

Parsimony vs. Complexity: A Comparison of Two-Level, Three-Level, and Cross-Classified Models Using Add Health and AHAA Data

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ABSTRACT

Multilevel modeling has become a common analytic technique across a variety of disciplines including education and other social and behavioral sciences. Such models are often used when researchers examine relationships between school and/or neighborhood characteristics and some individual-level outcome (e.g., academic achievement, high school completion). Although many samples are theoretically cross-classified between multiple level-2 units, the application of cross-classified random effects models is rare in such research. This paper compares model fit and parameter estimates from five different PROC MIXED multilevel modeling approaches—(a) a two-level model with students nested in schools and neighborhood variables included as contextual variables at Level 1, (b) a two-level model with students nested in neighborhoods and school variables included as contextual variables at Level 1, (c) a three-level model with students nested in schools nested in neighborhoods, (d) a three-level model with students nested in neighborhoods nested in schools, and (e) a cross-classified random effects model with students cross-nested in schools and neighborhoods. Example SAS[®] code for each of the modeling approaches is also included.

Keywords: MULTILEVEL MODELS, CROSS-CLASSIFIED DATA STRUCTURES, MODEL COMPARISON, SAS/STAT

INTRODUCTION

Multilevel modeling techniques are being used with increasing frequency by educational and other social science researchers, however, use of cross-classified random effects models (CCREMs; Raudenbush & Bryk, 2002) is rare in educational research (Beretvas, 2008). Although the increased use of multilevel modeling techniques is a vast improvement over single-level modeling from years past, the lack of CCREMs in education is particularly troubling given the theoretical cross-classified nature of many education data sets. For example, level-1 units (students) are often cross-classified by two level-2 factors (schools and neighborhoods) such that students from Neighborhood A might attend a school that students from Neighborhood B and Neighborhood C also attend, and students from the same neighborhood might attend different schools (Figure 1). However, educational researchers rarely model the data to account for cross-classification, despite the fact that such models are readily estimated using SAS PROC MIXED. Instead, when interested in examining school and neighborhood factors related to some individual-level outcome, researchers typically model the data in one of four different ways: (a) a two-level model with students nested in schools and neighborhood variables included as contextual variables at Level 1, (b) a two-level model with students nested in neighborhoods and school variables included as contextual variables at Level 1, (c) a three-level model with students nested in schools nested in neighborhoods, or (d) a three-level model with students nested in neighborhoods nested in schools.

When cross-classification of data is ignored, models are misspecified, causing them to lack the level of control necessary to detect important and possibly confounding effects, which, in turn, can lead to spurious conclusions. However, due to the sampling techniques often employed with large, complex sample surveys (i.e., schools are often the sampling frame unit and neighborhoods are not consciously included in the sampling process) the degree to which students are cross-classified between schools and neighborhoods is not always captured. Therefore, if the structure of the data does not reflect the theoretical cross-classification of students, schools, and neighborhoods, the suggested model misspecification and resulting bias when two- or three-level models are used may not be warranted. The purpose of this study is to examine and compare results from two-level, three-level, and cross-classified models, using data from the National Longitudinal Study of Adolescent Health (Add Health; National Longitudinal Study of Adolescent Health [Add Health], 2005) and the Adolescent Health and Academic Achievement study (AHAA; Adolescent Health and Academic Achievement Study [AHAA], n.d.). More specifically, five different model structures were examined and compared: (a) a two-level model with students nested in schools and neighborhood variables included as contextual variables at Level 1, (b) a two-level model with students nested in neighborhoods and school variables included as contextual variables at Level 1, (c) a three-level model with students nested in schools nested in neighborhoods, (d) a three-level model with students nested in neighborhoods nested in schools, and (e) a cross-classified random effects model with students cross-nested in schools and neighborhoods.

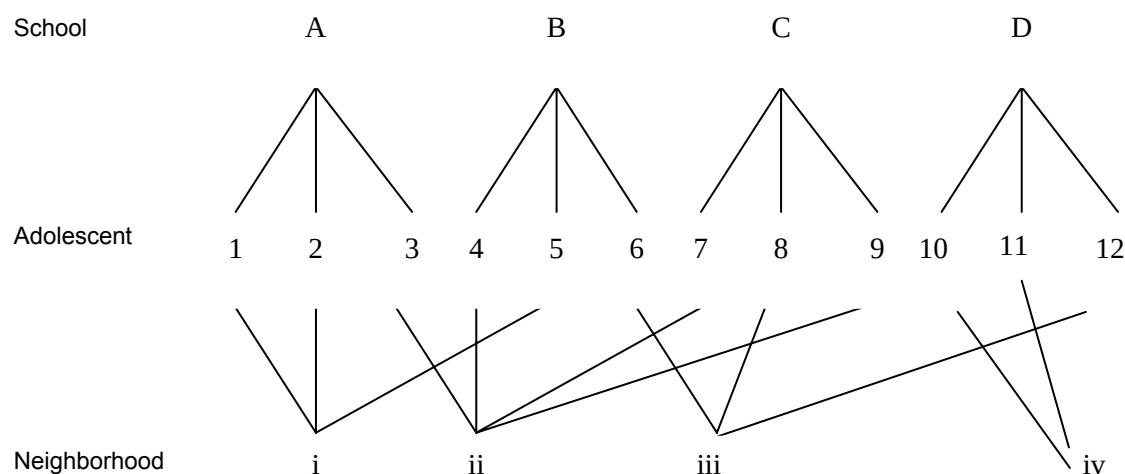


Figure 1. Example schematic of cross-classified data with adolescents nested within schools and neighborhoods.

METHOD

Data Sources

Data for the study were drawn from Wave I of Add Health (2005) and AHAA (n.d.)—nationally representative studies with foci on the relationship between social environments and adolescent education and health outcomes. Within these studies, data were obtained from numerous sources including questionnaires, interviews, and existing contextual databases (e.g., U.S. Census). All data used for the current study came from the restricted-use version of the data sources.

Add Health is a nationally representative longitudinal study that seeks to advance the understanding of the relationships between individuals and different social contexts (family, friends and peers, schools, and neighborhoods) and U.S. adolescents' development. To date, three waves of data have been collected—Wave 1 (1994-1995), Wave II (1995-1996), and Wave III (2001-2002). Data were collected through a complex sampling design that utilized a cluster sample, at the school level, with unequal probability of selection (Chantala & Tabor, 1999). Schools were selected to represent all high schools and middle schools in the U.S., thus the students attending the schools constitute a nationally representative sample of adolescents in Grades 7 to 12 (Tourangeau & Shin, 1999). However, in terms of neighborhoods and schools, Add Health data have an important limitation—the structure of the data does not provide information about the geographical relationship between schools and neighborhoods (i.e., we do not know which schools are in which neighborhoods). Thus, it is not possible to determine how many students attended schools outside their neighborhoods. However, we were able to calculate the structural cross-classification of schools and neighborhoods. The number of neighborhoods represented in schools ranged from 3 to 88. Conversely, the number of schools represented in neighborhoods was 1 to 3. The limited range of schools represented in neighborhoods led to a large proportion of singletons in these data (45%).

AHAA is an educational supplement to Add Health. Whereas Add Health provides a great deal of data on a variety of social contexts, it has limited academic-related information (Muller et al., 2007). By collecting official high school transcripts from all Wave III respondents who signed a Transcript Release Form and by compiling contextual information about the schools adolescents attended, AHAA provides the rich education-related data that Add Health is missing. Although AHAA was developed to supplement Add Health data, the data were selected separately from Add Health and were designed to create an educational data set that can be used in conjunction with Add Health or independently (Muller et al., 2007). When used with the Add Health data, researchers are able to capture a more holistic view of adolescent social, educational, and health-related behaviors and outcomes.

Measures

Adolescent academic achievement was the criterion variable examined in the study. Individual-level variables consisted of adolescent biological sex, age, race/ethnicity, and family socioeconomic status (SES). Neighborhood-level variables consisted of neighborhood affluence, neighborhood poverty, neighborhood racial composition, and urbanicity. School-level variables consisted of school-level SES, student body racial composition, and teacher education. Table 1 provides a summary of how each variable was operationalized and the data source for each variable.

Table 1
List of Operationalized Variables and Data Source

Variable	Operational Definition	Data Source ¹
Criterion Variable		
Academic achievement	Standardized scores on the Add Health Picture Vocabulary Test (AHPVT)	IH
Individual-level control variables		
Biological sex	Girl (0), boy (1)	IH
Age	Age in years, grand-mean centered	IH
Race/Ethnicity	Non-Hispanic White or non-Hispanic Asian (0), non-Hispanic Black, non-Hispanic Other, or Hispanic (1)	IH
Family SES	A composite variable calculated as the mean of standardized (z-score) measures of family income, parental educational level, and parental occupational prestige (Cronbach's $\alpha = .65$)	PI, IH
Neighborhood variables		
Neighborhood affluence	A composite variable calculated as a standardized (z-score) measure computed from the average proportion of neighborhood income, occupational prestige, and educational levels (Cronbach's $\alpha = .89$)	CD
Neighborhood poverty	A composite variable calculated as a standardized (z-score) measure computed from the average proportion of neighborhood poverty, single-parent households, and unemployment (Cronbach's $\alpha = .44$)	CD
Neighborhood racial composition	Proportion of White residents	CD
Urbanicity	Proportion of residents who live inside an urbanized area	CD
School variables		
School-level SES	A composite variable calculated as the mean of standardized (z-score) measures of school-level poverty, parental education, and parental occupational prestige (Cronbach's $\alpha = .80$)	PI, IH, AHAA
Student body racial composition	Proportion of White, non-Hispanic students	AHAA
Teacher education	Proportion of teachers with a Master's degree or higher	SA

Notes: ¹AHAA = Adolescent Health and Academic Achievement, IS = Add Health In-School Questionnaire, SA = Add Health School Administrator Questionnaire, IH = Add Health In-Home Interview, PI = Add Health Parent Questionnaire, and CD = Add Health Contextual Database.

Data analysis

Following a model-building strategy as discussed by Raudenbush and Bryk (2002), each of the five model structures (i.e., two-level models, three-level models, and CCREMs) were examined in order of complexity, starting with the simplest model that had no predictors and ending with the most complex model with multiple interaction terms. This process yielded six models for each model structure. Table 2 provides a summary of the variables (and corresponding levels)

included in each of the modeling approaches. All analyses were conducted using PROC MIXED in SAS v9.1.3. To allow comparison of models that differed in their fixed effects, all models were estimated using maximum likelihood estimation. Example PROC MIXED code for the unconditional model (Model 1) and the interaction model (Model 6) for each of the five model structures is provided in Figure 2.

Table 2
Summary of the Model Structure for Each Multilevel Model

	Two – Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
Model 1: Unconditional model	Level 1: None Level 2: None	Level 1: None Level 2: None	Level 1: None Level 2: None	Level 1: None Level 2: None	Level 1: None Level 2: None
Model 2: Level-1 control model	Level 1: Biological sex, age, race, family SES Level 2: None	Level 1: Biological sex, age, race, family SES Level 2: None	Level 1: Biological sex, age, race, family SES Level 2: None	Level 1: Biological sex, age, race, family SES Level 2: None	Level 1: Biological sex, age, race, family SES Level 2: None
Model 3: Neighborhood main effect model	Level 1: Biological sex, age, race, family SES, neighborhood affluence, poverty, racial composition, urbanicity Level 2: None	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity	Level 1: Biological sex, age, race, family SES Level 2: None Level 3: Neighborhood affluence, poverty, racial composition, urbanicity	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity Level 3: None	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity
Model 4: School main effect model	Level 1: Biological sex, age, race, family SES Level 2: School SES, student body racial composition, teacher education	Level 1: Biological sex, age, race, family SES, school SES, student body racial composition, teacher education Level 2: None	Level 1: Biological sex, age, race, family SES Level 2: School SES, student body racial composition, Teacher education Level 3: None	Level 1: Biological sex, age, race, family SES Level 2: None Level 3: School SES, student body racial composition, teacher education	Level 1: Biological sex, age, race, family SES Level 2: School SES, student body racial composition, teacher education
Model 5: Neighborhood and school main effect model	Level 1: Biological sex, age, race, family SES, neighborhood affluence, poverty, racial composition, urbanicity Level 2: School SES, student body racial composition, teacher education	Level 1: Biological sex, age, race, family SES, school SES, student body racial composition, teacher education Level 2: Neighborhood affluence, poverty, racial composition, urbanicity	Level 1: Biological sex, age, race, family SES Level 2: School SES, student body racial composition, teacher education Level 3: Neighborhood affluence, poverty, racial composition, urbanicity	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity Level 3: School SES, student body racial composition, teacher education	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity, school SES, student body racial composition, teacher education

Table 2
Summary of the Model Structure for Each Multilevel Model

	Two – Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
Model 6: Neighborhood and school interaction model	Level 1: Biological sex, age, race, family SES, neighborhood affluence, poverty, racial composition, urbanicity Level 2: School SES, student body racial composition, teacher education, school SES*affluence, school SES*poverty, Teacher education*affluence, teacher education*poverty	Level 1: Biological sex, age, race, family SES, school SES, student body racial composition, teacher education Level 2: Neighborhood affluence, poverty, racial composition, urbanicity, affluence* school SES, poverty*school SES, affluence*teacher education, poverty*teacher education	Level 1: Biological sex, age, race, family SES Level 2: School SES, student body racial composition, teacher education Level 3: Neighborhood affluence, poverty, racial composition, urbanicity, affluence* school SES, poverty*school SES, affluence*teacher education, poverty*teacher education	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity Level 3: School SES, student body racial composition, teacher education, school SES* affluence, school SES*poverty, teacher education*affluence, teacher education*poverty	Level 1: Biological sex, age, race, family SES Level 2: Neighborhood affluence, poverty, racial composition, urbanicity, school SES, student body racial composition, teacher education, affluence* school SES, poverty*school SES, affluence*teacher education, poverty*teacher education

```

title 'Unconditional Model - Students nested in Schools';
proc mixed data=one method= ml covtest noclprint;
class psu;
model PVTSTD1 = /solution;
random intercept/ sub= psu;
run;

title 'Interaction Model - Students nested in Schools';
proc mixed data= one method= ml covtest noclprint;
class psu;
model PVTSTD1 = new_age sex race family_ses z_affluence z_poverty N_prop_wht
prop_urban prop_master prop_white
school_ses school_ses*z_affluence school_ses*z_poverty
prop_master*z_affluence prop_master*z_poverty/ solution;
random intercept/ sub= psu;
run;

title 'Unconditional Model - Students nested in Neighborhoods';
proc mixed data=one method= ml covtest noclprint;
class neigh;
model PVTSTD1 = /solution;
random intercept/ sub= neigh;
run;

```

```

title 'Interaction Model - Students nested in Neighborhoods';
proc mixed data= one method= ml covtest noclprint;
class neigh;
model PVTSTD1 = new_age sex race family_ses prop_master prop_white school_ses
z_affluence z_poverty N_prop_wht
prop_urban school_ses*z_affluence school_ses*z_poverty
prop_master*z_affluence prop_master*z_poverty/ solution;
random intercept/ sub= neigh;
run;

title 'Unconditional Model - Students nested in Schools nested in
Neighborhoods';
PROC MIXED DATA=one METHOD = ML COVTEST noclprint;
CLASS Neigh PSU;
MODEL PVTSTD1 = /solution;
RANDOM int/ sub=neigh;
RANDOM int/ sub=psu(neigh);
run;

title 'Interaction Model - Students nested in Schools nested in
Neighborhoods';
PROC MIXED DATA=one METHOD = ML COVTEST noclprint;
CLASS Neigh PSU;
MODEL PVTSTD1 = new_age sex race family_ses prop_master prop_white
school_ses z_affluence
z_poverty N_prop_wht prop_urban z_affluence*school_ses
z_poverty*school_ses z_affluence*prop_master z_poverty*prop_master/solution;
RANDOM int/ sub=neigh;
RANDOM int/ sub=psu(neigh);
run;

title 'Unconditional Model - Students nested in Neighborhoods nested in
Schools';
PROC MIXED DATA=one METHOD = ML COVTEST noclprint;
CLASS Neigh PSU;
MODEL PVTSTD1 = /solution;
RANDOM int/ sub=psu;
RANDOM int/ sub=neigh(psu);
run;

title 'Interaction Model - Students Nested in Neighborhoods nested in
Schools';
PROC MIXED DATA=one METHOD = ML COVTEST noclprint;
CLASS Neigh PSU;
MODEL PVTSTD1 = new_age sex race family_ses prop_master prop_white
school_ses z_affluence
z_poverty N_prop_wht prop_urban z_affluence*school_ses
z_poverty*school_ses z_affluence*prop_master z_poverty*prop_master/solution;
RANDOM int/ sub=psu;
RANDOM int/ sub=neigh(psu);
run;

title 'Unconditional Model - Students Cross-nested in Neighborhoods and
Schools';
PROC MIXED DATA=one METHOD = ML COVTEST;
CLASS PSU Neigh;
MODEL PVTSTD1 = /solution;
RANDOM int/ sub=PSU;
RANDOM int/ sub=neigh;
run;

```

```

title 'Interaction Model - Students Cross-nested in Neighborhoods and
Schools';
PROC MIXED DATA=one METHOD = ML COVTEST;
    CLASS PSU Neigh;
    MODEL PVTSTD1 = affluence poverty N_prop_wht prop_urban prop_master
prop_white school_ses age sex race family_ses
affluence*school_ses poverty*school_ses affluence*prop_master
poverty*prop_master/solution ;
    RANDOM int/ sub=PSU;
    RANDOM int/ sub=neigh;
run;

```

Figure 2
Example PROC MIXED Code for 2-Level, 3-Level, and Cross-classified Random Effects Models

COMPARISON OF STATISTICAL RESULTS

The intraclass correlation coefficient (ICC) values for both two-level models, both three-level models, and the cross-classified model are presented in Table 3. The ICC values ranged from a high of .185 to a low of .002 across models. The two-level models indicated 14% and 19% clustering at the school or neighborhood level, respectively. A review of the ICC values produced by the three-level models suggested that the amount of clustering was highest at the third level. More specifically, when students were nested in schools nested in neighborhoods the ICC value for neighborhood was .183 and the ICC value for school was .002. This same pattern was noted when students were nested in neighborhoods nested in schools. In contrast, when we moved to the cross-classified model, where students were cross-classified between schools and neighborhoods, of these two levels, the school level accounted for more of the variance in AHPVT scores than did the neighborhood level (ICC= .117 vs. .049, respectively). However, this model generates a third ICC (neighborhood and school) which accounted for more variance in AHPVT scores than either neighborhoods or schools alone (.166).

Table 3
Intraclass Correlation Coefficient Comparison Table

	Two – Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
Neighborhood ICC	--	.185	.183	.046	.049
School ICC	.141	--	.002	.129	.117
Neighborhood + school ICC	--	--	--	--	.166

Table 4 contains the pseudo- R^2 values produced by each of the model structures. When students were nested in schools the two-level structure model pseudo- R^2 values ranged from .588 to .879. Similarly, the three-level model with school as the highest nesting structure had pseudo- R^2 values that ranged from .605 to .869. In addition, the CCREM pseudo- R^2 values were almost identical to the two-level model with students nested in schools (.589 to .879). The two-level model with students nested in neighborhoods produced pseudo- R^2 values from .704 to .928. Similarly, the pseudo- R^2 values for the three-level model with students nested in schools nested in neighborhoods ranged from .698 to .927.

Table 5 presents the model pseudo- R^2 changes for each model structure. Little variation in model fit occurred across the structures. For example, the neighborhood and school interaction model (Model 6) was never a better fitting model than the neighborhood and school main effect model (Model 5). Similarly, Model 5 was consistently a better fitting model than the neighborhood only model (Model 3) and the school only model (Model 4). Except for the comparison between the level-1 control model (Model 2) and the unconditional model (Model 1), the magnitude of the pseudo- R^2 changes for the different model comparisons were also relatively the same. The largest pseudo- R^2 change between Model 2 and Model 1 was found in the two-level neighborhood structure (.704) whereas the smallest change was found in the cross-classified (C-C) structure (.585).

Table 4
Model Pseudo- R^2 Comparison Table

	Two – Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
Model 1: Unconditional model	.000	.000	.000	.000	.000
Model 2: Level-1 control model	.588	.704	.698	.605	.589
Model 3: Neighborhood main effect model	.792	.884	.880	.796	.793
Model 4: School main effect model	.871	.893	.893	.839	.871
Model 5: Neighborhood and school main effect model	.877	.925	.924	.866	.878
Model 6: Neighborhood and school interaction model	.879	.928	.927	.869	.879

Table 5
Model Pseudo- R^2 Change Comparison Table

	Two – Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
Δ pseudo- R^2					
Model 6 to Model 5	.002	.003	.003	.003	.003
Model 5 to Model 4	.006*	.031*	.031*	.027*	.028*
Model 5 to Model 3	.084*	.040*	.044*	.070*	.073*
Model 5 to Model 2	.288*	.220*	.226*	.261*	.272*
Model 2 to Model 1	.588*	.704*	.698*	.605*	.585*

Table 5
Model Pseudo- R^2 Change Comparison Table

	Two – Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
	$\Delta -2LL$ (obtained χ^2)				
Model 6 to Model 5 (Δ df =4)	2.7	3.9	3.8	2.7	2.4
Model 5 to Model 4 (Δ df =4)	67.4	62.0	62.0	58.7	55.9
Model 5 to Model 3 (Δ df =3)	37.3	68.5	68.1	36.4	36.5
Model 5 to Model 2 (Δ df =7)	146.3	266.0	265.0	136.4	133.5
Model 2 to Model 1 (Δ df =4)	1205.4	1183.1	1184.0	1125.2	1108.8

* $p < .05$

Table 6 presents the results of the neighborhood and school main effect model (Model 5) when the model was estimated using both two-level structures, both three-level structures, and the cross-classified structure. In Model 5, the point estimates of the model intercept were nearly identical across all structures with the exception of the C-C structure (92.08 vs. > 94 for the others), but the standard errors of the intercept differed. Both the two-level and the three-level school models estimated the intercept standard errors to be greater than 0.90, whereas the two-level and the three-level neighborhood models estimated the standard errors to be 0.66. Finally, the C-C structure estimated the largest standard error (1.23).

The differences among the model structures in the parameter estimates and standard errors for the level-1 variables differed across the four variables. For example, the point estimates of the parameters for age were -0.17 for the two neighborhood models, but were -0.42 for the two school models. This parameter estimate was -0.40 for the C-C structure. Despite these differences in the point estimates, the standard errors were nearly identical across the five model structures (0.08 to 0.09). The other level-1 variables (biological sex, race, and family SES) evidenced nearly identical point estimates and standard errors across the structures examined.

Similar inconsistencies were evident for the neighborhood variables. The parameter estimates for neighborhood affluence were 0.70 for the two neighborhood models, but were 1.04 and 1.01 for the two-level and three-level school models, respectively, and 1.00 for the CCREM. In contrast, the standard errors for this parameter estimate were nearly identical across the five structures (0.24 to 0.26). Neighborhood racial composition and urbanicity evidenced notable differences in both the point estimates and the standard errors, with the two-level and three-level neighborhood models providing nearly identical results, but results that differed from those of the school-level models and the CCREM. Finally, the coefficients and standard errors for neighborhood poverty were nearly identical across the five structures examined.

The school-level factors (school SES, teacher education, and student body racial composition) yielded nearly identical point estimates and standard errors for the two neighborhood models, but these results differed from those of the other models. The point estimates for school SES were nearly the same across all of the structures (0.81 to 0.89), but the standard errors were larger for the two school models and the CCREM. Similarly, larger standard errors were obtained in the two school models and the CCREM for teacher education, and point estimates showed larger differences (ranging from -0.21 to 0.22). Student body racial composition evidenced larger point estimates (4.90 to 4.94) for the school-level models and the CCREM, and also presented larger standard errors (1.04 to .108) than were observed in the neighborhood structures.

An examination of the random effects results in Table 6 reveals similar inconsistency of the differences in estimates across these five structures. Across all structures, nearly identical values were obtained for the level-1 variance (162.40 to 163.64) and its standard error (2.23 to 2.28). In contrast, the variance of the neighborhood intercepts ranged from 1.57 (in the three-level school model) to 2.997 (in the two-level neighborhood model) and the standard errors of the neighborhood variances ranged from 0.66 (in the CCREM) to 1.10 (in the three-level neighborhood model). Similarly, the variance in the school intercepts differed across the structures examined, ranging from 0.14 (in the three-level neighborhood model) to 3.68 (in the two-level school model). However, the estimated standard errors of these parameter estimates were more consistent across the structures, ranging from 0.94 to 1.10.

Table 6
Neighborhood and School Main Effect Model (Model 5) Comparison Table (n=10,860)

	Two-Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
<i>Fixed Effects</i>					
Intercept	94.08* (0.92)	94.06* (0.66)	94.05* (0.66)	94.05* (0.93)	92.08* (1.23)
Age	-0.42* (0.09)	-0.17* (0.08)	-0.17* (0.08)	-0.42* (0.09)	-0.40* (0.08)
Biological sex	1.44* (0.25)	1.40* (0.25)	1.41* (0.25)	1.44* (0.25)	1.44* (0.24)
Race	-3.78* (0.33)	-3.67* (0.33)	-3.67* (0.33)	-3.79* (0.33)	-3.76* (0.33)
Family SES	4.72* (0.18)	4.74* (0.18)	4.74* (0.18)	4.70* (0.18)	4.70* (0.18)
Neighborhood affluence	1.04* (0.24)	0.70* (0.25)	0.70* (0.25)	1.01* (0.26)	1.00* (0.26)
Neighborhood poverty	0.05 (0.19)	0.05 (0.20)	0.05 (0.20)	0.08 (0.21)	0.08 (0.21)
Neighborhood racial composition	4.47* (0.95)	5.41* (0.87)	5.42* (0.87)	4.46* (1.00)	4.54* (1.02)
Urbanicity	-1.11* (0.47)	-0.89* (0.38)	-0.89* (0.38)	-1.10* (0.49)	-1.12* (0.50)
School SES	0.81* (0.37)	0.89* (0.29)	0.89* (0.30)	0.85* (0.38)	0.84* (0.38)
School-level teacher education	0.22 (0.999)	-0.09 (0.63)	-0.09 (0.63)	-0.21 (1.01)	0.15 (1.01)
Student body racial composition	4.95* (1.04)	4.41* (0.78)	4.40* (0.78)	4.90* (1.07)	4.93* (1.08)
<i>Error Variance</i>					
Level-1	163.64* (2.23)	163.34* (2.26)	163.30* (2.28)	162.42* (2.26)	162.40* (2.25)
Intercept (Neighborhood)	--	2.997* (0.75)	2.91* (1.10)	1.57* (0.71)	1.64* (0.66)
Intercept (School)	3.68* (0.94)	--	0.14 (1.10)	3.42* (0.97)	3.30* (0.96)

* $p < .05$. Values based on SAS Proc Mixed. Entries show parameter estimates with standard errors in parentheses.

The results for the neighborhood and school interaction model (Model 6) are presented in Table 7. Again, the model was estimated using both two-level structures, both three-level structures, and the C-C structure. As with the main effect model, the intercept values were very similar across structures; with the C-C structure yielding a slightly lower intercept than the others (91 vs. 94). The standard errors were more variable with the CCREM standard error of 1.75 being considerably higher than the next highest value of 0.94. Turning to the level-1 predictors we saw differences in the coefficients across the structures. For age, the estimate varied from -0.42 to -0.17, as it did in Model 5, and again the

standard errors were similar (ranging from 0.08 to 0.09). The other level-1 variables were very similar in the point estimates and the standard errors, which again mirrors what was seen for the neighborhood and school main effect models.

Inconsistencies were also evident for the neighborhood variables. For neighborhood affluence, not only did the point estimates and standard errors differ across structures, but also whether or not the estimate was statistically significant (at $\alpha = .05$). The estimate was statistically significant for the two-level school structure, but not statistically significant for the other structures. With the other neighborhood variables (neighborhood poverty, neighborhood racial composition, and urbanicity) there were inconsistencies in the point estimates and standard errors, but consistency in whether an effect was statistically significant. The pattern for these other variables was similar to what was seen in the neighborhood and school main effect models.

The estimates for school variables (school SES, teacher education, and student body racial composition) also varied across structures, and in some cases the differences were quite substantial. For school SES the C-C structure resulted in a point estimate of 0.20, which was not statistically significant. For the other structures the point estimates ranged from 0.72 to 0.78, and were statistically significant for three of the four structures. The point estimate for teacher education also varied considerably with a value of 1.93 for the C-C structure and values between -0.08 and 0.24 for the other structures. This divergence of the C-C structure from the other structures for these school variables is notably more substantial than what was seen in the main effect models.

None of the interaction terms were statistically significant for any of the structures, but the magnitude of point estimates and standard errors did vary across structures. The largest discrepancies were with the interaction of neighborhood affluence and school-level teacher education, where the point estimates ranged from 0.05 in the two-level school structure to 0.85 in both the neighborhood two-level and neighborhood three-level structure. In contrast, the interaction between neighborhood affluence and school SES showed little variation in the point estimates, which ranged from -0.06 to -0.01. Although the standard error varied across the structures, they were more similar than different for each of the interaction terms.

Consideration of the random effects in Table 7 shows a pattern that is very similar to what was seen in the main effect model of Table 6. Again, there were small differences across structures in the level-1 variance (162.4 to 163.6) and its standard error (2.23 to 2.28), and larger differences in the level-2 variances. The neighborhood variance estimates ranged from 1.56 in the three-level school structure to 2.88 in the two-level neighborhood structure. The school variance ranged from 0.07 in the three-level neighborhood structure to 3.61 in the two-level school structure.

Table 7
Neighborhood and School Interaction Model (Model 6) Comparison Table (n=10,860)

	Two-Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
<i>Fixed Effects</i>					
Intercept	94.16* (0.92)	94.14* (0.67)	94.14* (0.67)	94.12* (0.94)	91.43* (1.75)
Age	-0.42* (0.09)	-0.17* (0.08)	-0.17* (0.08)	-0.42* (0.09)	-0.40* (0.08)
Biological sex	1.44* (0.25)	1.41* (0.25)	1.41* (0.25)	1.44* (0.25)	1.44* (0.24)
Race	-3.78* (0.33)	-3.69* (0.33)	-3.69* (0.33)	-3.79* (0.33)	-3.76* (0.33)
Family SES	4.72* (0.18)	4.74* (0.18)	4.74* (0.18)	4.70* (0.18)	4.70* (0.18)
Neighborhood affluence	1.01* (0.44)	0.30 (0.46)	0.30 (0.46)	0.92 (0.48)	0.89 (0.49)
Neighborhood poverty	0.42 (0.36)	0.31 (0.36)	0.31 (0.36)	0.48 (0.40)	0.46 (0.40)
Neighborhood racial composition	4.23* (0.97)	5.11* (0.88)	5.12* (0.88)	4.32* (1.02)	4.31* (1.04)
Urbanicity	-1.08* (0.47)	-0.83* (0.38)	-0.83* (0.38)	-1.06* (0.49)	-1.08* (0.50)

Table 7
Neighborhood and School Interaction Model (Model 6) Comparison Table (n=10,860)

	Two-Level School Model (Students Nested in Schools)	Two-Level Neighborhood Model (Students Nested in Neighborhoods)	Three-Level Neighborhood Model (Students Nested in Schools Nested in Neighborhoods)	Three-Level School Model (Students Nested in Neighborhoods Nested in Schools)	Cross-Classified Random Effects Model (Students Cross- Nested in Schools and Neighborhoods)
School SES	0.72 (0.37)	0.78* (0.30)	0.78* (0.30)	0.76* (0.38)	0.20 (1.07)
School-level teacher education	0.24 (1.01)	-0.08 (0.64)	-0.08 (0.64)	0.23 (1.02)	1.93 (3.02)
Student body racial composition	5.19* (1.05)	4.68* (0.79)	4.68* (0.79)	5.15* (1.08)	5.18* (1.08)
Neighborhood affluence*	-0.02 (0.27)	-0.06 (0.24)	-0.06 (0.24)	-0.01 (0.28)	-0.03 (0.28)
school SES					
Neighborhood poverty*	0.28 (0.26)	0.21 (0.27)	0.21 (0.27)	0.27 (0.28)	0.25 (0.28)
school SES					
Neighborhood affluence*	0.05 (0.82)	0.85 (0.80)	0.85 (0.81)	0.18 (0.88)	0.22 (0.88)
school-level teacher education					
Neighborhood poverty*	-0.90 (0.74)	-0.63 (0.73)	-0.63 (0.73)	-0.94 (0.80)	-0.90 (0.80)
school-level teacher education					
<i>Error Variance</i>					
Level-1	163.61* (2.23)	163.35* (2.26)	163.33* (2.28)	162.41* (2.27)	162.40* (2.25)
Intercept (Neighborhood)	--	2.88* (0.74)	2.83* (1.07)	1.56* (0.71)	1.62* (0.66)
Intercept (School)	3.61* (0.95)	--	0.07 (1.08)	3.35* (0.97)	3.23* (0.96)

* $p < .05$. Values based on SAS Proc Mixed. Entries show parameter estimates with standard errors in parentheses.

CONCLUSIONS

Not only is the utilization of CCREMs in social and behavioral science rare, but our empirical understanding of CCREMs through simulation research is also limited. Thus, even though the findings from the current study are based on one database and therefore have limited generalizability, several summative statements are still warranted. First, findings from the current study contradict those from previous simulation and applied research. For example, according to previous simulation research findings, when cross-classification of data is ignored and models are misspecified as purely hierarchal 2-level models, fixed effects are not biased but standard errors are underestimated and variance components are biased (Myers & Beretvas, 2007). However, a slightly different pattern was seen when CCREMs and hierarchical 2-level models were compared using NELS:88 data; variance components varied across the models, yet neither the fixed effects nor the standard errors were appreciably affected when the cross-classification was ignored (Myers & Beretvas, 2007).

Second, although there was variation in the pseudo- R^2 values and parameter estimates across the nesting structures examined in the current study, similarities in the data were also evident. For example, the two-level school structure and the three-level school structure produced relatively similar pseudo- R^2 values, fixed-effect parameter estimates, variance components, and standard errors. The same pattern of relatively similar results also occurred with the two-level and three-level neighborhood structures. Furthermore, although results from the C-C structure were typically different from those obtained using the neighborhood structures, they were similar to values produced by the school structures. Given the cross-classified structure of the Add Health data (i.e., many neighborhoods associated with each school, but few schools associated with each neighborhood) these similarities are not surprising.

Third, given that the sampling process employed with the Add Health study is similar to those used with other national studies (i.e., sampling at the school level and not neighborhood-school combinations), the low level of cross-classification evident in these data is likely similar to the structure of other national databases. Thus, the question still remains – are CCREMs necessary if the structure of the data does not reflect the theoretical cross-classification of students, schools, and neighborhoods? Based on the nesting structures examined in the current study, although the three-level model with students nested in neighborhoods nested in schools and the CCREM produced similar point estimates and standard errors, these statistics, for all but two variables, were not identical. Therefore, it does not appear that they are interchangeable model structures. With that said, based on the limited findings from our study, even if data have low levels of cross-classification, if the data are theoretically cross-classified, researchers should still consider using CCREMs to avoid theoretical model misspecification. However, to better understand the empirical consequences of ignoring cross-classified data structures under a variety of conditions, more simulation research is needed.

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