Practical Assessment, Research, and Evaluation

Volume 27 Article 16

2022

Reimagining MTMM Designs for Examining Intersectionality in Latent Variables

Timothy R. Konold
University of Virginia

Elizabeth Sanders
University of Washington

Recommended Citation

Konold, Timothy R. and Sanders, Elizabeth (2022) "Reimagining MTMM Designs for Examining Intersectionality in Latent Variables," *Practical Assessment, Research, and Evaluation*: Vol. 27, Article 16.
DOI: https://doi.org/10.7275/3sh1-wb29
Available at: https://scholarworks.umass.edu/pare/vol27/iss1/16

Practical Assessment, Research & Evaluation

A peer-reviewed electronic journal.

Volume 27 Number 16, August 2022 ISSN 1531-7714

Reimagining MTMM Designs for Examining Intersectionality in Latent Variables

Timothy R. Konold, *University of Virginia*
Elizabeth A. Sanders, *University of Washington*

The present study represents a novel method not yet used in the quantitative intersectionality literature – the CT-C(M-1) model (Eid et al., 2003) – for measuring and understanding the similarities and uniquenesses among intersectional subgroups. Intersectionality is a conceptual framework from which to investigate and remedy the ways in which oppression manifests at the intersections of socio-politico-geo-temporal power structure contexts and individuals' interwoven experiences of racism, sexism, and other forms of marginalization (Cho et al., 2013). Specifically, we describe and illustrate the usefulness of the CT-C(M-1) model in intersectionality research through estimation of the latent variable structure of two school climate variables (engagement and support) using data from N = 165 schools in which Black non-Hispanic students' experience is centered as the reference category, and which other race-ethnicity subgroups are compared. Consistent with prior research, our substantive findings indicated that, while a large share of commonality among subgroups was observed, Black Hispanic students experienced school climate differently from the other groups. This analytic tool adds to the growing set of quantitative methods that can aid in advancing the second goal of intersectionality research – intervening in the status quo for true transformational change.

Keywords: Multimethod-Multitrait, CT-C(M-1), intersectionality, quantitative methods

Introduction

Rooted in Black feminist scholarship that exposed how race and gender operated multiplicatively as joint sources of discrimination (e.g., Dill, 1983; Collective, 1977; hooks, 1984), intersectionality was first posited by critical race theorist Kimberlé Crenshaw (1989, 1991) as a conceptual framework or lens from which to investigate and remedy the ways in which oppression manifests at the intersections of socio-politico-geo-temporal power structure contexts and individuals' interwoven experiences of racism, sexism, and other forms of marginalization (e.g., Bowleg, 2012; Cho et al., 2013; Collins & Bilge, 2020). For example, Black and White students might experience the climates of their school differently, and male and female students might also experience their school climate differently, but the joint effect of both race and gender may be more than the sum of the parts – the experience of being Black and female may be vastly different than the experience of being White and female.

Importantly, intersectionality scholars emphasize that the framework is not merely for examining differences among social identities, but rather, it is a lens with which to examine and intervene on social inequalities. As one perspective, Gillborn (2015) asserted that there are really two key components that should be part of all intersectionality research: 1) an empirical basis for understanding the nature and maintenance of social inequities, and 2) having the aim of fostering coalitions among subgroups to resist and change the status quo. Moreover, he argues that intersectionality research should not succumb to evaluating deficit-oriented questions that reify existing stereotypes and power structures, nor should it focus on never-ending subdivisions of social identities. Nevertheless, advocates also acknowledge that the two central goals of intersectionality research (uncovering and intervening on social inequities) may not be possible in all studies; as such, it is recommended that researchers be explicit about what how their work does or does not accomplish these aims (Agénor, 2020).

Quantitative Approaches to Intersectionality Research

Although intersectionality as a framework does not specify a particular method of scholarly inquiry, it can be argued that it is more suited to qualitative investigations, such as ethnographies and case studies, than other modes given the nuances and complexities that are involved (Syed, 2010). Despite this observation, quantitative approaches to intersectionality research have been on the rise over the past decade across the social and health sciences (Bauer et al., 2021a). One of the primary tools for testing for social inequities quantitatively has included modeling the effects of two or more (intersecting) subgroups on a given outcome, or testing whether subgroups have different predictor-outcome relations using interaction tests.

The general linear model (GLM), which is often the go-to machinery for modeling relationships among variables, includes an outcome of interest (Y) that is regressed on a set of substantive continuous predictors (X_p), wherein the relationships (b_p) between each pth predictor and outcome can be considered a partial association with respect to other predictors in the model, as follows:

$$
\begin{aligned}
Y &= b_0 + X_1 b_1 + X_2 b_2 + \cdots + X_p b_p \\
&= b_0 + \Sigma X_p b_p. \qquad (1)
\end{aligned}
$$

where bp is interpreted as the expected change in Y for a 1-unit increase in X_p, controlling for (or holding constant) all other predictors in the model. For example, controlling for student perceptions of teacher support (X_1), are the academic expectations teachers have for students (X_2) related to student engagement (Y)? In this form, no accommodations are made for the possibility that relationships might be different for subgroups in the sample. However, the model can be easily extended to accommodate evaluation of potential categorical group differences on the outcome through inclusion of K–1 dummy (D_k) variables that capture the intersecting subgroups of interest, with one group serving as the reference group[1] such that it is not directly tested for its comparative effect in the model), as follows:

$$Y = b_0 + \Sigma X_p b_p + \Sigma D_k b_k \qquad (2)$$

Here, potential subgroup differences on Y can be evaluated relative to the reference group. This model could test, for example, the research question: controlling for perceptions of teacher support (X_1) and their academic expectations for students (X_2), do Black Hispanic males (D_1) report more or less engagement (Y) than the reference subgroup of Black non-Hispanic males[2]?

More interestingly, equation 2 can be expanded to include X_p * Dk product (interaction) terms that provide for assessments of whether the relationship between a substantive regressor (X_p) and the outcome (Y) is different for a given group K than it is for the reference group[3], such as in equation 3 below.

---

[1] Effect coding can also be used in which the reference category is coded -1 for each of the D_k indicators, instead of 0. With dummy coding the intercept is the reference group mean and all other groups are compared to that reference category; with effect coding, the intercept is the sample average, and all other groups are compared to the average.

[2] We purposefully center our focus here and in the foregoing on persons who self-identify as Black, in keeping with hooks (1984) message of bringing the "margin" to the "center"; in other words, prioritizing our focus on historically minoritized and discriminated subgroups, especially Black persons in the U.S.

[3] This is true for dummy-coded groups; if effect coding is used, then the interaction tests evaluate whether the relationships differ among groups from the average relationship.

DOI: https://doi.org/10.7275/3sh1-wb29

$$Y = b_0 + \Sigma X_p b_p + \Sigma D_k b_k + \Sigma X_p D_k b_{pk}. \quad (3)$$

This model could, for example, test the research question: controlling for perceptions of teacher support (X1), is the relationship between academic expectations (X2) and engagement (Y) different for Black Hispanic males than for the reference group of Black non-Hispanic males? Importantly, in contrast to equations 1 and 2 that assume relationships among predictors and outcomes are the same for the entire sample, equation 3 explicitly allows for a formal evaluation of whether the X-Y relationships are different for subgroups.

While the foregoing was focused on a linear model framework (for metrical outcomes), it can also be extended to generalized linear models, with some added steps for appropriately evaluating interaction effects against a null of zero (e.g., logistic regression; Bauer, 2014; Bauer et al., 2021a). In addition to subgroup mean differences and interaction tests just described, quantitative intersectionality researchers have more recently recommended the use of multilevel models to evaluate contextualized intersectionality for understanding how institutional/structural characteristics interact with individual-level demographics (Agénor, 2020; Bauer et al., 2021a; Jang, 2018); as well as the use of classification algorithms and latent class analyses as ways for empirically deriving subgroups that share commonalities (Bauer et al., 2021b).

Multitrait-Multimethod (MTMM) Design

The primary focus of the present paper is on extending and demonstrating the usefulness of the correlated trait-correlated method minus one (CT-C(M-1); Eid, 2000) method as a tool for intersectionality-based research that focuses on both the measurement of unobservable (latent) constructs, as well as similarities and differences among different groups' perceptions of a target trait. This methodological tool was originally developed to accommodate the challenges inherent in understanding the influence of different methods (i.e., method effects) that might be used to measure traits that are latent in nature.

Interest in the influence of method effects on the measurement of traits was motivated in large part by the early work of Campbell and Fiske (1959) where the ideas of convergent and discriminant validity were introduced in the context of measuring traits across a variety of methods (e.g., self-reports vs. peer-reports, and verbal items vs. non-verbal items). Here, method effects refer to systematic sources of variance that are attributable to the manner in which data on a given construct are obtained, variances that are a function of the methods and tools used to obtain data on a given construct that would carry forward across the measurement of other constructs.

Evaluations of method effect influences continue to rely on multitrait–multimethod (MTMM) data collection designs in which multiple traits (MT; e.g., student engagement and motivation) are evaluated through the use of multiple methods (MM; e.g., student and teacher reports). At the same time, analysis of the resulting data has moved beyond observation of zero-order correlation matrices (Campbell & Fiske, 1959) and observed variable differences that assume method effects are equally strong across the different methods, and that confound trait and method sources of variance (De Haan et al., 2018; Liard & De Los Reyes, 2013). For example, Widaman (1985) developed a latent variable taxonomy of four potential trait factor specifications and a set of four possible method specifications, that when crossed resulted in a total of 16 model configurations. These models allowed for additive tests of successive complexity for evaluating the presence of method variance in the measurement of trait factors. In addition, Marsh (1989) described 20 variations that could be used to investigate data arising from MTMM designs.

Latent variable approaches to modeling MTMM data have been particularly useful for isolating common sources of trait variance across different methods, while also providing estimates of observed score variance that can be attributed to the use of these methods. When methods have been conceptualized as arising from evaluations obtained from different informants (e.g., students and teachers, child and parent, and mother and father), focus has been on understanding the extent to which observed variable ratings are influenced by the traits they are intended to measure vs. method effects that can be attributed to the use of different raters. Informant influences on observed ratings have been found across measurements of a variety of individual level traits including affective experiences (Bleidorn & Peters, 2011), child (Konold & Pianta, 2007) and adolescent (Konold & Glutting, 2008) behaviors, depression and anxiety (Eid et al., 2008), social-skills (Konold & Shukla, 2017), and life quality (Rajmil, Lopez, et al., 2013). Likewise, they have also been found to be prevalent in assessments of organizational structures and characteristics like neighborhood safety (Luo et al., 2014) and school climates (Konold & Cornell, 2015; Konold & Sanders, 2021). However, the reach of MTMM analyses has yet to be realized in examinations of intersectionality research.

The CT-C(M-1) Approach to MTMM

Arguably one of the more popular approaches for analyzing MTMM data within a latent variable framework has been the correlated trait-correlated method model (CT-CM: Jöreskog, 1971; Kenny, 1979). The CT-CM model specifies a set of correlated trait factors, a set of correlated method factors, and allows for the estimation of other sources of residual variance in the observed indicators. There are as many trait and method factors as are included in the MTMM design, and trait and method factor correlations are fixed to zero. Despite the intuitive appeal of this approach, estimation of these models often results in under-identified and/or Heywood cases (Kenny & Kashy, 1992; Marsh & Grayson, 1995). As a result, Eid (2000) introduced a variation of the CT-CM model that requires fewer assumptions and specifies one fewer method factor than the number of methods in the MTMM design, the correlated trait-correlated method minus one (CT-C(M-1)) approach. Figure 1 illustrates a model with six trait-specific method factors and two trait factors. Here, one method in the MTMM design serves as the reference group (right side of Figure 1) to which the remaining methods are compared (left side of Figure 1). Observed variables from the reference method serve as indicators of trait factors (first three indicators for ach trait), and the resulting reference trait factor is regressed on observed variables of the same trait obtained by different methods. This is illustrated on the right side of Figure 1 where reference group (RG) trait factor 1 is regressed on the non-reference group (NRG) trait factor 1 indicators, and the RG trait factor 2 is regressed on the NRG trait factor 2 indicators. In addition, method factors for the non-reference groups are specified for each trait in the MTMM design (left side of Figure 1). These represent trait-specific method factors. Consequently, the resulting M-1 method factors are residual factors with respect to the reference method factor, and reflect the extent to which their indicators are not explained by the reference method factor.

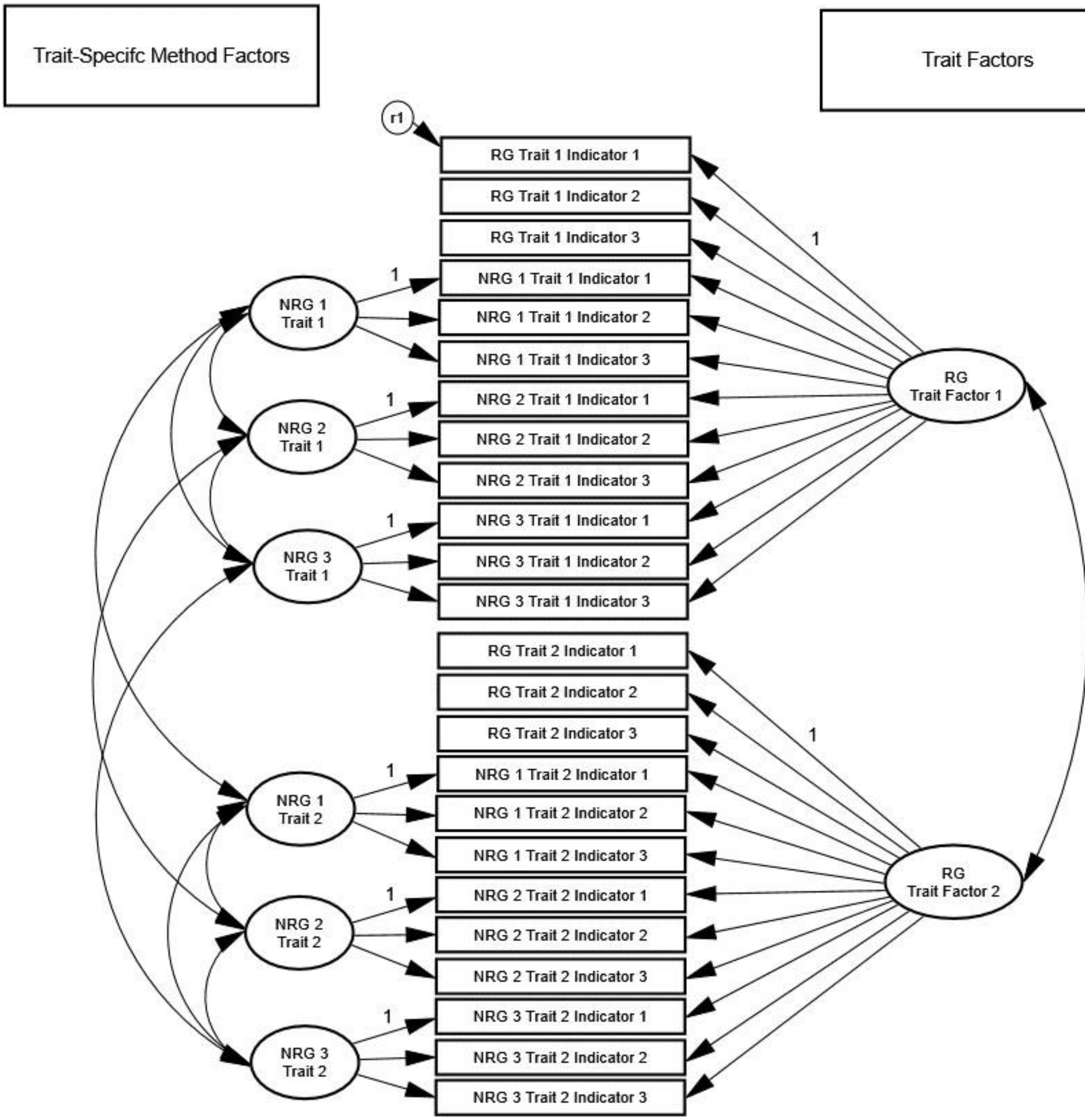
In the CT-C(M-1) model, the trait factors are free to be correlated with other traits, and method factor correlations are freely estimated. However, same trait and same method factor correlations are fixed to zero. Flexibility in the model allows for estimation of trait-specific method factors (as described above) when there is interest in evaluating whether method effects might have a different influence on different traits. Alternatively, a single method factor for each of the M-1 methods can be substituted for trait-specific method factors when there is reason to believe the methods have a similar influence across traits.

Illustration: Intersection of Race and Ethnicity with respect to Perceptions of Teacher Support and Personal Engagement

The focus of the current paper is to directly incorporate the intersecting subgroups into the construct modeling process as a structural regression model with group structured residual factors. More specifically, the current study demonstrates the use of the CT-C(M-1) structural regression model for school climate factors across race-ethnicity intersections. In keeping with the critical race theory origins of intersectionality, the analytic approach allows for purposefully centering on a marginalized group with which others are to be compared (e.g., hooks, 1984; Gillborn, 2015). This approach to measurement 1) makes explicit the similarities and differences among the subgroups' construct levels and construct-construct relationships, and 2) has the potential to inform policy interventions that can be tailored to the subgroups under study.

Prior research on the intersection between race and ethnicity in the U.S. has shown that persons who identify as Black and Hispanic (also known as Afro-Hispanic, Afro-Latino/x, and Black Latino/x) have uniquely different discriminatory experiences from those who only identify as one or the other (e.g., colorism, social exclusion, and authenticity questioning in their communities). Compared to the Hispanic

Figure 1. Illustrative Path Diagram of CT-C(M-1) Model with Two Traits as Rated by a Reference Group (RG) and three Non-Reference Groups (NRG)



Note. RG = reference group, NRG = non-reference group. Observed variables obtained by different informants represented in boxes; model estimated informant traits, and trait-specific method factors, shown in ovals. Curved double-headed arrows reflect correlations. Some factor correlations omitted for clarity, where all factor correlations were estimated with the exception of trait-specific method factors with their corresponding traits. All observed variable residual variances estimated but only illustrated for the first item (r1).

group as a whole, persons identifying as Black-Hispanic possess more Black phenotypical characteristics (Haywood, 2017), and are more likely to have higher educational attainment but yet lower economic returns on their education (Darity et al., 2002; Holder & Aja, 2021). Moreover, Black-Hispanic experiences have been largely underrepresented in educational research (Haywood, 2017)[4].

Thus, in addition to demonstrating a general method for assessing similarities (consistencies) and differences (uniquenesses) in measuring constructs and their relations, in the present demonstration we also focus on the intersectional experience of Black non-Hispanic students compared to Black Hispanic students, as well as the race-ethnicity combinations of White non-Hispanic and White Hispanic students. Specifically, our substantive research questions are as follows.

1) To what extent do race-ethnicity groups share a common viewpoint of teacher support and student engagement?
2) To what extent do subgroups' perspectives differ from the Black non-Hispanic reference group?
3) To what extent do the non-reference groups share a common perspective among one another that is not shared with the reference groups' perspective of the trait?

While these questions and our analyses do not provide specific potential policy intervention recommendations for improving school climate (the second aim of intersectionality research), the results of the forthcoming analysis could be used as a first step in providing data for policymakers to consider in reducing disparities where they exist.

Method

Sample

Data were obtained from the Virginia Secondary School Climate Survey (Cornell et al., 2020). The survey was administered anonymously online from January through March 2020. All 326 Virginia public schools serving a general education high school population were eligible to complete a statewide school climate survey. The school participation (N = 299) rate of 91.7% was achieved with the cooperation of the Virginia Department of Education and the Virginia Department of Criminal Justice Services, who endorsed the survey and encouraged participation.

A total of N = 117,717 students completed the survey. To improve data quality (Wise, 2017), a multi-stage screening procedure resulted in the removal of potentially invalid student responses. Following an established screening procedure to identify students who admit not being truthful (Cornell et al., 2012; Jia et al., 2016), 8.8% of the students were removed from the analytic sample on the basis of their responses to two embedded validity questions (i.e., "I am telling the truth on this survey," and "How many questions on this survey did you answer truthfully?") that have been shown to be effective in identifying students that give more exaggerated reports than other students (Cornell, et al., 2012; Cornell et al., 2014) . In addition, students were removed for indicating a grade level that did not exist at their school. An additional 0.4% of the students were excluded for completing the survey in less than six minutes, as it was judged that they would not have sufficient time to complete the survey in that time frame. See the technical report (Cornell et al., 2020) for additional information and description of these sampling procedures.

To create school-level averages that reflected school climate measurement, and to ensure that more than one student voice per race-ethnicity combination for each school was represented in analyses, the sample of N = 106,865 students (50.2% female) from 282 different schools was further reduced to those schools with at least two students from each of the four race-ethnicity groupings. This resulted in an analytic sample of N = 72,004 students (50.2% female) from 165 schools. Students were distributed across 9th (29.1%), 10th (26.8%), 11th (24.2%), and 12th (19.9%) grades, and across grades, race-ethnicity combinations were: Black non-Hispanic (19.9%), Black Hispanic (2.3%), White non-Hispanic (71.0%), and White Hispanic (6.8%).

Measures

Multilevel confirmatory factor analyses (CFA) of the support and engagement items used in the current study (Table 1) revealed good psychometric properties

[4] We note that there is evidence that some Hispanics view their ethnicity as integrated with their race (Gonzalez- Barrera & Lopez, 2015); however, in keeping with research by Haywood and others, in the present paper we treat race and ethnicity as intersecting identities.

(i.e., strong pattern coefficients and meaningful reliability estimates at the level of the informant and school) when examined on the basis of student responses (Konold & Cornell, 2015a). Factor loadings for the Support items ranged from .86-.87 at the student level (alpha reliability = .87) and from .95-.99 at the school level (Spearman-Brown reliability = .90). Factor loadings for the student Engagement items ranged from .84-.93 at the student level (alpha reliability = .89) and from .97-1.0 at the school level (Spearman-Brown reliability = .95). Descriptive statistics and alpha reliabilities for the current analytic sample are shown in Table 1.

Analytic Plan

We illustrate the usefulness of the CT-C(M-1) model for intersectionality research through focus on the measurement of two traits: student support and engagement, through three indicators for each, that were obtained from each of four informant groups that were specified on the basis of intersections of race and ethnicity: Black non-Hispanic (BNH), Black Hispanic (BH), White non-Hispanic (WNH), and White Hispanic (WH). Observed variables in the analysis were average item scores across students in these subgroups within each of the 165 schools. Our specification of the model involved use of the BNH[5] students as the reference group (Figure 2). Correlations between the two trait factors of support and engagement were freely estimated, and all non-reference group method factor correlations were also estimated (left side of Figure 2). Same trait and same method factor correlations were fixed to zero (see Eid et al., 2003). All analyses were conducted in Mplus version 8.7.

Results

The CT-C(M-1) model illustrated in Figure 2 where the Black non-Hispanic (BNH) group served as the reference demonstrated reasonable fit (TLI = .940, CFI = .950, RMSEA = .076, SRMR = .034). The sections below describe various model interpretations.

CT-C(M-1) Measurement Model

Completely standardized trait and method factor loadings are shown in columns 3 and 4 of Table 2. Trait loadings for BNH group were all strong and statistically significant. across both support and

Table 1. Common Items across Traits

Items	BNH			BH			WNH			WH		
	α	*M*	*(SD)*	*α*	*M*	*(SD)*	*α*	*M*	*(SD)*	*α*	*M*	*(SD)*
Support (Respect for Students)	.95			.90			.92			.92		
Most teachers and other adults at this school…												
S1:…care about all students		2.94	(0.21)		2.84	(0.36)		3.05	(0.14)		2.95	(0.31)
S2:…want all students to do well		2.60	(0.25)		2.47	(0.42)		2.70	(0.19)		2.59	(0.35)
S3:…treat students with respect		2.83	(0.23)		2.68	(0.42)		2.91	(0.16)		2.83	(0.36)
Engagement (Affective Engagement)	.96			.87			.98			.91		
E1: I like this school		2.80	(0.26)		2.80	(0.41)		2.80	(0.24)		2.81	(0.31)
E2: I am proud to be a student at this school		2.81	(0.26)		2.82	(0.39)		2.80	(0.24)		2.82	(0.32)
E3: I feel like I belong at this school		2.74	(0.24)		2.77	(0.40)		2.74	(0.21)		2.75	(0.29)

Note. BNH = Black non-Hispanic; BH = Black Hispanic; WNH = White non-Hispanic; WH = White Hispanic. α = sample-based Cronbach's alpha.

[5] Recall that we purposefully center our focus on persons who self-identify as Black, in keeping with hooks (1984) message of bringing the "margin" to the "center."

engagement items (Range = .89-.98, *p*'s < .001) indicating that reports from this group were good measures of the two traits. These reference group trait factors were then regressed on measures of the same trait obtained by the other, non-reference, groups in the model (i.e., the BNH trait factor was regressed on ratings obtained from BH, WNH, and WH groups) in order to evaluate the degree to which the reference group trait factors were related to reports of the same trait obtained by the non-reference groups.

Figure 2. Path Diagram of CT-C(M-1) Model of School Climate Factors as Rated by Black non-Hispanic (Reference Group), Black Hispanic, White non-Hispanic, and White Hispanic Students

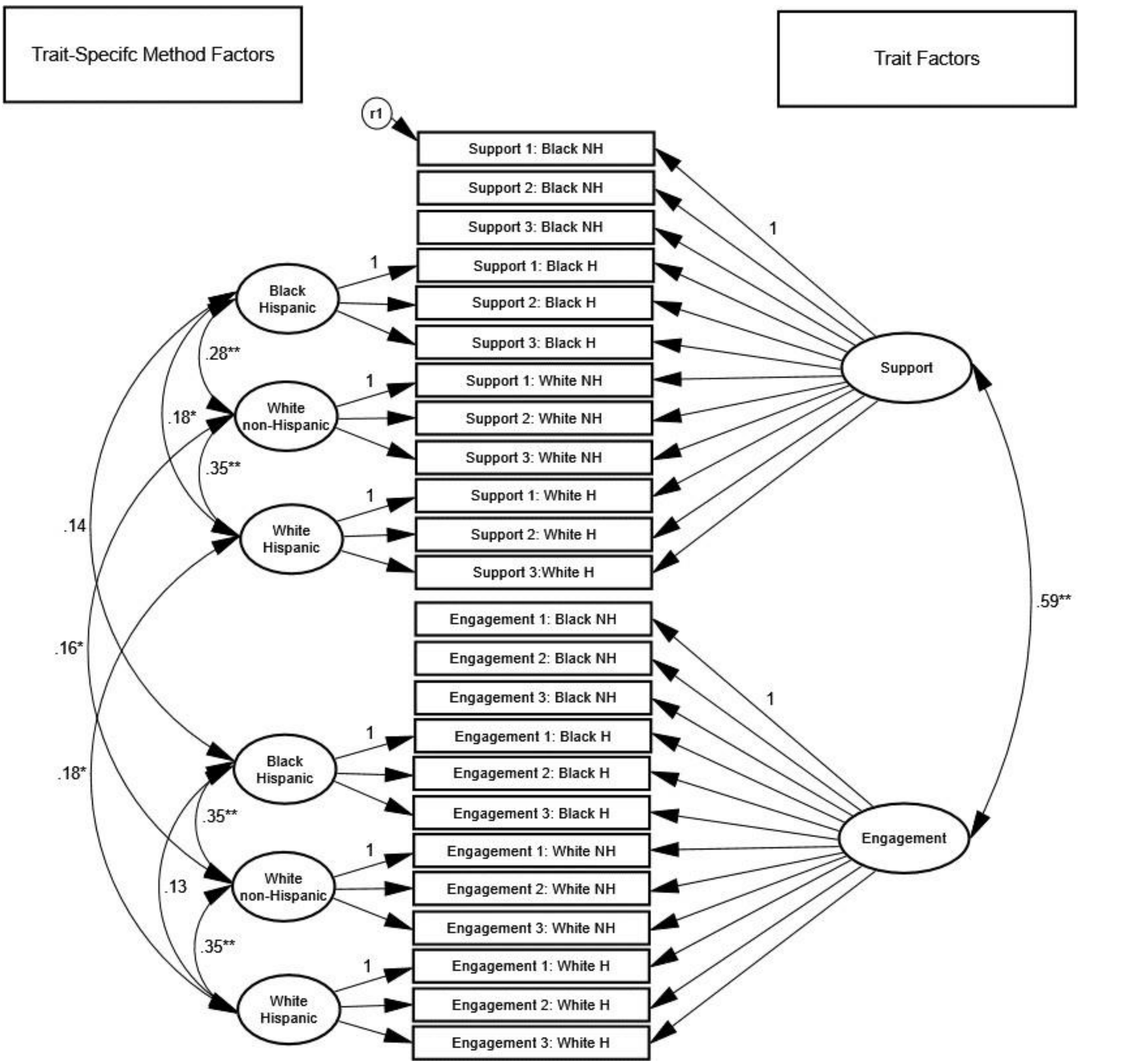


Table 2. CT-C(M-1) Standardized Factor Loadings, Consistency, and Method Specificity Results

		Loadings			
Informant	Item	Trait	Method	CO	MS
Black non-Hispanic (reference)	S1	.89**	--	1	--
	S2	.94**	--	1	--
	S3	.95**	--	1	--
	E1	.98**	--	1	--
	E2	.96**	--	1	--
	E3	.89**	--	1	--
Black Hispanic	S1	.33**	.82**	.15	.85
	S2	.32**	.75**	.16	.84
	S3	.29**	.86**	.11	.89
	E1	.56**	.61**	.46	.54
	E2	.48**	.77**	.28	.72
	E3	.36**	.70**	.21	.79
White non-Hispanic	S1	.61**	.71**	.44	.56
	S2	.63**	.69**	.48	.52
	S3	.64**	.57**	.58	.42
	E1	.83**	.51**	.73	.27
	E2	.81**	.53**	.70	.30
	E3	.79**	.55**	.67	.33
White Hispanic	S1	.40**	.76**	.23	.77
	S2	.43**	.78**	.15	.85
	S3	.34**	.88**	.14	.86
	E1	.59**	.63**	.47	.53
	E2	.58**	.75**	.38	.62
	E3	.58**	.62**	.47	.53

Note. CO = consistency, MS = method specificity, S1-S3 = support items, E1-E3 = engagement items.
*$p < .05$, ** $p < .001$.

Trait loadings for the non-reference groups' ratings of the same traits were moderate to large, and all were statistically significant, indicating that the BNH trait factor explained meaningful amounts of variance in the reports obtained by the other groups. Loadings were generally stronger for the engagement items across all non-reference groups. Consistency estimates that are free of both residual and unique method variance measure the proportion of non-reference group true score rating variance that was shared with the BNH group (see column 5 of Table 2). These too revealed greater consistency for the engagement items than the support items across groups. Moreover, there was somewhat greater consistency between the ratings of the BNH and WNH groups, than between the BNH and the WH and BH groups, with the BH group showing the least amount of consistency, particularly for items related to support.

Method factor loadings that are indicative of unique method variance attributable to the non-reference groups were also large and statistically significant across all items and groups. The proportion of variance in these reports that is unique to the non-reference informants, and not shared with the BNH group, is reflected in the corresponding method specificity coefficients (see column 6 of Table 2). Estimates ranged from .54 to .89 for BH, .27 to .56 for WNH, and .53 to .86 for WH. On average, the proportion of variance in reports of support and engagement that was unique to the non-reference informants was greater for BH (M = .77) and WH (M = .69) than for WNH (M = .40).

Correlations

Specifications of the investigated multilevel CT-C(M-1) model included fixing the trait factors and trait-specific method factors of the same name to zero. All other latent variable associations were freely estimated. Figure 2 shows the associations that are of primary interest, with some omitted for being less relevant to the current focus and for clarity of presentation. The trait factor association between the BNH group-based trait factors of support and engagement provides an indication of convergent validity and was found to be statistically significant and moderate in size (r = .59, p < .001).

Cross group trait-specific method factor associations. All non-reference group trait-specific method factor associations are partial correlations with respect to the BNH reference group reports of similarly named trait factors. These values are shown on the inner double headed arrows on the left side of Figures 1. Five of the six partial correlations among the non-BNH subgroups were moderate in size (r_{range} = .18 - .35) and statistically significant, suggesting that the BNH group reports of the same trait were unable to fully explain associations among the other informant groups. In other words, associations among BH, WNH, and WH trait ratings largely remained beyond what could be explained by BNH reports; and common perspectives among these three groups were not entirely shared with the BNH group. Four of these occurred between the two WNH-WH method factors and the two WNH-BH method factors, indicating that these groups shared a common view of the support and engagement traits that was not shared with the BNH group. The WH-BH associations were mixed, with these two groups sharing a common perspective of support that was not shared with the BNH group (r = .18, p < .05), and not sharing a common perspective of engagement beyond that which could be explained by the BNH group (r = .13, p > .05).

Common group trait-specific method factor associations. Correlations among non-reference group method factors between different traits evaluate the degree to which informant effects generalize between traits. These are shown on the left side of the outer double headed arrows in Figures 1. The WNH (r = .16, p < .05) and WH (r = .18, p < .05) support and engagement method factors correlations were statistically significant, whereas the BH association was not (r = .14, p > .05). Despite some being statistically significant, the distance of all associations from the upper limit of 1 also reflects the fact that these informant effects did not "perfectly generalize across traits" (Eid et al., 2003, p. 50), and that their differences from the BNH reference group perspective does differ across traits.

Discussion

The present study seeks to demonstrate how researchers can re-purpose a particular multitrait-multimethod (MTMM) analysis – the correlated trait-correlated method minus 1 (CT-C(M-1)) latent variable model (Eid et al., 2003) – for use in intersectionality research. Similar to other methods (e.g., the general linear model), this approach can estimate differences among intersectional groupings such as race-gender or race-ethnicity subgroups, but more importantly, the CT-C(M-1) analysis can also estimate shared construct(s) variance among the groups as separate from the unique parts of the construct(s) and their relations, as defined by the subgroups themselves (i.e., as "method" factors). As an added benefit, this model also takes an asset-based lens toward understanding subgroup differences (i.e., group similarities vs. "uniquenesses"), rather than historically more deficit-oriented approaches (i.e., one group differs from a "normative" group).

In the current demonstration, we addressed three questions in the context of our substantive example. First, to what extent do BNH, BH, WNH, and WH groups share a common viewpoint of support and engagement? Evidence in support of a shared common perspective was be evaluated through the resulting trait factor loadings and their corresponding consistency estimates, where Black and White non-Hispanic groups shared the strongest common perspective of support and engagement, with the bond being tightest for engagement. Similarly, the Black and White Hispanic groups' perspectives were more strongly associated with the BNH group's perspective of engagement than they were with support.

Second, to what extent do the non-reference groups' perspectives differ from the BNH reference group? Complementary to trait factor loadings and consistency estimates are the method factor loadings and method specificity estimates. Method factor loadings revealed relationships between group specific trait indicators (e.g., items) and method specific group factors that can be considered group structured residuals with respect to the BNH reference group trait factor. These were generally larger for the BH and WH subgroups, than for WNH. Method specificity estimates revealed the proportion of indicator variance by subgroup that was not shared with the BNH reference group. Here again, these followed a similar pattern as the method factor loadings, though they were somewhat higher for the BH engagement indicators than for the WH engagement indictors.

Last but not least, to what extent do the non-reference subgroups share a common perspective among one another that is not shared with the reference group's perspective of the traits? Given the results above that suggest that at least some of the perspectives of the non-reference subgroups were different from that of the BNH group on the two traits, examination of method factor correlations can point to areas of shared perspectives among the non-reference subgroups that was not shared with the BNH reference group. With respect to both support and engagement, these shared perspectives were greatest for WNHs and those of BHs and WHs, and were less pronounced between BH and WH groups, suggesting that the unique perspectives of BH and WH groups were not strongly related to each other. Finally, the relatively small associations between the non-reference subgroups (as method factors) and the two traits suggests that the unique perspectives of these groups are relatively trait-specific, and do not fully generalize across their perspectives of different traits.

In keeping with the twin goals of intersectionality research, our substantive aim was to uncover potential sources of differences in school climate for students from minoritized backgrounds as a means for laying the groundwork for discussion around potential interventions to improve marginalized students' school experiences. As was observed in our results, although the four subgroups shared similarities in the two school climate factors, they also exhibited meaningful differences. Most importantly, Black Hispanic students appeared to differ considerably in their school support ratings compared to the other three race-ethnicity subgroups, which is consistent with other scholarship around the uniquely difficult experiences of Black Hispanic students in the U.S. (e.g., Haywood, 2017; Vue et al., 2017). Such findings suggest that interventions could be put into place to support these students, ranging from staff professional development (in considering the engagement) to creatively developed after-school/weekend programs (in considering the support).

Limitations and Considerations

Like all research, the present study is not without limitations. For brevity and due to unequal subgroup sizes, we used school means as our observed variables, rather than a multilevel model that can incorporate individual and school-level construct measurement. However, it is important to note that our focus on the school level was because school climate is a school-level construct (Marsh et al., 2012; Stapleton, et al., 2016). In other applications in which meaningful constructs may reside at more than one level of a clustered data structure (e.g., students and schools), researchers are encouraged to consider multilevel extensions of the approach illustrated here that have been previously described (Koch et al., 2015) and illustrated (Konold & Sanders, 2021) in the literature. In addition, we had a limited number of observed variables per construct, which can sometimes make the modeling process more difficult. Eid et al. (2003) describes helpful strategies with limited numbers of observed variables, and Bayesian estimation methods have also been found to useful for navigating convergence issues that can arise in estimating MTMM structural models (Helm, et al., 2018).

We also acknowledge that our minimum threshold for having at least two student voices from each group, within a given school, may not provide the most reliable estimate of their perspective of a given trait where heterogeneity may exist. Further, for brevity, we examined race-ethnicity subgroups; however, other combinations (e.g., race-gender or race-gender-ethnicity subgroups) could certainly be considered in future work. Related, although the U.S. Census Bureau makes a distinction between ethnicity and race, a sizable portion of Hispanics view their ethnicity as integrated with their race (Gonzalez-Barrera & Lopez, 2015). Although all students in our analytic sample selected both an ethnicity and race category, it is possible that this distinction was not meaningful to all students. Fourth, these data represent only a sample of schools from Virginia and as such, our results are limited to student subgroups in this region of the U.S. Last but not least, all items were administered in English, which may be problematic in translation for Spanish-speaking youth. Despite these limitations, however, the value of the analytic approach we demonstrate for intersectionality research generalizes well beyond our specific sample and race-ethnicity intersections.

Conclusion

The present study represents a novel method not yet used in the quantitative intersectionality literature – the CT-C(M-1) model – for measuring and understanding the similarities and uniquenesses among intersectional race-ethnicity subgroups. As others have noted, qualitative approaches to studying intersectionality may be optimal in many circumstances (e.g., Cho et al., 2013; Syed, 2010); however, quantitative methods for studying intersectional questions are on the rise (e.g., multilevel and latent class models, among others; Bauer et al., 2021a,b). In addition, policymakers may be more likely to take note of research results from larger scale studies that represent more of their constituents (e.g., Jang, 2018), and as such, quantitative studies may be quite useful in advancing the second goal of intersectionality research – intervention against the status quo and true transformational change (Gillborn, 2015).

References

Agénor, M. (2020). Future directions for incorporating intersectionality into quantitative population methods in health research. *American Journal of Public Health, 110*(6), 803- 806. https://doi.org/10.2105/AJPH.2020.305610

Bauer, G.R. (2014). Incorporating intersectionality theory into population health research methodology: Challenges and the potential to advance health equity. *Social Science & Medicine, 110*, 10-17.

Bauer, G. R., Churchill, S. M., Mahendran, M., Walwyn, C., Lizotte, D., & Villa-Rueda, A. A. (2021a). Intersectionality in quantitative research: A systematic review of its emergence and applications of theory and methods, *SSM - Population Health, 14*. Published online first. https://doi.org/10.1016/j.ssmph.2021.100798.

Bauer, G. R., Mahendran, M., Walwyn, C., & Shokoohi, M. (2021b). Latent variable and clustering methods in intersectionality research: systematic review of methods applications. *Social Psychiatry and Psychiatric Epidemiology*. Published online first. https://doi.org/10.1007/s00127-021-02195-6

Bleidorn, W., & Peters, A. (2011). A multilevel Multitrait–Multimethod Analysis of Self– and Peer–Reported Daily Affective Experiences. *European Journal of Personality, 25*(5), 398-408. https://doi.org/10.1002/per.804

Bowleg, L. (2012). The problem with the phrase women and minorities: Intersectionality–An important theoretical framework for public health. *American Journal of Public Health 102,* 1267-1273. https://doi.org/10.2105/AJPH.2012.300750

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin, 56*, 81-105. https://doi.org/10.1037/h0046016

Cho, S., Crenshaw, K. W., McCall, L. (2013). Toward a field of intersectionality studies: Theory, application, and praxis. *Signs: Journal of Women in Culture and Society, 38*(4), 785-810. https://doi.org/10.1086/669608

Collins, P. H., & Bilge, S. (2020). *Intersectionality*. John Wiley & Sons. Collective, C. R. (1977). *A Black Feminist Statement* (pp. 210-218). na.

Cornell, D., Lovegrove, P., & Baly, M. (2014). Invalid survey response patterns among middle school students. *Psychological Assessment*, *26*, 277-287. doi 10.1037/a0034808

Cornell, D., Maeng, J., Huang, F., Edwards, K., Crichlow–Ball, C., Crowley, B., Ruffa, B., & Stohlman, S. (2020). *Technical report of the Virginia Secondary School Climate Survey: 2020 results for 9th–12th grade students and school staff.* Charlottesville, VA: School of Education and Human Development, University of Virginia.

Cornell, D., Klein, J., Konold, T., & Huang, F. (2012). Effects of validity screening items on adolescent survey data. *Psychological Assessment, 24*(1), 21–35. https://doi.org/10.1037/a0024824

Crenshaw, K. (1989). Demarginalizing the intersection of race and sex: A black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics. *University of Chicago Legal Forum, 1*(8), 139-167. Accessed online: https://baltimorewisdomproject.org/uploads/7/0/8/0/70800857/demarginalizing_the_intersection_of_race_and_sex_a_black_feminist_critique.pdf

Crenshaw, K. (1991). Mapping the margins: Intersectionality, identity politics, and violence against women of color." *Stanford Law Review 43*(6), 1241-1299. Accessed online: https://heinonline.org/HOL/LandingPage?handle=hein.journals/scal65&div=70&id=&page=

Darity Jr, W., Hamilton, D., & Dietrich, J. (2002). Passing on blackness: Latinos, race, and earnings in the USA, *Applied Economics Letters, 9*(13), 847-853, doi: 10.1080/13504850210149133

De Haan, A., Prinzie, P., Sentse, M., & Jongerling, J. (2018). Latent difference score modeling: A flexible approach for studying informant discrepancies. *Psychological Assessment, 30*(3), 358-369. http://dx.doi.org/10.1037/pas0000480

Dill, B. T. (1983). Race, class, and gender: Prospects for an all-inclusive sisterhood. *Feminist Studies, 9*, 131-50. doi: https://doi.org/10.2307/3177687

Eid, M. (2000). A multitrait-multimethod model with minimal assumptions. *Psychometrika, 65*, 241-261. doi: 10.1007/BF02294377

Eid, M., Lischetzke, T., Nussbeck, F. W., & Trierweiler, L. I. (2003). Separating trait effects from trait-specific method effects in multitrait-multimethod models: A multiple indicator CT-C(M-1) model. *Psychological Methods, 8*, 38-60. doi: 10.1037/1082-989X.8.1.38

Eid, M., Nussbeck, F. W., Geiser, C., Cole, D. A., Gollwitzer, M., & Lischetzke, T. (2008). Structural equation modeling of multitrait-multimethod data: Different models for different types of methods. *Psychological Methods, 13*, 230-253. doi: 10.1037/a0013219

Gillborn, D. (2015). Intersectionality, critical race theory, and the primacy of racism: Race, class, gender, and disability in Education. *Qualitative Inquiry, 21*(3), 277–287. https://doi.org/10.1177/1077800414557827

Gonzalez-Barrera, A., & Lopez, M. H. (2015). Is being Hispanic a matter of race, ethnicity or both? *Pew Research Center.* Accessed online: http://pewrsr.ch/1egbvPL

Haywood, J. M. (2017). Latino spaces have always been the most violent': Afro-Latino collegians' perceptions of colorism and Latino intragroup marginalization. *International Journal of Qualitative Studies in Education, 30*(8), 759-782. doi: 10.1080/09518398.2017.1350298

Helm, L.J., Castro-Schilo, L., Zavala-Rojas, D., DeCastellarnau, A., & Oravecz, Z. (2018). Bayesian estimation of the true score multitrait-multimethod model with a split-ballot design. *Structural Equation Modeling, 25*, 71-85.

Holder, M., & Aja, A. A. (2021). *Afro-Latinos in the U.S. Economy.* Rowman & Littlefield. hooks, b. (1984). *Feminist Theory: From Margin to Center.* Cambridge, MA: South End.

Jang, S. T. (2018). The implications of intersectionality on Southeast Asian female students' educational outcomes in the United States: A critical quantitative intersectionality analysis. *American Educational Research Journal, 55*(6), 1268–1306. https://doi.org/10.3102/0002831218777225

Jia, Y., Konold, T. R., & Cornell, D. (2016). Authoritative school climate and high school dropout rates. *School Psychology Quarterly, 31*(2), 289-303. https://doi.org/10.1037/spq0000139

Jöreskog, K. G. (1971). Simultaneous factor analysis in several populations. *Psychometrika, 36*, 409–426. doi: https://doi.org/10.1007/BF02291366

Kenny, D. A. (1979). *Correlation and Causation*. New York: Wiley.

Kenny, D. A., & Kashy, D. A. (1992). Analysis of multtrait-multimethod matrix by confirmatory factor analysis. *Psychological Bulletin, 112*, 165-172. doi: 10.1037/0033-2909.112.1.165

Koch, T., Schultze, M., Burrus, J., Roberts, R. D., & Eid, M. (2015). A multilevel CFA-MTMM models for nested structurally different methods. *Journal of Educational and Behavioral Statistics*, *40*, 477-510. https://doi.org/10.3102/1076998615606109

Konold, T. R., & Cornell, D. (2015a). Measurement and structural relations of an authoritative school climate model: A multi-level latent variable investigation. *Journal of School Psychology, 53*, 447-461. http:/dx.doi.org/10.1016/j.jsp.2015.09.001

Konold, T. R., & Cornell, D. (2015b). Multilevel multitrait-multimethod model of structurally different and interchangeable raters of school climate. *Psychological Assessment, 27*, 1097-1109. http://dx.doi.org/10.1037/pas0000098

Konold, T. R., & Glutting, J. J. (2008). ADHD and method variance: A latent variable approach applied to a nationally representative sample of college freshmen. *Journal of Learning Disabilities, 41*(5), 405–416. https://doi.org/10.1177/0022219408321111

Konold, T. R., & Pianta, R. C. (2007). The influence of informants on ratings of children's behavioral functioning: A latent variable approach. *Journal of Psychoeducational Assessment, 25*(3), 222–236. https://doi.org/10.1177/0734282906297784

Konold, T., & Sanders, E. A. (2021). The nature of rater effects and differences in multilevel MTMM latent variable models. *Measurement: Interdisciplinary Research and Perspectives, 18*(4), 177-195. https://doi.org/10.1080/15366367.2020.1746897

Konold, T. R., & Shukla, K. (2017). Estimating school climate traits across multiple informants: An illustration of a multitrait–multimethod validation through latent variable modeling. *Educational Assessment*, *22*(1), 54-69. https://doi.org/10.1080/10627197.2016.1271705

Liard, R. D., & De Los Reyes, A. (2013). Testing informant discrepancies as predictors of adolescent psychopathology: Why difference scores cannot tell you what you want to know and how polynomial regression may. *Journal of Abnormal Child Psychology, 41*, 1-14. doi: 10.1007/s10802-012-9659-y

Luo, Z., Breslau, J., Gardiner, J. C., Chen, Q., & Breslau, N. (2014) Assessing interchangeability at cluster levels with multiple-informant data. *Statistics in Medicine, 33*, 361-375. doi:10.1002/sim.5948.

Marsh, H. W. (1989). Confirmatory factor analysis of multitrait-multimethod data: Many problems and a few solutions. *Applied Psychological Measurement, 12*, 335-361. https://doi.org/10.1177/014662168901300402

Marsh, H. W., & Grayson, D. (1995). Latent variable models of multitrait-multimethod matrices. In R. Hoyle (Ed.), *Structural Equation Modeling: Concepts, Issues, and Applications* (pp. 177-198. Thousand Oaks, CA: Sage.

Marsh, H. W., Ludtke, O., Nagengast, B., Trautwein, U., Morin, A. J. S., Abduljabbar, A. S., & Koller, O. (2012). Classroom climate and contextual effects. Conceptual and methodological issues in the evaluation of group-level effects. *Educational Psychologist, 47*, 106-124.

Rajmil, L., López A. R., López-Aguilà S., & Alonso, J. (2013). Parent-child agreement on health-related quality of life (HRQOL): A longitudinal study. *Health and Quality of Life Outcomes, 11*, 101. doi: 10.1186/1477-7525-11-101

Stapleton, L. M., Yang, J. S., & Hancock, G. R. (2016). Construct meaning in multilevel settings. *Journal of Educational and Behavioral Statistics, 41*, 481-520.

Syed, M. (2010). Disciplinary and methodology in intersectionality theory and research. *American Psychologist*, 61-62. doi: 10.1037/a0017495.

Vue, R., Haslerig, S. J., & Allen, W. R. (2017). Affirming race, diversity, and equity through Black and Latinx students' lived experiences. *American*

Educational Research Journal, 54(5), 868-903. https://doi.org/10.3102/0002831217708550

Widaman, K. F. (1985). Hierarchically nested covariance structure models for multitrait-multimethod data. *Applied Psychological Measurement, 9*(1), 1-26.

Wise, S.L. (2017). Rapid-guessing behavior: Its identification, interpretation, and implications. *Educational Measurement: Issues and Practice, 36*, 52-61.

Citation:

Konold, T. R., & Sanders, E. A. (2022). Reimagining MTMM designs for examining intersectionality in latent variables. *Practical Assessment, Research, & Evaluation*, 27(16). Available online: https://scholarworks.umass.edu/pare/vol27/iss1/16/

Corresponding Author:

Timothy R. Konold
University of Virginia
Charlottesville, Virginia, USA

Email: konold [at] virginia.edu

Appendix A.

Example Mplus Code

```
TITLE: CT-C(M-1) Analysis Approach for Intersectional Latent Variable Measurement

DATA:  FILE IS data.csv;
! SUP = Support composite item average, with three items (1, 3, 4)
! ENG = Engagement composite item parcel average, with three items (1, 2, 8)
! BNH = Black, non-Hispanic
! BH = Black, Hispanic
! WNH = White, non-Hispanic
! WH = White, Hispanic
! m = school mean

VARIABLE:
       NAMES =
       USID
       SUP1BNHm SUP3BNHm SUP4BNHm ENG1BNHm ENG2BNHm ENG8BNHm
       SUP1BHm  SUP3BHm  SUP4BHm  ENG1BHm  ENG2BHm  ENG8BHm
       SUP1WNHm SUP3WNHm SUP4WNHm ENG1WNHm ENG2WNHm ENG8WNHm
       SUP1WHm  SUP3WHm  SUP4WHm  ENG1WHm  ENG2WHm  ENG8WHm;

USEVARIABLES =
       SUP1BNHm SUP3BNHm SUP4BNHm ENG1BNHm ENG2BNHm ENG8BNHm
       SUP1BHm  SUP3BHm  SUP4BHm  ENG1BHm  ENG2BHm  ENG8BHm
       SUP1WNHm SUP3WNHm SUP4WNHm ENG1WNHm ENG2WNHm ENG8WNHm
       SUP1WHm  SUP3WHm  SUP4WHm  ENG1WHm  ENG2WHm  ENG8WHm;

ANALYSIS:
       TYPE = General;
       INFORMATION = Expected;
       SDITERATIONS = 100;
       ITERATIONS = 500000;
       CONVERGENCE = 0.000050;
       H1ITERATIONS = 10000;
       H1CONVERGENCE = 0.000100;
       Estimator = ML;

MODEL:

! Scales set by reference group of BNH
! Spr = Support factor
! Eng = Engagement factor

Spr     by    SUP1BNHm SUP3BNHm SUP4BNHm SUP1BHm SUP3BHm SUP4BHm
              SUP1WNHm SUP3WNHm SUP4WNHm SUP1WHm SUP3WHm SUP4WHm;
Eng     by    ENG1BNHm ENG2BNHm ENG8BNHm ENG1BHm ENG2BHm ENG8BHm
              ENG1WNHm ENG2WNHm ENG8WNHm ENG1WHm ENG2WHm ENG8WHm;

BHspr  by     SUP1BHm  SUP3BHm  SUP4BHm;
WNHspr by     SUP1WNHm SUP3WNHm SUP4WNHm;
WHspr  by     SUP1WHm  SUP3WHm  SUP4WHm;

BHeng  by     ENG1BHm ENG2BHm ENG8BHm;
WNHeng by     ENG1WNHm ENG2WNHm ENG8WNHm;
WHeng  by     ENG1WHm ENG2WHm ENG8WHm;

! Trait and method factor variance (V) definitions
```

```
Spr (VSpr);
Eng (VEng);

! Trait and method factor variance (V) definitions, cont'd

BHspr  (VBHspr);
WNHspr (VBNHspr);
WHspr  (VWHspr);

BHeng  (VBHeng);
WNHeng  (VBNHeng);
WHeng  (VWHeng);

! correlations among traits & associated method factors fixed to 0

Spr with BHspr@0 WNHspr@0 WHspr@0;
Eng with BHeng@0 WNHeng@0 WHeng@0;

OUTPUT: standardized stdyx;
```