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Latent transition analysis with Auxiliary Variables: A demonstration of the ML 3-Step and BCH in Mplus

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Abstract ■ Latent transition analysis (LTA) is increasingly used to understand how individuals move among latent classes measured at multiple time points. LTA models often include auxiliary variables (e.g., covariates or distal outcomes) to explain class membership, predict transition probabilities, or examine later outcomes. Although measurement invariance is commonly assumed in LTA, it is not required for model estimation but is helpful for interpreting transitions as stability or change in the same construct. When auxiliary variables are included, testing and properly specifying measurement invariance becomes more complex if invariance is assumed. Implementing measurement invariance with recommended multi-step procedures, the ML three-step (ML 3-step) and the Bolck–Croon–Hagenaars (BCH) method, requires a sequence of model tests and modeling decisions. This tutorial provides a fully worked demonstration of how to evaluate measurement invariance in LTA and how to incorporate auxiliary variables using the ML 3-step and BCH approaches within Mplus. We introduce a practical workflow, address frequent modeling challenges, and provide annotated syntax using R and MplusAutomation for reproducibility. The goal of this tutorial is to offer applied researchers a transparent and accessible framework for drawing valid conclusions about subgroup stability and change.

Keywords ■ Latent transition analysis; Measurement invariance; Auxiliary variables; BCH; Maximum likelihood three-step method. **Tools** ■ R, MplusAutomation, Mplus.

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Introduction

Latent transition analysis (LTA) is a longitudinal extension of finite mixture modeling that estimates two or more latent class variables across time to capture changes in unobserved subpopulations. Transitions are modeled by regressing the latent class variable at each subsequent time point on the class variable from the previous time point, describing the probability of movement between classes over time. LTA is a useful framework for modeling change in heterogeneity because it flexibly accommodates different temporal structures and can be readily integrated into broader models that include covariates, predictors of transitions, and distal outcomes, collectively referred to as *auxiliary variables* in the mixture modeling literature. For example, researchers might use LTA to examine how students transition among motivational profiles across an academic year or how clients shift among response-to-intervention patterns.

The integration of auxiliary variables provides a context for researchers to address a broad array of substantively rich research questions, including what predicts latent class membership at each time point, what factors influence transitions across classes (covariate by transition interaction), and how class membership relates to later outcomes (distal outcomes). A recurring challenge across the family of mixture models, however, is determining which method to use to relate latent class membership to auxiliary variables while preserving the underlying measurement structure of the latent classes. Over the years, several strategies have been proposed to address this issue, each balancing the goals of interpretability, bias reduction, and model stability. Across the proposed approaches, the ones that have currently emerged as most useful are the ML 3-step (Vermunt, 2010; Asparouhov & Muthén, 2021) and the Bolck-Croon-Hagenaars (BCH) method (Bolck et al., 2004) because of their stability of application and reproducibility. In longitudinal contexts, these auxiliary methods must be combined with careful testing and specification of measurement invariance (MI) to ensure transitions and auxiliary effects are interpretable.

Initial strategies that linked latent class membership with auxiliary variables often relied on two-stage approaches, referred to as *classify–analyze* (Goodman, 1974; Bandeen-Roche et al., 1997), in which individuals were assigned to their modal class, and those assignments were used in subsequent analyses. While straightforward, these methods treated class assignments as error-free, leading to biased estimates and inflated associations (Nylund-Gibson et al., 2014). One-step approaches (e.g., Collins & Lanza, 2010; Muthén & Asparouhov, 2006), in which the latent classes and auxiliary relationships are estimated simultaneously, address that source of bias but introduce a different challenge, because auxiliary variables are included during class formation, they can reshape the latent classes themselves, altering the measurement model and reducing reproducibility (Vermunt, 2010). Multi-step approaches, including the maximum-likelihood three-step (ML 3-step) and BCH (Bolck et al., 2004; Bakk & Kuha, 2021), were developed to overcome these issues by preserving the measurement model and explicitly adjusting for classification uncertainty. To date, the ML 3-step and BCH methods are the most commonly used approaches and, as such, will be the focus of this tutorial.

The Current Article

Specifying multi-step auxiliary variable approaches in LTA can be complex, particularly when two or more latent class variables are defined over time. In the context of measurement invariance, multistep methods require careful implementation to ensure accurate correction for misclassification in the longitudinal model. The goal of this tutorial is threefold: 1) to provide a conceptual framework for measurement invariance (MI) in LTA with auxiliary variables, 2) a step-by-step workflow that is implementable in `Mplus` and the "MplusAutomation" package in `R` (Hallquist & Wiley, 2018), and 3) an applied example using ML 3-step and BCH under MI in the Supplementary Materials. This tutorial focuses on single-level LTA with binary indicators; extensions to ordinal indicators, multilevel LTA, or continuous-time models, are beyond the scope of this paper. The full syntax is provided in the Supplementary Materials to facilitate use by other scholars and to allow researchers to adapt these methods to their own data.

Measurement Invariance in Mixture Modeling

Establishing MI is an important step in mixture modeling when the interest is in making inferences about the equivalence of the emergent classes across groups, time, or experimental conditions. When MI is supported, inferences about latent class equivalence are justified, and the classes can be interpreted as representing the same underlying construct across the units being compared. Without MI, observed differences in class prevalence, covariate effects, or distal outcomes may reflect shifts in item functioning rather than true heterogeneity in the construct of interest.

Methodological work on MI in mixture models has largely focused on cross-sectional applications, specifically latent class analysis (LCA) and latent profile analysis (LPA). Much of this literature conceptualizes MI in terms of differential item functioning (DIF), where item parameters differ across levels of a grouping variable or continuous covariate (Masyn, 2017; Bakk, 2024). For latent profile models, similar questions arise regarding the equality of means, variances, and covariances when evaluating whether profiles carry the same meaning across groups (Olivera-Aguilar & Rikoon, 2017).

Extending MI to Latent Transition Analysis

Although most work on MI with mixtures has focused on cross-sectional mixture models, the same logic extends to longitudinal mixtures. In LTA, MI determines whether latent classes represent the same construct across time rather than across groups. When binary indicators are used (i.e., LCA as the measurement model), MI is evaluated by testing whether item-response probabilities are equivalent across time points (e.g., by comparing T1 and T2 latent classes). When MI holds, latent classes are substantively comparable, and transition probabilities reflect meaningful stability, change, or developmental processes. When MI does not hold, LTA can still be estimated, but transitions must be interpreted with respect to shifting class definitions rather than as stability in the same underlying construct.

Importantly, MI in LTA is both an empirical and theoretical issue, not a default assumption. Imposing invariance without testing may distort class definitions and lead to biased interpretations of stability, change, or relationships with auxiliary variables (Talley, 2021). Testing MI helps ensure that transitions reflect genuine developmental or intervention-related change, rather than artifacts of changing measurement properties across time.

Testing MI in LTA

Testing for measurement invariance in LTA involves both formal statistical comparison of nested models and substantive evaluation of class similarity across time. The statistical comparison evaluates whether item-response probabilities differ meaningfully across waves by contrasting an unconstrained model, in which these probabilities vary freely, with a constrained model, in which they are held equal across waves. Historically, this comparison was conducted using likelihood ratio tests (LRTs), where a significant LRT was taken as evidence that invariance constraints meaningfully reduced model fit. Although such LRTs were never appropriate for comparing models with differing numbers of classes (Nylund et al., 2007), early guidance suggested that they could be used when the number of classes was held constant and only measurement parameters were constrained.

More recent methodological work, however, demonstrates important limitations of this approach because constraining measurement parameters can induce non-regular likelihood conditions, violating the assumptions required for the likelihood ratio test statistic to follow a chi-square distribution. As a result, LRTs may be overly sensitive and detect trivial deviations from invariance as statistically significant. Recent simulation work by Bakk (2024) shows that the use of LRTs in mixtures is not uniformly reliable. Collectively, the literature suggests that LRTs should be interpreted with caution and that decisions about invariance should rely on a broader set of evidence, including information criteria, parameter similarity, and, when appropriate, simulation-based evaluation.

In addition to nested likelihood testing, researchers sometimes consider information criteria (ICs) such as the BIC, CAIC, and aBIC (Nylund et al., 2007). These indices are traditionally used for class enumeration in LCA/LPA, where lower values indicate better relative fit. However, Finch's (2015) simulation results demonstrated that ICs (AIC, BIC, CAIC, and aBIC) are generally unreliable for detecting measurement invariance in latent class models. Across conditions, none of the ICs consistently identified invariance or non-invariance, and their performance was highly sensitive to sample size, class-size imbalance, and the use of dichotomous indicators. Finch (2015) concluded that ICs may be useful for *narrowing* the set of plausible invariance structures but should not be expected to select the correct model. In contrast, the bootstrapped likelihood ratio test (BLRT) showed substantially higher accuracy and stability across conditions, highlighting its superiority for invariance testing, though unfortunately, the BLRT for nested MI models is not easily implemented in many commonly used software packages.

Given these limitations, all statistical model comparisons should be supplemented with substantive inspection of latent class profiles across time, for example, examining conditional item probabilities, class labels, and interpretability under both constrained and unconstrained specifications. If class structures remain substantively comparable when constraints are imposed, an invariant model may be justified even in the presence of modest statistical misfit. When evaluating measurement invariance in LTA, researchers should prioritize interpretability and class stability over small statistical differences in fit.

LTA: ML Three-Step Method

The maximum-likelihood three-step (ML 3-step) procedure has emerged as a widely used and flexible strategy for incorporating auxiliary variables in mixture models (Nylund-Gibson et al., 2014). Misclassification error from Step 1 is transformed into fixed logit offsets that are incorporated into the Step 3 model. Fixing these values ensures that auxiliary variable effects are estimated without altering the latent class or transition structure (for more, see Asparouhov & Muthén, 2021).

LTA: BCH Method

The Bolck–Croon–Hagenaars (BCH; Bolck et al., 2004) method is a widely recommended approach for incorporating auxiliary variables into mixture models, including LTA. Like the ML 3-step approach, BCH separates estimation of the measurement model from subsequent structural analyses, thus preserving latent class definitions and transition probabilities when auxiliary variables are introduced. Based on the Step 1 measurement model, `Mplus` computes posterior class membership probabilities and derives class-specific BCH weights (Asparouhov & Muthén, 2021), which are used in later analyses to adjust for classification uncertainty and approximate the results that would be obtained under error-free class membership.

The primary distinction between BCH and ML 3-step lies in how classification error is handled: ML 3-step corrects error at the class level, whereas BCH incorporates individual-level uncertainty through BCH weights. Because these weights more fully reflect posterior classification uncertainty, BCH is often regarded as a robust approach, particularly for distal outcome analyses. A practical limitation of BCH is the potential for negative weights, which are more likely when class separation is weak or when entropy is low; however, these arise from the weight construction rather than model misspecification. Despite this limitation, simulation studies consistently support BCH as a robust and unbiased method for auxiliary variable analyses in LTA.

Workflow for LTA: Assuming Measurement Invariance

In practice, implementing LTA with these multi-step approaches requires a systematic sequence of steps. Researchers typically begin by estimating separate latent class models at each time point to identify the number and general nature of the classes and to assess whether they are conceptually aligned across waves. When three or more waves are available, assuming full measurement invariance across all time points may be unrealistic. A common and practical strategy is pairwise testing, or evaluating invariance between adjacent waves (e.g., T1–T2, T2–T3). This approach allows researchers to identify segments of the study where class meaning remains stable and others where measurement properties shift. For example, measurement invariance may hold between T1 and T2 but not extend to T3, in which case the first two waves can be interpreted as reflecting stable class meaning, while the third reflects a different measurement structure or developmental transition.

The process typically follows a staged modeling approach, as detailed below. The workflow proceeds from enumeration to invariance testing and then to auxiliary modeling. If the invariant model is supported, it becomes the measurement foundation for subsequent transition and auxiliary analyses, including the ML 3-step approach.

Below, we outline a practical, step-by-step workflow for estimating an LTA model using the ML 3-step or BCH approach, assuming measurement invariance. The process involves the following steps:

1. testing for measurement invariance,
2. generating time-specific posterior probabilities using the invariant measurement model, and
3. estimating the final LTA model with auxiliary variables.

Phase 1: Enumeration

1.1. Latent Class Enumeration at Each Time Point (Exploratory Stage).

- Follow the enumeration recommendations (Masyn, 2013; Nylund-Gibson & Choi, 2018) to determine the optimal number of classes (K) for each wave.
- Plot classes at each wave to verify that classes are conceptually similar.
- If K differs across waves, or if class meaning cannot be aligned across waves, stop; this implies that measurement invariance is not plausible.

Phase 2: Testing for Measurement Invariance

2.1 Joint Configural Model (No Transitions).

- Estimate all time points jointly in a single model with no equality constraints across time.
- Do *not* include transition regressions (i.e., omit "c2 on c1").
- Confirm that classes appear aligned across waves.

2.2. Joint Full Measurement Invariance Model (No Transitions).

- Constrain all item–class parameters to be equal across time: (*i*) Thresholds for categorical indicators. (*ii*) Means/variances/loadings/intercepts for continuous indicators.
- Optional: Arrange classes using starting values based on order preference.

2.3. Compare Model Fit of the Full MI Model to the Unconstrained Configural Model.

- If full invariance is not supported, partial invariance may be evaluated by freeing item parameters while retaining constraints for remaining parameters to try to preserve class comparability.

2.4. Decide Whether to Proceed with an LTA Under Invariance.

- If the invariant (or partially invariant) model is still substantively interpretable and classes retain the same meaning, proceed to Phase 3.

Phase 3: Final LTA With Error-Corrected Auxiliary Variable Methods

Choose the auxiliary variable method. You may use either:

ML 3-Step Approach

Step 1. Produce time-specific posteriors with the invariant measurement fixed.

- Estimate the unconditional LCA model at each time point with measurement parameters fixed to the invariant values and save the modal class assignment based on posterior class probabilities.

Step 2. Compute misclassification matrices and prepare data for LTA.

- The ML 3-step approach extracts classification probabilities and misclassification matrices from the Step 1 model. These matrices summarize the probability that individuals assigned to a particular class are actually members of another class. These misclassification rates are then incorporated into Step 3 models to ensure valid estimation of covariate and distal outcome relationships. Use the misclassification matrix (from posteriors) to adjust class and transition relationships.

Step 3a. Estimate the unconditional LTA model with transitions.

- Before adding auxiliary variables, estimate the unconditional LTA model with transitions using logit values from the previous step. Estimate the model with measurement error rates fixed at the misclassification rates estimated in Step 1. Then estimate the overall LTA model "C2 on C1."

Step 3b. Add auxiliary variables (covariates or distal outcomes) with classification error correction.

- After inspection of Step 3a, estimate the Step 3b model with auxiliary variables included.

BCH Approach

Step 1. Generate BCH weights from the invariant measurement model.

Step 2. Extract the BCH weights.

- The BCH method computes class-specific, individual-level BCH weights based on posterior probabilities from the Step 1 model. These weights are constructed to preserve the measurement model, allowing for the incorporation of auxiliary variables without changing class definitions or transition probabilities. BCH weights correct classification error at the individual level, which is why BCH is often considered highly robust and less sensitive to class separation.

Step 3a. Estimate unconditional LTA with BCH weights.
Step 3b. Add auxiliary variables.

The following supplementary example demonstrates how this workflow can be implemented in practice using nationally representative longitudinal data.

Supplementary Material

Given the tutorial focus of this paper and to avoid redundancy, we do not present the applied example in detail in the main text. The Supplementary Material includes fully annotated code and an applied example adapted from Ing and Nylund-Gibson (2017); and we encourage readers to consult that paper for additional substantive background. Briefly, the example investigates how students' attitudes toward mathematics and science evolve over time and how these attitudinal trajectories relate to later academic outcomes. Using nationally representative longitudinal data from the Longitudinal Study of American Youth (LSAY; Miller, 2021), students in Grades 7, 10, and 12 are classified into latent attitudinal profiles at each wave, and transitions between those profiles are modeled over time.

To illustrate the workflow described in this tutorial, we apply it using the LSAY data in the Supplementary Materials. At each wave, we estimated a series of latent class models and consistently identified a four-profile solution ($K = 4$) that was conceptually interpretable across time. The classes reflected students' motivational orientations toward mathematics and science and were labeled based on their characteristic item-response patterns. Class shapes remained stable, and substantive interpretations were preserved for all four classes, providing strong evidence that the same latent classes were being measured at each wave and justifying treatment of the four classes at Grades 7, 10, and 12 as representing the same underlying classes over time.

The Supplementary Material presents all modeling steps, culminating in the incorporation of auxiliary variables (covariates and distal outcomes) into the error-corrected LTA model to obtain bias-adjusted estimates of predictors of class membership and transition probabilities. This example shows how full measurement invariance across all waves allows transitions to be interpreted as meaningful developmental movement among the same four profiles and demonstrates the practical implementation of the ML 3-step method within an invariant longitudinal latent class structure.

Discussion

The implementation of auxiliary variable approaches involves estimating a series of models, and this process becomes more complex in the context of LTA, where two or more latent class variables are estimated. This tutorial had three goals: (1) to outline a conceptual framework for evaluating measurement invariance (MI) in LTA with auxiliary variables; (2) to provide a practical workflow for implementing MI testing and multi-step auxiliary methods in `Mplus` and `R/MplusAutomation`; and (3) to illustrate the process with an applied LSAY example. Together, these contributions provide a coherent framework for implementing measurement invariance and auxiliary-variable methods in longitudinal mixture models.

We accomplished this by clarifying why MI is essential for interpreting transitions and auxiliary variable effects and by summarizing recent methodological work showing the limitations of relying solely on traditional LRT-based tests. We presented a step-by-step workflow, from enumeration and configural alignment through MI testing and corrected auxiliary variable modeling, designed for direct use in applied research. Lastly, we demonstrated the full workflow using LSAY data, showing how invariant measurement parameters can be incorporated into ML 3-step and BCH estimation to obtain bias-adjusted estimates of class membership, transitions, and distal outcomes.

In applied LTA, the 3-step approach to auxiliary variables provides an effective balance between preserving the substantive meaning of latent classes and obtaining statistically valid estimates of predictors and transitions. By separating the estimation of the measurement model from the structural relations and incorporating classification error derived from the measurement model, this approach yields bias-adjusted inferences about stability and change without allowing covariates or distal outcomes to redefine the latent classes.

MI in Cross-Sectional and Longitudinal Mixture Models. The logic of measurement invariance in LTA closely parallels that of multiple-group LCA/LPA. In a multiple-group setting (e.g., gender, treatment condition, ethnicity), researchers evaluate whether the same latent classes or profiles are represented across groups by testing equality constraints on item-class parameters. Violations of these constraints are interpreted as differential item functioning (DIF), indicating that the measurement model differs across groups. Establishing full or partial invariance ensures that between-group comparisons of class prevalence, covariate effects, or distal outcomes reflect true subgroup differences rather than artifacts of measurement.

Extending the Auxiliary Variable Model

Once the auxiliary variable model is specified, whether using the ML 3-step approach or BCH, it can serve as a foundation for a wide range of additional analyses. Muthén and Asparouhov (2011) describe this as the "arbitrary second model" framework, in which new model components can be added without re-estimating the latent class structure. For example, after establishing the auxiliary latent transition model, researchers can incorporate covariates to examine how individual characteristics predict transition probabilities. Conceptually, these effects are modeled as interactions between the covariate and the baseline latent class variable.

Beyond covariates, a variety of other extensions are possible. Distal outcomes can be added to evaluate whether specific transition patterns are associated with later achievement, behavioral functioning, or other developmental outcomes. Researchers may also include time-varying predictors to investigate how changes in contextual factors (e.g., classroom quality, family stress, intervention exposure) influence transitions from one class to another. Multi-group LTA can be specified to compare transition dynamics across groups such as gender, treatment vs. control, or linguistic background, again without changing the established measurement model. Finally, additional structural pathways—such as mediation, moderation, or sequential processes across waves—can be incorporated to test more complex developmental hypotheses while preserving the latent class and transition structure. This flexibility highlights the value of the multi-step framework: once the measurement and transition models are fixed, the auxiliary model becomes a stable platform from which increasingly sophisticated questions can be addressed.

Limitations and Considerations for Use

Despite their advantages, 3-step methods also have limitations that applied researchers should keep in mind. One important consideration is the potential presence of DIF when auxiliary variables are included. Because the measurement model is fixed in the third step, unmodeled DIF may bias structural parameters and lead to incorrect conclusions about covariate and distal relations (Arch & Nylund-Gibson, 2026). Recent methods for detecting DIF in mixture models, such as multiple-group LCA, residual-based approaches such as bivariate residuals and expected parameter change, penalized SEM (PSEM; Muthén, 2025), and model-comparison approaches (e.g., Collins & Lanza, 2010; Janssen et al., 2019; Bakk, 2024; Muthén, 2025; Masyn, 2017), offer promising tools and should be incorporated into applied workflows. More research is needed to understand how DIF influences both class enumeration and the estimation of structural relations in LTA.

An auxiliary variable approach not included in this tutorial is the two-step approach, in which the parameters of the measurement model (Step 1) are held fixed when the structural model is estimated (Step 2). Although a shortened version of the two-step approach is presented (Asparouhov & Muthén, 2021) , it does not include the multistage standard error adjustment discussed in Bakk and Kuha (2021), which is not yet available in `Mplus`.

Practical Recommendations for Applied Researchers

Although this tutorial provides step-by-step guidance for implementing measurement invariance and auxiliary variable methods in LTA, several practical considerations can further strengthen applied work. Researchers should report all candidate models—including alternative class solutions and invariance tests—to enhance transparency and reproducibility, and they should ground the substantive interpretation of classes in theory and empirical profile structure rather than relying solely on fit indices. Applied LTA studies should routinely test longitudinal measurement invariance, at a minimum comparing configural and full invariance models, and decisions about full or partial invariance should be justified using both statistical evidence and substantive reasoning, with clear documentation of any freed parameters. When incorporating auxiliary variables, researchers should rely on bias-adjusted approaches such as the ML three-step or BCH methods rather than classify–analyze or naive one-step models, particularly when the goal is to preserve the measurement structure of the latent classes. To facilitate replication, authors should provide sufficient detail about their analytic workflow—including syntax, number of starting values and replications, classification quality indices, and model constraints. Finally, in settings where software limitations preclude the use of the BLRT for invariance testing, researchers should base decisions on parameter similarity and the substantive interpretability of profiles rather than on p-values alone.

Future Directions for Methodological Research

Several promising avenues remain for future work extending the procedures outlined in this tutorial. Simulation studies are needed to evaluate the performance of MI testing strategies, ML 3-step and BCH corrections, and the robustness of auxiliary variable estimates under varied conditions (e.g., different sample sizes, transition structures, class separation, and degrees of noninvariance). Additional work is also needed to refine guidelines for partial measurement invariance in LTA, including principled strategies for freeing parameters and understanding how localized noninvariance affects the estimation and interpretation of transitions. Methodological extensions could also incorporate continuous or ordinal indicators, multilevel LTA, multi-domain LTA, or models with more than two time points. Finally, developing user-friendly tools in `R` or `MplusAutomation` to streamline invariance testing and posterior-merging steps would lower barriers to implementation and increase the accessibility of best practices in applied settings.

Together, these considerations position invariant LTA, as implemented through the ML 3-step or BCH frameworks, as a useful, flexible analytic tool for studying change in heterogeneous populations. By clarifying the measurement model, preserving class definitions, and providing valid auxiliary variable estimates, researchers can draw more interpretable and reproducible conclusions about stability, change, and predictors of developmental trajectories. We hope that the step-by-step guidance, annotated code, and practical recommendations offered in this tutorial will support researchers in applying these methods with confidence and clarity in their empirical work.

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