuous (e.g., age, self-efficacy scale score, number of available support systems) third variables that impact the direction or the strength of the relationship between the independent and dependent variables (Baron and Kenny, 1986). In evaluation research, a moderator variable may be a client, clinician, or agency characteristic that affects treatment outcome. Moderator variables often have an “if *W* then *X* will predict *Y*” conceptualization, such as, if my client scores low on a motivation scale (*W* group or score = low motivation), will she/he benefit from a homework facilitated cognitive-behavioral intervention (*X* predictor = treatment) for generalized anxiety (*Y* outcome = symptom reduction)? *Mediators*, on the other hand, are continuous (e.g., therapeutic alliance scale score, number of enacted coping behaviors) third variables that intervene between, or help to explain, the independent and dependent variable relationship (Baron and Kenny, 1986). Here, we conceptualize as *X* predicts *M*, which in turn, predicts *Y*. Researchers and practitioners interested in how the effects of psychosocial treatments are transmitted will be interested in mediating variable effects. For example, will the parenting behaviors (*Y*) of members of my parenting education group (*X*) depend of changes in individual member’s self-efficacy to parent successfully (*M*)? In summary, statistical moderators and mediators are the empirical methods for asking questions that complement those targeting treatment efficacy; this level of statistical analysis goes beyond: “does this treatment work?” to examine “for whom or under what conditions?” and “how?”

Moderators and mediators of intervention effects have been of increased interest in recent years, and across behavioral science research areas (e.g., Babor, 2008; Kazdin and Nock, 2003; Nock, 2007). Morgenstern and McKay (2007) describe a movement away from the *technology model* of psychotherapy research, which has produced over two decades of clinical trials characterized by continued advancement in methodological “technology” (e.g., strict inclusion/exclusion criteria, standardized measures, treatment manuals). This work has produced efficacy findings with sound internal (cause-effect conclusions), but perhaps sacrificed external (generalizability) and ecological (real-life representativeness) validity (see Hudson, 2009). Recent directions in social work research are targeting mediating risk

factors to be interrupted and mediating protective factors to be enhanced (Fraser, 2004). In fact, a database search of the social work literature shows a steady increase in the number of peer reviewed publications that referenced moderators or mediators of two variable relationships within the title. Since 1980, there has been a two-fold increase in articles that referenced moderation and a three-fold increase in those that referenced statistical mediation. Social work researchers, as those in other behavioral science disciplines, have begun to recognize the need to ask more complex questions of intervention effectiveness that speak to variations by agency, clinician, or client factors as well as questions about the mechanisms through which interventions produce their effects. Such directions have the capacity to inform a more clinically-relevant evidence base for practice (Magill, 2006).

The following article considers moderators and mediators in evaluation research. The goal of this work is to provide a concise guide to the statistical methods involved in testing these third variable effects, and the target audience is practitioners or beginning social work researchers. Conceptual definitions and statistical methods will be summarized. Next, studies from the research literature illustrate the application of moderator and mediator tests. For the purpose of conceptual cohesion, topics will be limited to clinical research in health and mental health, but understanding gained from this review can be easily applied to questions of etiology and to other service areas.

Conceptual Foundations: Methods for Testing Moderation and Mediation

Moderators and mediators of psychosocial treatment effect

Moderation—Moderating variable effects in evaluation research are most often client or treatment factors that at specific values, determine, enhance, or inhibit intervention effectiveness. For evidence-based practitioners, questions about whether the effect of treatment varies in client sub-groups or by degree of a characteristic are paramount. Does religious or non-religious status or level of social anxiety affect my client's receptivity to participation in a self-help group for alcohol abuse? Evidence-based questions might also speak to conditions of clinical efficacy at the therapist or agency level. Does therapist-client gender match result in more effective treatment for sexual trauma or does extent of ongoing supervision in cognitive-behavioral therapy impact efficacy in treating generalized anxiety?

In statistical terms, Cohen and Cohen (1983) describe a moderator variable as an interaction variable (W) that improves the accuracy of a specified independent (X , e.g., treatment) to dependent (Y , e.g., outcome) variable relationship. It is best, though not always the case, for W to be unrelated with X and Y , which provides a more easily interpreted statistic for the multiplicative interaction term ($X*W$; Baron and Kenny, 1986; Coulton and Chow, 1992; Koeske, 1992). For example, a brief educational intervention (X) targeting quality of life (Y) among older clients may be effective for married but not unmarried individuals (W) when compared to a pamphlet describing local social activities. Marital status may additionally have a significant effect on quality of life; in other words, there is a continued *main effect* of the moderator in the presence of an *interaction effect*. Here, we should be cautious in our interpretation of the main effect as it is the interaction that provides the better specified depiction. Figure 1 illustrates the conceptual model of a moderating variable effect.

Baron and Kenny (1986) describe the simplest case of dichotomous moderator (e.g., gender) and independent (e.g., treatment assignment to two groups) variables with the interaction variable, ($X*W$), acting as a significant predictor of Y in a factorial (or categorical) Analysis of Variance (ANOVA). The F test for the interaction examines the significance of the difference in cell means after accounting for the X and W main effects (Coulton and Chow, 1992). A visual plot of the values of X on Y as a function of W then allows for closer examination of the exact nature of the moderation relationship. Figure 2 shows a sample plot

of two categorical moderators using the example described above of marital status moderating the effectiveness of a brief educational intervention (compared to a social activities pamphlet) to enhance quality of life among older adults. We see a higher slope of change for those who were both treated and married and from this example, we may infer that being married allows these participants to improve via a brief educational intervention, while those that are unmarried may need a more substantial, and supportive, intervention.

Methods described by Cohen and Cohen (1983), Baron and Kenny (1986), and Aiken and West (1991) extend the capacities of the ANOVA to a linear regression framework that can accommodate both dichotomous (categorical) and continuous (numerical) X and W variables. In evaluation research, this is frequently the interaction of treatment condition (X) with a baseline measure of psychosocial functioning (W) that is hypothesized to impact the effect of treatment on the outcome measure of interest (Y). This is tested in a hierarchical regression model with the main effect variables in the first step (or initial model) and the addition of the interaction effect variables in the second step (or final model). The F test for the change in variance explained (R^2_{change}) as well as the t test for the interaction coefficient (XW) examines the significance of additional variance explained due to the inclusion of the XW interaction (Aiken and West, 1991; Jaccard et al., 1990). However, the problem of multicollinearity often arises, which is due to correlations among variables and results in reduced power to detect moderating variable effects (Holmbeck, 2002). To address this, the X and W variables can be centered at the mean ($X_{\text{mean}} - X_i$), producing a sample mean of zero and regression coefficients that are interpreted as the impact of the predictor on the Y slope with the other predictor held constant at its mean (Aiken and West, 1991; Coulton and Chow, 1992).

Unlike ANOVA models that produce a visual plot, regression procedures require additional analyses to determine the direction of the moderation relationship. This occurs in two ways. First, the conditional effects on X are computed at varying W values (± 1 standard deviation from the mean or at meaningful cut-points such as a diagnostic score) and the slopes of the regression line are plotted (Aiken and West, 1991; Cohen and Cohen, 1983). This approach transforms a continuous moderator into a categorical moderator and yields a figure analogous to Figure 2 except that it depicts a predicted (based on regression coefficients) rather than observed (based on sample means) slope for client change. Second, the significance of the X slope at each conditional value of W can be tested within a series of linear regression models that include the X variable (e.g., treatment), the conditional value of W (e.g., high motivation), and their interaction (Aiken and West, 1991). These regression equations then test at which value of W the X variable is statistically significant, for example, at what level of client baseline motivation will an intervention be most effective?

Moderator analysis in evaluation research has the capacity to examine evidence-based questions of: under what conditions and for whom are social work interventions effective? Two common methods for testing moderator variable effects have been described and the choice between them will depend primarily on whether variables are categorical or continuous. Conceptually, however, we emphasize the discrete nature of moderator effects such that the XY relationship varies at specified values of W . In contrast, mediators (M) are continuous variables, showing successive linear associations of X affects M , which in turn affects Y . There are also temporal distinctions that identify a moderator as a trait or state variable occurring prior to or simultaneously with X while mediating effects should follow X and precede Y in time.

Mediation—Analyses of statistical mediation (M) examine different evidence-based questions about the processes, or mechanisms, through which an X and Y relationship

occurs. In evaluation research, this is the “how” of behavior change. Social work practitioners may want to know what elements of an intervention are responsible for client outcomes such as, whether changes in depressive cognitions actually result in reduced depressive symptoms or if frequency of enacted progressive relaxation techniques results in lowered anxiety. Such questions lead to improved methods of treatment by identifying strategies most likely to produce a positive outcome. Mediators are statistically intervening variables. Sound theoretical foundations combined with proper temporal ordering will then distinguish a mediator from merely an alternative or additional cause of an X to Y association (Kazdin and Nock, 2003; Nock, 2007).

The work of Baron and Kenny (1986; Judd and Kenny, 1981) provides the most commonly employed approach to establishing statistical mediation. Often identified as the Causal Steps Approach and depicted in Figure 3, a series of linear regression models test the following conditions: (Model 1) the X path (e.g., strengths-based case management) should significantly predict the outcome Y (e.g., utilized resources among multi-stress families); (Model 2) the X path should significantly predict the mediator M (e.g., changes in self-efficacy to interact with service systems), (Model 3) the mediator should significantly predict the outcome (independent of X), and (Model 3) the direct effect of X on Y should be reduced or eliminated when M is controlled. The *indirect*, or mediated, effect is the difference between the *total* ($X \rightarrow M \rightarrow Y$) and the *direct* ($X \rightarrow Y$) effects. Statistical mediation is demonstrated by a loss (full mediation) or reduction (partial mediation) of the X coefficient significance (Baron and Kenny, 1986), by a statistical test of the difference between the total and direct effects, or by a test of the joint significance of the $X \rightarrow M$ and $M \rightarrow Y$ paths (MacKinnon et al., 1995; MacKinnon et al., 2002; Sobel, 1982). Finally, in contrast with statistical tests of moderation, mediation analyses will not yield readily interpreted graphics of causal relationships. The direction and magnitude of regression coefficients, however, approximate effect sizes at each path of the model and therefore provide valuable information about the nature of mediated relationships (MacKinnon et al., 2007).

Statistical methods for examining mediation effects have been of growing interest as evidenced by the sheer number of Baron and Kenny (1986) citations (over 9000) and by more recent work refining methodological recommendations. For example, attending to optimal statistical capacity (i.e., power) to detect a mediated effect, MacKinnon and colleagues (2002) have proposed a joint significance test of the $X \rightarrow M$ and $M \rightarrow Y$ paths based on a distribution of indirect effects rather than a normal theory (i.e., the Bell Curve) distribution. This is because simulation research has shown a non-normal distribution of indirect effects, which will result in higher Type II error rates (MacKinnon et al., 1998; cf. MacKinnon et al., 2002). Concerns about limited power also underlie arguments for significance testing based on bootstrap re-sampling procedures (Preacher and Hayes, 2008). The interested reader is encouraged to look at these works further (see also, MacKinnon et al., 2007), but social work practitioners assessing research on mediators of intervention effects and social work researchers planning mediation analyses are cautioned to consider the power and appropriateness of tests employed.

Recent methodological extensions—While the described methods advance ecological validity in social work evaluation research, capturing the clinical complexity encountered by practitioners is a daunting task. However, tests of moderation and mediation can be accommodated in methods of Hierarchical Linear Modeling (HLM, or Multi-Level Modeling [MLM]) and Structural Equation Modeling (SEM) when highly complex clinical questions are of interest. In HLM or MLM, variable computations and inclusion are similar to those described for linear regression. Conceptually, however, variables become time-varying predictors, which allow for examination of the dynamic nature of change, that is, of

the possibility that moderator or mediator relationships will shift over time (Stout, 2007). These methods additionally consider both within and between individual change. The predictive role of a measure of therapeutic alliance in relation to client compliance with therapist recommendations, for example, may differ over the course of treatment. It may be particularly important early on, and may become less important as environmental reinforcers become more salient in a client's life. In SEM, moderation is examined by considering within group models with constrained path coefficients (Jaccard and Wan, 1991). Here, the question is: is it correct to assume that the relationships among these variables are the same across groups? If they are not, a moderating effect is inferred. SEM can combine tests for moderation and mediation effects, and thus consider whether processes of change differ by specific client characteristics. Mediation tests in SEM are conceptually similar to those described for linear regression, but software packages include longitudinal, non-recursive (i.e., bidirectional), and multivariate capacities (e.g., AMOS; MPLUS). For evidence-based practitioners, a multivariate capacity (i.e., multiple mediators) is particularly important; it is a rare process of change that can be explained by a single mediating variable effect.

Social work practitioners may find themselves asking questions of multiple mediation, multiple moderation, moderated-mediation, and mediated-moderation. For multiple mediation, the extension is similar to that from simple to multiple linear regression, that is, multiple mediators can be entered into a single model. This has sound conceptual appeal by allowing for questions of relative mediator effects. Practitioners interested in the relative predictive roles of multiple processes of treatment (e.g., therapeutic alliance, client compliance with treatment goals, frequency of enacted coping behaviors, utilization of social or agency supports) are encouraged to look into evaluation research that considers multiple mediators simultaneously (see also Preacher and Hayes, 2008). Similarly, we can enter multiple interactions simultaneously because we are interested in determining which client characteristics are most predictive of whether or to what extent a client will respond to treatment. However, the caveat here is that if all remain significant, more complex interaction terms should be examined. Finally, mediation effects may only occur at specified levels of a moderator and conversely the effects of moderation interactions may be transmitted by mediators (see James and Brett, 1984; MacKinnon et al., 2007; Muller et al., 2005). Taken together, the described methods offer an empirical view of the clinical complexity so often encountered by social work practitioners and evaluation researchers.

Empirical Applications: Social Work Practice in Health and Mental Health

What treatment is most effective for this individual with that specific problem?

The following are a few examples of the described statistical methods targeting evidence-based questions of moderation, mediation, and their combination. Moderation research can examine clinical conditions under which interventions may be most effective. McBride and colleagues (2006) examined adult attachment styles (insecure and avoidant) as two potential moderators of Cognitive Behavioral (CBT) versus Interpersonal (IPT) therapy outcomes with major depressive disorder. It was hypothesized that insecurely-attached participants would have better outcomes in IPT than in CBT due to its attention to relational processes. Conversely, those with an avoidant attachment style would show more improvement in CBT than in IPT due to a relatively greater cognitive emphasis. This is an example of two intuitively useful questions of relevance to clinicians working with clients who suffer from depression. With a sub-sample from a completed randomized trial ($n = 56$), the authors used regression methods and tests of simple slopes (e.g., Aiken and West, 1991) to show that participants with an avoidant attachment style had better posttreatment outcomes (for three depression measures) in CBT than in IPT. The IPT hypothesis was not supported, but null moderation effects are also clinically informative as they rule out contraindications.

In a series of studies conducted by Karno and Longabaugh (e.g., 2003, 2005), the interaction of therapist behaviors in relation to client baseline measures of psychological functioning were tested as predictors of 1-year alcohol outcomes. These studies coded therapist behaviors (directiveness, focus on emotional material) to derive session-level ratings that were averaged across four treatment sessions in three alcohol interventions (CBT; Motivational Enhancement Therapy; 12-Step Facilitation; see Project MATCH, 1997). Using ANOVA models, a number of these interactions were supported such that the combination of high therapist focus on emotion and high patient depressive symptoms (Karno and Longabaugh, 2003) and high therapist directiveness and high patient trait reactance (Karno and Longabaugh, 2005) resulted in poorer drinking outcomes across treatments. Therefore, these findings offer two general clinical recommendations for practitioners working with depressed or reactant clients with alcohol use disorders.

In a repeated measures ANOVA framework across three time-points, Magill and colleagues (2009) looked at baseline marijuana use as a potential moderator of the effects of a brief hospital-based intervention among at-risk young adult drinkers. While both treatment groups (a single session Motivational Interview [MI] with personalized feedback on alcohol use compared to written feedback only [FO]) reduced marijuana use from baseline to 6 months, only MI participants continued to reduce marijuana use from 6- to 12-month follow-up. In addition, baseline status as a marijuana user (2×2 factorial ANOVA; Baron and Kenny, 1986) did not moderate drinking outcome. Thus, among young adults who use both alcohol and marijuana, an MI would still be an appropriate brief intervention for alcohol use and with preliminary evidence that some clinical benefit may generalize to marijuana.

What treatment is most effective and how does it come about?

Moderation studies examine the necessary conditions for treatment effectiveness, but sometimes whether a variable is a moderator or a mediator is an empirical question. Calvete, Corral, and Estevez (2008), used a sample of 298 women who had experienced intimate partner violence to examine engaged (e.g., problem solving, emotional expression) and disengaged (e.g., avoidance, denial) coping as moderators and mediators of the relationship between physical and psychological abuse and mental health symptoms. In SEM models by analytic framework (moderation, mediation), the authors showed coping did not moderate distress response to psychological or physical abuse. However, using a constrained (i.e., the *direct* [*total* – *indirect*] effect) path of the predictor to the outcome constrained as zero; see Holmbeck, 1997) and unconstrained model comparison with a corresponding Sobel (1982) test of the $X \rightarrow M$ and $M \rightarrow Y$ paths, the authors found that disengaged coping mediated the relationship between psychological abuse and mental health symptoms (anxiety, depression). These analyses offer valuable clinical understanding with regard to the importance of coping responses among clinical and nonclinical survivors of intimate partner abuse.

O'Hare, Shen, and Sherrer (2007) also examined coping behaviors in relation to client symptom functioning. Using SEM methods to model total, direct, and indirect paths, the authors showed that distress from maladaptive coping behaviors and drinking in response to negative affect were mediators of the relationship between reported distress related to traumatic events and current post-traumatic stress disorder symptoms. Both of the described studies were cross-sectional in design, but provide some temporality through mediation measures designed to draw on retrospective accounts of coping at the time of the traumatic event. Further, while specific treatment mechanisms were not examined, data on common processes of both natural and intervention-facilitated change (i.e., adaptive and maladaptive coping) can inform clinical guidelines as well as the design of subsequent social work interventions with trauma survivors.

While the preceding mediation studies provide a view of coping in relation to symptom functioning, the final empirical example shows the use of mediation methods to test intervention theory. Using the theory of planned behavior and self-efficacy theory, Schmiede and colleagues (2009) examined a 2-level multiple mediation model of four putative mechanisms of proximal change in HIV risk reduction. With a sample of 484 incarcerated adolescents who received a group-based educational intervention, education plus MI, or an informational control, the authors tested posttreatment changes in attitudes, norms, and self-efficacy regarding condom use (first level mediators) in relation to intention to practice safer sex (second level mediator) as mediators of reduced sexual risk behavior. An SEM model with corresponding joint significance tests (i.e., $X \rightarrow M$, $M \rightarrow Y$ paths; MacKinnon et al., 2002) demonstrated that self-efficacy regarding condom use mediated the relationship between both experimental treatment groups (group education, education plus MI) and safe sex intentions, and that safe sex intentions mediated the relationship between treatment and 3-month sexual risk behavior. Here, a theoretical model tested the purported mechanisms of a group-based prevention program and supported changes in self-efficacy and intention as mediators of reduction in follow-up adolescent sexual risk behavior.

Discussion

Evidence-Based Practice should not be mistaken for a Best Practice, or a *what treatment is most effective for what specific problem?*, orientation. Yet, its most common currency, the RCT, has led to some disappointment in social work and allied disciplines. When two “bonafide” interventions are compared rarely is one found statistically superior to the other (Wampold, 2001; Smith and Glass, 1977) and evidence-based practitioners may find themselves asking treatment questions that cannot be fully answered by the findings of efficacy research. Witkin and Harrison (2001) argue that “Social work practice involves seeing people as much for their differences as for anything that links them to classifiable problems or diagnoses” (p. 294). Social workers also operate in complex and often constrained service systems with clients presenting multiple clinical needs (Raynor, 1984). These conditions are reflected in the preferred methods of social work research, which favor qualitative or quasi-experimental approaches that allow for more nuance of understanding and for a closer representation of the clinical context, respectively. Evaluation questions that examine moderators and mediators have a similar capacity and can occur within the standards of internal validity that are achieved in an RCT design.

The moderation research reviewed inform the choice between two evidence-based treatments for depression based on a client’s attachment style (McBride et al., 2006), general clinical guidelines for working with depressed or reactant clients with alcohol use disorders (Karno and Longabaugh, 2003; 2005), and a viable brief treatment option for young adult alcohol users even if they are also marijuana users (Magill et al., 2009). In the mediation studies examined, we learned that maladaptive coping (e.g., avoidance, drinking alcohol) is one mechanism of the relationship between trauma and current mental health difficulties (Calvete et al., 2008; O’Hare et al., 2007). These findings can ground future intervention development while also offering psychoeducation material for therapists working with trauma survivors. In addition, the most salient aspects of an adolescent HIV risk reduction intervention were identified (Schmeide et al., 2009), which point to areas of emphasis for providers delivering and researchers further developing this intervention. Statistical tests of moderation and mediation can be methodologically complex, but by understanding the approaches summarized here, evidence-based social workers can capitalize upon this valuable area of clinical research.

Conclusions

The present work argues for, and summarizes the methods of, tests for statistical moderators and mediators in evaluation research. The empirical examples provided may capture the nature of evidence-based questions asked by practitioners pondering the conditions for and dynamics of client behavior change. For evaluation researchers, analyses of moderation and mediation can validate or refute practice theories that have intuitive and conceptual appeal, but remain an empirical question for study. This additionally fits with a critical and reflexive stance (see Taylor and White, 2001) where the broad applicability or the theorized inner workings of treatments are questioned rather than assumed. In the United States substance use and mental health literature, *mechanisms of behavior change* have entered the forefront of the dialogue (see e.g., Kazdin, 2007; Longabaugh, 2007). “A mechanism of change refers to the process or series of events through which one variable leads to or causes change in another variable” (Kazdin and Nock, 2003; Nock, 2007, p. 5S), and this is consistent with the definition of a statistical mediator. Of longer standing interest is *patient-to-treatment matching*, which is the primary realm of statistical moderators. Both of these areas represent movement toward a more clinically relevant and ecologically valid evidence-base for practice.

As a movement, EBP may have barriers to broad-scale, or broad-stroke, implementation just as it is questionable whether individual practitioners should be told exactly how their decision-making is to occur. The described methods, however, reflect an attempt at integration, and subsequent research findings may be synthesized for ease of consumption, or assessed individually for critical appraisal. Social work research can thus benefit from greater attention to this methodology, and with knowledge gained through the present review, practitioners’ evidence-based knowledge needs may be more effectively met.

Acknowledgments

This work was supported by training grants T32 AA07459 and K23 AA018126 from the National Institute on Alcohol Abuse and Alcoholism. The author would like to thank Drs. Apodaca, Longabaugh, O’Hare, and Stout for their mentorship as well as Dr. Nadine Mastroleo for her valuable comments on this manuscript.

References

- Aiken, L.S.; West, S.G. Multiple Regression: Testing and Interpreting Interactions. Thousand Oaks: Sage; 1991.
- Babor T. Treatment for Persons with Substance Use Disorders: Mediators, Moderators, and the Need for a New Research Approach. International Journal of Methods in Psychiatric Research. 2008; 17(S1):S45–S49. [PubMed: 18543362]
- Baron RM, Kenny DA. The Mediator-Moderator Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. Journal of Personality and Social Psychology. 1986; 51:1173–1182. [PubMed: 3806354]
- Calvete E, Corral S, Estevez A. Coping as a Mediator and Moderator Between Intimate Partner Violence and Symptoms of Anxiety and Depression. Violence Against Women. 2008; 14:886–902. [PubMed: 18667404]
- Cohen, J.; Cohen, P. Applied Multiple Regression/Correlation Analyses for the Behavioral Sciences. Hillsdale, NJ: Erlbaum; 1983.
- Coulton C, Chow J. Interaction Effects in Multiple Regression. Journal of Social Service Research. 1992; 16:179–199.
- Fraser MW. Intervention Research in Social Work: Recent Advances and Continuing Challenges. Research on Social Work Practice. 2004; 14:210–222.
- Holmbeck GN. Toward Terminological, Conceptual, and Statistical Clarity in the Study of Mediators and Moderators: Examples From the Child-Clinical and Pediatric Psychology Literatures. Journal of Consulting and Clinical Psychology. 1997; 65:599–610. [PubMed: 9256561]

- Holmbeck GN. Post-Hoc Probing of Significant Moderational and Mediation Effects in Studies of Pediatric Populations. *Journal of Pediatric Psychology*. 2002; 27:87–96. [PubMed: 11726683]
- Hudson CG. Decision-Making in Evidence-Based Social Work: Science and Art. *Smith College Studies in Social Work*. 2009; 79:155–174.
- Jaccard, J.; Turrissi, R.; Wan, CK. *Interaction Effects in Multiple Regression Analysis*. Newbury Park, CA: Sage; 1990.
- Jaccard J, Wan CK. Measurement Error in the Analysis of Interaction Effects Between Continuous Predictors Using Multiple Regression: Multiple Indicator and Structural Equation Approaches. *Psychological Bulletin*. 1991:348–357.
- James LR, Brett JM. Mediators, Moderators, and Tests for Mediation. *Journal of Applied Psychology*. 1984; 69:307–321.
- Judd CM, Kenny DA. Process Analysis: Estimating Mediation in Treatment Evaluation. *Evaluation Review*. 1981; 5:602–619.
- Karno MP, Longabaugh R. Patient Depressive Symptoms and Therapist Focus on Emotional Material: A New Look at Project MATCH. *Journal of Studies on Alcohol*. 2003; 64:607–615. [PubMed: 14572181]
- Karno MP, Longabaugh R. Less Directiveness by Therapists Improves Drinking Outcomes of Reactant Clients in Alcoholism Treatment. *Journal of Consulting and Clinical Psychology*. 2005; 73:262–267. [PubMed: 15796633]
- Kazdin AE. Mediators and Mechanisms of Change in Psychotherapy Research. *Annual Review of Clinical Psychology*. 2007; 3:1–27.
- Kazdin AE, Nock MK. Delineating Mechanisms of Change in Child and Adolescent Therapy: Methodological Issues and Research Recommendations. *Journal of Child Psychology and Psychiatry*. 2003; 44:1116–1129. [PubMed: 14626454]
- Koeske GF. Moderation Variable in Social Work Research. *Journal of Social Service Research*. 1992; 16:159–177.
- Longabaugh R. The Search for Mechanisms of Change in Behavioral Treatments for Alcohol Use Disorders: A Commentary. *Alcoholism: Clinical and Experimental Research*. 2007; 31(S3):21S–32S.
- MacKinnon DP, Fairchild AJ, Fritz MS. Mediation Analysis. *Annual Review of Psychology*. 2007; 58:593–614.
- MacKinnon, DP.; Lockwood, C.; Hoffman, J. A New Method to Test for Mediation. Paper Presented at the Annual Meeting of the Society for Prevention Research; Park City, UT. 1998.
- MacKinnon DP, Lockwood CM, Hoffman JM, West SG, Sheets V. A Comparison of Methods to Test the Significance of the Mediated Effect. *Psychological Methods*. 2002; 7:83–104. [PubMed: 11928892]
- MacKinnon DP, Warsi G, Dwyer JH. A Simulation Study of Mediated Effect Measures. *Multivariate Behavioral Research*. 1995; 30:41–62. [PubMed: 20157641]
- Magill M. The Future of Evidence Based Practice: Who Will Answer the Call for Clinical Relevance? *Journal of Social Work*. 2006; 6:101–115.
- Magill M, Barnett NP, Apodaca TR, Rohsenow DR, Monti PM. The Role of Marijuana Use in Brief Motivational Intervention with Young Adult Drinkers Treated in an Emergency Department. *Journal of Studies on Alcohol and Drugs*. 2009; 70:409–414. [PubMed: 19371492]
- McBride C, Atkinson L, Quilty LC, Bagby RM. Attachment as Moderator of Treatment Outcome in Major Depression: A Randomized Control Trial of Interpersonal Psychotherapy Versus Cognitive Behavior Therapy. *Journal of Consulting and Clinical Psychology*. 2006; 74:1041–1054. [PubMed: 17154734]
- Morgenstern J, McKay JR. Rethinking the Paradigms That Inform Behavioral Treatment Research for Substance Use Disorders. *Addiction*. 2007; 102:1377–1389. [PubMed: 17610541]
- Muller D, Judd CM, Yzerbyt VY. When Moderation is Mediation and Mediation is Moderated. *Journal of Personality and Social Psychology*. 2005; 89:852–863. [PubMed: 16393020]
- Nock MK. Conceptual and Design Essentials for Examining Mechanisms of Change. *Alcoholism: Clinical and Experimental Research*. 2007; 31(S3):4S–12S.

- O'Hare T, Shen C, Sherrer M. Validating the Posttraumatic Symptom Scale with Persons who Have Severe Mental Illness. *Research on Social Work Practice*. 2007; 17:720–728.
- Preacher KJ, Hayes AF. Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models. *Behavior Research methods*. 2008; 40:879–891. [PubMed: 18697684]
- Project MATCH Research Group. Matching Alcoholism Treatments to Client Heterogeneity: Project MATCH Posttreatment Drinking Outcomes. *Journal of Studies on Alcohol*. 1997; 58:7–29. [PubMed: 8979210]
- Raynor P. Evaluation with One Eye Closed: The Empiricist Agenda in Social Work Research. *British Journal of Social Work*. 1984; 14:1–10.
- Schmiege SJ, Broaddus MR, Levin M, Bryan AD. Randomized Trial of Group Interventions to Reduce HIV/STD Risk and Change Theoretical Mediators Among Detained Adolescents. *Journal of Consulting and Clinical Psychology*. 2009; 77:38–50. [PubMed: 19170452]
- Silverman WH. Cookbooks, Manuals, and Paint-by-Numbers: Psychotherapy in the 90's. *Psychotherapy*. 1999; 33:207–15.
- Smith D. The Limits of Positivism in Social Work Research. *British Journal of Social Work*. 1987; 17:401–416.
- Smith D. 'The Limits of Positivism Revisited', *Social Work and Social Sciences Review*. Special Issue: Evidence-based practice-I. 2002; 10:27–37.
- Smith ML, Glass GV. Meta-Analysis of Psychotherapy Outcome Studies. *American Psychologist*. 1977; 32:752–760. [PubMed: 921048]
- Sobel, ME. Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. In: Leinhardt, S., editor. *Sociological Methodology*. Washington, DC: American Sociological Association; 1982. p. 290-312.
- Stout RL. Advancing Analysis of Treatment Process. *Addiction*. 2007; 102:1539–1545. [PubMed: 17610542]
- Taylor C, White S. Knowledge, Truth and Reflexivity: The Problem of Judgment in Social Work. *Journal of Social Work*. 2001; 1:37–59.
- Wampold, BE. *The Great Psychotherapy Debate: Model, Methods and Findings*. Mahwah, NJ: Lawrence Erlbaum; 2001.
- Webb S. Some Considerations on the Validity of Evidence-Based Practice in Social Work. *British Journal of Social Work*. 2001; 31:57–80.
- Witkin SL, Harrison WD. Whose Evidence and for What Purpose? *Social Work*. 2001; 46:293–296. [PubMed: 11682970]

Figure 1.

Conceptual model of moderator variable effect.

Notes. *X* = independent variable, for example, type of social work treatment. *W* = moderator variable, or most often, a client or agency characteristic. *Y* = dependent variable or specific outcome of interest.

Figure 2.

Example: The effect of a brief social work intervention on elder adult quality of life: The moderating effect of marital status.

Figure 3.

Conceptual model of a mediating variable effect.

Notes. Where X is the independent variable (e.g., treatment), Y is the dependent variable (e.g., outcome), and M is the mediator (e.g., the hypothesized process through which treatment affects outcome). The solid arrow is the total effect and the dashed arrow is the direct effect, or reduced total effect after accounting for the mediating variable. The difference between the total and direct effect is the mediated effect.