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Latent Class Analysis: A Guide to Best Practice

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Abstract

Latent class analysis (LCA) is a statistical procedure used to identify qualitatively different subgroups within populations who often share certain outward characteristics. The assumption underlying LCA is that membership in unobserved groups (or classes) can be explained by patterns of scores across survey questions, assessment indicators, or scales. The application of LCA is an active area of research and continues to evolve. As more researchers begin to apply the approach, detailed information on key considerations in conducting LCA is needed. In the present article, we describe LCA, review key elements to consider when conducting LCA, and provide an example of its application.

Keywords

latent class analysis, social determinants of health, National Survey of Children's Health, behavior problems, ADHD

Latent class analysis (LCA) is a statistical procedure used to identify qualitatively different subgroups within populations that share certain outward characteristics (Hagenaars & McCutcheon, 2002). Subgroups are referred to as

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latent groups (or classes). To detect the latent groups, LCA uses study participants' responses to categorical indicator variables. When indicators are continuous, latent profile analysis, a similar statistical technique, is used. In this article, we focus on LCA, but much of the information presented also applies to latent profile analysis.

In more technical terms, LCA is used to detect latent (or unobserved) heterogeneity in samples (Hagenaars & McCutcheon, 2002). It is a special case of person-centered mixture modeling that identifies latent subpopulations within a sample based on patterns of responses to observed variables (B. O. Muthén & Muthén, 2000). The assumption underlying LCA is that membership in unobserved classes can cause or explain patterns of scores across survey questions, assessment indicators, or scales (B. O. Muthén & Muthén, 2000; Wolke et al., 2013). Based on the statistical theory, individuals' scores on a set of indicator variables are driven by their class membership. This concept is similar to the notion of a latent construct driving scores on scale items in factor analysis procedures (Kline, 2016).

LCA was first introduced in 1950 (Lazarsfeld, 1950) and has since undergone a number of revisions and advancements (for a full summary, see Clogg, 1981, 1995; Hagenaars, 1990; Vermunt, 1997; Nylund-Gibson & Choi, 2018). As LCA continues to evolve, scholars have debated several key issues: (a) selecting indicator variables, (b) selecting the final class model, and (c) deciding how to include covariates and which statistics to report in studies. Because of these debates, a number of recent systematic reviews have been conducted to summarize the LCA literature (e.g., Killian et al., 2019; Petersen et al., 2019; Ulbricht et al., 2018). Results from the reviews indicated reporting practices varied widely and studies rarely tested advanced models, such as longitudinal LCA models, measurement invariance models, or models with covariates.

Because of the continued evolution of LCA, in this article, we provide a review of LCA and its advancements. In particular, we focus on foundational decisions in conducting LCA, including selecting indicator variables and choosing a final class model. We briefly mention how to include covariates in models and also provide our perspective of best practices in reporting. Prior to presenting this information, however, we summarize the similarities and differences between LCA and cluster analysis.

LCA and Cluster Analysis

Researchers may wonder what differentiates LCA from cluster analysis. The two statistical procedures are similar in a number of ways; for example, they are both considered "person-oriented analyses" (Collins & Lanza, 2010), which use patterns of scores across cases to identify individuals who can be grouped together. In contrast, variable-centered approaches look for relationships among variables. In both cluster analysis and LCA, a series of solutions are generated—each with one more class than the previous one. Researchers use statistical and theoretical criteria to decide which solution is best.

Despite these similarities, cluster analysis and LCA make different assumptions about the data and use different statistical procedures. In cluster analysis, the assumption is that the cases with the most similar scores across the analysis variables belong in the same cluster (Norusis, 1990). LCA, on the other hand, is based on the assumption that latent classes exist and explain patterns of observed scores across cases. In cluster analysis, variable means are used to define "nearness" of cases; therefore, analysis variables should be continuous. In LCA, because the analysis variables are categorical, cross-tabulations are used as the input information (Collins & Lanza, 2010). Case membership in clusters is determined in cluster analysis. In LCA, *probabilities* of class membership are obtained, not clear-cut assignments. However, both procedures can generate categorical classification variables for use in other analyses.

Limitations of LCA

Although LCA is a powerful statistical procedure, it has limitations. LCA assigns individuals to classes based on their probability of being in classes given the pattern of scores they have on indicator variables (B. O. Muthén & Muthén, 2000). Proper class assignment is not guaranteed. Also, because class assignment is based on probabilities, the exact number or percentage of sample members within each class cannot be determined. Furthermore, researchers usually assign names to the identified classes and, because of the complexity of the classes, may advertently engage in "naming fallacy," wherein the name of the class does not accurately reflect the class membership. Researchers need to consider these limitations when publishing study findings.

Software

LCA can be conducted using several commercial and free statistical packages, including STATA (StataCorp LLC, 1985-2019), SAS (SAS Institute Inc., 2016), R (Venables & Smith, 2019), and M*plus* (L. K. Muthén & Muthén, 1998-2017). Packages have been developed specifically for conducting LCA, including LatentGold (Vermunt & Magidson, 2016) and poLCA for R (Linzer & Lewis, 2011). Most recent research has used M*plus* (Killian et al., 2019; Petersen et al., 2019). M*plus* is a syntax-driven statistical package that can be used for both basic LCA modeling and modeling with issues, such as complex survey design and missing data (Muthén & Muthén).

LCA Decisions

Conducting LCA requires researchers to make a number of statistical and theoretical decisions. These decisions often intersect; however, for clarity, we discuss them as discrete steps.

Selection of Participants

LCA has been used to study a variety of issues and vulnerable populations, such as mental health among Black youth (Rose et al., 2017), adolescent perceptions of in-school discrimination (Byrd & Carter-Andrews, 2016), and young Malawaian adults with or at-risk for HIV (Weller & Small, 2015). As with all research, the choice of the population in LCA studies needs to be theoretically justified.

LCA can be particularly useful for identifying subgroups of individuals who could benefit from a common intervention based on their shared characteristics. For example, LCA has been used to identify latent classes based on youth's experience with vicarious and anticipated strain (Weller et al., 2013). Four classes of strain were identified and then linked to appropriate interventions.

Sample Size

Sample size is an evolving area of study in the LCA literature. As with other types of structural equation modeling (SEM), the answer to the question of what is an appropriate sample size for LCA is, "more is better, but it depends." Based on numerous studies, Nylund-Gibson and Choi (2018) suggest that 300 or more cases is desirable. But smaller samples may be adequate with simpler models (fewer indicators and classes) and "well-separated" classes (Nylund-Gibson & Choi). Potential analysis problems with low sample sizes include poor functioning fit indices, convergence failures, and failure to uncover classes with low memberships (Nylund-Gibson & Choi). Another approach to determining sample size is to conduct Monte Carlo simulations (L. K. Muthén & Muthén, 2002). However, this approach is most commonly used in LCA methodological papers (e.g., Kim & Wang, 2019; Lythgoe et al., 2019; Shin et al., 2019).

Selecting Indicator Variables

Once the sample has been selected, researchers will select the indicator variables that will be used to define the hypothesized unobserved classes. Currently, no consensus exists on the number of indicator variables to include in a model, but generally more indicator variables lead to better results (Wurpts & Geiser, 2014). Studies have used as few as four indicator variables (Travis & Combs-Orme, 2007), whereas other studies have used more than 20 indicators (Rosato & Baer, 2012). Although researchers can use LCA as an exploratory statistical approach, theory should guide the choice of indicator variables. Having a strong theoretical rationale for using specific indicator variables makes the process of identifying the classes easier, helps with interpreting the results, and results in class solutions that have clearer application to practice.

After indicators have been chosen, decisions must be made about whether they will be recoded or analyzed with their original response options. Polytomous variables maybe collapsed into a smaller set of options for a number of reasons including theory and previous research. For example, if risk status is of interest in class formation, multiple response categories associated with negative outcomes may be collapsed into a "risk present" category and the rest collapsed into a "risk not present" category. Cell sizes may also influence recoding decisions; responses with small cell sizes may need to be collapsed into larger categories. Finally, collapsing multiple response options into two or three options makes it easier to interpret the class solution when indicator variables have fewer levels. At this stage, researchers should consider reverse coding variables if it will help in the interpretation of classes. For example, if risk status is of interest, the indicator variables should be coded so that higher scores indicate risk (e.g., 0 = *risk not present*, 1 = *risk present*).

Structuring the Data Set

A number of tasks help prepare data files from general statistics programs for analysis in a program to be used for the LCA. For researchers using M*plus* (L. K. Muthén & Muthén, 1998-2017), for example, we recommend recoding missing values for all variables into a numeric value outside the range of response options or using −999. It is also helpful to sort the data file by subject identification variable so new variables generated by the LCA can be merged back into the data set and aligned with confidence with the correct IDs. An abbreviated file with only the class variables, subject ID, and potential covariates can be saved for use in the LCA program; alternatively, the entire file may be saved. It is also useful to print frequencies for the analysis variables from a general statistics program to confirm later that the LCA software has read the text file correctly.

Estimators

Prior to conducting LCA, researchers may need to decide which estimator to use. LCA models can be performed using a variety of estimators, and software programs often have a default estimator (e.g., M*plus* defaults to maximum likelihood; L. K. Muthén & Muthén, 1998-2017). However, the choice of an estimator depends on criteria, such as sample size, number of variables, computation speed, and the management of missing data (B. O. Muthén et al., 2015). Selecting an estimator also depends on the reporting conventions in researchers' discipline. For example, some professions prefer probit over logit regression results. Because the selection is based on a range of criteria, we suggest researchers new to LCA use the default estimators until they begin to conduct more advanced LCA models.

Conducting LCA

The standard procedure for conducting LCA is to conduct a sequence of models, starting with a one-class model and then specifying models with one additional class at a time. Researchers then compare the models based on statistical and substantive criteria. Researchers continue to run models with one additional class at a time until the best model is identified. For example, if the two-class model fits the data better than the one-class model, then the three-class model should be run and compared with the two-class model. Typically, model quality improves with additional classes until an optimal solution is found, and then model quality begins to deteriorate. Although comparing models based on criteria sounds uncomplicated, researchers will find that in practice the process of choosing the best model is often not straightforward. Moreover, researchers will often have to include various combinations of indicator variables prior to finding a final class model.

Selecting a Class Solution: Statistical Criteria

Prior to reviewing the statistical criteria, researchers can use to select a final class model. However, we first acknowledge that the criteria used to decide the number of classes is a continuously evolving (and sometimes debated) area of inquiry. Nonetheless, statistical criteria should always be evaluated in conjunction with interpretability (B. O. Muthén & Muthén, 2000; Shanahan et al., 2013; Stringaris et al., 2013). A class solution with superior statistics is not useful if it makes no sense theoretically.

Although there is no consensus about the *best* criteria for comparing latent class solutions, there is some agreement that to select a final model (a) multiple fit statistics should be used (or at least reported); (b) the Bayesian information criterion (BIC) may be the most reliable fit statistic and should routinely be reported (Nylund et al., 2007; Vermunt, 2002); and (c) theoretical interpretability should be considered in choosing a solution (B. O. Muthén & Muthén, 2000; Nylund et al., 2007; Shanahan et al., 2013; Stringaris et al., 2013). To evaluate model fit based on statistical criteria, we recommend researchers make a table with statistical information for each class solution. Often such tables are included in articles reporting LCA results.

A number of statistical criteria are used to evaluate model fit. In this article, we review the most common fit statistics. The most reported is the Bayesian Information Criterion (BIC; Killian et al., 2019). Some researchers consider it the most reliable indicator of model fit (Nylund et al., 2007; Vermunt, 2002). The BIC rewards parsimony in models and can be used to compare competing LCA solutions. Lower BICs indicate better fit. Other information criterion (IC) can also be examined, including the Akaike information criterion (AIC), sample-size adjusted Bayesian information criterion (SABIC), and consistent Akaike information criterion (CAIC). Lower ICs also indicate better fit. Nylund-Gibson and Choi also introduce the concept of using an elbow plot of fit statistics to examine model fit. With this approach, researchers plot a fit statistic and identify where the fit visually changes.

Other fit statistics can also be used to select a final class, such as likelihood tests (i.e., Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (Lo et al., 2001; Vuong, 1989) and the bootstrapped likelihood ratio test (McLachlan & Peel, 2000). These statistics provide a *p* value, which indicates if one model is statistically better than another (Nylund et al., 2007). Researchers can also use the Bayes factor (BF) and correct model probability (Masyn, 2013), both of which require computation by the researcher. A full review of fit criteria can be found in other publications (see Nylund-Gibson & Choi, 2018).

In addition to evaluating fit, researchers need to review classification diagnostics (Masyn, 2013). Although diagnostic statistics are not used to select the final class model, they are important for consideration. It should be noted that historically some of the diagnostics were used to select a final model (B. O. Muthén, 1998-2004); however, suggestions on their use have recently changed (Nylund-Gibson & Choi, 2018). The *average latent class posterior probability* is the average probability of the class model accurately predicting class membership for individuals (B. O. Muthén & Muthén, 2000). The average latent posterior probabilities are presented in a matrix with diagonals representing the average probability of a person being assigned to a class given his or her scores on the indicator variables used to create the classes. Higher diagonal values (i.e., closer to 1.0) are desirable. Off-diagonal elements in the posterior probability matrix contain probabilities of cases that belong in one class being assigned to another class in the current solution. Lower values off the diagonal (i.e., closer to 0) are desirable. Some researchers using LCA use a .80 cutoff for acceptable diagonal probabilities (Weden

& Zabin, 2005). Others suggest a cutoff value of greater than .90 (B. O. Muthén & Muthén, 2000). We agree that greater than .90 is ideal; but if other criteria are met and the model is theoretically supported, probabilities between .80 and .90 are acceptable. Although meeting the .90 criterion for all average latent class posterior probabilities is not required when other criteria are met, values less than .80 should be considered unacceptable.

Entropy is another diagnostic statistic (Wang et al., 2017). It indicates how accurately the model defines classes. In general, an entropy value close to 1 is ideal (Celeux & Soromenho, 1996) and above .8 is acceptable. There is no agreed upon cutoff criterion for entropy (B. O. Muthén, 2008); however, it may be difficult to publish a study with an entropy below .6. Researchers are encouraged to examine and report entropy, but not to rely on the value to determine the final class solution.

Researchers may also want to consider the number of sample members in each class. There are no existing guidelines on determining class size (Muthén, personal communication, May 4, 2011). Previously, LCA scholars have contended that researchers should not have class sizes with fewer than 50 cases (B. O. Muthén & Muthén, 2000) and classes should not contain less than 5% of the sample (Shanahan et al., 2013). However, these suggestions have been relaxed and a number of publications have included class sizes smaller than 5% or 50 cases (e.g., O'Donnell et al., 2017). The important issues to consider when deciding if a class size is too small is whether the model fit statistics support the selected model, and whether the small class makes conceptual sense. As researchers consider the size of each class, they need to also consider the sample size.

Including Covariates in LCA

An evolving topic in the LCA literature is including covariates in models. Including covariates in LCA allows researchers to answer questions such as "Does the composition of the classes differ by sociodemographic characteristics?" Previously, researchers would include covariates in the same model as the model used to identify the class solution (Vermunt, 2010). This one-step approach, however, can result in flawed, miss-specified models (Nylund-Gibson & Masyn, 2016). The one-step approach has been replaced with a number of newer approaches. Currently, researchers are encouraged to employ either a new three-step approach (Asparouhov & Muthén, 2014; B. O. Muthén & Muthén, 2000; Vermunt, 2002) or the Bolck et al.'s (2004) approach. Both of these approaches require researchers to identify the measurement model (e.g., the final class model using fit statistics) and then add covariates. In the models with covariates, researchers fix the measurement parameters to those obtained in the model without covariates. Because nuances of including covariates in LCA models vary by statistical software and the approaches used, researchers are encouraged to consult articles with details on the topic (e.g., Asparouhov & Muthén 2014; Nylund-Gibson & Choi, 2018; Nylund-Gibson & Masyn, 2016; Vermunt & Magidson, 2016).

Interpretation and Implication for Practice

LCA assumes that latent class membership helps explain the patterns of individuals' scores on the indicator variables used to derive the classes. Class solutions represent typologies that can help researchers and practitioners understand commonalities and differences across individuals that have implications for practice and future research. Researchers who develop typologies must interpret classes theoretically and explain the implications of class membership for practice. We have found it helpful to use theory or previous research to inform the number of classes we anticipated finding (Bowen et al., 2007; Weller et al., 2013).

Validating the LCA Model

A final and critical step in applying LCA is to validate the selected class solution. Although it is possible to publish LCA results without validation, we argue that this step is imperative for ensuring the typology is relevant to practice. Validating the model involves determining if class assignments are related as expected to relevant outcomes.

Reporting the Results

To present clear results and justified conclusions, LCA reports need to detail study procedures and results with clarity and coherence (Appelbaum et al., 2018). In addition, LCA studies should include the items listed in Table 1. Despite variation in researchers' perspectives (e.g., Nylund et al., 2007; Schreiber, 2017) on which model statistics to report, we recommend reporting the BIC and at least two additional fit indices, as well as entropy, the percentage and size of the smallest class, and the smallest off-diagonal value of the average latent class posterior probability matrix. If other criteria are used to evaluate the model, researchers should also report this information.

Example of an LCA Report

In the following example of an LCA report, we aimed to (a) identify latent profiles of social determinants of health among Black adolescents, and (b)

Table 1. Information to Include in an LCA Report.

- Rationale for the selected indicator variables, if based on theory
- Rationale for conducting exploratory models, if not based on theory
- Data characteristics (e.g., descriptive statistics, missing data)
- Statistical package and year
- Estimation method
- Criteria used for selecting class model, both statistical (e.g., BIC, SABIC, CAIC) and substantive
- Table that includes at least two fit criteria, entropy, and smallest average latent class posterior probability
- Figure of identified classes
- Number of sample or percentage of sample in each class

Note: LCA = latent class analysis; BIC = Bayesian Information Criterion; SABIC = sample-size adjusted BIC; CAIC = consistent Akaike information criterion.

examine whether the profiles were associated with behavior problems and attention deficit/hyperactivity disorder (ADHD). To guide this analysis, we used a social determinants of health framework (Secretary's Advisory Committee on Health Promotion and Disease Prevention Objectives for 2020, 2010). This framework includes social- and place- based conditions that promote health and address disparities. Using this framework, we were able to identify co-occurring social determinants of health and examine whether the classes based on the determinants were associated with mental health outcomes among a nationally representative sample of Black adolescents.

Method

Participants

We conducted secondary data analysis using data from caregivers who completed the 2016 and 2017 National Surveys of Children's Health (Child and Adolescent Health Measurement Initiative, 2016). The data are from caregivers of noninstitutionalized youth aged 0 to 17 years from the District of Columbia and all 50 states. A complex data collection procedure was used to ensure caregivers were randomly selected for participation. Furthermore, in homes where multiple youths reside, one youth was randomly selected to be the focus of the survey. Therefore, data from this data set are generalizable to all Hispanic, non-Hispanic Black, and non-Hispanic White youth in the United States. For the current study, we used a subpopulation of the sample; results from the current study are generalizable to only noninstitutionalized U.S. Black adolescents (aged 12-17 years). The current study was considered exempt from human subjects review by the appropriate university's institutional review board.

Measures

Mental health outcomes. The National Survey of Children's Health (NSCH) collects caregiver report data on whether a provider ever told the caregivers their adolescent had a mental health condition. The Center provides coding recommendations (for full information about coding, see Child and Adolescent Health Measurement Initiative, 2018), which we used. We examined whether adolescents currently had behavior problems or ADHD. Items used to measure the two outcomes were coded dichotomously (*yes current*, *no never*; *or previously told but not currently*).

Indicators of social determinants of health. To identify profiles of social determinants of health, we included 10 indicator variables. *Adequate insurance coverage* was measured as children having current health insurance that usually or always meets their needs, allows them to see needed providers, and generates either reasonable or no out-of-pocket expenses. Based on this information, this variable was coded dichotomously (*has adequate insurance coverage or does not have adequate insurance coverage*). *Transition to adult health care* was measured as a doctor speaking alone with an adolescent during a preventative checkup and doctors actively discussing and working with an adolescent to gain skills and understand transitions into adult health care if needed. Based on this information, this variable was coded dichotomously (*received adequate transition to adult healthcare* or *did not receive adequate transition to adult health care*). If one of the criterion variables received a positive response and the remainder were legitimately skipped or missing, youth were coded as *received adequate transition*.

School engagement was measured as a child caring about doing well in school and completing all required homework. Children whose caregivers responded to both of these statements as "definitely true" were coded as *engaged in school*, whereas children whose caregivers responded "somewhat true" or "not true" were coded *not engaged in school. After-school activities* was measured by child involvement in sports teams or lessons, clubs or organizations, or any other organized activities, such as music, dance, language, or other arts; participation was coded dichotomously (*participated in activity* or *did not participate*). *Food insufficienc*y was based on caregivers selecting the statement that best described the food situation in the adolescent's home in the previous 12 months. This variable was coded with four options ([a] *we could always afford to eat good nutritious meals*, [b] *we could always afford enough* *to eat but not always the kinds of food we should eat*, [c] *sometimes we could not afford enough to eat*, [d] *often we could not afford enough to eat*).

Experiencing discrimination based on race or ethnic origin and *presence of a mentor* (measured as an adult outside of the home who the child can rely on for advice or guidance) were coded dichotomously (*yes* or *no*). Neighborhood and school safety were coded according to level of caregiver agreement with the statement that their child is safe in the relevant environment (*definitely agree, somewhat agree, somewhat disagree*, or *definitely disagree*). Neighborhood support was generated from three survey items: (a) people in a neighborhood helping one another, (b) watching one another's children, and (c) knowing where to go for help. If caregivers responded "definitely agree" to at least one item and "somewhat agree" or "definitely agree" to the remaining two items, neighborhood support was considered present; responses were then coded dichotomously (*live in supportive neighborhoods* or *do not live in supportive neighborhoods*).

Covariates. Consistent with previous research using data from the NSCH, we included the following control variables: gender, income based on federal poverty level, highest level of education, and primary language spoken in the home (e.g., Butler et al., 2015; Weller et al., 2018; Weller et al., 2019).

Analysis. We used M*plus* 8.2 to conduct all analyses (L. K. Muthén & Muthén, 1998-2017). Due to the complex survey design, our models included a cluster variable and sampling weights. We specified the maximum likelihood estimation with robust standard errors (B. O. Muthén et al., 2015). To address missing data, in these models, we used the likelihood based estimation default in M*plus* (Asparouhov, 2016).

To identify profiles of social determinants of health (Aim 1), we first estimated a one class model and then added classes until we identified the model with the best fit. We examined model fit based on our theoretical understanding of the social determinants of health (Secretary's Advisory Committee on Health Promotion and Disease Prevention Objectives for 2020, 2010) and the following statistical criteria: (a) the BIC, with lower BIC indicating better model fit (Nylund et al., 2007), and (b) the BF, with values of 3 or higher being desirable (Masyn, 2013). LMR or bootstrapped likelihood ratio test were not examined because they cannot account for the complex data (B. O. Muthén, 2016). We reported other fit statistics to demonstrate other types of model quality statistics researchers can report.

Although not used to select a final model, we also examined several diagnostic criteria. First, we sought an entropy above .8, even though no definitive conventional cutoff criterion exists (B. O. Muthén, 2008). We further sought to have the lowest average latent class posterior probability be .80 or higher (Nagin & Land, 1993; Weden & Zabin, 2005).

After we identified the best class model, we then assigned each case to a specific class based on their posterior class membership probabilities and then fixed the measurement parameters of the LCA model (Asparouhov & Muthén, 2014; Vermunt, 2010). Although we did not specify a research question related to covariates, including the covariates were consistent with previous research using the NSCH data set and allowed us to demonstrate how covariates can be included in LCA models. Using the new three-step approach to including covariates (and distal outcomes), we specified multiple covariates and mental health outcome as auxiliary variables.

Last, we used pairwise Wald tests results (produced during the new three-step approach mentioned above) to examine whether profiles of social determinants of health were associated with four mental health outcomes (Aim 2). We assessed for significant differences between classes and the outcomes by examining the 95% confidence intervals. Because we took advantage of the strengths of the new three-step approach and had a complex data set, we were unable to apply advanced approaches to addressing missing data in this step of data analysis. Therefore, for these models only, a total of 73 cases (4%) were removed. Cases missing data did not differ significantly by gender, income, or level of parental education. However, compared with cases without missing data, cases missing data were significantly less likely to live in a primarily English-speaking home (*OR* = −1.485, 95% CI [−2.832, −0.138])

Results

Results generalized to noninstitutionalized non-Hispanic Black adolescents (aged 12-17 years) in the United States (N = 1,836). Table 2 presents sample characteristics and responses to indicator variables. As shown, for example, 46.3% of the sample was female and 59% lived below the 200% poverty level. The table also shows 15.4% of youth experienced discrimination based on their race and 86.2% of youth had a mentor. The majority (78.5%) of youth were adequately covered by health insurance, but only 14.7% of youth received adequate transition to adult health care. Over half of youth resided in safe neighborhoods (53.8%) and attended safe schools (61.4%); however, 44.3% reported that their neighborhood was supportive. Most youth (80.3%) participated in at least one after-school activity and 52.4% were engaged in school.

Table 2. Sample Characteristics of Black Adolescents (Aged 12-17 Years) in the United States, 2016 and 2017 ($N = 1,836$).

	Unweighted *n* (Weighted %)
Sociodemographics	
Gender	
Female	875 (46.3)
Male	961 (53.7)
Poverty level	
<199%	875 (41.0)
>200%	961 (59.0)
Highest level of education	
<High school	74 (10.7)
>High school graduate	1,697 (89.3)
Primary language	
Other than English	48 (4.5)
Social determinants of health indicators	
Adequate insurance coverage	
Adequate insurance coverage	1,335 (78.5)
Does not have adequate insurance coverage	386 (21.5)
Transition to adult health care	
Received adequate transition to adult health care	284 (14.7)
Did not receive adequate transition to adult health care	1,526 (85.3)
School engagement	
Cares about doing well and does homework	1,055 (52.4)
Cares about doing well OR does homework	608 (40.9)
Does not care about doing well and does not do homework	138 (6.7)
After-school activities	
Participated in at least one activity	1,473 (80.3)
Did not participate	317 (19.7)
Mentor	
Yes	1,537 (86.2)
No	193 (13.8)
Experienced discrimination	
No	1,469 (84.6)
Yes	275 (15.4)
Social determinants of health indicators	
Food sufficiency	
We could always afford to eat good nutritious meals	1,039 (50.0)

(continued)

Table 2. (continued)

	Unweighted *n* (Weighted %)
We could always afford enough to eat but not always the kinds of food we should eat	568 (35.5)
Sometimes we could not afford enough to eat	145 (11.1)
Often we could not afford enough to eat	31 (3.4)
Neighborhood support	
Live in supportive neighborhoods	820 (44.3)
Do not live in supportive neighborhoods	924 (55.7)
Neighborhood safety	
Definitely agree	1,017 (53.8)
Somewhat agree	639 (36.7)
Somewhat or definitely disagree	124 (9.5)
School safety	
Definitely agree	1,108 (61.4)
Somewhat agree	575 (34.4)
Somewhat or definitely disagree	68 (4.1)
Mental health variables	
Behavior problems	187 (11.9)
Attention deficit/hyperactivity disorder	231 (13.4)

Identify Latent Profiles of Social Determinants of Health (Aim 1)

Results from the LCA supported aim one, which suggested classes of social determinants of health existed among Black adolescents in the United States. Table 3 presents LCA results for different class models. As shown in Table 3, the BIC suggested a four-class model. The BF indicated a four- or five-class model were in the moderately acceptable range (Wagenmakers, 2007). Because the BIC is considered the most reliable fit statistic in LCA (and the BF suggested the model has moderate support), we selected a four-class model. However, it is important to note that none of the other fit criteria indicated a four-class model. Inconsistent findings across fit indicators are common in LCA models (Nylund-Gibson & Choi, 2018), which makes the agreement among researchers about using the BIC to assess model fit valuable. Although entropy is not used to select a final model, it is important to note the four-class model had adequate entropy (i.e., above the cutoff of .80). Also, the lowest value on the off diagonal of the average latent class posterior probability was acceptable (i.e., above .80).

Table 3. Evaluating Class Solutions.

	Model fit criteria						
Models	LL	AIC	BIC	SABIC	AWE	CAIC	BF
1 Class	−11681.92	23393.83	23476.56	23428.91	23435.29	23427.79	0.000
2 Class	−11106.38	22274.75	22445.73	22347.24	22360.43	22344.93	0.001
3 Class	−10975.44	22044.88	22304.11	22154.79	22174.79	22151.29	0.044
4 Class	−10884.00	21894.01	**22241.48**	22041.33	22068.13	22036.63	**3.001**
5 Class	−10834.87	21827.74	22263.46	22012.48	22046.09	22006.59	**4.322**
6 Class	−10789.39	21768.77	22292.73	21990.92	22031.34	21983.84	—

	Diagnostic criteria				
Models	Smallest class count (*n*)	Smallest class size (%)	Entropy	ALCPP	VLMR-LRT
1 Class	1836	100	—	—	—
2 Class	790	43	0.687	**0.896**	0.1285
3 Class	45	2	**0.827**	**0.909**	0.5646
4 Class	50	3	**0.811**	**0.834**	0.8159
5 Class	50	3	0.746	**0.747**	0.8148
6 Class	29	2	0.763	**0.749**	0.5384

Note: N = 1,836. The model became unstable with the 7-class model. Bold text indicates model met fit criteria. LL = log-likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-size adjusted BIC; AWE = approximate weight of evidence criterion; CAIC = consistent Akaike information criterion; BF = Bayes factor; ALCPP = average latent class posterior probability; VLMR-LRT = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test.

Figure 1 shows a graphic representation of the four-class model. The x-axis lists the names of the social determinants of health indicator variables. The y-axis provides the average probability of class membership for each of the indicators; as the number approaches 1, the probability of class membership is higher. All indicator variables were coded with higher scores reflecting access to promotive factors; therefore, probabilities closer to 1 are desirable.

Figure 1 also illustrates the characteristics of the four classes based on responses to the 10 indicators. A majority of Black adolescents (58%) were in the *Promotive Factors* class. This class had access to all of the promotive indicators of social determinants of health. Conversely, a small percentage of the sample (3%) were in the *Limited Access to Promotive Factors* class; which, with the exception of neighborhood safety and involvement in after-school activities, had a low probability of access to promotive factors. The *Access to Health Care (6%)* and *Barriers in the Physical Environment (33%)* classes had similar profiles. However, compared with the *Barriers in the*

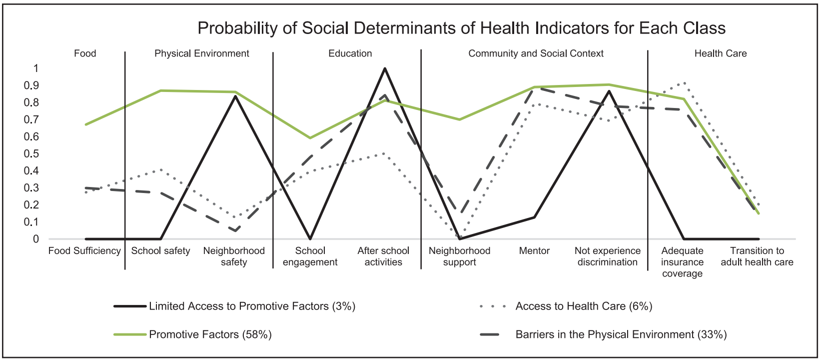

Figure 1. Latent profiles of social determinants of health.
Note: $N = 1{,}836$. Figure illustrates the characteristics of the four classes based on responses to the 10 indicators. A majority of Black adolescents (58%) were in the *Promotive Factors* class. Conversely, a small percentage of the sample (3%) were in the *Limited Access to Promotive Factors* class. The *Access to Health Care (6%)* and *Barriers in the Physical Environment (33%)* classes had similar profiles. However, compared with the *Barriers in the Physical Environment* class, the *Access to Health Care* class had slightly higher probabilities of access to several of the promotive factors.

Physical Environment class, the *Access to Health Care* class had slightly higher probabilities of access to several of the promotive factors. Although not a central focus of this study, results from the new three-step approach to incorporating covariates into LCA models demonstrated no significant differences in sociodemographic composition of the classes (see the appendix).

Association Between Classes and Mental Health Outcomes (Aim 2)

Findings from the pairwise Wald test supported aim two, which indicated class membership may be differentially associated with the likelihood of adolescents currently having behavior problems or ADHD (see Table 4). As shown, for example, the odds ratio for *Promotive Factors* class having behavior problems was 0.97 (or 3% lower) compared with *Barriers in the Physical Environment* class 95% CI [0.23, 1.70]. Conversely, the odds ratio for *Promotive Factors* class having ADHD was 1.29 as large (or 29% higher) compared with *Barriers in the Physical Environment* class 95% CI [0.35, 2.23].

Discussion of Example

Using current advancements and best practices in LCA methods, our illustrative example identified four latent profiles of social determinants of

Table 4. Mental Health Outcomes by Class Membership.

	Behavior problems		ADHD	
Latent class	*OR* [95% CI]	*p*	*OR* [95% CI]	*p*
Limited access to promotive factors (reference)				
Access to health care	1.11 [−1.42, 3.63]	.39	0.27 [−0.46, 1.01]	.467
Promotive factors class	3.99 [−4.74, 12.72]	.37	0.80 [−1.12, 2.72]	.416
Barriers in the physical environment	3.85 [−4.60, 12.29]	.37	1.03 [−1.47, 3.52]	.420
Access to health care (reference)				
Promotive factors class	3.61 [−0.48, 7.70]	.08	2.91 [−0.93, 6.75]	.138
Barriers in the physical environment	3.48 [−0.64, 7.60]	.10	3.74 [−1.67, 9.15]	.176
Promotive factors class (reference)				
Barriers in the physical environment	0.98 [0.23, 1.70]	.01	1.29 [0.35, 2.23]	.007

Note: N = 1,836. All models control for gender, primary language in the home, income, and highest level of parental education level. *OR* = odds ratio; CI = confidence interval; ADHD = attention deficit/hyperactivity disorder.

health among a nationally representative sample of noninstitutionalized Black adolescents in the United States. Results are somewhat consistent with the few other studies that have identified latent profiles of promotive factors among Black adolescent (e.g., Liu et al., 2019). For example, we identified four classes and a majority of the sample was in a *Promotive Factors* class, thus indicating slightly more than half of Black youth in the United States have access to promotive social determinants of health. Individuals in this class may benefit from universal community and school interventions. Unlike a previous study (Liu et al., 2019), which identified classes with similar patterns of school and neighborhood safety, we identified a class with low school safety and high neighborhood safety (*Limited Access Promotive Factor* class). Individuals in this class would likely benefit from targeted school-based interventions focused on improving school safety. Results appear to underscore the importance of the social determinants of health framework.

Although some differences were found between class memberships and mental health outcomes, differences were only found between two classes (*Promotive Factors* class and *Barriers in the Physical Environment* class) and not necessarily in the expected direction. Results need to be interpreted with caution because the presence of a current mental health condition was based on caregivers reporting whether a provider told them their adolescent had a mental health condition. Given potential racial biases in diagnostic practices as well as previous research consistently finding discrepancies in caregiver-reported versus youth-reported mental health outcomes (e.g., Breland-Noble & Weller, 2012) and disparities in access to providers (e.g., Cook et al., 2019), the prevalence of mental health conditions may be underreported in this study, which, by extension, may indicate that the current findings do not accurately portray the relationship between mental health conditions and class membership. In sum, the current study provides instruction and an illustrative example of LCA. Furthermore, it adds to the limited research on latent profiles of Black youth and indicates heterogeneity in access to social determinants of health exists among Black adolescents.

Appendix. Multinomial Logistic Regression Results Comparing Profiles of Capital by Covariates.

Profile	Covariates	Logit	*SE*	*p*	*OR*	[95% CI]
Limited access to promotive factors class						
Access to health care class	Female	−0.44	1.10	−0.40	0.64	[0.07, 5.58]
	Primary language	18.36	1.04	17.68	—	—
	Income	0.91	1.23	0.74	2.48	[0.22, 27.69]
	Parental education level	26.06	0.75	34.56	—	—
Promotive factors class	Female	−0.90	1.01	−0.90	0.41	[0.06, 2.92]
	Primary language	17.38	0.93	18.67	—	—
	Income	−0.38	1.04	−0.37	0.68	[0.09, 5.19]
	Parental education level	25.77	0.63	40.71	—	—
Barriers in the physical environment class	Female	−0.92	1.02	−0.91	0.4	[0.05, 2.93]
	Primary language	17.79	0.00	—	—	—
	Income	0.26	1.05	0.25	1.29	[0.17, 10.11]
	Parental education level	24.62	0.00	—	—	—
Access to health care class						
Promotive factors class	Female	−0.46	0.48	−0.96	0.63	[0.25, 1.62]
	Primary language	−0.98	0.98	−0.99	0.38	[0.06, 2.58]
	Income	−1.29	0.67	−1.92	0.28	[0.07, 1.03]
	Parental education level	−0.29	0.57	−0.51	0.75	[0.25, 2.28]
Barriers in the physical environment class	Female	−0.48	0.53	−0.91	0.62	[0.22, 1.74]
	Primary language	−0.57	1.04	−0.55	0.57	[0.07, 4.33]
	Income	−0.65	0.73	−0.89	0.52	[0.13, 2.18]
	Parental education level	−1.44	0.75	−1.91	0.24	[0.05, 1.04]

(continued)

Appendix (continued)

Profile	Covariates	Logit	*SE*	*p*	*OR*	[95% CI]
Promotive factors class						
Barriers in the physical environment class	Female	−0.02	0.23	−0.09	0.98	[0.62, 1.54]
	Primary language	0.41	0.93	0.44	1.5	[0.24, 9.31]
	Income	0.64	0.24	2.74	1.9	[1.20, 3.01]
	Parental education level	−1.15	0.63	−1.82	0.32	[0.09, 1.10]

Note: N = 1,836. *SE* = standard error; *OR* = odds ratio; CI = confidence interval.
$^{*}p \leq .05$.

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