Distinguishing Mediational Models and Analyses in Clinical Psychology: Atemporal Associations Do Not Imply Causation

E. Samuel Winer,[1] Daniel Cervone,[2] Jessica Bryant,[1] Cliff McKinney,[1]
Richard T. Liu,[3] and Michael R. Nadorff[1,4]

[1] *Mississippi State University*
[2] *University of Illinois at Chicago*
[3] *Alpert Medical School of Brown University*
[4] *Baylor College of Medicine*

Purpose: A popular way to attempt to discern causality in clinical psychology is through mediation analysis. However, mediation analysis is sometimes applied to research questions in clinical psychology when inferring causality is impossible. This practice may soon increase with new, readily available, and easy-to-use statistical advances. Thus, we here provide a heuristic to remind clinical psychological scientists of the assumptions of mediation analyses. **Approach:** We describe recent statistical advances and unpack assumptions of causality in mediation, underscoring the importance of time in understanding mediational hypotheses and analyses in clinical psychology. Example analyses demonstrate that statistical mediation can occur despite theoretical mediation being improbable. **Conclusion:** We propose a delineation of mediational effects derived from cross-sectional designs into the terms *temporal* and *atemporal* associations to emphasize time in conceptualizing process models in clinical psychology. The general implications for mediational hypotheses and the temporal frameworks from within which they may be drawn are discussed. J. Clin. Psychol. 72:947–955, 2016.

Keywords: mediation; methodology; theory; time; temporal

Establishing causality is a major challenge and has been a topic of recent intellectual activity in psychology (Gawronski & Bodenhausen, 2014). One standard criterion for establishing causality is temporal precedence, or the demonstration that a purportedly causal mechanism occurs, in time, before the variable it has theoretically brought about (MacKinnon, Fairchild, & Fritz, 2007). One technique that is commonly used in psychology to help establish causality is mediational research design and analyses (Hayes & Scharkow, 2013; MacKinnon et al., 2007; Spencer, Zanna, & Fong, 2005). Indeed, finding a mediational relationship between multiple variables has been called the "primary focus of contemporary research" in psychology (Kazdin, 2007, p. 5), because of its prospective ability to imply causality. However, various influential theoretical papers and texts on mediational design and analysis (Hayes, 2013; Hayes & Scharkow, 2013; MacKinnon et al., 2007; Zhao, Lynch, & Chen, 2010) do not emphasize the crucial assumption of temporal precedence in mediational design, and many empirical papers claim to have produced evidence of mediation without longitudinal data. This results in a misunderstanding of precisely what mediation means in regard to how processes unfold *over time* (Frewen, Schmittmann, Bringmann, & Borsboom, 2013).

Meditational analyses primarily yield the relationship of the mediator and outcome variables when partialing out the relationship between the predictor and mediator variables. This

We are most grateful for feedback from two anonymous reviewers. We wish to especially thank one anonymous reviewer who suggested the inclusion of a representative literature search, subdisciplinary citations, and extended data analyses, all of which greatly strengthened this manuscript.

Please address correspondence to: E. Samuel Winer, Mississippi State University, Department of Psychology, P.O. Box 6161, Mississippi State, MS 39762. E-mail: e.samuel.winer@msstate.edu

Published online in Wiley Online Library (wileyonlinelibrary.com/journal/jclp). DOI: 10.1002/jclp.22298

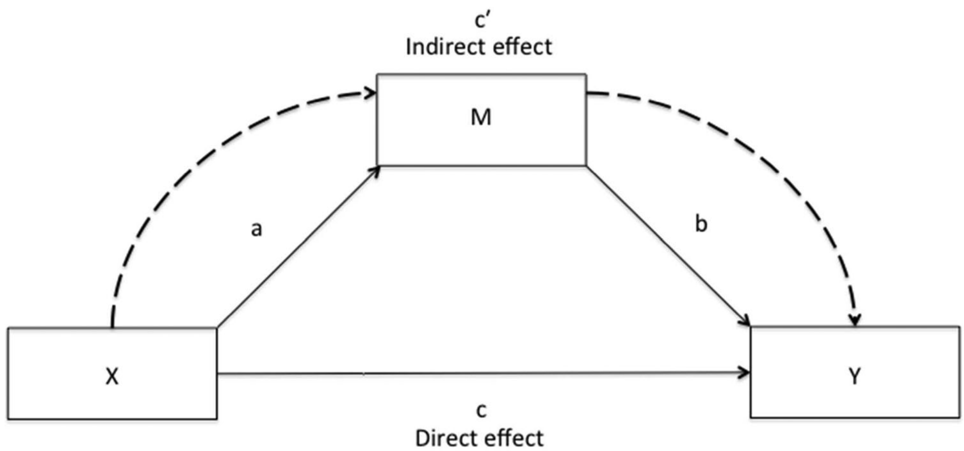

Figure 1. Mediational model highlighting direct and indirect pathways from the independent variable (X) to the dependent variable (Y).

statistical result is not evidence for a causal chain in which a predictor variable leads to a mediator variable, which leads to an outcome variable. These two interpretations are sometimes represented as synonymous in psychological science, which risks the reification of interindividual difference variables (i.e., traits or diagnoses) as intraindividual structures and processes (Borsboom & Cramer, 2013; Borsboom, Mellenbergh, & Van Heerden, 2003; Cervone, 2004, 2005; Spencer et al., 2005). This theoretical leap can in turn result in meretricious theories and clinical misapplication.

Thus, the ability for a researcher to easily disambiguate these two explanations is vital. In this article, we address this conflation by offering a consistent way to differentiate two types of results that provide evidence of statistical mediation, drawing on earlier work (Baron & Kenny, 1986) and more recent advances in meditational modeling (Hayes, 2013; MacKinnon et al., 2007; Preacher, 2015; Preacher & Hayes, 2004). We address the importance of a temporal component in understanding mediational analyses and suggest a bifurcation of the discussion of statistically significant mediational results into the terms *temporal* and *atemporal* associations. Last, we provide example analyses from our data to illustrate the potential pitfalls faced if researchers do not make such a distinction. The importance of proper interpretation of mediational analyses has been noted before (e.g., Kazdin, 2007). However, in light of recent advances in and dissemination of powerful statistical methods of mediation analysis (Hayes, 2013, 2014; Hayes & Scharkow, 2013), providing a unique theoretical and statistical analysis that emphasizes the importance of time in interpreting mediation is particularly timely.

Evaluating Mediation Statistically

An assessment of the proper use of mediational hypotheses must include a discussion of the history and current status of evaluating mediation statistically. Mediation implies a relationship between variables that cannot be reversed. X caused M, which caused Y; X happened first, then M, then Y (see Figure 1). Baron and Kenny's (1986) seminal work on exhibiting mediation by means of multiple regression led to the widespread use of mediational analyses in psychology. In this influential paper, the authors attempted to elucidate the difference between mediation and moderation and help future researchers maintain the distinction between the two. They do so by establishing a method to assess whether a third variable, M, mediates the relationship between two other variables, X and Y.

The method is as follows. First establish that X significantly predicts Y (Figure 1; path c), and then establish that X significantly predicts M (path a). If both relationships are significant, then test mediation by performing a multiple regression with X as the initial step and M as the second step. If the relationship between X and Y is no longer significant, then M mediates the relationship between X and Y (path c′). Importantly, the partial regression coefficient for M from this multiple regression should be significant. If these conditions are met, mediation might be inferred. In addition, testing whether X is significant in the multiple regression can help determine whether the mediation is full or partial. The mediation amounts to an indirect effect: X has a direct effect on Y (path c), but X has an indirect effect on Y through M (path c′).

Following Baron and Kenny, methods have been established for testing a categorical dependent variable through the use of logistic regression (MacKinnon & Dwyer, 1993) and within-subject designs (Judd, Kenny, & McClelland, 2001). These methods represent potential advances allowing researchers to assess statistically whether a hypothesized internal variable is in effect explaining the relationship of two associated variables.

Bootstrapping techniques, introduced primarily over the past ten years to psychological research, have subsequently revolutionized mediational analyses by increasing statistical power to find significant relationships (e.g., MacKinnon et al., 2007). Such analyses create a large number of synthetic samples that allow a researcher to estimate, by assessing indirect effects, how likely a proposed relationship is to occur in a larger distribution than collected data can allow for. The most recent release building on the PROCESS work of Preacher and Hayes (e.g., Hayes, 2013, 2014) allows researchers to examine up to *76* different mediation and moderation path models, including multiple mediator models containing up to *10* statistical mediators. Given that this release contains a freely available macro for SPSS or SAS (Hayes, 2014) that works in tandem with those programs' multiple regression syntax, it is likely that this already popular method will become the default analytic technique used as evidence for mediational hypotheses for the next generation of clinical psychological scientists. Indeed, PROCESS has been heralded in a recent edition of a popular graduate statistics textbook as "pretty much the best thing to happen to moderation and mediation analysis in a long time" (Field, 2013, p. 393).

PROCESS holds great promise for consistent, highly powered, and statistically defensible mediational analyses of indirect effects (Hayes & Scharkow, 2013). However, the ready availability of these new techniques may also introduce a spate of mistakenly interpreted causal relationships because of the seductive appeal of more advanced statistical methods to seem more scientifically credible regardless of whether they are theoretically defensible (Borsboom et al., 2003; Lilienfeld & Marino, 1999).

Reconciling Mediation Design and Mediation Analyses in Clinical Psychology

Mediation research is on the rise in clinical psychology. As of August 23, 2015, searching PsycINFO across all fields using the search term "mediat*" yields 110 articles identified in the Journal of Clinical Psychology from 1980 to the present. Over this roughly 35-year period, the majority of the identified articles (n = 50) have appeared since 2011. This rapid increase in mediation research in clinical psychology does not by itself suggest the need for a heuristic reminder or introduction to the assumptions of causal mediation; that depends on the quality of the research being conducted and the knowledge researchers have of the basic assumptions of mediation. Gelfand, Mensinger, and Tenhave (2009), for example, reviewed a random sample of 50 English-language, psychologically relevant mediation studies citing Baron and Kenny (1986) (out of 410 published in the first 9 months of 2002). They found that 54% of the mediation studies used cross-sectional designs, but in only 12 of these was the possibility of alternative temporal orders of variables mentioned.

Recent articles in other subdisciplines have also examined basic temporal assumptions associated with mediation design and analyses, further suggesting the current need for a heuristic paper on mediation in clinical psychology. Roe (2012) discussed the problems of temporal order and temporal illusions in cross-sectional mediation for health psychologists; Lindenberger, von Oertzen, Ghisletta, and Hertzog (2011) reminded developmental psychologists that mediation analysis of cross-sectional data cannot substitute for data collected over time; Spector and Meier (2014) focused on temporal issues in nonexperimental research in industrial-organizational psychology; Spencer et al. (2005) previously outlined the potential misuse and misapplication of mediation analysis in social psychology, suggesting that the use of statistical mediation has become necessary for papers in that subdiscipline to be considered important and capable of evidencing causal relationships; and last, Maxwell and Cole (2007) recently raised concerns regarding how mediation is investigated in cross-sectional designs in general, using hypothetical data to suggest that the manner in which researchers investigate mediational hypotheses can generate biased findings and misleading interpretations.

Thus, considering the wellspring of mediation analytic techniques available, the increasing number of papers featuring mediation in clinical psychology, and the increase in cautionary notes regarding the use of such analyses and need for their reconciliation with mediational hypotheses in other related subdisciplines, a similar discourse aimed at a clinical psychology audience that contains example analyses and heuristic language to allow researchers to avoid misinterpretations is warranted.

Temporal and Atemporal Research and Mediation Analyses

Impressive recent advances in statistical methods, and the intricacy and detail paid to their development, often stand in relative contrast to the consideration given to theory that accompanies mediation analyses. In other words, there has been limited theory or discussion on the role time plays in constituting a theoretical framework within which mediational hypotheses and interpretations make sense. A result of this has been a vocabulary in the psychological literature that lacks the ability to distinguish between *atemporal* (i.e., unrelated to time) and *temporal* research.

Implicitly underlying all mediation methodology is a temporal component (Judd et al., 2001; Kazdin, 2007). Mediational models contain arrows pointing unidirectionally from one variable to the next, with each variable constituting a separate stage of the model—i.e., each coming one *after* another. It is the responsibility of the researcher to apply this methodology to data that, in turn, has some manner of either design-based (multiple samples for each subject) or conceptual longitudinality (Kazdin, 2007). Importantly, if a temporal component is absent from a research design, then despite the ability to statistically show that a certain variable, M, mediates a relationship between two variables, X and Y, there is no theoretical justification for the assumption that these variables happen in a sequence. Judd et al. (2001) noted: “In the absence of clear conditions that establish the causal effect of a treatment variable, ‘mediational’ analyses can ultimately do nothing to help make the causal arguments that are implicit in the terminology used” (p. 131).

To properly conceptualize *temporal* design-based mediation, a theoretical space is constructed in which X operates before M, which then operates before Y, all in a causal progression. Following this conceptualization, statistical analyses are conducted to see if data reveal the hypothesized relationships, thus providing evidence that supports a causal conclusion. An example of temporal mediation can be seen in the work of Cervone (2004), in which a theoretical model (Knowledge and Personality Architecture) posits that, within a single person, underlying mechanisms operate in a causative manner. To test this, longitudinal data are collected and analyses are conducted to demonstrate that these causal mechanisms occur *over time*.

In cross-sectional research, mediation can of course be demonstrated via statistical criteria (Baron & Kenny 1986; Hayes, 2013, 2014; Hayes & Scharkow, 2013; MacKinnon & Dwyer, 1993; MacKinnon et al., 2007); however, unlike analyses accompanying temporal mediational models, atemporal mediational analyses do not provide support for a theory of *why* mediation is occurring causally, because they do not draw from either longitudinal data or previous results that have established a causal relationship among the variables of the model. Importantly, not all cross-sectional designs have entirely ambiguous temporal order. For example, in investigating genetic contributing factors through Mendelian randomization, one can more confidently posit a cross-sectional mediational design with a genetic variant as the predictor that causes an outcome only through a particular environmental exposure (see VanderWeele, 2015, for an extended discussion). However, cross-sectional designs in which variables are associated via ambiguous temporal order are much more common. In such cases, it is quite important that the researcher does not conclude that a causal relationship has been demonstrated, *no matter what statistical analyses reveal*.

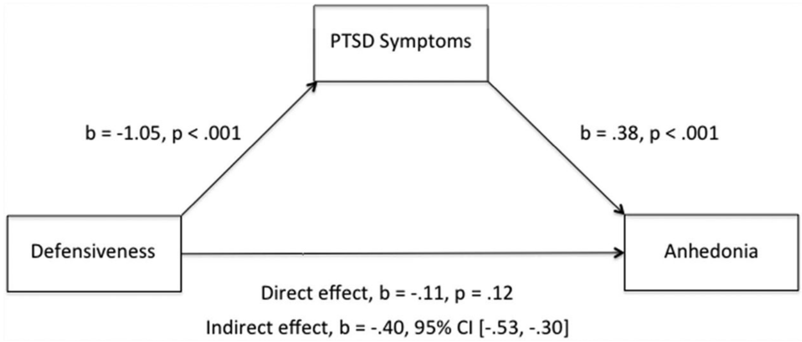

Figure 2. The relationship between defensiveness and anhedonia is mediated by PTSD symptoms.

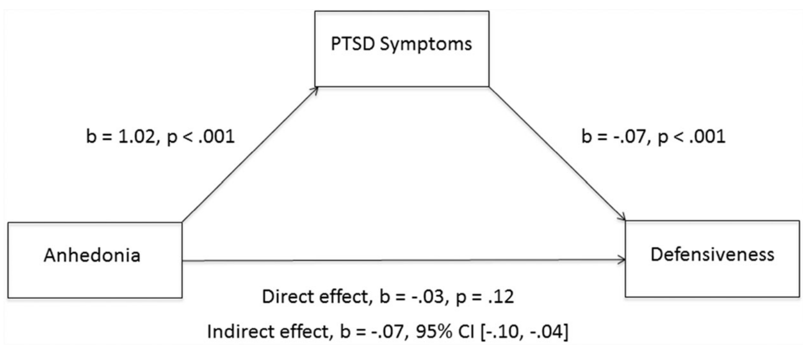

Figure 3. The relationship between anhedonia and defensiveness is mediated by PTSD symptoms.

Example Analyses

We here report example analyses from our own data to illustrate how to best consider atemporal associations resulting from mediational analyses of cross-sectional data. To provide an example of clinical interest, we used the PROCESS macro for SPSS recently introduced by Hayes (2013) that is becoming the standard (Hayes, 2013; Hayes, 2014; Hayes & Scharkow, 2013) and most accessible form of arbitrating mediational effects. In PROCESS, indirect effect analysis and bootstrapping methods allow for more specific analyses of indirect mediational relationships. However, this advance may also run the risk of further reifying mediational relationships as causal.

Using cross-sectional data collected as part of larger studies (Nadorff, Anestis, Nazem, Harris, & Winer, 2014; Winer, Drapeau, Veilleux, & Nadorff, in press), we examined the relationship between defensiveness, as measured by the shortened version of the Marlowe-Crowne Social Desirability Scale (Strahan & Gerbasi, 1972); anhedonia, as measured by the Specific Loss of Interest and Pleasure Scale (Winer, Veilleux, & Ginger, 2014); and symptoms of posttraumatic stress disorder (PTSD), as measured by the Post-Traumatic Checklist (Blanchard, Jones-Alexander, Buckley, & Forneris, 1996). We wished to examine initially if individuals who were less defensive (X) would be more likely to endorse PTSD symptoms (M), and if this would in turn lead to elevated anhedonia (Y), which may result from longstanding, intense anxiety. This mediational model (Figure 2) was indeed significant, which might then lead researchers to describe a causal, temporal relationship between the three variables. We then tested whether the directional relationship we initially demonstrated was meaningful by switching the positions of defensiveness and anhedonia, forming a model (Figure 3) in which anhedonia (X) leads to both symptoms of PTSD (M) and, ultimately, defensiveness (Y). Even with the independent and dependent variables reversed, *the mediation model remained significant*.

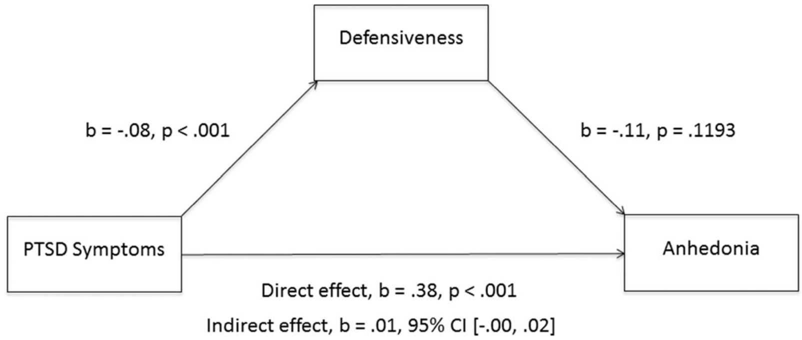

Figure 4. The relationship between PTSD symptoms and anhedonia is not mediated by defensiveness, but the direct effect of PTSD symptoms on anhedonia is significant.

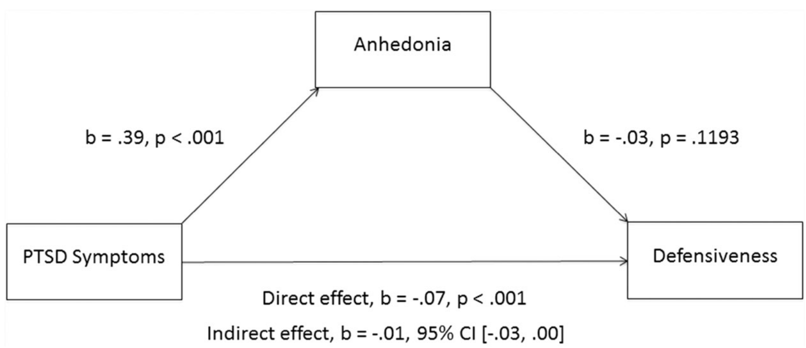

Figure 5. The relationship between PTSD symptoms and defensiveness is not mediated by anhedonia, but the direct effect of PTSD symptoms on defensiveness is significant.
Note. Figures 4 and 5 yield similar statistical results.

In the previous examples, PTSD was treated as a potential mediator between the other two variables. Many other statistical mediation models could be examined with these data. For example, PTSD could be conceptualized as an independent variable that was presumed to affect anhedonia (the DV), both directly and through defensiveness (the mediator). For this model (Figure 4), the pathway from PTSD symptoms to defensiveness remained significant, but the path from defensiveness to anhedonia was not. Furthermore, the model's direct effect was significant, indicating a significant relationship between PTSD symptoms and anhedonia, whereas the indirect effect was not (PTSD symptoms → defensiveness → anhedonia).

Additionally, we tested a model (Figure 5) where the mediator and independent variable were reversed, such that PTSD symptoms (X) led to anhedonia (M), which led to defensiveness (Y). This model displayed the same pattern as the last: the path from X to M was significant, but the path from M to Y was not, and the direct effect was significant, but the indirect effect was not. Thus, models 4 and 5 yield similar statistical results (as did models 2 and 3), and without temporal ordering of the variables, there is little justification for favoring one model over the other.

Models 2 and 3 demonstrate statistical mediation, but it is unlikely that both can occur in sequence, over time. When mediation occurs in a bidirectional fashion, how are we to know which direction is temporally "correct"? The answer, made obvious by the second analysis (Figure 3), is that without longitudinal data, neither of these analyses tells us anything about time. In fact, framed in the absurd context of this reciprocal analysis, it becomes clear that interpretations regarding the first analysis may actually be more dangerous, because the initial plausibility of a temporal relationship makes the relationship meretricious. Despite not indicating mediation, models 4 and 5 point to a similar issue: Although these models yield similar statistical results, drawing from cross-sectional data does not allow one model to be privileged over the other.

Atemporal Associations

Despite the potential issues raised when comparing the four analyses above, it is of critical importance to re-emphasize that statistical mediation *was unequivocally demonstrated* in Figures 2 and 3. A predictor variable was shown to statistically predict an outcome variable, and then in a subsequent model, this relationship was attenuated due to the inclusion of a significant mediator variable. Often a developmental or temporal relationship is proposed in an attempt to make sense of such findings, which constitutes misunderstanding.

A reworked explanation for our first set of analyses could be as follows: "PTSD is uniquely and *atemporally associated* with anhedonia; PTSD is related to anhedonia while defensiveness is not, when accounting for the shared relationship among all three variables." This explanation provides value for future research, but also avoids potential misinterpretation of atemporal associations as temporal in nature.

Toward Temporal Design

Conceptualizing statistically significant mediational findings resulting from cross-sectional designs as atemporal associations provides a built-in check to ensure that mere statistical mediation is not interpreted as a process developing over time. Importantly, longitudinal designs do not solve the inferential problems of causality, however. Indeed, unambiguous temporal sequences that produce correlations between variables do not provide definitive evidence of causality (e.g., Cole & Maxwell, 2003; Maxwell & Cole, 2007; Mitchell & Maxwell, 2013; Preacher, 2015). For example, two-time-point designs in which a predictor variable is measured or manipulated at wave 1, the outcome variable is measured at wave 2, but the mediator variable is measured at either wave 1 or wave 2, do not allow temporal ordering of a mediational model to be inferred. However, this additional vocabulary and subsequent signal to researchers of the limitations of conclusions drawn from statistical analyses conducted on cross-sectional data may prove crucially important in clinical psychological research, when interpretations of causality among symptoms can result in translation to applied clinical settings.

Conclusion

In an attempt to clarify the lexicon, we have emphasized the use of the terms *atemporal* and *temporal* associations to clarify whether a research design allows for the statistical assessment of mediational hypotheses. With the release (Hayes, 2013, 2014) and dissemination (Hayes & Scharkow, 2013) of new instruments that will advance our ability to investigate mediation, this distinction may be particularly timely so as to help avoid misinterpretations of causality. We believe that this additional vocabulary will help researchers clarify whether temporal or developmental interpretations are being made with cross-sectional data. It should be noted that such interpretations are common in the discipline of psychology, and we thus included work *from our laboratories* as an exemplification.

Statistical evidence of mediation does not imply causation. Unlike correlation, however, mediational analyses are graphically represented as a temporal, causal model, and thus allow for more seductive but ultimately false conclusions to be drawn. Hopefully, distinguishing between temporal and atemporal associations precludes researchers from operating within atemporal conceptual frameworks but nevertheless forming temporal conclusions. This would result in not only a usage of mediation much closer in line with the connotations of a middling term but also improved congruence between temporal hypotheses and statistical results.

References

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51, 1173–1182.

Blanchard, E. B., Jones-Alexander, J., Buckley, T. C., & Forneris, C. A. (1996). Psychometric properties of the PTSD checklist (PCL). Behaviour Research and Therapy, 34, 669–673.

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. Annual Review of Clinical Psychology, 9, 91–121. doi:10.1146/annurev-clinpsy-050212-185608

Borsboom, D., Mellenbergh, G. J., & Van Heerden, J. (2003). The theoretical status of latent variables. Psychological Review, 110, 203.

Cervone, D. (2004). The architecture of personality. Psychological Review, 111, 183–204.

Cervone, D. (2005). Personality architecture: Within-person structures and processes. Annual Review of Psychology, 56, 423–452.

Cole, D. A., & Maxwell, S. E. (2003). Testing mediational models with longitudinal data: Questions and tips in the use of structural equation modeling. Journal of Abnormal Psychology, 112, 558–577. doi:10.1037/0021-843X.112.4.558

Field, A. (2013). Discovering statistics using IBM SPSS statistics. Thousand Oaks, CA: Sage.

Frewen, P. A., Schmittmann, V. D., Bringmann, L. F., & Borsboom, D. (2013). Perceived causal relations between anxiety, posttraumatic stress and depression: Extension to moderation, mediation, and network analysis. European Journal of Psychotraumatology, 4. doi:10.3402/ejpt.v4i0.20656

Gawronski, B., & Bodenhausen, G. V. (2014). Theory and explanation in social psychology. New York: Guilford Press.

Gelfand, L. A., Mensinger, J. L., & Tenhave, T. (2009). Mediation analysis: A retrospective snapshot of practice and more recent directions. The Journal of General Psychology, 136, 153–178.

Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York: Guilford Press.

Hayes, A. F. (2014). Process for SPSS and SAS [macro]. Retrieved from: http://www.Afhayes.com/introduction-to-mediation-moderation-and-conditional-process-analysis.Html. 2014, from http://www.afhayes.com/introduction-to-mediation-moderation-and-conditional-process-analysis.html

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? Psychological Science, 24, 1918–1927. doi:10.1177/0956797613480187

Judd, C. M., Kenny, D. A., & McClelland, G. H. (2001). Estimating and testing mediation and moderation in within-subject designs. Psychological Methods, 6, 115–134.

Kazdin, A. E. (2007). Mediators and mechanisms of change in psychotherapy research. Annual Review of Clinical Psychology, 3, 1–27. doi:10.1146/annurev.clinpsy.3.022806.091432

Lilienfeld, S. O., & Marino, L. (1999). Essentialism revisited: Evolutionary theory and the concept of mental disorder. Journal of Abnormal Psychology, 108, 400–411.

Lindenberger, U., von Oertzen, T., Ghisletta, P., & Hertzog, C. (2011). Cross-sectional age variance extraction: What's change got to do with it? Psychology and Aging, 26, 34–47.

MacKinnon, D. P., & Dwyer, J. H. (1993). Estimating mediated effects in prevention studies. Evaluation Review, 17, 144–158.

MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. Annual Review of Psychology, 58, 593–614. doi:10.1146/annurev.psych.58.110405.085542

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. Psychological Methods, 12, 23–44. doi:10.1037/1082-989x.12.1.23

Mitchell, M. A., & Maxwell, S. E. (2013). A comparison of the cross-sectional and sequential designs when assessing longitudinal mediation. Multivariate Behavioral Research, 48, 301–339.

Nadorff, M. R., Anestis, M. D., Nazem, S., Harris, H. C., & Winer, E. S. (2014). Sleep disorders and the interpersonal-psychological theory of suicide: Independent pathways to suicidality? Journal of Affective Disorders, 152–154, 505–512. doi:10.1016/j.jad.2013.10.011

Preacher, K. J. (2015). Advances in mediation analysis: A survey and synthesis of new developments. Annual Review of Psychology, 66, 825–852.

Preacher, K. J., & Hayes, A. F. (2004). Spss and sas procedures for estimating indirect effects in simple mediation models. Behavior Research Methods, Instruments, & Computers, 36, 717–731.

Roe, R. (2012). What is wrong with mediators and moderators? European Health Psychologist, 14, 4–10.

Spector, P. E., & Meier, L. L. (2014). Methodologies for the study of organizational behavior processes: How to find your keys in the dark. Journal of Organizational Behavior, 35, 1109–1119.

Spencer, S. J., Zanna, M. P., & Fong, G. T. (2005). Establishing a causal chain: Why experiments are often more effective than mediational analyses in examining psychological processes. Journal of Personality and Social Psychology, 89, 845–851. doi:10.1037/0022-3514.89.6.845

Strahan, R., & Gerbasi, K. C. (1972). Short, homogeneous versions of the marlowe-crowne social desirability scale. Journal of Clinical Psychology, 28, 191–193.

VanderWeele, T. (2015). Explanation in causal inference: Methods for mediation and interaction. New York: Oxford University Press.

Winer, E. S., Drapeau, C. W., Veilleux, J. C., & Nadorff, M. R. (in press). Anhedonia, suicidal ideation, and suicide attempts in a large student sample. Archives of Suicide Research.

Winer, E. S., Veilleux, J. C., & Ginger, E. J. (2014). Development and validation of the specific loss of interest and pleasure scale (SLIPS). Journal of Affective Disorders, 152–154, 193–201. doi: 10.1016/j.jad.2013.09.010

Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206.