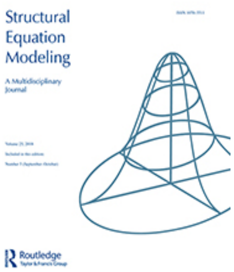

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A Comparison of Approaches for Estimating Covariate Effects in Nonparametric Multilevel Latent Class Models

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The inclusion of covariates improves the prediction of class memberships in latent class analysis (LCA). Several methods for examining covariate effects have been developed over the past decade; however, researchers have limited to the comparisons of the performance among these methods in cases of the single-level LCA. The present study investigated the performance of three different methods for examining covariate effects in a multilevel setting. We conducted a simulation to compare the performance of the three methods when level-1 and level-2 covariates were simultaneously incorporated into the nonparametric multilevel latent class model to predict latent class membership at each level. The simulation results revealed that the bias-adjusted three-step maximum likelihood method performed equally well as the one-step method when the sample sizes were sufficiently large and the latent classes were distinct from each other. However, the unadjusted three-step method significantly under-estimated the level-1 covariate effect in most conditions.

Keywords: covariate effects, latent class models, multilevel modeling

INTRODUCTION

Observational units in behavioral or social science studies often are hierarchically clustered within a higher level unit. For example, individuals are nested within a group, and measurement occasions are nested within an individual. The latent class analysis (LCA) (Goodman, 1974; Lazarsfeld & Henry, 1968) has been extended to account for the dependence due to the multilevel data structure by adopting the random-effects approach (Bryk & Raudenbush, 1992; Goldstein, 1995; Snijders & Bosker, 1999). A number of researchers have introduced extensions of LCAs that assume different forms of random effects at the higher level (e.g., Asparouhov & Muthén, 2008; Di & Bandeen-Roche, 2011; Finch & French, 2013; Henry & Muthén, 2010; Vermunt, 2003; 2004). The present study will focus on the nonparametric multilevel latent class model (MLCM) (Vermunt, 2003) as the approach to accommodate a nested data structure.

Vermunt's (2003) nonparametric MLCM includes a discrete random effect at a higher level to account for the dependency due to the multilevel data structure. The discrete random effect is characterized by a number of latent classes following the multinomial distribution, relying on the assumption that each higher level unit is assigned to one of the higher level latent classes. Thus, one key feature of this nonparametric approach is to provide classification information for both higher and lower level units (e.g., Bassi, 2009; Bijmolt, Paas, & Vermunt, 2004; da Costa & Dias, 2014; Finch & Marchant, 2013; Onwezen et al., 2012; Pirani, 2013; Rindskopf, 2006; Rüdiger & Hans-Dieter, 2013). Moreover, the nonparametric MLCM does not require unverifiable distributional assumptions regarding the random effect (Aitkin, 1999) and is computationally less intensive (Vermunt & Van Dijk, 2001).

An important modeling issue in the LCA is the use of covariates. The inclusion of covariates in the model improves

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the prediction of class memberships and facilitates the identification of the latent classes (Clogg, 1981; Dayton & Macready, 1988; Hagenaars, 1993). For the nonparametric MLCM, covariates can be introduced at both levels 1 and 2 to predict latent class memberships (Henry & Muthén, 2010; Vermunt, 2003). Specifically, level-2 covariates can be included to predict latent class memberships at both individual and group levels. This means that level-2 covariates can predict the probability that a group belongs to a particular level-2 class and the probability that an individual belongs to a level-1 latent class. On the other hand, level-1 covariates can be used to predict level-1 class membership. The covariate effects in nonparametric MLCMs are usually estimated by multinomial logistic regression (Henry & Muthén, 2010).

Pirani's (2013) study offers an empirical example demonstrating the use of covariates in MLCAs. She investigated Europeans' experiences and perceptions of social exclusion using nonparametric MLCMs with level-1 and level-2 covariates. In particular, she included sex, age, and occupational status as level-1 covariates, and individual responsibility, GDP, and social protection (the percentage of GDP spent on social protection) as level-2 covariates to predict latent class membership at the individual and country levels, respectively. She noted that the level-2 covariates had an important role in understanding the perceptions of social exclusion in European regions given different social, economic, cultural, and political contexts. As she demonstrated, the inclusion of level-2 covariates allows for a better explanation of contextual or environmental differences. Other applications of covariates at both level1 and level 2 can be found in da Costa and Dias (2014), Finch and Marchant (2013), and Rüdiger and Hans-Dieter (2013).

Recently, exploratory methods for estimating covariate effects in the context of mixture modeling have received increased attention (e.g., Asparouhov & Muthén, 2014; Lanza, Tan, & Bray, 2013; Vermunt, 2010). Two approaches have been discussed primarily in the literature: the one-step method and the three-step method. The one-step method assesses the covariate effect at the same stage of identifying the latent class structure. This means that the parameters defining the structure of the latent classes and the covariate effects are estimated simultaneously (e.g., Bandeen-Roche, Miglioretti, Zeger, & Rathouz, 1997; Dayton & Macready, 1988; Hagenaars, 1990, 1993). The three-step method, in contrast, examines the covariate effects in a stepwise manner (e.g., Asparouhov & Muthén, 2014; Bakk, Tekle, & Vermunt, 2013; Bolck, Croon, & Hagenaars, 2004; Lanza et al., 2013; Vermunt, 2010). The classical (unadjusted) three-step method proceeds as follows. The first step of the procedure is identifying the underlying number of latent classes; individuals are then assigned to latent classes based on their posterior class membership probabilities, and subsequently, the association between a set of covariates and latent classes memberships is examined by ANOVA or regression analysis.

The main advantage of the three-step method over the one-step method is that the class solutions are not distorted by the inclusion of covariates (Bakk et al., 2013; Bakk & Vermunt, 2016; Vermunt, 2010). For the one-step method, the inclusion of covariates may affect class enumeration, resulting in distorted latent class solutions, and it potentially changes the substantive meaning of the latent classes. However, such a distortion is less likely to occur in the three-step method, because class enumeration and the estimation of covariate effects are made separately. This implies that, in comparison with the one-step method, the three-step method can avoid potential problems that can arise when the two steps (class enumeration and the estimation of covariate effects) take place simultaneously (Bakk et al., 2013).

Despite these advantages, a potential problem of the classical three-step method is that the covariate parameters are severely underestimated (Bolck et al., 2004). To address this shortcoming, Bolck et al. (2004) developed a correction method, the three-step Bolck-Croon-Hagenaars method (BCH method), in which the third step of the classical three-step method was modified using the reweighted frequency table. Vermunt (2010) also suggested an alternative bias-adjusted three-step method, the maximum likelihood three-step method (this method will be called the ML method in this paper), making it possible to obtain corrected standard errors (SEs) and accommodate continuous covariates. Bakk et al. (2013) proposed a more integrative framework of the bias-adjusted three-step method that can deal with both covariates and distal outcomes. These methods were implemented in software such as Latent GOLD Version 5.0 (Vermunt & Magidson, 2013) and Mplus Version 7.1 (Muthén & Muthén, 2012).

The bias-adjusted three-step method can be applied to explore various relationships between latent class memberships and external variables (e.g., covariates and distal outcomes) in such a way that covariates are used to predict latent class memberships (Vermunt, 2010), or latent class memberships can predict distal outcomes (Asparouhov & Muthén, 2014).

More recently, Lanza et al. (2013) proposed a new three-step method for estimating the effects of continuous distal outcomes without making distributional assumptions. Bakk and Vermunt (2016) refined their approach by improving estimates of SEs using resampling methods. Gudicha and Vermunt (2011) showed that the bias-adjusted three-step method performs well with continuous indicators. The simulation study by Bakk and Vermunt (2016) also demonstrated that the bias-adjusted three-step method is robust against the violation of the normality assumption in predicting class memberships when using continuous distal outcomes. Moreover, the bias-adjusted three-step method was applied to other mixture models such as latent Markov models (Bartolucci, Montanari, & Pandolfi, 2015; Di Mari, Oberski, & Vermunt, 2016), regression mixture models (Kim, Vermunt, Bakk, Jaki, & Van Horn, 2016), latent profile analysis (Dziak, Bray, Zhang, Zhang, & Lanza, 2016), and LCAs with multiple discrete latent variables (Bakk et al., 2013).

Recent work further extended the bias-adjusted three-step method for the situations in which data arise from hierarchical structures. Bennink, Croon, and Vermunt (2015) proposed a bias-adjusted three-step method for micro–macro analysis, which explains the relationship between level-2 external variables through level-1 predictors. Their model is analogous to 2-1-2 mediation models, because the effect of level-2 independent variables on the outcome variable (at the same level) is mediated by the level-2 latent class memberships defined by the level-1 indicators.

The bias-adjusted three-step method for micro–macro analysis proceeds as follows: The first step is to identify a latent class model at level-2 (measurement model), where level-1 predictors are used as indicators. The second step is to assign groups to the level-2 latent classes by aggregating the level-1 predictors. The third step, then, is to investigate the association between level-2 latent classes and level-2 external variables while correcting for the classification errors that have occurred in the second step.

The simulation study by Bennink et al. (2015) showed that the bias-adjusted three-step method yielded unbiased parameter estimates for both the BCH or ML methods regardless of the classification rules applied (modal or proportional assignment). The one-step method also recovered true values equally well compared with the bias-adjusted three-step method, whereas the unadjusted three-step method underestimated the covariate effects at level-2 under most conditions.

A number of studies have explored the use of several methods for evaluating covariate effects at the individual level (e.g., Bakk, Oberski, & Vermunt, 2014; Bakk et al., 2013; Bolck et al., 2004; Vermunt, 2010). However, researchers are often interested in exploring covariate effects at different levels of a hierarchy. To our knowledge, Bennink et al. (2015, 2016) have investigated the covariate effects in the multilevel setting, but their studies focused only on the situation where level-2 covariates are expected to affect the level-2 outcome directly or indirectly through a level-2 latent class. These studies did not cover the case in which level-1 and level-2 covariates predict class membership at each level simultaneously. The present study aims to fill this gap and therefore focuses on investigating the performance of three methods for estimating covariate effects when both level-1 and level-2 covariates are simultaneously incorporated into the nonparametric MLCM to predict latent class membership at each level. We carried out a simulation study to explore and compare the three methods of evaluating covariate effects: the one-step method, the classical three-step method, and the ML method.

The remainder of the paper is organized in this manner: We first describe the specifications of MLCMs with level-1 and level-2 covariates, followed by an introduction of the three-step method for evaluating covariate effects in a nonparametric MLCM. We also present the simulation design and results and use an empirical example to illustrate the evaluation of the covariate effects. We then conclude with a discussion and final remarks.

MLCMs with Level-2 and Level-1 Covariates

MLCMs with level-2 and level-1 covariates can be formally specified as follows: Let Y_{gij} be the response to an indicator j of an individual i in group g, where $g = 1, \ldots, G$, $i = 1, \ldots, n_g$, and $j = 1, \ldots, J$. The vector $\mathbf{Y_{gi}}$ denotes the J indicators for an individual i in group g, and $\mathbf{Y_g}$ denotes the full responses of all subjects in group g. The Z_{gq} refers to one of the Q level-2 covariates, and $\mathbf{Z_g}$ is the level-2 covariate vector. The Z_{giw} is one of the W level-1 covariates, and $\mathbf{Z_{gi}}$ is the vector of Z_{giw}.

The nonparametric MLCM is defined by two separate equations for the higher and lower levels, which are graphically represented in Figure 1. As Figure 1 shows, the MLCM incorporates a discrete latent variable (H_g) at the higher level with L latent classes, in addition to the one at the lower level (X_{gi}) with M latent classes. The outcomes of these discrete latent variables can be conceptualized as latent classes at two different levels consisting of groups or individuals that are internally homogenous within each class but distinct among classes in terms of response patterns.

For the individual level, the probability density of the individual's response i in group g given level-1 covariates can be written as follows:

$$P(\mathbf{Y_{gi}} = \mathbf{y_{gi}}|H_g = l, \mathbf{Z_{gi}}) = \sum_{m=1}^{M} P(X_{gi} = m|H_g = l, \mathbf{Z_{gi}}) \times \prod_{j=1}^{J} f(Y_{gij} = y_{gij}|X_{gi} = m). \tag{1}$$

The term $P(X_{gi} = m|H_g = l, \mathbf{Z_{gi}})$ is the latent class probability. This parameter represents the distribution of conditional latent class probabilities given a level-2 latent class (l) and a set of level-1 covariates ($\mathbf{Z_{gi}}$); it can be parameterized by means of a multinomial distribution, as shown in Equation 2:

$$P(X_{gi} = m|H_g = l, \mathbf{Z_{gi}}) = \frac{\exp(\gamma_{0lm} + \sum_{w=1}^{W} \gamma_{mw} Z_{giw})}{\sum_{m'=1}^{M} \exp(\gamma_{0lm'} + \sum_{w=1}^{W} \gamma_{m'w} Z_{giw})}. \tag{2}$$

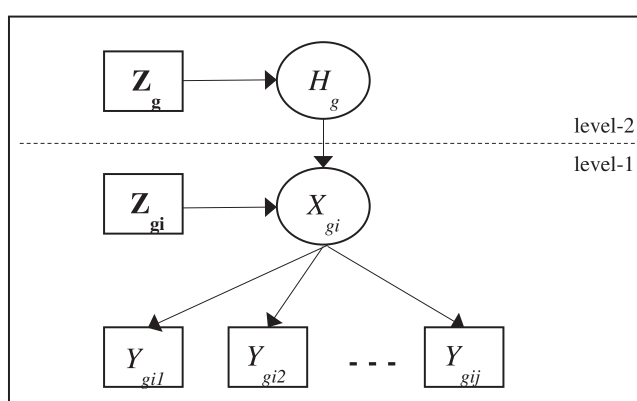

FIGURE 1 Nonparametric MLCM with level-2 and level-1 covariates.

Note that the logit parameter γ_{0ml} can be rewritten as $\gamma_{0ml} = \gamma_m + u_{lm}$, where the discrete random variable u_{lm} varies across level-1 classes, capturing differences between the L classes at level-2 (Bijmolt et al., 2004; Henry & Muthén, 2010). The parameter γ_{mw} represents the class-specific effects of the wth covariate at level-1 (Z_{giw}) on latent class membership m. These logit parameters are subjected to identification constraint; that is, $\sum_{m=1}^{M} \gamma_{0ml} = \sum_{m=1}^{M} \gamma_{mw} = 0$ for the effect coding and $\gamma_{01l} = \gamma_{1w} = 0$ or $\gamma_{0Ml} = \gamma_{Mw} = 0$ for dummy coding.

The conditional response probability $f(Y_{gij} = y_{gij}|X_{gi} = m)$ in Equation 2 represents the probability of observing a certain response pattern y_{gij} for a variable j of subject i in group g given the latent class m. This parameter can take different forms of probability distributions depending on the types of observed responses. When the indicators are categorical, the parameter can be expressed using logit equations as shown in Equation 3:

$$f(Y_{gij} = y_{gij}|X_{gi} = m) = \frac{\exp(\beta_{0j} + \beta_{jm})}{\sum_{m'=1}^{M} \exp(\beta_{0j} + \beta_{jm'})}, \tag{3}$$

where β_{0j} denotes the intercept for indicator j, and β_{jm} indicates a class-specific effect, which characterizes the nature of the discrete latent variable X_{gi}.

For the group level, the marginal density of the response vector of group g is

$$P(\mathbf{Y_g} = \mathbf{y_g}|\mathbf{Z_g}, \mathbf{Z_{gi}}) = \sum_{l=1}^{L} P(H_g = l|\mathbf{Z_g}) \times \left(\prod_{i=1}^{n_g} \sum_{m=1}^{M} P(X_{gi} = m|H_g = l, \mathbf{Z_{gi}}) \prod_{j=1}^{J} f(Y_{gij} = y_{gij}|X_{gi} = m) \right). \tag{4}$$

Equation 4 shows that level-1 classes are indicators of the discrete latent variable at level-2 (H_g). Thus, the state of level-1 classes (e.g., class separations) has a direct impact on the composition of the level-2 latent classes (Lukočiené, Varriale, & Vermunt, 2010).

The first term, $P(H_g = l|\mathbf{Z_g})$, is represented by a vector with each element expressing the probabilities of g being in the level-2 class l $(l = 1, \ldots, L)$ given level-2 covariates ($\mathbf{Z_g}$). Because the level-2 classes are assumed to be exhaustive and mutually exclusive, elements of this vector can be conceptualized as class sizes, and thus the sum of this vector equals one. The parameter can be expressed as:

$$P(H_g = l|\mathbf{Z_g}) = \frac{\exp(\alpha_{0l} + \sum_{q=1}^{Q} \alpha_{lq} Z_{gq})}{\sum_{l'=1}^{L} \exp(\alpha_{0l'} + \sum_{q=1}^{Q} \alpha_{l'q} Z_{gq})}, \tag{5}$$

where α_{0l} denotes the category effect of the level-2 latent classes and α_{lq} represents the class-specific effect of the qth covariate (Z_{gq}) on level-2 latent class memberships.

The Bias-Adjusted Three-Step Method of Estimating Covariate Effects in MLCMs

The bias-adjusted three-step method for nonparametric MLCMs proceeds as follows: In the first step, the MLCM representing the relationship between latent classes and their indicators is built. The MLCM in the first step of the analysis with nonparametric specifications can be presented as

$$P(\mathbf{Y}_g = \mathbf{y_g}) = \sum_{l=1}^{L} P(H_g = l) \left(\prod_{i=1}^{n_g} \sum_{m=1}^{M} P(X_{gi} = m|H_g = l) \prod_{j=1}^{J} f(Y_{gij} = y_{gij}|X_{gi} = m) \right). \tag{6}$$

The numbers of both level-1 and level-2 classes are determined during this step. A number of prior studies related to model selection in MLCMs have suggested that the Bayesian information criterion (BIC) (Schwarz, 1978) is a great measure to determine the number of latent classes for both the iterative approach (Lukočiené, Varriale, & Vermunt, 2010) and the simultaneous approach (Yu & Park, 2014). For the application of the BIC, applying a number of groups as the sample size for the penalty term yields better performance than applying the total sample size, because using the latter as the penalty term is too harsh, which results in poor performance (Lukočiené et al., 2010; Yu & Park, 2014).

In the second step, using the model chosen in the previous step, groups and individuals are assigned to latent classes based on their posterior class membership probabilities at each level (Bennink et al., 2015; Clogg, 1981; Goodman, 1974; Hagenaars, 1990). The posterior probabilities at the group and the individual levels can be easily obtained by using Bayes' rule as seen in Equations 7 and 8, respectively.

$$P(H_g = l|\mathbf{Y_g} = \mathbf{y_g}) = \frac{P(H_g = l)P(\mathbf{Y_g} = \mathbf{y_g}|H_g = l)}{P(\mathbf{Y_g} = \mathbf{y_g})}. \tag{7}$$

$$P(X_{gi} = m|\mathbf{Y_{gi}} = \mathbf{y_{gi}}) = \frac{P(X_{gi} = m)P(\mathbf{Y_{gi}} = \mathbf{y_{gi}}|X_{gi} = m)}{P(\mathbf{Y_{gi}} = \mathbf{y_{gi}})}. \tag{8}$$

When assigning groups and individuals, the most common classification rule is modal assignment, in which each unit is assigned to the class with the highest posterior probability. Specifically, the modal assignment rule can be expressed as the following. Let W_g denote the assigned class for group g, and W_{gi} indicate the assigned class for individual i in group g. Then, higher and lower level units are assigned to a single class for which the posterior membership probability is the largest (Bolck et al., 2004). This method is also referred to as hard partitioning.

Although the modal assignment rule yields a minimum risk of misclassification (Frühwirth-Schnatter, 2006; Skrondal & Rabe-Hesketh, 2004), the assignment is still made with a certain degree of uncertainty, particularly when the dominant posterior latent class probability is unclear. In such a case, some observational units are inappropriately assigned, resulting in a certain amount of classification error. These classification errors at the higher and the lower levels can be quantified using the conditional probabilities, $P(W_g = s|H_g = l)$ and $P(W_{gi} = t|X_{gi} = m)$, respectively.

$$\begin{aligned} P(W_g = s|H_g = l) &= \sum_{y_g} P(W_g = s, \mathbf{Y_g} = \mathbf{y_g}|H_g = l) \\ &= \sum_{y_g} P(\mathbf{Y_g} = \mathbf{y_g}|H_g = l)P(W_g = s|\mathbf{Y_g} = \mathbf{y_g}) \\ &= \sum_{y_g} \frac{P(\mathbf{Y_g} = \mathbf{y_g})P(H_g = l|\mathbf{Y_g} = \mathbf{y_g})P(W_g = s|\mathbf{Y_g} = \mathbf{y_g})}{P(H_g = l)} \\ &= \frac{\frac{1}{G}\sum_{g=1}^{G} P(H_g = l|\mathbf{Y_g})w_g}{P(H_g = l)}, \text{ and} \end{aligned} \tag{9}$$

$$\begin{aligned} P(W_{gi} = t|X_{gi} = m) &= \sum_{y_{gi}} P(W_{gi} = t, \mathbf{Y_{gi}} = \mathbf{y_{gi}}|X_{gi} = m) \\ &= \sum_{y_{gi}} P(\mathbf{Y_{gi}} = \mathbf{y_{gi}}|X_{gi} = m)P(W_{gi} = t|X_{gi} = m) \\ &= \sum_{y_{gi}} \frac{P(\mathbf{Y_{gi}} = \mathbf{y_{gi}})P(X_{gi} = m|\mathbf{Y_{gi}} = \mathbf{y_{gi}})P(W_{gi} = t|X_{gi} = m)}{P(X_{gi} = m)} \\ &= \frac{\frac{1}{n_g}\sum_{i=1}^{n_g} P(X_{gi} = m|\mathbf{Y_{gi}})w_{gi}}{P(X_{gi} = m)}, \end{aligned} \tag{10}$$

where $w_g = P(W_g = s|\mathbf{Y_g})$ and $w_{gi} = P(W_{gi} = t|\mathbf{Y_{gi}})$. Note that $P(W_g = s|H_g = l)$ and $P(W_{gi} = t|X_{gi} = m)$ represent the conditional probabilities that groups and individuals originally belonging to level-2 class l and level-1 class m are falsely assigned to class s and t, where l and m differ from s and t, respectively. Based on the modal assignment rule, the weights $P(W_g = s|\mathbf{Y_g})$ and $P(W_{gi} = t|\mathbf{Y_{gi}})$ are equal to one for the class with the largest posterior class probability and zero otherwise.

The third step is to estimate the relationships between covariates ($\mathbf{Z_g}$ and $\mathbf{Z_{gi}}$) and the assigned class memberships (W_g and W_{gi}), taking into account biases caused by the classification errors in the second step. The relationships between covariates and the class memberships can be represented as

$$P(W_g = s|\mathbf{Z_g}) = \sum_{l=1}^{L} P(H_g = l|\mathbf{Z_g})P(W_g = s|H_g = l). \tag{11}$$

$$P(W_{gi} = t|\mathbf{Z_{gi}}) = \sum_{m=1}^{M} P(X_{gi} = m|\mathbf{Z_{gi}})P(W_{gi} = t|X_{gi} = m). \tag{12}$$

Equations 11 and 12 indicate that $P(W_g = s|\mathbf{Z_g})$ and $P(W_{gi} = t|\mathbf{Z_{gi}})$ are linear combinations of posterior class probabilities and classification errors at each level. Vermunt's bias-adjusted ML method presumes that the models described in Equations 11 and 12 are latent class models at two levels, in which assigned class memberships (W_g and W_{gi}) serve as single indicators at the higher and lower levels, respectively. Based on this assumption, covariate effects can be assessed by estimating the parameters of the latent class models, while classification errors, $P(W_g = s|H_g = l)$ and $P(W_{gi} = t|X_{gi} = m)$, are assumed to be known and fixed (Vermunt, 2010). Conversely, the alternative bias-adjusted three-step BCH method reformulates Equations 11 and 12 into reweighted forms by multiplying the inverse of the rescaled classification error (Bolck et al., 2004). Then, simple cross-tabulations or ANOVAs can be implemented to estimate the association between the class membership and covariates.

SIMULATION STUDY

Previous studies have suggested that the performance of methods for assessing covariate effects is strongly associated with *sample sizes* and *class separation* (Bakk et al., 2013; Bolck et al., 2004; Di Mari et al., 2016; Vermunt, 2010). Separation among classes usually refers to the extent of heterogeneity among latent classes; it is strongly associated with the concept of classification error because it quantifies the classification uncertainty of observational units. For MLCMs, when level-1 or level-2 classes are poorly separated, there is greater uncertainty in assigning groups or individuals into latent classes with an increased likelihood of classification errors.

In this simulation study, the class separation at higher and lower levels was manipulated through patterns of class-specific parameters following previous simulation studies (e.g., Kim, 2014; Lukočiené et al., 2010; Nylund, Asparouhov, & Muthén, 2007; Tofighi & Enders, 2007; Yang & Yang, 2007). Class separation at the higher level was controlled by patterns of conditional latent class probabilities, $P(X_{ig} = m|H_g = l)$, and class separation at the lower level was manipulated via patterns of conditional response probabilities, $P(Y_{gij} = y_{gij}|X_{gi} = m)$. Note that class separation in the MLCM is not only influenced by the pattern of the class-specific parameters, but also is associated with other factors, such as sample size, number of latent classes, number of item or categories, and class sizes. Lukočiené et al. (2010) described how those factors affect class separation at two levels.

Simulation design

We designed a simulation study to compare the relative performance of the one-step method, the classical three-step method, and the bias-adjusted three-step ML method in the situation where covariate effects at two levels are assessed simultaneously. Because the BCH method and the ML method yielded similar results when covariate effects were evaluated at the individual level (Vermunt, 2010) and the group level (Bennink et al., 2015), we only considered the ML method for analyses. We evaluated the relative performance of the three methods by examining the efficiency and bias in the parameter estimates. Following the approach used by Vermunt (2010), we measured parameter bias by comparing average estimated values with true population values, while efficiency was evaluated by calculating the ratio of the estimated SEs and standard deviations (SDs) of parameter estimates over simulation replications. An observed ratio closer to one indicates that a method is more efficient.

Data were generated from the population model: two level-2 classes and three level-1 classes with six dichotomous indicators and two numeric covariates (one at each level) with five categories scored (−2, −1, 0, 1, and 2). Six design factors were manipulated: (1) level-2 sample sizes, (2) level-1 sample sizes, (3) conditional latent class probabilities, (4) conditional response probabilities, (5) magnitude of level-2 covariate effects, and (6) magnitude of level-1 covariate effects.

We manipulated the level-2 sample size (i.e., the number of groups) and the level-1 sample size (i.e., the number of individuals in a group) to investigate the effects of sample size at both levels. There were 50 or 100 groups (G) with 10, 30, or 50 individuals per group (n_g) to represent small, medium, and large samples. These specifications resulted in six levels of total sample sizes: 500; 1,000; 1,500; 2,500; 3,000; and 5,000.

We use the term *class distinctness* to characterize the pattern of class-specific parameters. We chose two patterns of conditional latent class probabilities to generate different degrees of separation among level-2 classes: more distinctive conditions and less distinctive conditions, respectively. For more distinctive conditions, the true population values of the parameters differed greatly among the classes in which larger differences in the values yielded more distinguishable classes, therefore inducing more separated classes. For less distinctive conditions, on the other hand, the true population parameter values were more evenly distributed. Such patterns resulted in less distinguishable classes, therefore inducing less separated classes.

Likewise, two different levels of class separation at level-1 were created by manipulating the pattern of conditional response probabilities. The values were set to differ greatly among the level-1 classes in the conditions designed for more distinctive classes, but the values were more evenly distributed in less distinctive conditions. The exact parameter values used in the simulation study are summarized in the Appendix.

The magnitude of covariate effects was manipulated through logit parameters, representing the association between covariates and class memberships. A higher value of this parameter corresponds with larger covariate effects. The logit parameters for covariate effects at level-1 were assumed to be 2 and 2 for large ($\gamma_{11} = 2$, $\gamma_{21} = 2$), 1 and 1 for moderate ($\gamma_{11} = 1$, $\gamma_{21} = 1$), and 0 and 0 for no effect ($\gamma_{11} = 0$, $\gamma_{21} = 0$) conditions, while the third class was set as the reference category. Similarly, the logit parameters for the level-2 covariate effect were set to 2, 1, and 0, representing large ($\alpha_{11} = 2$), moderate ($\alpha_{11} = 1$), and no effect ($\alpha_{11} = 0$) conditions where the second class was selected as the reference category. The sizes of the higher-level latent classes were assumed to be equal, which implies that groups have equal probabilities of belonging to each higher-level latent class.

Analysis

A factorial simulation experiment was performed to evaluate the effects of six manipulated factors and to compare the relative performance of the three methods. The design yielded 144 $(2 \times 2 \times 2 \times 2 \times 3 \times 3)$ conditions by crossing six design factors. For each simulation condition, 100 replications were simulated according to the parameter specifications listed in the Appendix. We used the Latent GOLD 5.0 Syntax Module (Vermunt & Magidson, 2008) to generate data, estimate model parameters, save the posterior latent class probabilities of individuals as well as groups,[1] and estimate level-2 and level-1 covariate effects by applying the three methods. We then averaged the obtained parameter estimates and their SEs across all 100 replications for each condition. The SD of the parameter estimates over simulation replications was also calculated.

The specifications of the simulation design yielded diverse MLCM structures, from highly separated to extremely poorly separated clusters and classes. We used the measures of classification quality ($R^2_{entropy}$ measures) at each level to ensure that our design covered a wide range of latent cluster and class structures. The eight controlled factors resulted in the $R^2_{entropy.high}$ ranging from 0.158 to 1

[1] The modal assignment rule was used to assign individuals and groups into level-1 and level-2 latent classes.

and the $R^2_{entropy.low}$ ranging from 0.271 to 1. The average $R^2_{entropy.high}$ and $R^2_{entropy.low}$ across all conditions were 0.774 (SD = 0.248) and 0.745 (SD = 0.154), respectively.

Simulation results

Table 1 presents the parameter estimates of the level-2 covariate effects, the average estimated SEs, and the computed SDs of parameter estimates for the three methods over six sample size conditions. In general, the bias in the level-2 covariate parameters (i.e., the discrepancy between the estimated and true population values) tended to decrease as the level-2 sample size increased. The results also showed that all three methods recovered parameters well when level-2 covariate effects were moderate and none.

When the covariate effect was large, the classical three-step method had the largest overall bias (average bias less than 10%). In particular, the classical three-step method underestimated the parameters when the sample sizes were relatively small (total sample size < 1,500), but the underestimation vanished as the sample sizes increased. A similar pattern of results was found for the ML method, but parameter estimates obtained from the ML method were slightly less biased (average bias less than 5%). The one-step method, alternatively, slightly overestimated the parameters under the same conditions (average bias less than 5%).

When comparing the average estimated SEs with SDs across replications, the one-step method was the most efficient approach, showing that the average ratios of SEs and SDs were almost equal to one (average ratio = 1.03). The average ratio obtained from the classical three-step method was below one under the conditions of large and medium covariate effects, indicating that overall SEs tended to be underestimated (average ratio = 0.82). The ML method also yielded underestimated SEs under the same conditions (average ratio = 0.85), but the average ratio was a bit closer to one in comparison with the classical three-step method. Moreover, the SEs were slightly overestimated for both three-step methods when covariate effects were small. These results are consistent with previous studies investigating covariate effects at a single level using the modal assignment (Bakk et al., 2013, 2014; Vermunt, 2010).

Table 2 presents the parameter estimates of the level-1 covariate, the averaged SEs, and the SDs of parameter estimates across six sample size conditions. As Table 2 shows, the parameter bias tended to decrease as the level-1 sample sizes increased; this pattern suggested that having more level-1 samples allowed all three methods to estimate level-1 covariate parameters more precisely.

Among the three methods, the classical three-step method performed the worst, showing the largest parameter bias (average bias less than 30%). This method yielded downward-biased parameter estimates, except for conditions of small covariate effects and such underestimations were more severe when the covariate effects were large (average bias more than 40%), in contrast, the parameter estimates obtained from the one-step method were slightly overestimated (average bias less than 5%). The ML method underestimated the parameters,

TABLE 1
Average Estimated Level-2 Covariate Effect (α), SEs, and SDs Under Six Sample Size Conditions

Samples		*One-Step*			*Classical Three-Steps*			*ML Three-Steps*		
n_g	G	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*
					$\alpha_{11} = 2$					
10	50	2.11	0.73	0.75	1.42	0.45	0.59	1.46	0.50	0.66
	100	2.07	0.57	0.57	1.55	0.26	0.39	1.60	0.30	0.43
30	50	2.08	0.65	0.65	1.49	0.82	1.01	1.55	0.81	1.05
	100	2.11	0.64	0.49	2.12	0.27	0.91	2.09	0.35	0.89
50	50	2.15	0.66	0.67	2.46	0.97	1.10	2.20	0.98	1.11
	100	2.09	0.48	0.45	2.24	0.77	0.94	2.12	0.78	0.87
					$\alpha_{11} = 1$					
10	50	1.15	0.47	0.50	1.02	0.26	0.27	1.04	0.28	0.28
	100	1.06	0.32	0.34	1.01	0.18	0.20	1.02	0.18	0.20
30	50	1.08	0.34	0.35	1.14	0.29	0.30	1.12	0.30	0.31
	100	1.08	0.25	0.23	1.01	0.20	0.21	1.03	0.21	0.22
50	50	1.07	0.33	0.33	1.15	0.29	0.30	1.12	0.30	0.31
	100	1.03	0.23	0.21	1.10	0.21	0.24	1.08	0.21	0.22
					$\alpha_{11} = 0$					
10	50	0.03	0.30	0.20	0.02	0.22	0.13	0.02	0.23	0.14
	100	0.00	0.19	0.12	0.00	0.15	0.09	0.00	0.15	0.09
30	50	0.01	0.22	0.13	0.02	0.21	0.13	0.02	0.21	0.13
	100	0.02	0.19	0.10	0.01	0.15	0.10	0.01	0.15	0.10
50	50	0.02	0.20	0.13	0.02	0.20	0.13	0.02	0.20	0.13
	100	0.01	0.16	0.09	0.01	0.15	0.09	0.01	0.15	0.09

TABLE 2
Average Estimated Level-1 Covariate Effect (γ), SEs, and SDs Under Six Sample Size Conditions

Samples		*One-Step*			*Classical Three-Steps*			*ML Three-Steps*		
G	n_g	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*
					$\gamma_{11} = 2$					
50	10	2.20	0.49	0.86	1.07	0.12	0.41	1.55	0.32	0.51
	30	2.13	0.21	0.82	1.27	0.09	0.23	1.62	0.21	0.46
	50	2.03	0.18	0.81	1.37	0.06	0.21	1.78	0.18	0.37
100	10	2.19	0.36	0.94	1.03	0.09	0.39	1.65	0.23	0.53
	30	2.12	0.34	0.83	1.05	0.10	0.16	1.68	0.32	0.41
	50	2.09	0.16	0.14	1.39	0.05	0.20	1.90	0.14	0.34
					$\gamma_{11} = 1$					
50	10	1.09	0.41	0.46	0.58	0.13	0.26	0.92	0.29	0.46
	30	1.05	0.20	0.43	0.63	0.08	0.26	0.91	0.21	0.24
	50	1.01	0.12	0.41	0.62	0.06	0.23	0.98	0.16	0.18
100	10	1.04	0.24	0.25	0.56	0.09	0.16	0.90	0.22	0.44
	30	1.05	0.20	0.12	0.55	0.09	0.13	0.94	0.22	0.20
	50	1.01	0.12	0.08	0.63	0.05	0.13	0.96	0.14	0.18
					$\gamma_{11} = 0$					
50	10	0.07	0.30	0.25	0.02	0.11	0.07	0.04	0.26	0.23
	30	0.01	0.13	0.09	0.01	0.08	0.05	0.01	0.14	0.11
	50	0.01	0.10	0.05	0.01	0.06	0.03	0.01	0.12	0.08
100	10	0.02	0.15	0.08	0.02	0.07	0.05	0.03	0.19	0.13
	30	0.01	0.15	0.06	0.01	0.08	0.03	0.03	0.18	0.07
	100	0.01	0.09	0.03	0.00	0.05	0.02	0.01	0.11	0.07

particularly when level-1 sample sizes were small (n_g = 10), but such downward bias lessened as the level-1 sample size increased (average bias less than 10%). This pattern suggested that level-1 covariate parameters were more precisely estimated under larger sample size conditions.

The results indicated that the classical three-step method severely underestimated SEs, particularly when covariate effects were medium and large (average ratio = 0.39). The one-step method also underestimated the SEs under the same conditions, but the downward bias was less severe than the classical three-step method (average ratio = 0.73). The underestimation bias of the ML method was comparable to the one-step method (average ratio = 0.70), and such bias was more evident when the covariate effect was large, and the level-1 sample size was small.

Table 3 illustrates the parameter estimates of the level-2 covariate, the averaged SEs, and the SDs of parameter estimates under the four conditions of class distinctness. Table 3 shows that the parameter estimates were closer to the true values under the conditions in which the level-2 classes were more distinctive. This result indicated that a greater degree of class separation at level-2 provides better recovery of the level-2 covariate parameters.

The results also indicated that the one-step method slightly overestimated the parameters in all conditions. The ML method, on the other hand, performed well when level-2 classes were more distinctive (average bias less than 5%), regardless of level-1 class distinctiveness. In line with previous studies (Bakk et al., 2013; Bennink et al., 2015), the SEs obtained from the classical three-step method were the smallest among the three methods. The one-step method slightly overestimated the SEs in all conditions (average ratio = 1.18); however, the SEs obtained from the ML method were slightly underestimated when level-2 covariate effects were medium and large (average ratio = 0.85), but overestimated under conditions where the covariate effects were small (average ratio = 1.56).

Table 4 exhibits the parameter estimates of the level-1 covariate, the averaged SEs, and the SDs of parameter estimates under four conditions of class distinctness. In general, the level-1 covariate parameters were precisely estimated under conditions in which level-1 classes were more distinctive. We observed severe underestimation with the classical three-step method; this pattern was more evident, particularly when level-1 covariate effects were large, and level-1 classes were less distinctive (average bias more than 60%), compared with more distinctive level-1 classes (average bias less more than 40%).

Note, however, that the one-step and three-step ML methods performed well in terms of parameter recovery (average bias less than 10% for both methods), even though the former method slightly overestimated the parameters. The latter slightly underestimated when level-1 covariate effects are large, but slightly overestimated under moderate and small conditions. Interestingly, the performance of the three-step ML method was not only affected by class distinctness at the same level (level-1), but also interacted with the distinctness of the level-2 classes. More specifically, the largest bias was observed under the condition in which both

TABLE 3
Average Estimated Level-2 Covariate Effect (α), SEs, and SDs Under Four Class Distinctness Conditions

Class Distinctness		*One-Step*			*Classical Three-Steps*			*ML Three-Steps*		
Lv1	*Lv2*	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*
					$\alpha_{11} = 2$					
More	More	2.08	0.54	0.54	2.03	0.39	0.47	2.02	0.45	0.49
	Less	2.04	0.63	0.59	2.22	0.96	1.31	2.24	1.02	1.31
Less	More	2.12	0.65	0.64	1.93	0.41	0.55	1.95	0.43	0.54
	Less	2.21	0.68	0.66	1.92	0.60	1.19	1.86	0.58	1.10
					$\alpha_{11} = 1$					
More	More	1.03	0.27	0.27	1.07	0.26	0.27	1.06	0.27	0.27
	Less	1.08	0.35	0.34	1.11	0.22	0.26	1.09	0.25	0.26
Less	More	1.05	0.29	0.29	1.08	0.26	0.27	1.08	0.26	0.27
	Less	1.14	0.46	0.45	1.03	0.21	0.25	1.04	0.22	0.25
					$\alpha_{11} = 0$					
More	More	0.02	0.18	0.12	0.02	0.18	0.11	0.02	0.18	0.11
	Less	0.01	0.21	0.14	0.01	0.18	0.12	0.01	0.19	0.12
Less	More	0.01	0.19	0.12	0.01	0.18	0.12	0.01	0.18	0.12
	Less	0.02	0.25	0.17	0.02	0.18	0.12	0.02	0.18	0.12

TABLE 4
Average Estimated Level-1 Covariate Effect (γ), SEs, and SDs Under Four Class Distinctness Conditions

Class Distinctness		*One-Step*			*Classical Three-Steps*			*ML Three-Steps*		
Lv2	*Lv1*	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*	*Estimate*	*SE*	*SD*
					$\gamma_{11} = 2$					
More	More	2.02	0.21	0.42	1.21	0.10	0.53	1.96	0.21	0.37
	Less	2.08	0.39	0.69	0.70	0.09	0.10	1.73	0.37	0.74
Less	More	2.04	0.20	0.49	1.14	0.08	0.46	1.94	0.17	0.46
	Less	2.18	0.37	0.77	0.69	0.07	0.27	1.63	0.19	0.65
					$\gamma_{11} = 1$					
More	More	1.01	0.13	0.37	0.72	0.10	0.25	1.05	0.16	0.37
	Less	1.08	0.34	0.47	0.52	0.10	0.21	1.12	0.35	0.55
Less	More	1.02	0.11	0.37	0.69	0.07	0.07	0.99	0.12	0.12
	Less	1.06	0.28	0.23	0.46	0.06	0.15	1.02	0.19	0.35
					$\gamma_{11} = 0$					
More	More	0.01	0.10	0.06	0.01	0.09	0.05	0.02	0.12	0.08
	Less	0.04	0.24	0.14	0.01	0.10	0.06	0.04	0.34	0.22
Less	More	0.01	0.08	0.05	0.01	0.05	0.03	0.01	0.08	0.04
	Less	0.03	0.19	0.19	0.01	0.06	0.04	0.02	0.13	0.09

level-1 and level-2 classes were less distinctive among four possible conditions (average bias less than 10%), and this pattern was particularly prominent when the covariate effect was large (average bias less than 40%). Conversely, the smallest bias was found when the classes were more distinctive at both levels (average bias less than 5%).

The estimated SEs of the covariate effects tended to decrease as the lower-level classes became more distinctive. The one-step method performed better than the three-step ML method regarding efficiency, and this pattern was more pronounced when the covariate effect was large (average ratio = 0.49 for the one-step method; average ratio = 0.43 for the ML method). This result is consistent with Bakk et al. (2013) results, which demonstrated that the SE bias of the ML method is slightly higher than the SE bias of the one-step method under the condition of strong covariate effects with nominal indicators.

EMPIRICAL EXAMPLE

Participants

To illustrate the application of the three methods for evaluating covariate effects at two levels, we used data from the motivated identity construction in a cultural context 2008–2011 (Vignoles & Brown, 2011), which consists of two large-scale surveys studies. The aim of the study was to examine the strengths of identity motives, sources of motive satisfaction, and cultural beliefs and value across different nations. Detailed information on the study is available on the UK data archive (http://www.data-archive.ac.uk/).

To capture maximum cultural diversity between and within nations, we focused on the study 2, as participants in the study 1 were high school students from 19 nations (Time 1) and 16 nations (Time 2), and participants in the study 2 were adults from 36 nations. The sample in the study 2 consisted of 8746 participants (56% females, mean age = 35.0, SD = 13.0) from 64 cultural groups in 36 nations.

Measures

The study 2 investigated constructs related to motivated identity construction such as collectivism, favoritism, and differential cultural trust of in-group and out-group members. Among many constructs, contextualism beliefs are an important part of cultural collectivism that cover a range of different contexts: family, social groups, position in society, the place one comes from, occupation, where one lives, social position, role in society, and educational achievement (Owe et al., 2013).

We selected six items from the contextualism scale, which originally consisted of 14 items (Owe et al., 2013). The chosen six items surveyed opinions on whether people change easily, the importance of one's social position, and the importance of where one comes from. The original items were rated on 6-point scales ranging from 1 (completely disagree) to 6 (completely agree). Responses were dichotomized into disagree and agree to be consistent with the simulation design in the present study.

A single covariate at each level was included in the analysis; the level-2 covariate was region, which broadly divided countries into six categories based on geographical location (Africa, Asia, Europe, North America, South America, and Oceania), and the selected level-1 covariate was gender with two categories (male or female).

Analysis

An analysis was performed using the selected items and the covariates at two levels. We first built an MLCM model for contextualism beliefs based on the six selected items. The data were fit to 16 models with a different latent structure of two to five classes at each level. According to extant literature, BIC with number of groups as the sample size for the penalty term was used to determine the number of latent classes. Among the 16 models, the model with two classes at the country level (GClass) and three classes at the individual level (Class) showed the lowest BIC value with excellent fit to data ($R^2_{entropy.high}$ = 0.81, $R^2_{entropy.low}$ = 0.75), thus selected as a final model. Once the final model was selected, the effects of covariates were then assessed using the three methods, one-step method, the classical three-step method, and the bias-adjusted three-step ML method. The analyses are carried out using the Latent GOLD 5.0 Syntax Module (Vermunt & Magidson, 2013).

Results

The estimated conditional response probabilities of the final model are presented in Table 5. The results suggested that individuals in Class 1 rarely endorsed the items related to "personal change," but individuals in Class 3 tended to answer the same items positively. Conversely, individuals in Class 2 answered positively to the items related to the "importance of social position" and "where people come from." Although there were some minor differences in response patterns, we named three classes according to the pattern of estimated conditional response probabilities: Class 1 was referred to as the Mover class, Class 2 as the Social-Oriented class, and Class 3 as the Stayer class with respect to their attitudes toward understanding people.

Table 6 shows the probabilities of the individual-level classes conditional on country-level classes and gender. The countries in GClass 1 had a dominant Stayer class, showing that about 62% of the males and 63% of females were in this class, whereas the countries in GClass 2 had no dominant class but were more evenly distributed. Note that 37% of the males in GClass 2 valued achieving a high social position, while only 32% of females considered social positions important.

Table 7 shows the countries classified into each country-level class (GClass), with estimated GClass sizes of 54% and 46%. The results indicated that countries from the same continent are likely to be in the same GClass, showing that GClass 1 primarily comprised countries in Europe and Northeast Asia, whereas GClass 2 comprised countries from South America and Africa.

After identifying the level-1 and level-2 classes, we calculated classification errors at each level using posterior class membership probabilities. We then applied the classical three-step and ML methods to evaluate the covariate effects at each level. For the one-step method, we assessed the covariate effects while selecting the number of classes. Table 8 reports the estimates of the covariate effects on the class memberships and their SEs at both levels.

TABLE 5
Conditional Response Probabilities on Six Selected Items

Indicators	*Stayer*	*Social-oriented*	*Mover*
You can always substantially change the kind of person you are.	0.08	0.32	0.70
No matter what kind of person you are, you can always change a lot.	0.06	0.38	0.91
To understand a person well, it is essential to know about his/her role in society.	0.13	0.84	0.14
To understand a person well, it is essential to know about which social groups he/she is a member of.	0.29	0.78	0.31
One can understand a person well without knowing about the place he/she comes from.	0.39	0.68	0.57
To understand a person well, it is essential to know about the place he/she comes from.	0.08	0.77	0.13

TABLE 6
Conditional Latent Class Probabilities Given Country-Level Classes and Gender

		Class		
Gender	*GClass*	*Stayer*	*Social*	*Mover*
Male	1	0.62	0.21	0.17
	2	0.34	0.37	0.29
Female	1	0.63	0.19	0.18
	2	0.36	0.32	0.32

TABLE 7
Predicted Country-Level Class Membership

GClass 1 (54%)	*GClass 2 (46%)*
Belgium, Egypt, Georgia, Germany, Hungary, Iceland, Italy, Japan, Lebanon, New Zealand, Norway, Romania, Russia, Singapore, Spain, Sweden, Turkey, Great Britain, United States, Thailand	Brazil, Chile, China, Colombia, Ethiopia, Ghana, Malaysia, Namibia, Oman, Philippines, Uganda, Peru, Cameroon

TABLE 8
Estimates of Covariate Parameters, SEs, and *P*-values of the Three Compared Methods

	GClass1			Stayer			Mover		
Methods	α_{11}	*SEs*	p	γ_{11}	*SEs*	p	γ_{21}	*SEs*	p
One-Step	−0.60	0.17	<0.01	−0.14	0.07	<0.05	0.04	0.08	<0.05
Classical	−0.62	0.11	<0.01	−0.10	0.06	<0.05	−0.01	0.06	<0.05
ML	−0.62	0.14	<0.01	−0.14	0.08	<0.05	−0.01	0.08	<0.05

As shown in Table 8, the ML methods provided parameter estimates similar to those of the one-step method at both levels. However, the classical three-step method underestimated the level-1 covariate parameters as compared to the other two methods. Moreover, similar to the results of the simulation study, the SEs obtained from the classical three-step method was smaller than those from other two methods. These results were in agreement with the findings in the simulation study; that is, the ML method performed similarly to the one-step method when there were sufficient sample sizes at individual levels (N = 8,652) and classes at both levels were well-separated ($R^2_{entropy.high} = 0.81$, $R^2_{entropy.low} = 0.75$).

DISCUSSION AND CONCLUSION

The purpose of the current study was to examine the relative performance of three approaches for estimating covariate effects in the context of an MLCM. We were particularly interested in whether existing methods for LCAs with single-level covariates can be generalized to situations where both level-1 and level-2 covariates effects are simultaneously estimated. To answer this question, we conducted a simulation study by manipulating level-1 and level-2 sample sizes, level-1 and level-2 class distinctness, and the magnitude of level-1 and level-2 covariate effects. We evaluated the simulation results with respect to the bias in covariate parameters and the efficiency of the SEs.

The findings of the current study regarding bias in parameter estimates were generally consistent with those of previous studies (Bakk et al., 2013; Bennink, Croon, & Vermunt, 2013; Di Mari et al., 2016; Vermunt, 2010); the classical three-step method yielded serious underestimation of covariate parameters. However, we observed such serious downward bias only on the level-1 covariate parameters, whereas the level-2 covariate parameters were less biased. We also found that the ML method performed well under the conditions of having a sufficient number of samples and a distinct class structure; this method performed as well as the one-step method regarding parameter recovery and the accuracy of the SEs. Nevertheless, under the conditions of small sample sizes and less distinctive classes, the three-step ML method yielded biased parameter estimates and SEs at both the individual and group levels. These results are in agreement with previous simulation studies assessing covariate effects at the individual level (e.g., Asparouhov & Muthén, 2014; Bakk et al., 2013). One possible explanation for this pattern is the nature of the ML estimation procedure for LCA, which exaggerates the heterogeneity of latent classes and consequently underestimates the amount of the classification error (Vermunt, 2010).

The findings related to sample size effects are consistent with previous simulation results. In general, a larger number of groups or group sizes led to better performance in recovering the covariate parameters and their SEs. One notable finding is that covariate parameters at both levels were particularly sensitive to the sample sizes at level-1. This result may be due to the model specification of a nonparametric MLCM, in which level-1 sample sizes affect the composition of both level-1 and level-2 latent classes. Although we did not examine how large of a sample is needed to guarantee good performance, a group size of 10 individuals was clearly not enough.

We found that class distinctness also affects the precision of covariate parameter estimates and their SEs. The simulation results revealed that a larger bias was associated with having less distinct classes at both levels. One important finding of our study is that bias was not only affected by class distinctness at a single level, but it also was associated with interactions of class distinctness at two levels. Specifically, conditions with less distinctive classes at both levels produced the largest bias among four possible conditions, while the lowest bias in the estimated parameters and their SEs were found under more distinct classes at both levels.

The findings of the current study suggested that sample sizes and class distinctness play important roles in accurately estimating covariate parameters. Therefore, we recommend that researchers take the importance of those two factors into consideration and assess how level-1 and level-2 classes are separated in advance by using measures such as $R^2_{entropy}$, which is provided by most software for MLCMs (e.g., Latent Gold or Mplus). Information about class separation can guide the selection of the appropriate method to obtain more reliable and unbiased results.

Based on the findings in the present study, we recommend using the ML method for estimating covariate effects in MLCMs, particularly when the sample sizes are sufficiently large, and the classes are well separated. However, in cases where the sample sizes are limited, and latent classes are poorly separated, the one-step method is a more favorable approach over the stepwise methods. We do not recommend the classical three-step method for estimating covariate effects in an MLCM because the parameters are severely downward-biased at the level-1.

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REFERENCES

Aitkin, M. (1999). A general maximum likelihood analysis of variance components in generalized linear models. *Biometrics*, *55*, 117–128. doi:10.1111/biom.1999.55.issue-1

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling*, *21*, 329–341. doi:10.1080/10705511.2014.915181

Asparouhov, T., & Muthén, B. (2008). Multilevel mixture models. In G. R. Hancock, & K. M. Samuelson (Eds.), *Advances in latent variable mixture models* (pp. 27–51). Charlotte, NC: Information Age.

Bakk, Z., Oberski, D. L., & Vermunt, J. K. (2014). Relating latent class assignments to external variables: Standard errors for correct inference. *Political Analysis*, *22*, 520–540. doi:10.1093/pan/mpu003

Bakk, Z., Tekle, F. B., & Vermunt, J. K. (2013). Estimating the association between latent class membership and external variables using bias-adjusted three-step approaches. *Sociological Methodology*, *43*, 272–311. doi:10.1177/0081175012470644

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural Equation Modeling*, *23*, 20–31. doi:10.1080/10705511.2014.955104

Bandeen-Roche, K., Miglioretti, D. L., Zeger, S. L., & Rathouz, P. J. (1997). Latent variable regression for multiple discrete outcomes. *Journal of the American Statistical Association*, *92*, 1375–1386. doi:10.1080/01621459.1997.10473658

Bartolucci, F., Montanari, G. E., & Pandolfi, S. (2015). Three-step estimation of latent markov models with covariates. *Computational Statistics & Data Analysis*, *83*, 287–301. doi:10.1016/j.csda.2014.10.017

Bassi, F. (2009). Latent class models for marketing strategies: An application to the Italian pharmaceutical market. *Methodology*, *5*, 40–45. doi:10.1027/1614-2241.5.2.40

Bennink, M., Croon, M. A., Kroon, B., & Vermunt, J. K. (2016). Micro-macro multilevel latent class models with multiple discrete individual-level variables. *Advances in Data Analysis and Classification*, *10*, 139–154. doi:10.1007/s11634-016-0234-1.

Bennink, M., Croon, M. A., & Vermunt, J. K. (2013). Micro-macro multilevel analysis for discrete data: A latent variable approach and an application on personal network data. *Sociological Methods and Research*, *42*, 431–457. doi:10.1177/0049124113500479

Bennink, M., Croon, M. A., & Vermunt, J. K. (2015). Stepwise latent class models for explaining group-level outcomes using discrete individual-level predictors. *Multivariate Behavioral Research*, *50*, 662–675. doi:10.1080/00273171.2015.1074879

Bijmolt, T. H. A., Paas, L. J., & Vermunt, J. K. (2004). Country and consumer segmentation: Multi-level latent class analysis of financial product ownership. *International Journal of Research in Marketing*, *21*, 323–334. doi:10.1016/j.ijresmar.2004.06.002

Bolck, A., Croon, M. A., & Hagenaars, J. A. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, *12*, 3–27. doi:10.1093/pan/mph001

Bryk, A. S., & Raudenbush, S. W. (1992). *Hierarchical linear models: Applications and data analysis methods*. Thousand Oaks, CA: Sage.

Clogg, C. C. (1981). New developments in latent structure analysis. In D. J. Jackson, & E. F. Borgotta (Eds.), *Factor analysis and measurement in sociological research* (pp. 215–246). Beverly Hills, CA: Sage Publications.

da Costa, L. P., & Dias, J. G. (2014). What do Europeans believe to be the causes of poverty? A multilevel analysis of heterogeneity within and between countries. *Social Indicators Research*, *122*, 1–20. doi:10.1007/s11205-014-0672-0

Dayton, C. M., & Macready, G. B. (1988). Concomitant-variable latent-class models. *Journal of the American Statistical Association*, *83*, 173–178. doi:10.1080/01621459.1988.10478584

Di, C. Z., & Bandeen-Roche, K. (2011). Multilevel latent class models with dirichlet mixing distribution. *Biometrics*, *67*, 86–96. doi:10.1111/j.1541-0420.2010.01448.x

Di Mari, R., Oberski, D. L., & Vermunt, J. K. (2016). Bias-adjusted three-step latent Markov modeling with covariates. *Structural Equation Modeling*, *23*, 649–660. doi:10.1080/10705511.2016.1191015

Dziak, J. J., Bray, B. C., Zhang, J., Zhang, M., & Lanza, S. T. (2016). Comparing the performance of improved classify-analyze approaches for distal outcomes in latent profile analysis. *Methodology*, *12*, 107–116. doi:10.1027/1614-2241/a000114

Finch, W. H., & French, B. F. (2013). Multilevel latent class analysis: Parametric and nonparametric models. *The Journal of Experimental Education*, *82*, 307–333. doi:10.1080/00220973.2013.813361

Finch, W. H., & Marchant, G. J. (2013). Application of multilevel latent class analysis to identify achievement and socio-economic typologies in the 20 wealthiest countries. *Journal of Educational and Developmental Psychology*, *3*, 201–221. doi:10.5539/jedp.v3n1p201

Frühwirth-Schnatter, S. (2006). *Finite mixture and markov switching models*. Springer Series in Statistics. New York, NY: Springer.

Goldstein, H. (1995). *Multilevel statistical models*. London: Arnold.

Goodman, L. A. (1974). The analysis of systems of qualitative variables when some of the variables are unobservable. Part I: A modified latent structure approach. *American Journal of Sociology*, *79*, 1179–1259. doi:10.1086/225676

Gudicha, D. W., & Vermunt, J. K. (2011). Mixture model clustering with covariates using adjusted three-step approaches. In B. Lausen, D. Van den Poel, & A. Ultsch (Eds.), *Algorithms from and for nature and life: Studies in classification, data analysis, and knowledge organization* (pp. 87–93). Heidelberg: Springer-Verlag GmbH.

Hagenaars, J. A. (1990). *Categorical longitudinal data-loglinear analysis of panel, trend and cohort data*. Thousand Oaks, CA: Sage.

Hagenaars, J. A. (1993). *Loglinear models with latent variables*. Thousand Oaks, CA: Sage.

Henry, K. L., & Muthén, B. (2010). Multilevel latent class analysis: An application of adolescent smoking typologies with individual and contextual predictors. *Structural Equation Modeling*, *17*, 193–215.

Kim, M., Vermunt, J., Bakk, Z., Jaki, T., & Van Horn, M. L. (2016). Modeling predictors of latent classes in regression mixture models. *Structural Equation Modeling*, *23*, 601–614. doi:10.1080/10705511.2016.1158655

Kim, S.-Y. (2014). Determining the number of latent classes in single- and multi-phase growth mixture models. *Structural Equation Modeling*, *21*, 263–279. doi:10.1080/10705511.2014.882690

Lanza, T. S., Tan, X., & Bray, C. B. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling*, *20*, 1–26. doi:10.1080/10705511.2013.742377

Lazarsfeld, P. F., & Henry, N. W. (1968). *Latent structure analysis*. Boston, MA: Houghton Mifflin.

Lukočiené, O., Varriale, R., & Vermunt, J. K. (2010). The simultaneous decision(s) about the number of lower- and higher-level classes in multilevel latent class analysis. *Sociological Methodology*, *40*, 247–283. doi:10.1111/j.1467-9531.2010.01231.x

Muthén, L. K., & Muthén, B. O. (2012). *Mplus user's guide* (7th ed.). Los Angeles, CA: Muthén & Muthén.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, *14*, 535–569. doi:10.1080/10705510701575396

Onwezen, M. C., Reinders, M. J., Lans, V. D. I., Sijtsema, S. J., Jasiulewicz, A., Guardia, M. D., & Guerrero, L. (2012). A cross-national consumer segmentation based on contextual differences in food choice benefits. *Food Quality and Preference*, *24*, 276–286. doi:10.1016/j.foodqual.2011.11.002

Owe, E., Vignoles, V. L., Becker, M., Brown, R., Smith, P. B., Lee, S. W. S., … Jalal, B. (2013). Contextualism as an important facet of individualism-collectivism: Personhood beliefs across 37 national groups. *Journal of Cross-Cultural Psychology*, *44*, 24–45. doi:10.1177/0022022111430255

Pirani, E. (2013). Evaluating contemporary social exclusion in Europe: A hierarchical latent class approach. *Quality and Quantity*, *47*, 923–941. doi:10.1007/s11135-011-9574-2

Rindskopf, D. (2006). Heavy alcohol use in the "Fighting Back" survey sample: Separating individual and community level influences using multilevel latent class analysis. *Journal of Drug Issues*, *36*, 441–462. doi:10.1177/002204260603600210

Rüdiger, M., & Hans-Dieter, D. (2013). University and student segmentation: Multilevel latent class analysis of students' attitudes toward research methods and statistics. *British Journal of Educational Psychology*, *83*, 280–304. doi:10.1111/j.2044-8279.2011.02062.x

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, *6*, 461–464. doi:10.1214/aos/1176344136

Skrondal, A., & Rabe-Hesketh, S. (2004). *Generalized latent variable modeling: Multilevel, longitudinal and structural equation models*. Boca Raton, FL: Chapman & Hall.

Snijders, T. A. B., & Bosker, R. J. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. Thousand Oaks, CA: Sage.

Tofighi, D., & Enders, C. (2007). Identifying the correct number of classes in growth mixture models. In G. R. Hancock, & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 317–341). Greenwich, CT: Information Age.

Vermunt, J. K. (2003). Multilevel latent class models. *Sociological Methodology*, *33*, 213–239. doi:10.1111/j.0081-1750.2003.t01-1-00131.x

Vermunt, J. K. (2004). An EM algorithm for the estimation of parametric and nonparametric hierarchical nonlinear models. *Statistica Neerlandica*, *58*, 220–233. doi:10.1046/j.0039-0402.2003.00257.x

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*, 450–469. doi:10.1093/pan/mpq025

Vermunt, J. K., & Magidson, J. (2008). *LG-Syntax user's guide: Manual for Latent GOLD 4.5 syntax module*. Belmont, MA: Statistical Innovations.

Vermunt, J. K., & Magidson, J. (2013). *Technical guide for Latent GOLD 5.0: Basic, advanced, and syntax*. Belmont, MA: Statistical Innovations.

Vermunt, J. K., & Van Dijk, L. A. (2001). A nonparametric random coefficient approach: The latent class regression model. *Multilevel Modelling Newsletter*, *13*, 6–13.

Vignoles, V., & Brown, R. (2011). *Motivated identity construction in cultural context, 2008–2011* (Study No. 6877) [Computer file]. Colchester, Essex: UK Data Archive [Distributor].

Yang, C. C., & Yang, C. C. (2007). Separating latent classes by information criteria. *Journal of Classification*, *24*, 183–203. doi:10.1007/s00357-007-0010-1

Yu, H.-T., & Park, J. (2014). Simultaneous decision on the number of latent clusters and classes for multilevel latent class models. *Multivariate Behavioral Research*, *49*, 232–244. doi:10.1080/00273171.2014.900431

APPENDIX

Specifications of the Conditional Latent Class Probabilities for More- and Less-Distinct Classes

		Parameters		
Higher level	*Lower level*	$P(H_g)$	$P(X_{gi}\|H_g)$	$P(Y_{gij}\|X_{gi})$
More	More	$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$	$\begin{bmatrix} .8 & .1 \\ .1 & .1 \\ .1 & .8 \end{bmatrix}$	$\begin{bmatrix} .8 & .8 & .8 & .8 & .8 & .8 & .8 & .8 \\ .2 & .2 & .2 & .2 & .8 & .8 & .8 & .8 \\ .2 & .2 & .2 & .2 & .2 & .2 & .2 & .2 \end{bmatrix}$
	Less	$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$	$\begin{bmatrix} .8 & .1 \\ .1 & .1 \\ .1 & .8 \end{bmatrix}$	$\begin{bmatrix} .7 & .7 & .7 & .7 & .7 & .7 & .7 & .7 \\ .3 & .3 & .3 & .3 & .7 & .7 & .7 & .7 \\ .3 & .3 & .3 & .3 & .3 & .3 & .3 & .3 \end{bmatrix}$
Less	More	$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$	$\begin{bmatrix} .7 & .15 \\ .15 & .15 \\ .15 & .7 \end{bmatrix}$	$\begin{bmatrix} .8 & .8 & .8 & .8 & .8 & .8 & .8 & .8 \\ .2 & .2 & .2 & .2 & .8 & .8 & .8 & .8 \\ .2 & .2 & .2 & .2 & .2 & .2 & .2 & .2 \end{bmatrix}$
	Less	$\begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$	$\begin{bmatrix} .7 & .15 \\ .15 & .15 \\ .15 & .7 \end{bmatrix}$	$\begin{bmatrix} .7 & .7 & .7 & .7 & .7 & .7 & .7 & .7 \\ .3 & .3 & .3 & .3 & .7 & .7 & .7 & .7 \\ .3 & .3 & .3 & .3 & .3 & .3 & .3 & .3 \end{bmatrix}$