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Theoretical and Quantitative Disconnect When Modeling Adverse Childhood Experiences Using a Common Factor Framework: An Argument for Causal Indicator Models in Stressor Research

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ABSTRACT

Adverse childhood experiences (ACEs) are highly impactful stressors that increase individuals' risk for a plethora of negative developmental and health outcomes. Furthermore, minoritized groups and under-resourced individuals are at higher risk for ACEs, positioning these stressors as possible mechanisms driving health disparities. Given this fact, a strong methodological foundation is necessary to ensure maximal clinical value. As emphasized by Jensen et al. (https://doi.org/10.1111/cdev.14050), this foundation must begin with rigorous ACEs measurement—a goal that requires careful matching between ACEs measures and the scoring procedures used. To amplify their message while advocating for an alternative approach that may better reflect the conceptualization of ACEs, we write this commentary to highlight the merits of causal indicator models as a better match between theory and methodology.

Adverse childhood experiences (ACEs) are a group of stressors occurring before age 18 that are known to strongly impact human health and development (Bhushan et al. 2020). Although ACEs do not represent all stressors that impact health and well-being, a large body of research supports ACEs as developmentally critical forms of adversity that increase a person's risk for a plethora of somatic (Holman et al. 2016; Luiz et al. 2018; Pape et al. 2021; Rubinstein et al. 2020) and mental health problems (Albott et al. 2018; Carbone 2021; Hoppen and Chalder 2018) across the lifespan. Consequently, a solid methodological foundation is needed to ensure that ACEs research effectively informs intervention efforts at the individual and policy level (McBain et al. 2023). As adeptly noted by Jensen et al. (2024), few methodological characteristics are more foundational than the conceptualization, measurement, and modeling of ACEs in health research. These authors also noted, in a manner so apt it must be quoted verbatim: "in some ways, the translation of ACEs research to practice has outpaced psychometric work to develop and confirm robust measurement approaches" (Jensen et al. 2024, e171). We completely agree.

In their article, Jensen et al. (2024) clearly demonstrated the utility of measurement modeling approaches to incorporate critical nuances necessary to ensure the rigor and equity of ACEs research. We appreciate these points and are writing here with the mindset of "yes, and" to simultaneously amplify this message and also introduce a modeling perspective that better aligns with how ACEs are conceptualized in order to support the identification of more precise strategies for treating ACE-associated health conditions. Given the wide breadth of developmental processes influenced by major life stressors in general and ACEs in particular (Gilgoff et al. 2024; Slavich 2016), we hope this article will be a useful reference for researchers and health care providers who are interested in improving the conceptualization, measurement, and impact of ACE screening and response activities to maximize clinical benefit.

Before getting into our primary argument, we want to acknowledge that ACE conceptualization, screening, response, and prevention is a multi-faceted topic that, to discuss comprehensively, requires a longer article than this commentary. As two clinical psychologists with expertise in stress assessment and measurement modeling techniques, though, we focus here on these aspects, as opposed to other topics that also arise from reading Jensen et al. (2024).

1 | Latent Variable Modeling of ACEs

In their study, Jensen et al. (2024) used latent variable modeling following a common factor framework—arguably the most popular measurement modeling approach for aggregates outside of sum/average scores—and well articulated the different components of latent variable models. In doing so, they illustrated how measurement invariance testing within a common factor framework can provide information necessary to determine if their ACEs questionnaire assessed ACEs equally across different groups of people—in their case, different racial/ethnic groups. This research highlights the potential use of measurement modeling to help ensure that developmental ACEs research is conducted with health equity in mind. To those who are unfamiliar with these approaches and have not yet read Jensen et al. (2024), we encourage you to read the article, as we want to avoid being repetitive and/or reducing the impact of their contribution.

The "and" part of our "yes, and" is that although we agree wholeheartedly with this mission, we encourage researchers aiming to achieve this goal to apply measurement modeling techniques that better complement current conceptualizations of stressor exposure and the goals of stressor exposure inventories, such as the ACEs questionnaire (Felitti et al. 1998). We are specifically referring to the goal of assessing discrete acute or chronic experiences that will be perceived as highly undesirable and potentially result in unmet needs (e.g., neglect) or additional obstacles to healthy development (e.g., lack of two parents to provide learning opportunities and support). Such experiences henceforth will be referred to as "stressors" or "ACEs" in contrast to "stress", which is the subjective, experiential response to stressors/ACEs.

A critical conceptual feature of common factor models is the assumption that the latent variable, estimated using the shared variance among a set of indicators (e.g., ACEs items), is what *causes* the responses. For this reason, common factor models are sometimes referred to as "reflective" models because the observable indicators *reflect* the latent variable by which they are caused. Said another way, "latent adversity" estimated using ACEs as the indicators in a common factor model assumes that adversity *causes the ACEs* that individuals endorse. Consequently, common factor models feature a local independence assumption in that any correlation between the indicators is assumed to be due to the causal influence of the underlying latent factor.

In contrast, we expect most stress researchers would conceptualize ACEs as discrete adverse experiences, or collections of such experiences, that either do or do not happen as a function of life circumstance, rather than as events caused by a latent trait of "adversity" that is inherent to an individual (a criticism that has already been raised in the developmental psychology literature; e.g., see McLaughlin et al. 2023). To make this point more concrete using an example definition from Jensen et al. (2024), thresholds for indicators (i.e., individual ACEs items) in common factor latent variable models indicate what level of latent adversity is needed before it becomes likely that a specific ACE is endorsed, indicating that the occurrence of individual ACEs is partially conditional on total adversity experienced. Although there are certainly contextual factors that might predispose individuals to experience multiple ACEs, we would argue this is not the same thing as "latent" adversity itself. As opposed to a trait inherent to an individual, we believe it more plausible that ACEs are organic events stemming from a child's environment that contribute to their experience of adversity, as opposed to events caused by their person-specific "adversity" propensity.

As illustrated by Rhemtulla et al. (2020), these conceptual distinctions are not simply putting different colors of paint on the same machine. Using a combination of hypothetical examples and re-analysis of published data, Rhemtulla et al. (2020) convincingly demonstrated the issues that can result from fitting common factor models to noncomplimentary data. Specifically, they simulated data generated from a formative "multiple-indicators multiple-cause" (MIMIC) model and then fitted a common factor model to these data. This mismatch resulted in meaningful and unpredictable bias that directly undermined the validity of the results. Consequently, these distinctions should not be disregarded as philosophical differences with little tangible relevance. Rather, they can result in very real negative consequences for the clinical utility of ACEs research that in turn informs screening protocols, case conceptualizations, and treatment planning.

This is not to say that we believe ACEs aggregation through measurement models is inappropriate. To the contrary, we would like to use this space to advocate for what we believe to be a more appropriate framework—namely, causal indicator models (see Diamantopoulos et al. 2008). Causal indicator models flip the direction of the causal arrows between indicators and latent variables in the common factor framework (Figure 1)—indicators such as endorsed ACEs are what cause the broader construct of interest (i.e., experienced adversity). In contrast to how common factor latent variables are "reflective", causal indicator models are often referred to as "formative" because the observable indicators *form the latent variable*. Conceptually, causal indicator models are similar to the common composites in which ACEs are totaled; however, standard composites assume that the indicators that are modeled fully define the aggregate of interest.

Conversely, both common factor models and causal indicator models (but not composite models) incorporate latent variables and the concept of measurement error. A key statistical distinction between latent variables in a common factor framework versus a causal indicator framework concerns where the measurement error exists. Specifically, in a common factor framework, the latent variable has no measurement error—rather, the error terms are associated with the indicators used to estimate the latent construct. Conversely, in a causal indicator model, the error term is on the latent variable, representing all the causes of the latent variable not included as indicators in the model. For example, this error term could represent unmeasured experiences of adversity that are pertinent to health outcomes [e.g., the traditional ACEs questionnaire (Felitti et al. 1998) does not ask about experiences of peer victimization that are associated with negative outcomes such as depression and anxiety; Forbes et al. 2019], or environmental context that might amplify or buffer the impact particular experiences have on latent adversity, or individual differences in cognitive response styles that might modulate how adverse experiences are internalized. In fact, the potential for adversities to be correlated due to external factors such as the environment, rather than to "latent adversity," violates the abovementioned assumption of local independence inherent to common factor models. These key differences between different aggregation options are summarized in Table 1.

Importantly, the concept and evaluation of measurement invariance take a different form for causal indicator models and—truth be told—there has been much less work undertaken to develop tools for this line of inquiry compared to common factor models (more on this issue below, after addressing the target article's focus on measurement invariance). However, Diamantopoulos and Papadopoulos (2010) proposed three types of measurement invariance for causal indicator models measures, which we will list in ascending order of strictness. First, *structure invariance* describes equality of the pattern of "salient" (i.e., nonzero) indicator weights that define the structure of the model across groups or time points. Second, *slope invariance* describes the extent that each indicator's contribution to the latent construct is equal across groups or time points. Third, *residual variance* describes the equality of variance of the latent error term (sometimes referred to as a "disturbance term") across groups. Sample interpretations for when these levels of invariance are not supported (i.e., noninvariance is observed) are provided in Table 2 using Jensen et al. (2024) research question of measurement invariance of adversity and ACEs as a function of race/ethnic groups as a use case.

2 | Practical Issues

Before concluding, it is important to acknowledge that, relative to common factor models, there is a meaningful dearth in

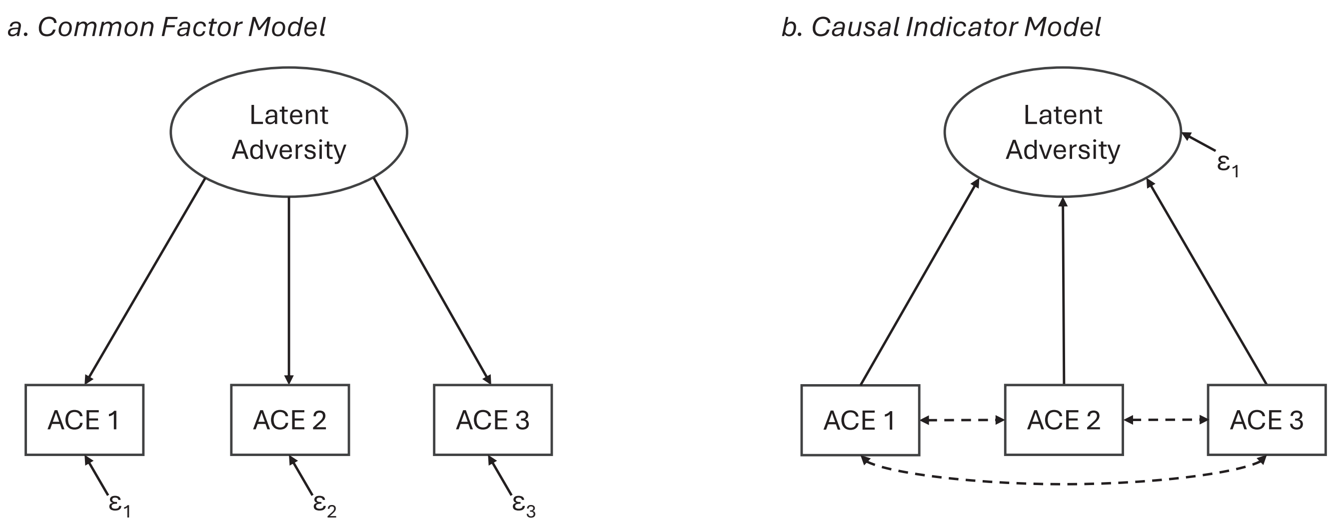

FIGURE 1 | Visual Comparison of Common Factor and Causal Indicator Models. Ovals illustrate latent variables (i.e., adversity), rectangles illustrate observed variables (i.e., ACE items), and ε indicates error terms. Dotted lines in 1b indicate correlations between the indicators for the causal indicator model [as opposed to the common factor model which has a local independence assumption for indicators consistent with the assumption that any correlation between the indicators is due to the causal influence of the latent factor (Hanafiah 2020)].

TABLE 1 | Main differences between common factor, composite, and causal indicator models.

Main difference	Common factor model	Composite model	Causal indicator model
Reflective vs. formative	Reflective	Formative	Formative
Latent variable?	Yes	No	Yes
Error term on indicators?	Yes	No	No
Error term on latent variable?	No	No	Yes
Local independence assumption?	Yes	No	No

TABLE 2 | Sample interpretations of causal indicator model measurement noninvariance.

Type of noninvariance	Nonequality of...	Interpretive example
Structure noninvariance	Nonzero indicator weights	All 9 measured ACEs contributed to adversity for Race A; however, only 7 of the 9 measured ACEs contributed to adversity for Race B
Slope noninvariance	Indicator contribution to latent construct	Divorce contributed more to adversity for Race A than Race B
Residual noninvariance	Variance of the latent error term	There was more error in the estimation of the latent variable for Race A than Race B

tools and resources to estimate causal indicator models. This problem is likely partially attributable to the lack of interest or awareness in formative measurement modeling by applied researchers that results in less incentive among methodologists, operating in a positive feedback loop. We hope to improve this disconnect with this article. Here, we will briefly touch on some of the key nuances and obstacles of fitting causal indicator models.

Critically, this type of formative measurement model is statistically under-identified in isolation (Bollen and Lennox 1991), requiring that additional information be modeled. One solution is to include two conceptually appropriate, conditionally independent variables as reflective indicators (i.e., akin to a standard common factor model) of the latent variable that is otherwise being modeled as formative (Diamantopoulos and Papadopoulos 2010; Jarvis et al. 2003), resulting in what is termed a "multiple-indicators multiple-cause" (MIMIC) model. Consistent with the causal assumptions of reflective models described above, these indicators should be theoretically caused by adversity. Although this solves the statistical issue, there has been significant criticism regarding the conceptual limitations of relying on formative models in which key estimates (e.g., the association between ACEs and latent adversity) are estimated relative to other variables (see Bollen and Diamantopoulos 2017; Rhemtulla et al. 2015).

Given the lack of options that are accessible to many applied researchers, we want to advocate for these obstacles to be approached as an opportunity for collaboration between quantitative methodologists and applied researchers, both to build a more rigorous science as well as to build out tools for formative modeling well-suited to applied research questions. Clearly, there is important conceptual and methodological work to do to advance the practical utility of these models. Thankfully, there is ongoing work to develop tools to facilitate more widespread use of formative models. For example, see Schuberth (2023) for a recent tutorial on how to incorporate composites into structural equation models. Although this tutorial is not about causal indicator models themselves, this is still an excellent resource to implement formative models that lack some of the conceptual—statistical disconnect found in common factor models of stressors that we discuss above.

3 | Conclusion

In conclusion, we agree with Jensen et al.'s (2024) argument that in order to ensure that research on ACEs benefits all people, we need to improve the psychometric rigor of ACEs research. To complement their discussion of common factor models, we introduce the option of causal indicator models which, by focusing less on the commonalities between ACEs, is much better suited to developing precision stress profiles in ways that might increase the translational value of this work for patients and their health care providers. By describing causal indicator models as an alternative modeling framework that may more closely correspond to the conceptualization and measurement theory of stressor measures, we hope to both amplify their basic message and add additional considerations for those aiming to promote health equity through high-quality ACE screening, response, and prevention.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

There are no data associated with this article.

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