Reasons for Testing Mediation in the Absence of an Intervention Effect: A Research Imperative in Prevention and Intervention Research

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ABSTRACT. Objective: Mediation models are used in prevention and intervention research to assess the mechanisms by which interventions influence outcomes. However, researchers may not investigate mediators in the absence of intervention effects on the primary outcome variable. There is emerging evidence that in some situations, tests of mediated effects can be statistically significant when the total intervention effect is not statistically significant. In addition, there are important conceptual and practical reasons for investigating mediation when the intervention effect is nonsignificant. **Method:** This article discusses the conditions under which mediation may be present when an intervention effect does not have a statistically significant effect and why mediation should always be considered important. **Results:** Mediation may be present in the following conditions: when the total and mediated effects are equal in value, when the mediated and direct effects have opposing signs, when mediated effects are equal across single and multiple-mediator models, and when specific mediated effects have opposing signs. Mediation should be conducted in every study because it provides the opportunity to test known and replicable mediators, to use mediators as an intervention manipulation check, and to address action and conceptual theory in intervention models. **Conclusions:** Mediators are central to intervention programs, and mediators should be investigated for the valuable information they provide about the success or failure of interventions. (*J. Stud. Alcohol Drugs, 79,* 171–181, 2018)

MEDIATION ANALYSIS IS USED to investigate the mechanisms by which prevention and intervention programs achieve their effects. Much methodological research has been conducted on mediation analysis, and applied mediation research can be found in many fields, including medicine, epidemiology, and the social sciences. However, results from mediation analyses are usually reported after a statistically significant intervention effect on an outcome has already been found. And often, researchers who fail to find a statistically significant intervention effect do not proceed with significance tests of hypothesized mediators because of the belief that mediation cannot be present if an intervention effect is not present (Apodaca & Longabaugh, 2009). This is, in part, because of early methodological work on tests of mediation requiring an intervention effect to be present in order for mediation to be deemed statistically significant (Baron & Kenny, 1986; Judd & Kenny, 1981). However, recent methodological research has shown that mediation effects can be present in the absence of a total or overall effect (Kenny & Judd, 2014; O'Rourke & MacKinnon, 2015), meaning that researchers may find true significant mediation effects even if the intervention effect on an outcome is not statistically significant.

Intervention researchers are interested in mediators because they provide information about how an intervention was successful in changing an outcome (Botvin, 2000; Huebner & Tonigan, 2007; MacKinnon, 1994, 2008). The importance of investigating mediating processes underlying interventions is now widely acknowledged in many different research areas (Bryan et al., 2007; Insel & Gogtay, 2014; MacKinnon, 2008), including alcohol treatment research (Longabaugh & Magill, 2011; Magill et al., 2015; Morgenstern & Longabaugh, 2000). The purpose of this article is to describe circumstances in which mediation may be present without a statistically significant intervention effect and to explain the methodological and conceptual reasons for always investigating mediation in prevention and intervention research even in the absence of an intervention effect, with specific attention to alcohol treatments.

Mediation in prevention and intervention research

Researchers commonly examine relationships between two variables, such as the effect of randomization to an intervention (X) on a dependent variable (Y). Additional information can be obtained if a measure of a mediating variable is also available. In a single-mediator model (Figure 1), X transmits its effects on Y through a third variable, the mediator (M). Within the context of prevention and intervention research, X is a randomized or nonrandomized intervention (such as a 12-step program), M is a mechanism through which the intervention works, and Y is a health-related outcome. Mediation analysis is important to prevention and

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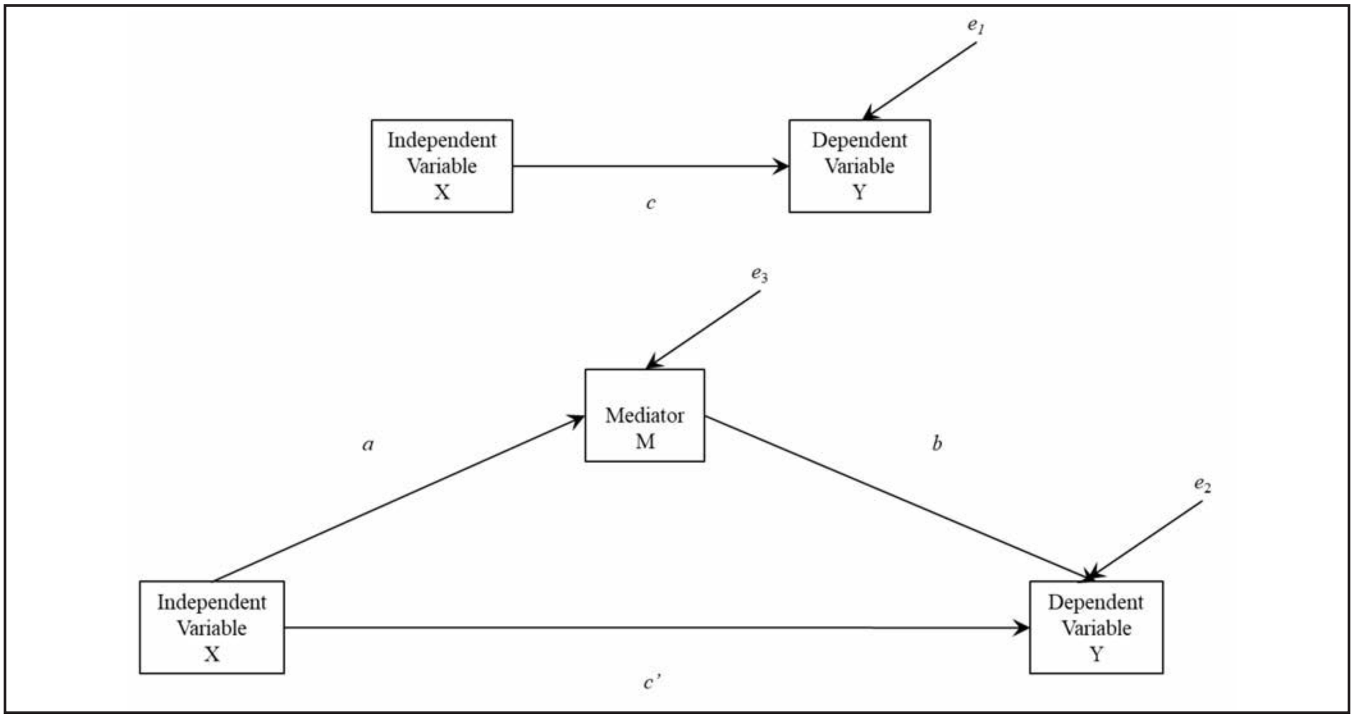

FIGURE 1. Path diagram for regression and single-mediator models (MacKinnon, 2008)

intervention research because it can explain how an intervention program influences the behavior it is intended to change. For a variable to be conceptually considered a mediator, a researcher must specify an a priori hypothesis about how the intervention will influence the outcome through the mediator (Longabaugh, 2007; MacKinnon, 2008). It is the causal links from X to M to Y and theoretical background for mediation that determine whether a variable is a mediator and that differentiate mediators from confounders (MacKinnon et al., 2000).

In prevention and intervention research, mediators are also referred to as mechanisms of change (MOCs) or mechanisms of behavior change (MOBCs). Many articles have noted the importance of MOBCs in prevention and intervention research (Apodaca & Longabaugh, 2009; Huebner & Tonigan, 2007; Longabaugh, 2007; Longabaugh et al., 2005, 2013; Longabaugh & Magill, 2011). Researchers also distinguish between two types of mediators: active ingredients of treatment, which are the components of a program that bring about the desired behavior change, and MOBCs, which are "patient" variables, or the actual processes through which the active program components cause the desired behavior change (Longabaugh, 2007; Longabaugh et al., 2005; Longabaugh & Magill, 2011; Nock, 2007).

Psychological and behavioral mediators are central to many alcohol treatments. For example, 12-step or Alcoholics Anonymous (AA) programs are hypothesized to reduce alcohol use through mediating mechanisms such as increased self-efficacy, coping skills, motivation, spirituality and religiousness, positive social networks, and decreased depression (Connors et al., 2001; Hoeppner et al., 2014; Kelly, 2017; Kelly et al., 2009, 2010, 2011a, 2011b, 2012; Tonigan, 2003). Hypothesized mediators of motivational interviewing (MI) on alcohol use are client- and therapist-related behaviors such as client positive change talk, positive intentions, increased sense of discrepancy, therapist feedback, and reduced therapist MI-inconsistent behaviors (Apodaca & Longabaugh, 2009; Mastroleo et al., 2014; Morgenstern et al., 2012; Moyers et al., 2009; Vader et al., 2010). Cognitive behavioral therapy (CBT) has hypothesized mediators of motivation to change, craving, self-efficacy, and coping (Hartzler et al., 2011; Hunter-Reel et al., 2010; Kiluk et al., 2010; Subbaraman et al., 2013; Witkiewitz et al., 2011, 2012), although prior research on coping as a mediator of CBT provides conflicting results (Morgenstern & Longabaugh, 2000). The mediators of AA were examined using data from Project MATCH (Matching Alcoholism Treatments to Client Heterogeneity), a large-scale intervention designed for patients with alcohol use disorder. Project MATCH had no total intervention effect, but significant mediators of the different treatment arms continue to be identified (Maisto et al., 2015). In addition, some of the mediators of CBT have been examined using data from another large-scale study, the Combined Pharmacotherapies and Behavioral Interventions for Alcohol Dependence (COMBINE) Study (Hartzler et al., 2011; Witkiewitz et al., 2011, 2012).

Mediation model

The following regression equations represent the models necessary for assessing the mediated effect using common tests of mediation.

$$Y = i_1 + cX + e_1 \quad (1)$$

$$Y = i_2 + c'X + bM + e_2 \quad (2)$$

$$M = i_3 + aX + e_3 \quad (3)$$

In these equations, X is the independent variable (here, a randomized intervention), M is the mediating variable, and Y is the outcome variable. From Equation 1, c is the effect of X on Y (also known as the total effect). From Equation 2, b is the effect of M on Y controlling for X and c' is the effect of X on Y controlling for M (the direct effect). From Equation 3, a is the effect of X on M. The coefficients e_1, e_2, and e_3 are unexplained variability in the equations, and i_1, i_2, and i_3 are the intercepts for the equations.

There are two methods for calculating the mediated effect. The first method uses Equations 2 and 3 and multiplies the coefficient relating X to M (a) and the coefficient relating M to Y (b), resulting in a product of coefficients, ab. This quantity measures the extent to which X influences M (a) and M influences Y (b). The second method subtracts the direct effect in Equation 2 (c') from the total effect in Equation 1 (c), resulting in a difference in coefficients $c - c'$. This quantity, which is the difference between the total effect and the direct effect, gives the difference in the intervention effect that results from adding the mediator (McCaul & Glasgow, 1985). These two effects ab and $c - c'$ are the mediated (or indirect) effects. The mediated effects are equal for ordinary least squares regression ($ab = c - c'$), but may not be equal for special cases such as for categorical data analysis (MacKinnon, 2008; MacKinnon & Dwyer, 1993). Rearranging this equality, the total effect is equal to the sum of the mediated effect ab and the direct effect ($c = ab + c'$).

Tests of mediation fall into three general categories (MacKinnon et al., 2002a). The first test, the product of coefficients test, assesses the statistical significance of the mediated effect ab by computing a z statistic for the effect using a standard error derived by Sobel (1982). Confidence limits for the mediated effect ab can also be calculated using the nonnormal distribution of the product of a and b or using resampling methods (MacKinnon et al., 2004, 2007a; Tofighi & MacKinnon, 2011). The second test uses the difference in coefficients and also computes a z statistic using one of several derived standard errors (Clogg et al., 1992; Freedman & Schatzkin, 1992; McGuigan & Langholtz, 1988). The third and most well-known test is the causal steps test, which assesses statistical significance of mediation using the steps outlined by Baron and Kenny (1986) and Judd and Kenny (1981). Using the Baron and Kenny (1986) method, the following conditions must hold for mediation to be present:

I. The effect of X on Y (c path) must be significant.
II. The effect of X on M (a path) must be significant.
III. The effect of M on Y controlling for X (b path) must be significant.

Another causal steps test is the joint significance test (MacKinnon, 2008; MacKinnon et al., 2002a), which assesses the statistical significance of mediation by requiring statistically significant z or t statistics for both the a and b coefficients.

Statistical mediation with alcohol outcomes

In alcohol preventive interventions and treatments, special statistical considerations must be made to account for the large number of zeros in the data (Buu et al., 2011, 2012; Horton et al., 2007; Kypri, 2007). An example from the literature is the analysis of a treatment designed to reduce alcohol use in incarcerated women returning to their communities, which used zero-inflated negative binomial models to investigate drinking outcomes with a high proportion of zeros (Stein et al., 2010). Methods such as logistic and Poisson regression can be used to examine mediation with categorical or count outcomes (MacKinnon, 2008; MacKinnon & Dwyer, 1993), but these methods do not automatically account for zero inflation in the data. Also, when logistic regression is used for mediation, the product of a and b is not equivalent to the difference $c - c'$, and the difference $c - c'$ may be biased (Coxe & MacKinnon, 2010; MacKinnon et al., 2007b). However, building on the work of Imai et al. (2010), methods for assessing mediation with zero-inflated count data have been developed that extend beyond the logistic regression framework, such as zero-inflated negative binomial models that examine mediation in two stages using causal inference (Wang & Albert, 2012).

Statistically significant mediation in the absence of an intervention effect

According to Web of Science, the Baron and Kenny (1986) article on steps for testing mediation has been cited more than 32,000 times as of this writing (Google Scholar reports that the Baron and Kenny article has been cited more than 73,000 times). It is likely that researchers using the causal steps mediation test on their own data are responsible for many of these citations. We conducted a brief review on Google Scholar of the 100 most recent articles that cited Baron and Kenny. Of the 97 available articles (3 were abstracts only), 64 (66%) specifically used the causal steps mediation test. (The remaining 33 articles either used another mediation test, cited Baron and Kenny in the context of discussing more modern mediation methods, cited the article in conducting a moderation analysis, or were methodological articles.) As a result of Step 1 from the causal steps

TABLE 1. Conditions with significant mediation and nonsignificant intervention effects

Condition	Circumstance	Effects
I.a)	When $ab = c$ with large n and small effects.	$ab = c$
I.b)	When $ab = c$ with small n and large effects.	$ab = c$
II.	When ab and c' have opposing signs.	$ab = +, c \;\; = -$ $ab = -, c' = +$
III.	With multiple mediators, when $b_1b_2b_3 = ab$.	$b_1b_2b_3 = ab$
IV.	When two specific mediated effects have opposing signs.	$a_1b_1 = +, a_2b_2 = -$ $a_1b_1 = -, a_2b_2 = +$

test, each researcher using this test of mediation would have concluded that mediation was not present if a total effect was not present in their data (and in fact, three surveyed articles reported stopping at Step 1 because of a nonsignificant total effect).

Recent research has shown that Baron and Kenny's (1986) Step 1 is not a requirement for mediation. Furthermore, methodological studies using empirical simulation have shown that the mediated effect may be statistically significant even when the total effect is not (Fritz et al., 2015; Fritz & MacKinnon, 2007; Kenny & Judd, 2014; MacKinnon, 2008; MacKinnon et al., 2002a; O'Rourke & MacKinnon, 2015). Table 1 presents situations in which the test of mediation may be statistically significant when the test of the intervention effect is not (further described below).

Condition I: When ab = c. When the mediated effect and the total effect are equal in a sample (ab is equal to c such that c' is zero), the test of the mediated effect may be statistically significant when the test of the total effect is not, and thus the test of the mediated effect may have more statistical power to detect effects than the test of the total effect (O'Rourke & MacKinnon, 2015; Shrout & Bolger, 2002; Taylor et al., 2008). Analytical and simulation work have confirmed this finding (Kenny & Judd, 2014; O'Rourke & MacKinnon, 2015). The difference in statistical power between the two tests is such that in some situations, the power of the test of the mediated effect reaches Cohen's (1988) satisfactory level of .8 when power of the test of the total effect is far below an adequate level of .8. This occurs most often with small sample sizes and large effects and with large sample sizes and small effects. For example, analytically computing statistical power for the mediated and total effects with a sample size of 1,000 and small (.14) effect sizes for a and b ($ab = c = .14*.14 = .02$) shows that the power to detect the mediated effect is .986, whereas the power to detect the total effect is just .089. To emphasize this, the power to detect the mediated effect is 11.08 times larger than the power to detect the total effect in this condition, even though the effects themselves are equal in size. This analytical example is shown in Figure 2.

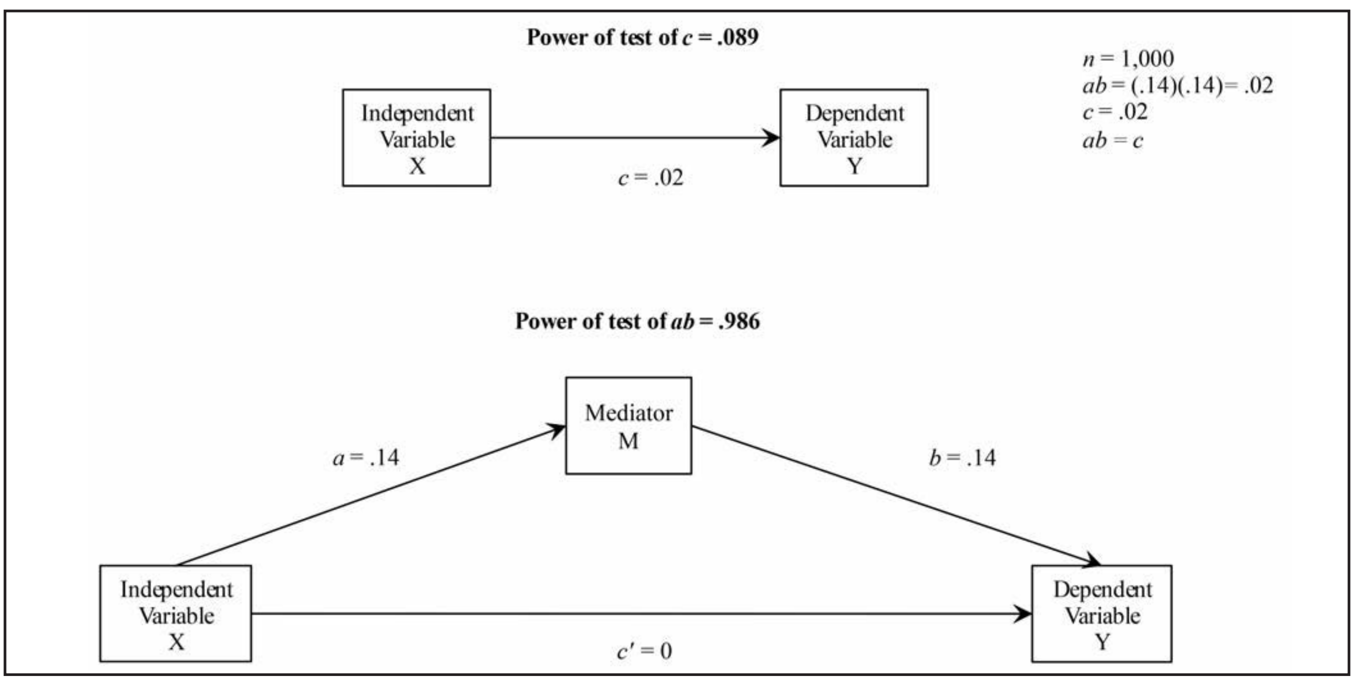

FIGURE 2. Example of when power of the test of mediation is greater than power of the test of the total effect

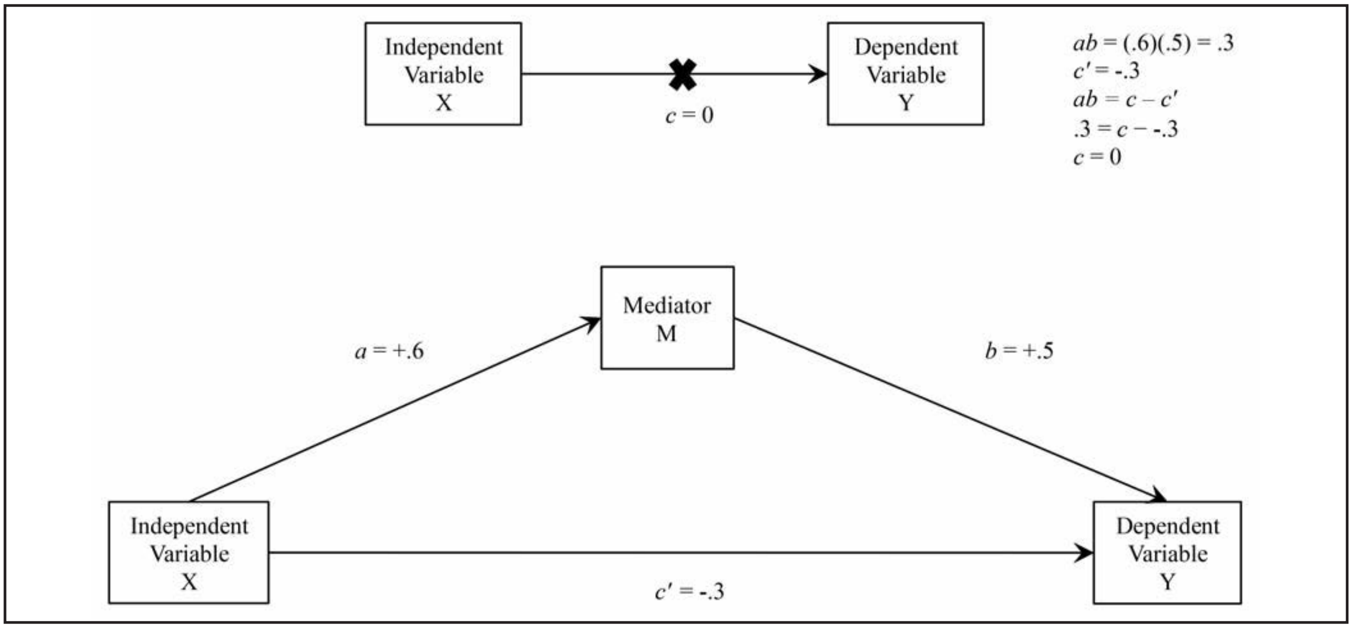

FIGURE 3. Example of inconsistent mediation in which *ab* and *c*′ have opposing signs

This finding has many important implications for the alcohol intervention literature, in which interventions that are designed to target mediators may not result in significant total effects. A well-known example from the alcohol treatment literature is Project MATCH (described earlier; Project MATCH Research Group, 1997), in which the overall study found no matching effects (i.e., no overall intervention effect on alcohol outcomes). However, using modern mediation modeling techniques, Maisto et al. (2015) found that the matching effects on alcohol outcomes were mediated by both therapeutic alliance and self-efficacy.

Furthermore, the difference in power is greater when mediators are distal (i.e., M is more closely related to Y than to X). The statistical power of the test of mediation is greater when b is larger than a because of collinearity between the intervention and the mediator (Fritz et al., 2012; Hoyle & Kenny, 1999; Kenny & Judd, 2014; O'Rourke & MacKinnon, 2015). As a result, testing for mediation in the absence of an intervention effect would be more appropriate when there is evidence that the mediator is more closely related or measured closer in time to the outcome than to the intervention (although the test of mediation may also have more power for proximal mediators as well). However, statistical power is greatest when the a and b effects are close to equal, holding the value of ab constant (Kenny & Judd, 2014).

Condition II: When ab *and* c′ *have opposing signs.* Another situation in which mediation may be present when the total effect is nonsignificant occurs for the case of inconsistent mediation. If inconsistent mediation is present and the mediated and direct effects have opposite signs (e.g., the mediated effect is positive while the direct effect is negative), the total effect in the sample may be near zero while the mediated effect is statistically significant (MacKinnon, 2008; MacKinnon et al., 2000, 2002a, 2007b; Taylor et al., 2008). Figure 3 shows a hypothetical example of inconsistent mediation.

In the case of inconsistent mediation, a researcher could fail to find a statistically significant intervention effect even if a mediated effect exists. An example from the literature comes from the "In Control: No Alcohol!" intervention (Vermeulen-Smit et al., 2014). The authors found that the intervention significantly increased the perceived harm of drinking, controlling for mediators ($c' = .17$), and that the intervention increased the frequency of children signing a nondrinking agreement with their parents ($a = .25$), but that the nondrinking agreement significantly decreased the perceived harm of drinking ($b = -.18$), resulting in a negative mediated effect. Although the total effect was significant in this example, it is a demonstration of a way in which inconsistent mediation can occur in alcohol research.

Condition III: With multiple mediators, when mediated effects are equal. The power to detect mediated effects may also be greater for models with multiple mediators than for models with a single mediator or models examining an intervention effect only. O'Rourke and MacKinnon (2015) found that adding an additional mediator to the causal chain (a sequential multiple-mediator model) increased power over and above a single mediator when the mediated effects from the models were equal. For example, when $n = 500$ and the single-mediator effect and sequential two-mediator effect are equal with a value of .02, analytical power to detect the single-mediator effect is .766, whereas analytical power to

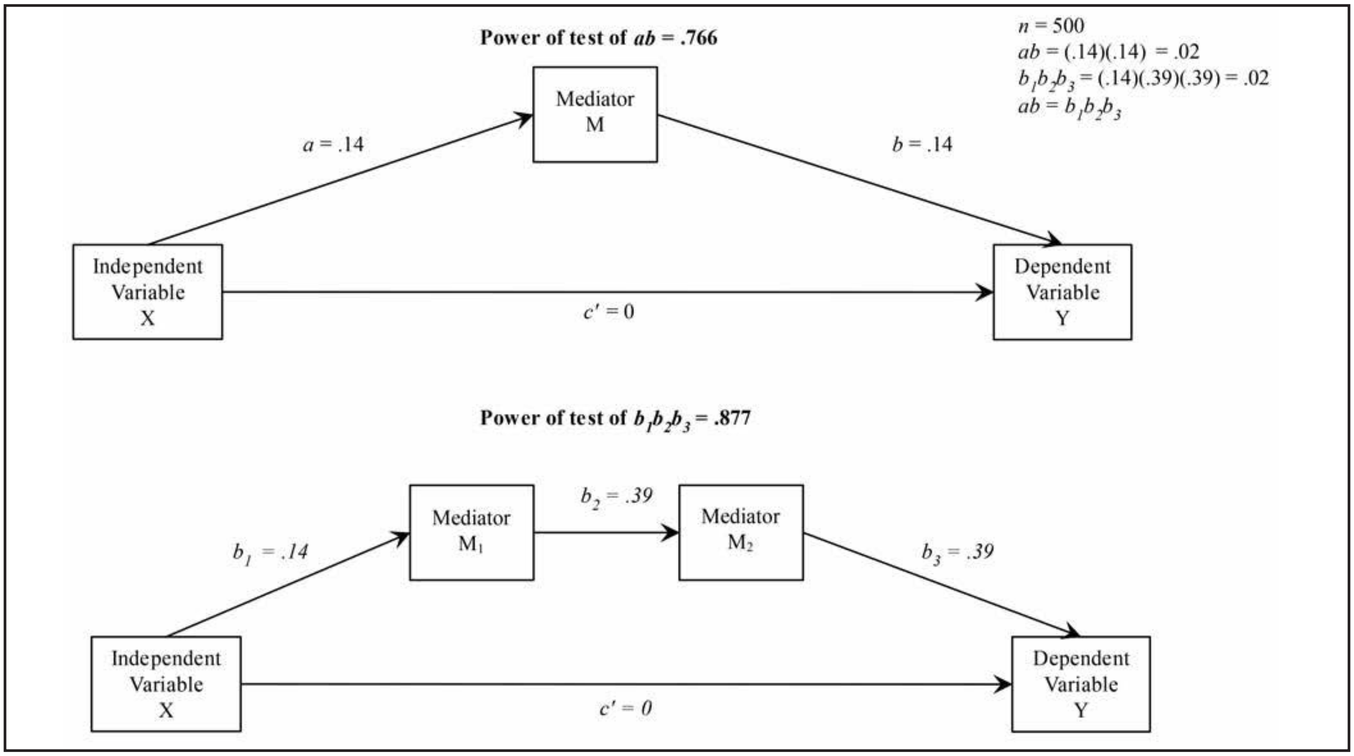

FIGURE 4. Example of when power of test of a multiple-mediator effect is greater than power of test of single-mediator effect

detect the two-mediator effect is .877. This example is shown in Figure 4, in which the mediator effect values are equal across models.

Consider a hypothetical example building on existing alcohol treatment literature. Kelly et al. (2011b) found that in the MATCH aftercare sample, AA attendance increased spirituality/religiousness (S/R), which in turn increased the percentage of days abstinent (PDA), a single-mediator effect with a standardized value of .07 (a = .23, b = .29; Kelly et al., 2011b, Tables 4 and 5). Imagine we were able to use the same data to examine a sequential two-mediator model, in which AA attendance increased church attendance, which in turn increased S/R, which in turn increased PDA, and which gave us a sequential two-mediator effect equal to .07 as well. Although the individual paths from AA attendance → church attendance → S/R → PDA would be larger to equal the effect of .07, the power to detect the two-mediator effect of .07 would be larger than the power to detect the single-mediator effect that was equal in value.

Condition IV: When specific mediated effects have opposing signs. Inconsistent mediation occurs in parallel multiple-mediator models as well when specific mediated effects have opposing signs (MacKinnon, 2008; MacKinnon et al., 2007b). If mediators have opposing signs in a parallel multiple-mediator model, they effectively cancel each other out with respect to the intervention effect, resulting in a nonsignificant test of the sample intervention effect (see Figure 5 for a hypothetical example).

A real example from the alcohol literature comes from Bekman et al. (2010), in which the authors found that for females, the influence of depression on adolescent alcohol use was significantly positively mediated by perceptions but significantly negatively mediated by expectancies, with no total effect. Inconsistent mediation can be present in sequential multiple-mediator models as well, in which the multiple-mediated effect is opposite in sign from the direct effect. Considering these multiple-mediator circumstances, researchers with a priori multiple-mediator hypotheses may be even more likely to identify statistically significant mediators from hypothesized multiple-mediator models in the absence of a statistically significant intervention effect.

Conceptual reasons for testing mediation in the absence of an intervention effect

Recent methodological advancements make it clear that researchers may detect statistically significant mediated effects when they have not found a statistically significant intervention total effect. However, there are several conceptual reasons for proceeding with mediation in the absence of an intervention effect as well. Mediators are part of several theories that form the foundation of behavior change in prevention and intervention research, such as personality theory, tension-reduction theory, and social learning theory (Bandura, 1977; Leonard & Blane, 1999). The following reasons highlight the theoretical importance of mediators

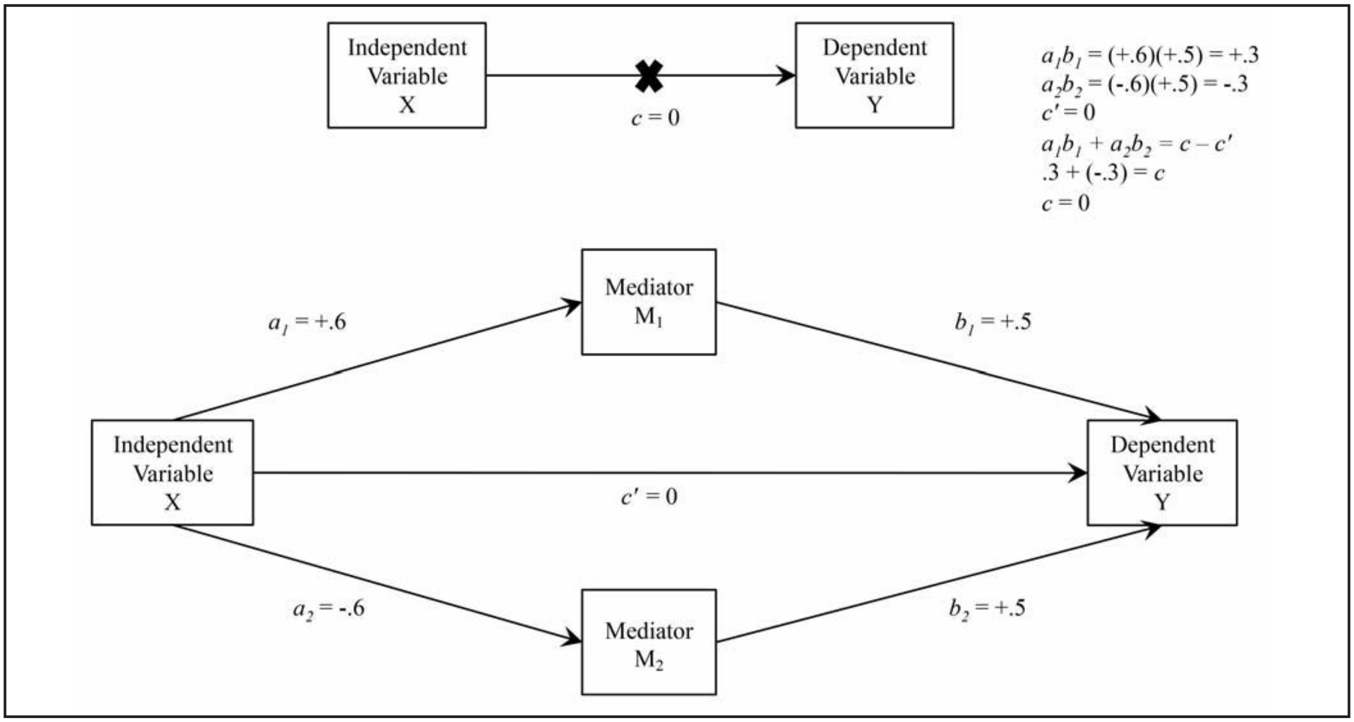

FIGURE 5. Example of inconsistent mediation with a multiple-mediator model where a_1b_1 and a_2b_2 have opposing signs

in prevention and intervention research, regardless of the statistical significance of the intervention effect.

Known, replicable mediators. Prevention and intervention programs are inherently mediation models, in that the programs are designed to change the ultimate outcome of behavior through some intermediate mechanism. Some programs have mediators that have been identified and replicated in the literature, such as social norms, participant and client interactions in interventions, and self-regulation. For example, MI influences substance use positively through client change talk, intention, and discomfort with current behavior. MI influences substance use negatively through therapist behaviors that are inconsistent with MI (Apodaca & Longabaugh, 2009). Another example is AA, in which the AA program influences drinking behaviors positively through increased motivation, increased self-efficacy, better coping, and positive social networking (Kelly et al., 2009). Examples from prevention are Project ALERT, in which the drug prevention program's influence on drug use was mediated by resistance self-efficacy (Longshore et al., 2007) and Project STAR, which found mediating influences of social norms on drug use (MacKinnon et al., 1991). Conducting mediation analysis provides a way to evaluate the consistency of program effects on mediators across many studies. However, many studies assessing the efficacy of intervention programs fail to include mediators in modeling of program effects (Longabaugh & Magill, 2011).

Manipulation check. Mediators also provide a manipulation check of whether a program changed the construct it was designed to change (MacKinnon, 1994, 2011; MacKinnon & Dwyer, 1993). If a program fails to influence the targeted mediator (or mediators), the program may fail to influence the targeted outcome as well (McCarthy et al., 2007). This could be because of unsuccessful components of the program, or because the mediating measures are invalid or unreliable (MacKinnon, 2011). When there is no effect of the mediator on the outcome, program effects on mediators can be an indication that either the program effects on the outcomes may emerge later or that the mediator was not critical in affecting the outcomes (MacKinnon, 2008; MacKinnon & Dwyer, 1993). For example, in the Motivational Interventions for Drug and Alcohol Misuse in Schizophrenia (MIDAS) trial, no overall intervention effect (in this example, an intent-to-treat effect) was found on psychotic symptom outcomes. However, there was an intent-to-treat effect on the mediator, the amount of substance used. There was no link between the amount of substance used and psychotic symptoms (Barrowclough et al., 2010, 2013). This example illustrates that even when there is no statistically significant mediated effect, mediators provide valuable information on which portions of the program were successful or unsuccessful over and above the analysis of the intervention effect.

Action theory and conceptual theory. The MIDAS example above also highlights that there are two distinct theoretical links for prevention and intervention program models, known as action theory and conceptual theory (Chen, 1990; MacKinnon, 2008). Action theory is the theory relating the program to the mediators and aids researchers in determining how a prevention or intervention program can effectively change a mediator. Conceptual theory is the theory relating the mediators to the outcome and is used to improve understanding of how the mediators work to influence the targeted outcome. Action theory and conceptual theory are important for understanding how a program achieves its effects via a mediator, and many researchers have advocated for the use of action theory and conceptual theory when designing prevention and intervention programs (Lipsey, 1993; MacKinnon et al., 2002b). Thus, mediation analysis provides information on action theory and conceptual theory not provided by the test of the intervention on the outcome. The additional information that mediators provide on how programs work makes them useful tools for theory development and refinement (MacKinnon, 2011). In particular, the lack of a statistically significant intervention effect may be attributable to the failure of the intervention to change the mediator (action theory failure), or the mediator may not be related to the outcome (conceptual theory failure), or it could be both action and conceptual theory failure. Mediation analysis provides a way to understand intervention effects, regardless of whether that intervention effect is statistically significant. Results from mediation analyses can inform researchers about which program components need to be strengthened or require improved measures (MacKinnon, 2008). Intervention and prevention programs will be more efficacious and more cost effective in the future if critical (and noncritical) mechanisms can be identified using mediation analysis (Cerin & MacKinnon, 2009; MacKinnon & Dwyer, 1993).

Considering the intervention effect

We note that the test of the intervention effect on the outcome is the most important test of an intervention. Our point is that there is additional information when measures of mediating processes are available, and this information would be missed if statistical mediation analysis were not conducted. For example, if there was no intervention effect, the initial test of the intervention effect would indicate that the intervention does not have its desired effect. The lack of intervention effect could be attributable to opposing significant indirect effects that are conceptually important, so in this instance a researcher would gain more information by conducting mediation analysis after finding this nonsignificant intervention effect.

Also, requiring a statistically significant total intervention effect is useful because it can quickly reduce the number of active interventions being used and increase the use of successful interventions. In this way, the test of the intervention effect can serve as a benchmark to decide whether to conduct further analyses, or to start the evaluation of a new intervention program. However, if measures of mediating variables are included in a study, it is important to investigate mediation analysis for its own theoretical and practical importance, and mediation analysis helps extract the most information possible from a completed intervention in order to further science.

The importance of conducting mediation analysis and tests of total effects leads to several issues regarding reporting the results of an intervention study. As mentioned previously, when examining models that contain additional variables such as mediators, researchers will often discuss intervention effects first, followed by additional steps for mediation analyses (Baron & Kenny, 1986; Judd & Kenny, 1981). However, given that tests of the intervention effect may be nonsignificant and the mediation relation is the main effect of interest, a question arises of how to report such results in publications. There are several ways one could structure the results. First, authors could choose to publish the results for the intervention effect and the mediated effect separately in two publications. Second, authors could present results in the traditional manner, reporting the nonsignificant intervention effect and then reporting the mediated effect. Third, the authors could first present the effect of interest, the mediated effect, and then report the nonsignificant total effect. We would like to highlight here that, as described above, the nonsignificant intervention effect and the mediated effect each provide valuable information about how an intervention achieved (or failed to achieve) its effects, and each should be reported and discussed in this light.

A limitation of continuing to probe for further effects after the intervention effect is tested is a possible increase in Type 1 errors. It follows that there is a probability that some effects investigated after testing significance of the intervention effect—including mediated effects—will be significant because of chance. The same procedures used in regression and analysis of variance can adjust for the multiplicity problem in mediation analysis, such as controlling the false discovery rate, Bonferroni, and Scheffé methods (Benjamini & Hochberg, 1995; Mundfrom et al., 2006; Perlmutter & Myers, 1973).

Conclusion

Although mediators are common targets of program models in prevention and intervention research, researchers may overlook valuable information that could be gleaned from examining mediation when the overall intervention effect on the outcome is nonsignificant. There is statistical evidence that mediation can exist in the absence of an intervention effect, and there are sound conceptual reasons for examining mediating mechanisms even when an intervention effect is not statistically significant. Analysis of mediating variables provides additional information from the test of the total intervention effect.

A parsimonious model is not always a better choice (Cochran & Chambers, 1965[1]), because complex patterns of behavior change must be modeled in a way that reflects this complexity (Longabaugh, 2007). Failing to model the complexity of behavior change may lead researchers to ignore essential components of behavior change and consequently overlook meaningful effects. There is increasing awareness of and recommendation for mediators as valuable tools for assessing mechanisms of change in the development of a broad range of interventions (Insel & Gogtay, 2014; Longabaugh & Magill, 2011). We encourage prevention and intervention researchers with hypothesized mediation mechanisms to examine mediated effects in an effort to increase understanding of how interventions work to change behavior and also how they fail to change behavior. These analyses extract additional information from expensive research projects and provide a more complete picture of the effects of interventions. In this way, tests of mediation are an essential resource for researchers who are interested in determining the mechanisms by which intervention programs achieve their effects.

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[1]"When asked what can be done in observational studies to clarify the step from association to causation, Sir Ronald Fisher replied: 'Make your theories elaborate'" (Cochran & Chambers, 1965, p. 252).

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