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Ten Frequently Asked Questions About Latent Transition Analysis

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Abstract

Latent transition analysis (LTA), also referred to as latent Markov modeling, is an extension of latent class/profile analysis (LCA/LPA) used to model the interrelations of multiple latent class variables. LTA methods have become increasingly accessible and in-turn are being utilized in applied research. The current article provides an introduction to LTA by answering 10 questions commonly asked by applied researchers. Topics discussed include: (1) an overview of LTA; (2) a comparison of LTA to other longitudinal models; (3) software used to run LTA; (4) sample size suggestions; (5) modeling steps in LTA; (6) measurement invariance; (7) the inclusion of auxiliary variables; (8) interpreting results of an LTA; (9) the nature of data (e.g., longitudinal, cross-sectional); and (10) extensions of LTA. An applied example of LTA is included to help understand how to build an LTA and interpret results. Finally, the article suggests future areas of research for LTA. This article provides an overview of LTA, highlighting key decisions researchers need to make to navigate and implement an LTA analysis from start to finish.

Translational Abstract

Latent transition analysis (LTA) is a widely used method that explores change among latent classes. The application of these models in psychological research involves a model building process that integrates theoretical considerations throughout. This article answers ten frequently asked question about the use and interpretation of these models, including recent modeling advances and future directions.

Keywords: latent transition analysis, mixture modeling, latent Markov modeling, applied mixture modeling, LTA FAQ

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Latent transition analysis (LTA) is a statistical method for describing patterns in data using multiple latent class variables. Often identified as a longitudinal model, LTA is uniquely positioned to describe stability and change in categorical states across time. This article provides a pedagogical introduction to LTA—the statistical model, steps to build the model, and practical issues around specification and interpretation. Additionally, we discuss advanced modeling possibilities and extensions of LTA.

Interest in LTA has increased significantly in recent years and has proven to be an important analytic approach for answering questions in a range of areas, including development, health, and psychology research. A systematic review of article that apply or discuss LTA methods published in psychology journals show an upward trend in the use of LTA from 2008–2019 as depicted in Figure 1. Despite this increase, relative to other longitudinal approaches, LTA requires an investment in technical understanding building off latent class and latent profile analysis, and computational resources that have recently become more accessible. Although LTA is one approach from an expanding list of available longitudinal methods, we believe that this framework is a valuable approach for social scientists to consider when asking questions about change. Given the interest in LTA and capability of this method to approach difficult questions with a unique lens, further resources designed to be accessible to applied researchers are needed. For readers that are new to this modeling approach, this article provides an opportunity to develop a conceptual understanding of LTA, as well as a guide to address the practical questions that arise when conducting LTA.

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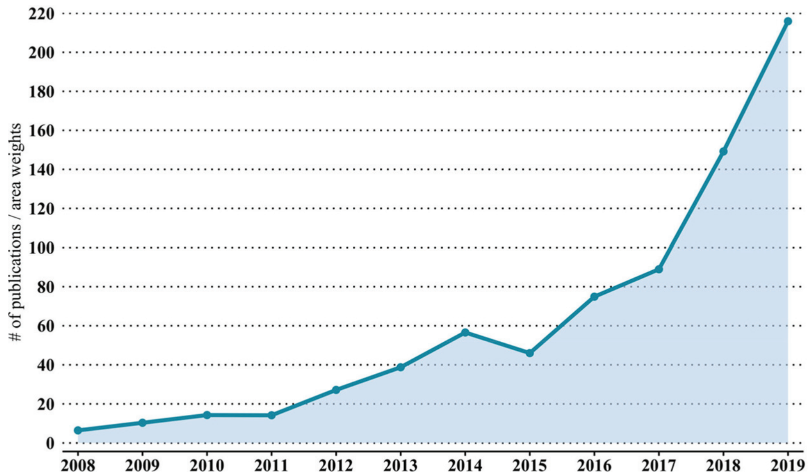
Figure 1
LTA Publication Trends in Psychology and Education From 2008 to 2019



Note. LTA = latent transition analysis. See the online article for the color version of this figure.

Given that the development of mixture modeling best practices is still in its relative infancy, our discussion of LTA presents the latest recommendations for specifying these models. There is ongoing research regarding the specification and best practices of this model. Nevertheless, LTA has helped researchers answer an array of meaningful research questions. Some examples include the identification and tracking of (a) dual-factor mental health classes throughout high school (Moore et al., 2019); (b) changes in children's mental health profiles in response to family interventions (Connell et al., 2008; Zhang & Slesnick, 2018); (c) the stability of elementary students' risk profiles regarding reading disabilities (Swanson et al., 2016); (d) the acculturation process of immigrant Hispanic adolescents (Lee et al., 2020); and (e) psychiatric comorbidity from middle childhood to adolescence (McElroy et al., 2017). Each of these applications addresses a critical question-involving a developmentally salient transition period. Such transitions are a defining feature of human systems and development processes in which LTA is uniquely qualified to provide insight.

By answering 10 frequently asked questions (FAQs) that an applied researcher new to this modeling approach might ask, this article fulfills a gap, namely an accessible treatment of the LTA framework with practical recommendations and an applied example. This article is an extension of a previous article outlining 10 frequently asked questions about latent class analysis (LCA; Nylund-Gibson & Choi, 2018), which borrows the creative format of question and answer demonstrated in Curran et al. (2010). Beyond introducing the mechanics of LTA, this article provides resources for more advanced applications, and suggests modeling directions for researchers wishing to conduct less conventional LTA models. In addition, we provide extensive R (R Core Team, 2021) and MplusAutomation (Hallquist & Wiley, 2018) code for the applied example used in this article, as well as an annotated output to aid in model interpretation. Together, this article provides the tools needed for researchers to conduct their LTA models.

Question 1: What Is Latent Transition Analysis?

LTA is a flexible mixture modeling technique used to model the relationship among multiple latent class variables, usually in a longitudinal context. LTA is an extension of LCA and LPA, allowing researchers to explore unobserved typologies or subgroups within a given population. Expanding on these models, LTA allows researchers to track changes in latent class membership. LTA provides the opportunity to reconceptualize latent class variables that may be commonly modeled as static with a dynamic lens (Hagenaars & McCutcheon, 2002). LTA falls within the family of hidden Markov models (Langeheine, 1988), but is a special case characterized by having multiple items for each latent variable, where the latent class variable at a future time point is regressed onto a previous latent class variable.

The transition probabilities are often the information of primary interest in an LTA. The transitions describe the joint distribution of the latent class variables, interpreted as the change among the latent classes over time. Specifically, they describe the probability of being in class k at *time* t, given the individual's latent class membership at *time* t-1; that is, if subject 1 was in latent class 2 at time point 1, the transition probability describes how likely this person is to be in latent class 2 at time point 2. The LTA model provides a framework that allows identification of unobserved heterogeneity within a given population, to model discontinuous change in class membership over time, and investigate covariate and distal outcome relations to better understand the classes and transitions. Integral to the utilization of LTA in research is the understanding of model specification, how the models' estimated parameters describe change over time, and the interpretation of results. Like LCA and LPA, the measurement parameters in LTA include item probabilities or item means and variances, thus, how the observed items relate to the latent class variable. Unique to LTA are the estimated transition probabilities, which are the structural parameters related to the movement of individuals among the classes, described in detail further on in this article.

LTA Model Parameters: Measurement Parameters

For the measurement model of LTA, any model within the latent variable framework that generates a latent class variable can be used, but the most commonly used are either LCA or LPA models. Parameter descriptions for each model follow.

Latent Class Analysis

For an LTA model with categorical items, the measurement parameters are the item probability parameters. Consider an example with M number of binary latent class items (indicators), u_1, u_2, . . . u_J, that are observed in n individuals. In LCA, the items are assumed to be independent measures of the underlying latent class variable, C, which has K latent classes. Once the latent class is accounted for, the items are assumed to be independent from each other, otherwise known as the conditional independence assumption. The observed items are decomposed to be a function of a class-specific item probability, specifically,

$$P(u_j = 1) = \sum_{k=1}^{K} P\left(u_j = 1 | C = k\right). \tag{1}$$

Here, $P(u_j = 1)$ describes the probability that the item u_j is one, or the marginal probability. This observed probability is decomposed into the sum of conditional item probabilities that vary by class, thus $P(u_j = 1|C = k)$. The class-specific item probabilities are expressed as individual thresholds on the inverse logit scale, specifically,

$$P\left(u_j = 1 | C = k\right) = \frac{1}{1 + exp(\tau_{jk})}. \tag{2}$$

Here, τ_{jk} is the item threshold, which is the negative of the logit value, ω_{jk}, thus $\tau_{jk} = -\omega_{jk}$. Large values of the threshold relate to relatively low item probabilities, whereas small item thresholds relate to large item probabilities (e.g., close to 1.0). Mplus provides the estimate of the threshold as a negative logit (e.g., $-\omega_{jk}$).

The class size parameters, or class proportions (π_k), are expressed on the multinomial logistic regression formulation, specifically,

$$\pi_k = P(C = k) = \frac{exp(\alpha_k)}{\sum_{k=1}^{K} exp(\alpha_k)}, \tag{3}$$

where $\alpha_k = 0$ for identification. Each individual is a member of only one latent class, with item responses assumed to be independent, and conditional on class membership. The conditional item probabilities, $P(C = k)$, describes the relationship between the indicator and the latent class variable, which are the measurement parameters of the LCA model, while the class size parameters, π_k, are considered the structural parameters of the LCA model. These parameters are estimated as logits, but are often converted to probabilities presented as a percentage, such as in $\pi_1 = .52$ indicating that Class 1 is 52% of the sample.

Latent Profile Analysis

For LTA models with continuous items, the measurement model is composed of LPA rather than LCA variables. In LPA, item means vary conditionally across classes. Additionally, because the items are continuous, item variances and covariances can also be allowed to vary across classes (Masyn, 2013). The relation between the observed items and the latent class variable in LPA is specified as

$$f(y_i) = \sum_{k=1}^{K} P(c = k) f(y_i | c = k), \tag{4}$$

where $\boldsymbol{y}_i$ is the vector of responses for individual i on the set of observed item means and the latent categorical variable, c, has K classes ($c = k$; $k = 1, 2, \ldots, K$). For continuous items (i.e., $\boldsymbol{y_i}$) the multivariate normal distribution is used for $f(\boldsymbol{y}_i \mid c)$, which implies that the items are assumed to be normally distributed (e.g., within-class normality) with class-specific means, and the possibility of class-specific variances and covariances. LPA models provide the flexibility of allowing item variances and covariances to be estimated to be either class varying or class-invariant; thus, special attention to alternative models is important. Research has demonstrated that the item variance specification will impact the number and type of latent classes that emerge (Bauer & Curran, 2003). Consideration of alternative models is therefore important (e.g., Diallo et al., 2016, Masyn, 2013).

Transition Probabilities

LTA builds upon the LCA or LPA model as the measurement model, traditionally having the same set of latent class items at multiple time points. In addition to the structural and measurement parameters, the LTA estimates transition probability parameters (τ_{ikm}) that describe movement among the latent classes. Based on the multinomial logistic regression of one latent class variable onto another (e.g., C1 → C2), transition probability parameters are used to describe the movement of individuals between classes from one time point to another. A transition probability, τ_{ikm}, is the probability of individual i being in latent class k at time point t, given that they were in latent class m in the previous time point t-1. Items are thus given an additional subscript t to describe which time point they belong to (u_{tj}).

Considering an example where there are three classes at each time point, the relationship of the latent class time point variables can be expressed as,

$$\tau_{ikm} = P(C_{it} = k \mid C_{i(t-1)} = m) = \frac{exp(\alpha_k + \beta_k d_{i1} + \beta_{2k} d_{i2})}{\sum_{q=1}^{3} exp(\alpha_q + \beta_q d_{i1} + \beta_{2q} d_{i2})}, \tag{5}$$

where τ_{ikm} is the transition probability for subject i who is in latent class k ($k = 1, 2, 3$) at *time t* assuming they were in latent class m ($m = 1, 2, 3$) at the *time t*-1, the previous time point. In this example, d_1 and d_2 are dummy variables indicating class membership at *time t*, where the last class is omitted. The odds ratio given by $\exp(\beta_k)$ is the ratio of odds of being in class k at *time t* versus class 3 (reference class), for those in class m at time point t-1. The transition probabilities are the parameters of interest that describe the change among the emergent latent classes and are compiled in a transition probability matrix (see applied example in Question 9).

Using the LTA framework, researchers explore the probabilities of transitions among the latent classes. Restrictions on the transition probability parameters can be included and should be motivated by meaningful research questions or to incorporate theory into the model; for example, once a student visits the counseling office, a restriction could be put on the transition matrix so that the student cannot transition back to a latent class characterized by not having visited the office. Transition matrices may be fixed to equality across transition points if there is theoretical justification, which would be assuming *stationarity* of the transition probabilities. Imposed when there are more than two time points (e.g., two or more transition points), this restriction tests if individuals are changing between latent classes at each time point transition. Models with and without specified stationary restrictions can be compared using likelihood ratio tests and other tests of model fit (Nylund, 2007).

It is also possible to test if individual cells of the transition matrix are statistically equivalent. This approach is useful for testing specific hypotheses such as impact of a treatment across multiple groups. A researcher may, for example, have an interest in investigating whether a targeted intervention decreases the likelihood of a child remaining a victim after receiving an antibullying intervention. Conducting such a study requires specific labeling of transitions in the multiple group context and then testing equality of the specific transition probabilities. The labeling of these transition probabilities (as demonstrated in Supplement A) would be extended to a multiple group context and then tested to see if empirically supported.

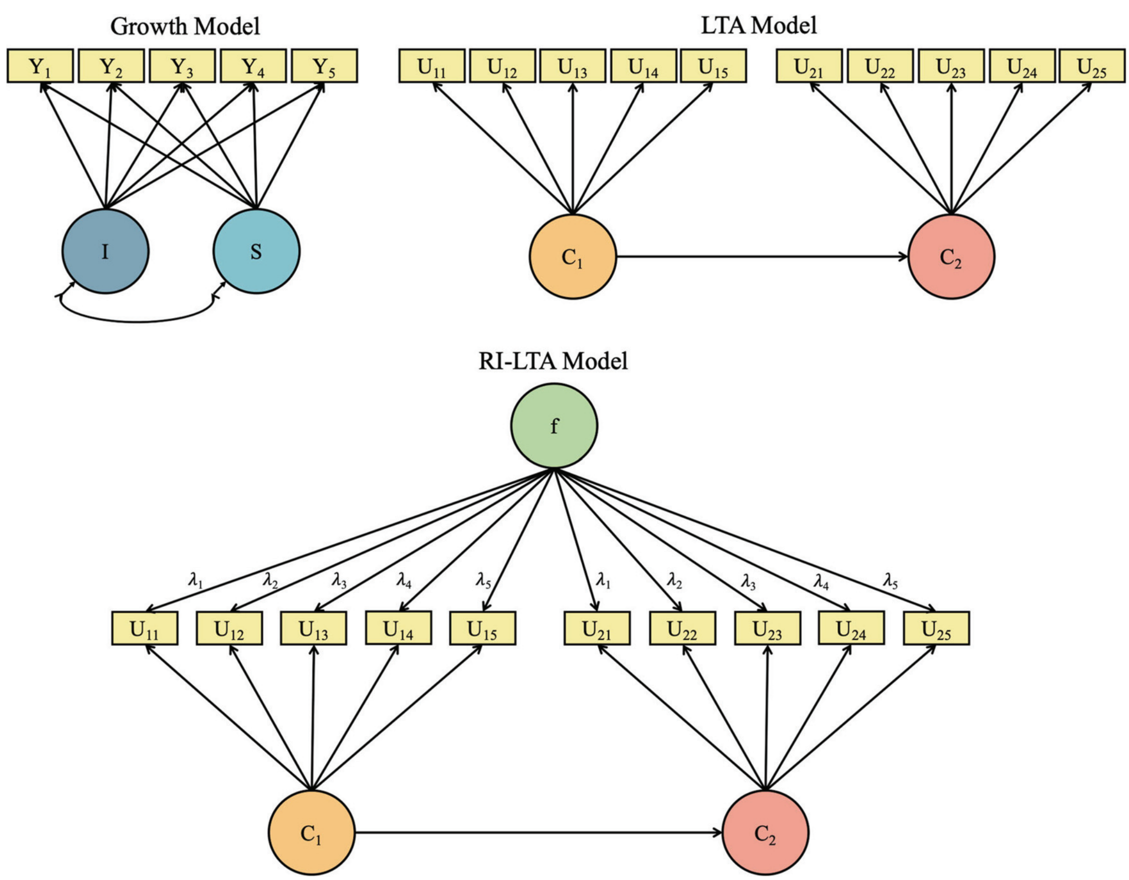
Additionally, constraints of the transition parameters can be specified to test for the presence of patterns in the transition probability matrix, for example, to test for positive transitions or the absence of negative transitions (i.e., stage-sequential development; Collins & Flaherty, 2002). Other versions of transition constraints can be estimated and tested, following hypotheses in which change occurs in a specified pattern. The flexibility of parameter specification for LTA models allows for the exploration of specific and nuanced research questions. This flexibility also comes with increased responsibility as a researcher to carefully consider each of the many specification details and assumptions implied by such a complex model.

Question 2: How Does LTA Compare With Other Longitudinal Models?

Among the larger landscape of latent variable models that accommodate longitudinal data, the latent growth curve model is arguably the most common model of change (e.g., Curran et al., 2010; Duncan et al., 2013; Singer & Willet, 2003). Although the LTA model and the latent growth model both provide a method to model longitudinal change, they approach change in different ways. The basic growth model estimates parameters that describe continuous change across an entire time period; that is, the change pattern across a span

Figure 2

Path Diagram of the Growth Model (Left), LTA Model (Right), and Random Intercept LTA Model (Below)



Note. LTA = latent transition analysis. See the online article for the color version of this figure.

of time is described using growth parameters (e.g., level/intercept and trend/slope growth latent factors and their variances; Preacher et al., 2008). The LTA model, however, utilizes an autoregressive approach to model discrete time-point to time-point change using transition probabilities (see Figure 2).

These models are not competing models; rather, they are different ways to describe changes, and each addresses specific research questions. LTA may be the appropriate model when change is assumed to be discontinuous, and it can answer research questions such as "Do individuals exhibit reliable response patterns for the latent class items across time points, and if so, are individuals likely to stay in the same class or transition to a different class between time points?" Latent growth models, on the other hand, assume continuous change and are used when answering research questions that address the average rate of change over a given time, such as "What is the average rate of change year to year in educational achievement?" The way the models each describe these relationships sets the two longitudinal models apart.

There are many extensions to the growth model, including those that incorporate an autoregressive component (Bollen & Curran, 2004), thus combining aspects of the growth model and the autoregressive part of the LTA model. Additionally, repeated measures LCA (Lanza & Collins, 2006) can be used with longitudinal data on a single item repeated across time points captured by a single latent class variable. Researchers can choose from a wide range of longitudinal models, of which only a few are mentioned here (for a more general discussion of longitudinal modeling, see Collins & Lanza, 2009; Graham et al., 2009). Although the LTA model is the focus of this article, the choice of which longitudinal model to use depends on the research questions being addressed and the available data.

A recent and important addition to the landscape of LTA is the random intercept LTA model (RI-LTA; Muthén & Asparouhov, 2020). This model builds on LTA by adding a random intercept, measured by the observed indicators across all time points, which captures individual trait-like characteristics (see Figure 2). Initial results show that this model improves overall model fit relative to regular LTA and simulation results fitting more precise transition estimates in the conditions studied. This is an important contribution of the LTA modeling framework, estimating transition probabilities that are separated from between-subjects variation (Muthén & Asparouhov, 2020). Given that findings show that RI-LTA improves fit compared to LTA, the RI-LTA should be considered among models when using LTA. Further study is needed to better understand how this model performs more broadly across modeling contexts, and how and when it should be used in the enumeration and model building process.

Question 3: What Software Can I Use to Fit an LTA?

Various proprietary and open-source programs are available for use to estimate LTA models. The most widely used proprietary software for modeling LTAs include: Mplus (Muthén & Muthén, 1998–2017), Latent Gold (Vermunt & Magidson, 2005), and the PROC LCA/LTA package in SAS (Lanza et al., 2015).

A few available open-source software packages in R are capable of fitting LTA models. These include the R packages `OpenMx` (Boker et al., 2011) and `LMest` (Bartolucci et al., 2017). Although both of these packages estimate LTA models, they have limited capabilities for adding predictors and outcomes using current integration approaches (e.g., the maximum likelihood (ML) three-step approach [ML 3-step]; Vermunt, 2010). Other R packages support specification of mixture models but are limited in their capacity to estimate LTA models; these include: `depmixS4` (Visser & Speekenbrink, 2010) and `mixtools` (Benaglia et al., 2009). The widely used `lavaan` package (Rosseel, 2012) does not support estimation of categorical latent variables.

Another option for estimating mixture models in R is to use the R package `MplusAutomation` (Hallquist & Wiley, 2018), which allows users to call Mplus from the RStudio user interface. Although MplusAutomation is open-source, it requires Mplus to estimate models (e.g., users must have Mplus installed on their hard drives). The MplusAutomation approach has a number of benefits including the ability to specify and run large sets of models and efficiently extract relevant output into publication-formatted figures and tables. An example of the R/MplusAutomation code used to run the science attitudes LTA model is provided in Supplement B.

There are pros and cons to using any software, and ultimately, when comparing packages that estimate mixture models (or any software), the user's preference, training, and exposure often dictates the decision about which software to use. Utilizing R is cost-effective, because it is free and has vast user-support resources afforded by its extensive community. This being said, researchers choosing to use R often initially encounter a steep learning curve. Mplus provides a good balance between accessibility and highly flexible specification, estimation, and modeling capabilities. Mplus software also includes extensive user support, worked examples with syntax, and a useful archive of modeling support on the discussion board. The combined strengths of R and Mplus afforded by the MplusAutomation package provide advanced modeling functionality to users, allowing for the benefits of the R environment for using code to manage and write models and document data processing decisions, while using Mplus to estimate mixture models. Latent Gold has a user-friendly, point-and-click interface that includes a wide range of mixture models, including LTA, with helpful user support. Each software package is suitable for estimating an LTA, and it is up to the researcher to choose which software best fits their purposes and experience.

Question 4: What Sample Size Is Required to Fit an LTA?

As with any statistical model, sample size requirements must be considered in LTA. Recommendations for the sample size required to ensure accurate estimation of the LTA parameters are sparse. In mixture modeling generally, the the most common issues relating to sample size include the ability to recover the true latent classes in a population and the power to efficiently estimate accurate model parameters. Particularly, in the LTA context, power to accurately measure the transition probabilities is of central interest.

Although few simulation studies have been conducted to establish the needed sample size for LTA, progress has been made in describing practical guidelines for applied research (Baldwin, 2015; Tein et al., 2013). However, no consensus exists regarding a one-size-fits-all sample size recommendation strategy. Due to the large set of parameters estimated in LTA, sufficient sample size requirements will depend on a range of factors that vary by modeling context, making a general sample size recommendation untenable.

Model characteristics that impact sample size in the LTA context include the quantity of transition matrices (e.g., time points); magnitude and separation of transition probabilities (e.g., the number of latent classes (k); the separation between classes and items; relative and absolute class size; and the number and type of indicators (binary, polytomous, continuous).

Regarding power for the LTA model, the interaction of model characteristics described above is important to consider. The size of the transition probability matrix is determined by the number of classes at each time point. Similarly, as with LCA, between-class separation and within-class homogeneity are two desirable attributes that increase power (Masyn, 2013). Measurement models with clear classification require smaller sample sizes compared to poorly defined measurement models (Lubke, 2019).

In practice, the recommendations for LTA are based on research from cross-sectional LCA and LPA models, because there is very limited simulation research for LTA models. For LCA, some researchers have suggested a minimum sample size of 500 (Finch & Bronk, 2011), whereas others recommend a minimum sample ranging from 300 to 1,000 (Nylund-Gibson & Choi, 2018). A recent simulation study indicated that larger sample sizes are needed for LTA than what is commonly seen in applied research (e.g., $N > 500$ Baldwin, 2015). Although no minimum general sample size guideline exists, researchers close to the lower boundary of sufficient sample size can have more confidence in the correct estimation of LTA model parameters if the models have (a) homogenous classes, (b) high between-class separation, (c) large transition probabilities, (d) larger class sizes at t = 1, and (e) a larger sample size (Baldwin, 2015).

Question 5: What Are the Modeling Steps for Specifying an LTA Model?

Addressing how to specify an LTA model can be complex depending on the nature of the research questions being asked. Building an LTA model consists of several modeling steps that are outlined by Nylund (2007). Similar to other latent variable contexts, the model-building process in LTA has two components: (a) the measurement model and (b) the structural model. In many LTAs, the measurement model used is a series of cross-sectional mixture models considered at several time points. The structural model then relates the latent class variables to each other over time using a multinomial logistic regression of one latent class variable on another. If there are more than two time points and thus more than two latent class variables, most commonly, each is regressed on the latent variable preceding it in the time sequence (t-1; lag 1). As with LCA or LPA, auxiliary variables (i.e., covariates and distal outcomes) can be incorporated into the structural model in LTA. More specifically, after the selection of items, the modeling process typically includes (a) class enumeration (measurement model); (b) a test for measurement invariance (MI); (c) LTA specification/estimation; and (d) the option to consider associations with auxiliary variables (i.e., covariates and/or distal outcomes).

Class Enumeration

Once items for the model have been selected, class enumeration is conducted on the model using the recommended best practices from cross-sectional LCA/LPA which relies on a set of fit indices and theoretical considerations (Masyn, 2013; Morgan, 2015; Morovati, 2014; Nylund et al., 2007); that is, enumeration for the first latent class variable, or first time point, would be done, and then the enumeration procedure would be repeated for the second or later latent class variables (e.g., time points). It has been suggested that enumeration in LTA may be conducted in the context of a full LTA model (Lanza et al., 2013)—that is, enumeration is considered using the model with multiple latent class variables estimated concurrently (see e.g., Collins & Lanza, 2009, p. 190). Recent simulation study results, however, suggest this could lead to bias in enumeration decisions made for the time specific latent class variables (Talley, 2020), and thus this is not recommended. Additionally, little is currently known about enumeration in the RI-LTA context. Thus, we currently recommend proceeding through enumeration at each time point independently, then specifying the LTA model, and then specifying the RI-LTA model.

Measurement Invariance (MI)

After enumeration is completed, comparison of the emergent classes from each time point can be used to explore similarities or differences in the emergent classes. If the emergent classes appear to be similar in both number and type, and there is theoretical rationale for them to be invariant (Masyn, 2017), then measurement invariance can be tested. Invariance affords researchers statistical and interpretive advantages; thus it is common practice to test for the possibility of MI across the latent class variables (see Question 6). The structural components of the model are estimated after deciding on where invariance is supported, because the parameters of the structural components of the model (e.g., transition probabilities) would be estimated differently depending on this specification.

Latent Transition Analysis

Once class enumeration and MI testing has been completed, the LTA model will be specified. To specify an LTA model in Mplus, the latent categorical variables from the previous step are regressed onto each other (e.g., C1 → C2, which is "C2 ON C1" in Mplus). This specification is the multinomial regression and will produce the transition probabilities that describe the joint distribution of the latent classes. This model is demonstrated in the applied example included in this article and annotated input and output are included in Supplement A.

RI-LTA

After estimating the LTA model, an RI-LTA could also be considered. Using the LTA model as a starting point, then adding the random intercept to the model, either as a latent factor or latent categorical variable. The RI-LTA model with a latent factor model is demonstrated in the applied example and model syntax is included in Supplement B. At present, given the recency of the RI-LTA, we considered the RI-LTA model after specifying the LTA and its specification (e.g., MI, structural invariance, etc.). However, with more understanding of this model, and when and how it should be considered in the modeling process, the ordering of these modeling steps could change.

Auxiliary Variables

Covariates and/or distal outcomes can be incorporated into the LTA model to explore variables that might predict or be influenced by classes and/or transitions; for example, covariates may be time-invariant, or time-varying based on the structure of the data (Nylund, 2007). Another possibility is to model how transition estimates change in the presence of covariates, which can be considered a special case of moderation (e.g., Muthén & Asparouhov, 2011). The ML three-step approach (Vermunt, 2010) and more recently the method proposed by Bolck, Croon, and Hagenaars (2004), referred to as the BCH method (Asparouhov & Muthén, 2021) can be used in LTA contexts with auxiliary variables and can accommodate multiple latent class variables, in addition to auxiliary variables. The ML three-step approach in the LTA is described in detail in Nylund-Gibson et al. (2014) using Mplus and the BCH method for LTA in Asparouhov and Muthén (2021). These procedures are discussed further in Question 7.

Question 6: What Does Measurement Invariance Imply in the Context of LTA?

In the context of LTA, MI can be considered from several perspectives, given that there are multiple latent class variables and possibly multiple transition matrices and/or group comparisons. The first and perhaps most common way to think of invariance in LTA is across latent class variables (e.g., multiple time points). For researchers investigating group differences, multiple group invariance of an LTA model can be conducted, similar to traditional MI in factor analysis. Lastly, MI can be conceptualized with respect to two or more sets of transition probabilities (i.e., equality of transition matrices).

Longitudinal MI

In most applications of LTA found in the literature, it is assumed that the measurement of the latent classes is the same across time, which is termed *longitudinal measurement invariance.* To assess longitudinal MI, class enumeration is conducted independently at each time point, followed by testing for equivalence of the item threshold parameters or the class-specific item probabilities across time points. In other words, the question is asked, "Are the emergent latent classes the same across time?" If thresholds differ substantially and substantively across time points, these solutions are likely noninvariant; that is, the classes are qualitatively different across time.

The LTA model does not necessitate longitudinal MI, despite the abundance of applications of LTA that assume it. MI is often desirable for model parsimony (e.g., less parameters are estimated) and interpretation of model parameters, though not necessary to interpret LTA results. It is possible to have qualitatively different class solutions or response pattern item probabilities across time in LTA. If measurement parameter results are found to look prima facie similar across time points, as in this study's example (i.e., four-class solutions were found in seventh and 10th grades with thresholds that are approximately the same across time points), it is reasonable that MI would be empirically evaluated.

Structural MI

A second way to conceptualize MI for LTA models is with the structural parameters, specifically the transition probabilities over time. For single-group analysis, MI of the transition probabilities would imply that the transition matrices are the same across time, known as *stationary transition probabilities* (Nylund et al., 2006). *Stationarity* is an assumption that implies that movement among the latent classes over transition points are constrained to be the same; that is, it assumes that the transition probabilities relating the first and second latent class variables (e.g., C2 on C1) are the same as the transition probabilities at later transition points in the Markov chain (e.g., C3 on C2). This is a restrictive assumption which can be empirically tested to address specific research hypotheses; for example, when considering science attitudes, it seems fairly unlikely that stability and change will be similar between different developmentally salient transition periods (e.g., starting high school and starting college). Another plausible example would be comparing transition probabilities between pre- and post-treatment, where interest may be in testing if the post-treatment transition probabilities are equivalent to pretreatment transitions.

Although many applications of LTA found in the literature assume MI (e.g., Mustafić et al., 2019; Swanson et al., 2016), imposing this assumption is not required, nor will it always be appropriate when fitting a latent transition model. In cases where this is a correct specification, MI may help to reduce bias (Nylund, 2007) and aid in the clarity of model interpretation, similar to MI in a factor analytic framework (Millsap, 2011); however, an LTA without measurement invariance is certainly possible, where interpretation of the transition probabilities will be relative to the respective classes.

Multiple Group MI

Multiple group MI is a useful method to address questions about whether LTA item thresholds, transitions, and class sizes are similar or statistically distinct across observed groups. In the context of LTA, multiple group invariance can be conceptualized similarly to MI in the factor analytic context. Here, the equivalence of the measurement parameters is tested (e.g., item thresholds in LCA; item means in LPA) across an observed group (e.g., gender, treatment status, etc.). A research question in-line with the multiple group approach in the context of an intervention study might be "Are the classes of science attitudes between seventh and 10th grades the same for students in the control and treatment groups?"

If MI is established across item threshold parameters, groups can be considered equivalent across time, which then allows for the equality of the transition probabilities to be assessed (Schmiege et al., 2018). Testing the equivalence of transition probabilities would be addressing research questions such as, "Are the transition probabilities the same across time for each group?" or "Are people moving among the latent classes similarly across groups?" Invariance is often tested by equating sets of parameters across groups (e.g., item thresholds), but it is possible to consider partial measurement invariance where only specific item thresholds are held equal (see the partial measurement invariance below). Multiple group LTA allows researchers to better understand similarities and differences across known groups and investigate nuanced MI questions.

MI Testing Procedure

Traditional testing of MI involves estimating nested models with different stages of constrained parameters, then comparing the model fit of the two nested models relative to each other (Meredith, 1993). This method can be used to assess invariance across latent class variables and across multiple observed groups (Masyn, 2017). Note that in longitudinal invariance, the structural parameters in the LTA model are often left unconstrained; therefore, the relative class sizes across latent variables (i.e., π_k) as well as the transition probabilities are freely estimated. Although this is the most common practice, either of the structural parameters may also be tested for invariance to address specific research questions. It is advisable to test measurement parameters before proceeding to making comparisons of transition probabilities or class prevalence across groups as item threshold invariance may indicate that the classes are qualitatively distinct and consequently quantitative comparisons will not be appropriate.

When evaluating the plausibility of measurement invariance, we use the technique of comparing nested models by comparing the fit of the two or more nested models, specifically using the difference in each models' log-likelihood values. This technique, applied widely across many areas of statistics, can be applied in LTA and involves fitting a nested model (i.e., invariant model) and a parent model (i.e., noninvariant). The parent model in this context is the noninvariance model, which allows the measurement models to be different across the groups, thus has more parameters and fewer degrees of freedom than the nested model with constrained measurement parameters (e.g., Bollen, 1989; Finch, 2015). The two models' log-likelihood values are used in Equation 6 to assess the log-likelihood ratio test, making the needed adjustment when ML with robust standard errors are used (i.e., MLR in Mplus; Satorra & Bentler, 2010). The general form of the log-likelihood ratio test (LRT) difference equation can be expressed as follows,

$$LRT = -2[logL(\hat{\theta}_r) - logL(\hat{\theta}_p)], \tag{6}$$

where $\mathrm{logL}(\hat{\theta}_r)$ is the log likelihood value for the more restricted (e.g., the invariant model) and $\mathrm{logL}(\hat{\theta}_p)$ is the log likelihood value for the unrestricted model (e.g., the noninvariance model). The p-value for the LRT is calculated and used to determine if the constrained parameters significantly worsen model fit. That is, if $p >$ .05, there is no evidence of a significant difference between the fit of the two models and the more parsimonious invariance model is retained. If $p < .05$, we would conclude that the invariance constraints significantly increase model misfit, indicating we should support the noninvariance model. When using the robust ML estimator, an adjustment of the LRT values is necessary (LRT-SB; Satorra & Bentler, 2010). The LRT-SB is calculated in our example (Mplus, n.d.) which is estimated with MLR and demonstrated in Supplement B using the science attitudes example.

In the context of multigroup LTA models, invariance is specified by including a categorical grouping variable (e.g., Mplus syntax; KNOWNCLASS). To implement constraints across groups for any of the model parameters, labels mentioning the parameters within a group-specific model command can be added (e.g., Mplus syntax: MODEL group1:). Although this procedure will sound familiar to those who have conducted multigroup invariance in the factor analytic context, the complexity of the LTA model poses unique challenges in deciding degrees of acceptable misfit.

The standard methods for testing for MI rely on nested model testing (Bollen, 1989). In the context of LTA, this method may be considered conservative as it is sensitive to sample size and the quantity of parameters being tested for invariance. The comparison relies on the simultaneous equating of a large number of model parameters (e.g., item probability parameters for all classes). It is not uncommon for nested model testing to support noninvariance in contexts where invariance appears to be supported by visual inspection of the model parameters and conditional item probability plots. In articles that use LTA, there is a tendency for MI to not be formally tested, rather MI is assumed after studying the unconditional item probability plots. While understandable, this may lead to bias in the structural relationships if assuming MI in fact is not warranted, though there is no way to adequately quantify this bias yet. More research is needed to improve confidence in claims about MI, explorations for partial MI and its implication on structural parameters.

Partial MI

In the case where measurement noninvariance is found, researchers may want to determine whether noninvariance is isolated to a subset of items. Partial MI allows for the group or time difference to be specified when needed, while still constraining some parameters to equality. Partial MI is more flexible and has the statistical advantage of reducing the number of parameters estimated relative to full noninvariance. Therefore, the solution will be more parsimonious and may result in a model which is more straightforward to interpret. Exploring partial MI is usually done in one of two ways: either using a forward approach (sometimes called free baseline), where equality constraints are added one parameter at a time, or a backward approach (sometimes called constrained baseline) where the equality assumption is relaxed for model parameters in a stepwise fashion (Kim et al., 2016). In both cases, nested models are compared using LRT difference tests as described in Equation 6. Kim et al. (2016) recommends the forward approach because it shows greater accuracy in detecting DIF and due to the backward approach being prone to Type I error (Kim & Yoon, 2011; Stark et al., 2006). Although the backward approach has been found to perform well in the context of full measurement invariance (Kim & Yoon, 2011), the forward method is most commonly used.

Question 7: How Do I Include Auxiliary Variables to Fit LTA Models?

A question that researchers often propose when conducting LTA is, "Do the latent classes or transition patterns have meaningful associations with variables not included in the measurement model?" How the latent classes relate to external variables, covariates and distal outcomes, is often a research question of central interest and may provide context about the practical meaning of the latent classes. These relations help describe the characteristics of the individuals who compose the classes, how the classes relate to each other with respect to the covariates, whether the classes predict a temporally postceding variable (e.g., distal outcome), and if transition probabilities are influenced by covariates (i.e., a covariate-by-transition interaction effect). After the number of classes is decided, incorporation of covariates and/or distals with the latent variable model is often an important step in conducting an LTA. Latent class regression involves multinomial regression of the latent class variable on covariate(s), which results in the comparison of the odds of being in a given class relative to the reference class for a unit change in the covariate(s). Distal outcomes may also be included resulting in the estimation of the mean of the distal outcome(s) for each latent class, which is then compared using post hoc analyses (see Nylund-Gibson et al., 2019). The inclusion of covariates and distal outcomes in mixture modeling is an active area of research that extends beyond the LTA context; thus it is only described generally here in relation to LTA models.

Recommended procedures for auxiliary variable integration have been studied in a recent simulation study and results suggest that auxiliary variables should be included after the class enumeration process is conducted (i.e., enumerate the latent class variable separately without covariates; Nylund-Gibson & Masyn, 2016). The recommendation is to proceed through the class enumeration process for each latent class variable independently, select a final unconditional model, and then include predictors (covariates) and distal outcomes using one of the multistep procedures (Nylund-Gibson et al., 2014; Vermunt, 2010). Currently, the ML three-step approach (Vermunt, 2010) and method proposed by (Bakk & Vermunt, 2016; Bolck et al., 2004; Asparouhov & Muthén, 2014) are both available in the LTA content.

Given the complexity of the LTA model, covariates and distal outcomes can be included in the model in many ways; for example, when considering covariates, researchers may be interested in differences in the latent classes (e.g., Mplus syntax: C on X) or how the transitions vary as a function of covariates (e.g., an interaction; Muthén & Asparouhov, 2011). Given that LTA involves multiple latent variables, the latent class variable can be regressed on the covariates to have time specific relations. The questions driving the research would determine the specific covariate relations that would be specified. Covariates may also be included as time-invariant or time-varying given the availability of data (Nylund, 2007).

Alternatively, a categorical covariate could be included as a grouping variable to see how group differences impact the model parameters. Instead of regressing the latent class variable on the categorical covariate, a multiple group model could thus be specified which would allow for exploring whether the latent classes and transition probabilities are the same across levels of the grouping variable (e.g., male/female/other or treatment/intervention).

The decision to use a multiple-group/MI approach, a covariate/auxiliary variable approach, or a combination of the two, depends on theoretical considerations. The two approaches reflect different initial points of view in their hypotheses about variable interrelations. The covariate approach starts with the assumption of a single population of research participants, but the participants vary in terms of latent class membership, and this variance can be explained by covariates where group membership is just one of several possible covariates (e.g., grade point average, depressive symptoms). Covariates can be used to predict latent status membership and latent status transitions. A multiple-group approach assumes that there are distinct (observed) subgroups in the data that represent different populations (e.g., ethnicity, gender, generational cohort, experimental condition), where the researcher believes it is possible that the latent class structure and/or the transitions are different across groups. In multiple-group LCA and LTA, group membership allows for all model parameters to be different across groups, where a covariate approach only estimates specific covariate relations.

Relations with distal outcome can be predicted from the last time point, estimated for each transition path, or related to a Mover-Stayer higher order variable (e.g., Nylund, 2007). Traditionally in mixture models, we include distal outcomes and allow the distal outcomes means and/or proportions to vary across class. This allows researchers to test for pairwise class differences to assess for distal outcome effects. Nylund-Gibson et al. (2019) discuss different approaches to estimate distal outcome relations with latent class variables. Having multiple latent class variables in LTA adds a layer of complexity as it may be relevant to explore how distal outcome means vary as a function of one or more of the latent class variables. Further, it may be of interest to see how the pattern of change over time may relate to distal outcomes. This question can be explored using a confirmatory higher order latent class variable, similar to a higher order Mover-Stayer latent class variable but with more classes. In this approach, multiple distinct mover and stayer trajectories may be specified in line with theory and these trajectories classes may be used to relate to a distal outcome. This type of higher-order confirmatory LTA model is demonstrated in Nylund-Gibson et al. (2018).

Question 8: How Do I Interpret the Results of an LTA Model?

The results of LTA models can be separated into measurement and structural parameters with interpretation requiring these cross-sectional and longitudinal components to be considered together. For measurement parameters, which describe the classes, interpretation is the same as it would be in an LCA or LPA. The set of parameters unique to LTA are the transition probabilities. An illustration of LTA that presents the interpretation and resulting write-up of an LTA model is provided below.

Transition probabilities provide information about changes in class membership over time. Transition probabilities describe the change process as shifts between *classes*. This is typically done across time points but can also be conducted with co-occurrence models utilizing cross-sectional data. These model parameters are estimated as logits in the multinomial logistic regression relating the T+1 class variable to the latent variable which proceeds it. These logit parameters are most commonly converted to probabilities and displayed in a transition probability matrix. When we establish longitudinal MI, the diagonal of the transition probability matrix can be interpreted as stability estimates and off-diagonal elements as instability estimates (Nylund et al., 2006). Without longitudinal MI, the transition probabilities are interpreted as the probability of changing between qualitatively distinct classes.

Applied Example: Heterogeneity in Science Attitudes

In this sample Results section of an LTA, data from the Longitudinal study of American Life (LSAL, formally called the LSAY; Miller, 2015) is used to explore variation in students' science attitudes. Data collection for the LSAL, funded by the National Science Foundation (NSF), began in 1987 and has followed participants into adulthood. In the present example, data on science attitudes collected from youth during the fall of their seventh-grade year are used for Time 1 and data collected during the spring of their 10th-grade year are used for Time 2. Each student's latent class membership is thus determined by their endorsement response pattern on the science attitude indicators. The transition of individuals across the science attitude latent classes measured in seventh and 10th grade is modeled.

Class Enumeration

Independent LCA models were fit to the five science attitudes indicators ("I enjoy science"; "Science is useful"; "Science helps logical thinking"; "Need science for a good job"; "Will use science often as an adult") measured in seventh and 10th grade. Table 1 presents the sample size, demographic characteristics, variable descriptions, and endorsement proportions for each time point. Class enumeration for each time point and fit information is presented in Table 2. Based on the fit indices presented, the results support the four-class solution for seventh and 10th grade (also referred to as Time 1 and Time 2). Specifically, five out of six fit indices (i.e., *BIC, SABIC, CAIC, BLRT,* and *VLMR-LRT*) support the four-class solution for Grade 7, and four out of six fit statistics (i.e., *BIC, SABIC, BLRT, VLMR-LRT,*) support the four-class solution for Grade 8.

The conditional item probability plots presented in Figure 3 were used to interpret the emergent solution and aid in labeling the classes. Before proceeding to the structural component of the model, it is common to compare the emergent classes across time to look for similarities in classes (see Figure 3). The emergent classes at both time points were labeled *Proscience With Elevated Utility* (i.e., high probability of endorsement for all items), *Ambivalent With Elevated Utility* (that is, moderate endorsement probability for the three items "science is useful," "science helps logical thinking," and "need science for a good job," with a higher probability of endorsement for the items "I enjoy science" and "will use science often as an adult"), *Ambivalent With Minimal Utility* (that is, moderate endorsement probability for the three items of "I enjoy science," "science is useful," and "science helps logical thinking," with a higher probability of endorsement for the items "need science for a good job" and "will use science often as an adult"), and *Antiscience With Minimal Utility* (i.e., low probability of endorsement for all items). Given that four classes emerged at both grades and response patterns were visually similar we explored for measurement invariance.

Measurement Invariance (MI)

To explore if there was empirical support for measurement invariance, a model was specified where the item thresholds were specified to be equal across the 7th and 10th grade, but the class size (e.g., structural parameters) were not constrained to be equal. The four science attitude class sizes may shift in size when specifying the LTA model. The resulting classes from the LTA model with measurement invariance are presented in the bottom panel of Figure 4 and class size for each pattern is presented in Table 3.

To test if there is empirical support for measurement invariance, we compared the model fit for the noninvariant and invariant measurement models using the log likelihood ratio difference test (LRT; Bollen, 1989; Nylund, 2007). Specifically, after estimating each of the models, we calculate the difference in the log likelihood multiplied by –2 for the two nested models using the Satorra-Bentler adjustment (Mplus, n.d.). The result for the applied example can be found in Table 4 and is calculated as follows: *LRT* = –2(–14,458.24 – (–14,447.71) = 21.05. We can estimate the *p*-value for the log likelihood difference using a χ^2 distribution with *df* equal to the difference in model parameters. The results of the adjusted LRT test supported measurement invariance across the time points, $\chi^2(20) = 18.23$, $p = .57$; that is, there was support that constraining the conditional item probabilities to be equal across Grades 7 and 10 did not significantly increase model misfit. This result implies that instead of estimating grade-specific measurement parameters, there is empirical support to estimate one set of measurement parameters that are constrained to be equal, that is to specify measurement invariance.

The four classes across the two time points result in a total of 16 (4^2) possible transition patterns, which are presented in Table 3. The transition pattern with the highest frequency, 16% of the sample, were students who were in the *Antiscience With Minimal Utility* class in 7th grade and remained in that class in 10th grade. The second highest frequent pattern, consisting of 5% of the sample, is distinguished by being in the *Ambivalent With Minimal Utility* class in 7th grade and transitioning to the *Antiscience With Minimal Utility* class in 10th grade. A small portion of the sample was found to follow a trend in science attitudes of reporting being *ambivalent* toward science in 7th grade and transitioning to the more negative attribution of *antiscience* in 10th grade.

RI-LTA Model

An RI-LTA model was estimated, by adding a random intercept factor after specification of the invariant LTA model. Table 4 includes the model fit for LTA and RI-LTA models for comparison and Table 5 presents the transition probabilities for each of these models. Comparing fit between these models, the RI-LTA demonstrates slightly better fit with respect to the *ABIC*, whereas the *BIC* supports the LTA model, noting that we cannot estimate LRT tests when comparing a model with and without the random intercept (Muthén & Asparouhov, 2020). Additionally, comparing estimated transition probabilities for the LTA and RI-LTA models, there are minimal differences. Taken together, in this example,

Table 1
Descriptive Information for the Five Science Attitudes for 7th and 10th Grade Used in the LTA

Variable name	Item label	Endorsement proportion	*n*
Fall, 7th grade (*N* = 3,061)			
AB39M	I enjoy science	.61	3,042
AB39T	Science is useful in everyday problems	.40	2,988
AB39U	Science helps logical thinking	.49	2,992
AB39W	Need science for a good job	.40	3,012
AB39X	Will use science often as an adult	.46	3,043
Fall, 10th grade (*N* = 2,258)			
GA33A	I enjoy science	.58	2,219
GA33H	Science is useful in everyday problems	.43	2,205
GA33I	Science helps logical thinking	.51	2,203
GA33K	Need science for a good job	.42	2,207
GA33L	Will use science often as an adult	.42	2,219

Note. LTA = latent transition analysiis.

Table 2
Fit Statistics for Class Enumeration for the LSAL at Time 1 (T1) and Time 2 (T2)

Model	*K*	LL	BIC	SABIC	CAIC	AWE	BLRT *p*	VLMR LRT *p*
Fall seventh grade (T1)	1	−10,250.60	20,541.34	20,525.45	20,546.34	20,596.47	—	—
(*N* = 3,061)	2	−8,785.32	17,658.93	17,623.97	17,669.93	17,780.22	<.001	<.001
	3	−8,693.57	17,523.59	17,469.57	17,540.59	**17,711.04**	<.001	<.001
	4	−8,664.09	**17,512.79**	**17,439.71**	**17,535.79**	17,766.40	**<.001**	**<.001**
	5	−8,662.39	17,557.54	17,465.39	17,586.54	17,877.31	.672	1
	6	−8,661.54	17,604.01	17,492.80	17,639.01	17,989.94	.835	1
Fall 10th grade (T2)	1	−7,658.79	15,356.19	15,340.30	15,361.19	15,409.80	—	—
(*N* = 2,258)	2	−6,073.81	12,232.56	12,197.61	12,243.56	12,350.50	<.001	<.001
	3	−5,988.36	12,107.99	12,053.98	**12,124.99**	**12,290.27**	<.001	<.001
	4	−5,964.45	**12,106.51**	**12,033.43**	12,129.51	12,353.12	**.004**	**<.001**
	5	−5,961.68	12,147.30	12,055.16	12,176.30	12,458.25	.367	.364
	6	−5,961.26	12,192.79	12,081.59	12,227.79	12,568.07	.560	1

Note. *K* = number of classes; LSAL = Longitudinal study of American Life; LL = model log likelihood; BIC = Bayesian information criterion; SABIC = sample size adjusted BIC; CAIC = consistent Akaike information criterion; AWE = approximate weight of evidence criterion; BLRT = bootstrapped likelihood ratio test; VLMR-LRT = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test; *p* = *p*-value; Bold = best fit statistic for each individual statistic.

there seems to be minimal additional fit and information gained by adding the random intercept to the LTA model, perhaps because the time points are relatively far apart from each other (e.g., seventh and 10th grade). Additionally, of the five factor loadings estimated in the RI-LTA model, only one was large and significant, suggesting that in this application the items we used are more state than trait-like thus LTA is sufficient for this application. As a result we interpret the transition probabilities for the LTA model, as it is the more parsimonious model.

The transition probabilities are shown in Table 5, where the diagonals of the matrix represent stability and are bolded. The most stable classes from fall of seventh grade to fall of 10th grade were the *Antiscience With Minimal Utility* class and the *Proscience With Elevated Utility* class, with transition probabilities of .56 and .52, respectively. That is, 56% of the individuals in the *Antiscience With Elevated Utility* in seventh grade (Time 1) remained in that class by 10th grade (Time 2), and 52% of the individuals in the *Antiscience With Elevated Utility* class remained in that class by 10th grade (see Figure 4). Overall, the lowest levels of stability in science attitudes between seventh grade and 10th grade were for students in the *Ambivalent With Elevated Utility* and *Ambivalent With Minimal Utility* classes, with only 27% and 30% of the participants remaining in the same class in 10th grade, respectively.

As depicted in Figure 4, for students who were in the *Proscience w Elevated Utility* class in seventh grade, 15% of them transitioned to the *Ambivalent With Elevated Utility*, 12% transitioned to *Ambivalent With Minimal Utility*, and the remaining 22% transition into the *Antiscience With Minimal Utility* class. Interestingly, a high percentage of students in the top two attitudinal classes remained in the top two attitudinal classes (67% and 59%), whereas those in the bottom two attitudinal classes stayed in the bottom two (66% and 72%), demonstrating that early science-attitude formation is impactful, evidenced by the stability of remaining in their early attitudinal classes.

Question 9: Must I Have Longitudinal Data to Fit an LTA Model?

Longitudinal data is not necessary for an LTA model. Traditionally, however, most applications of LTA have utilized longitudinal data characterized by having the same set of variables measured over time, where each set of variables identifies a time-specific latent class variable. In this context, the transition probabilities are interpreted as describing the transitions over time; however, the LTA model is simply a multinomial logistic regression model connecting latent class categorical variables. There is nothing inherent in the statistical expression that requires data to be longitudinal. In fact, positioning LTA as a model without longitudinal data opens up modeling opportunities for studying the relations among two latent class variables that are measured on the same individuals.

Considering an individual cross-sectionally, there may be interest, for example, in understanding how classes of substance-use profiles are related to the profiles of sexual-risk behaviors (Connell et al., 2009) or violent behaviors (Jeon et al., 2017). The research aim, in the cross-section version of the LTA model, is estimating the probability of individuals' jointly belonging to two or more latent class variables. Similar to a traditional LTA, the influence of covariates on the joint class probability and the impact of the joint classes on distal outcomes can be estimated; for example, a higher probability of individuals belonging to two classes simultaneously may be observed among individuals with specific demographic characteristics. These models are described as *co-occurrence* models but can also be referred to as *joint-LTA* models (Jeon et al., 2017). The utility of the co-occurrence model is to describe patterns in populations across multiple domains simultaneously.

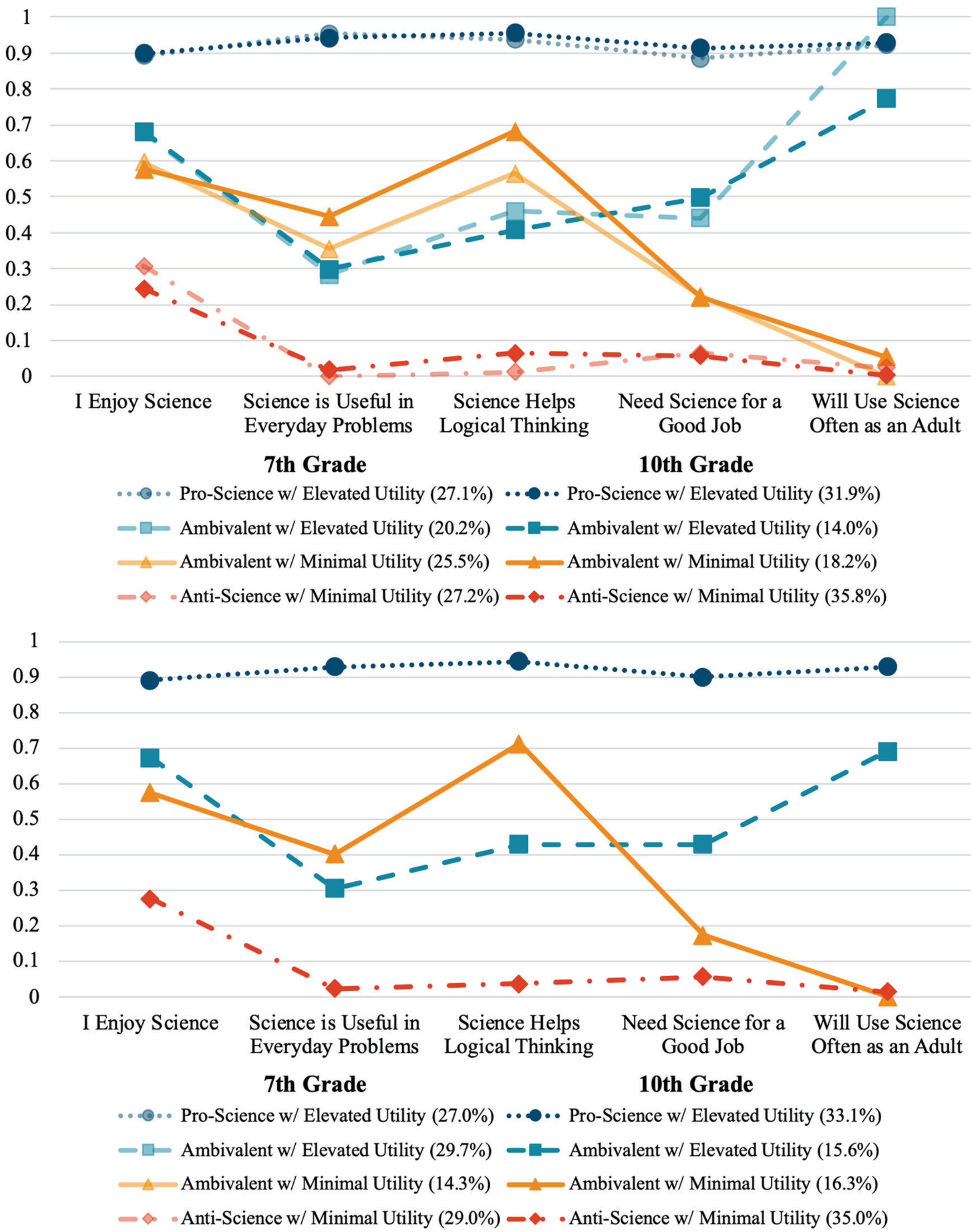
Due to the lack of sequential order in a co-occurrence LTA model, the simple Markov chain specification can be relaxed to allow for the association between a given LCA with any other LCA comparison in the set. In a traditional LTA, this approach corresponds to models that incorporate relationships with previous time points (e.g., lag 1, lag 2 or lag $l + 1$) in specific pairs, or all possible relations between LCA's.

Question 10: What Extensions of the LTA Model Are Possible?

The flexibility of the LTA model in the larger latent variable context provides a vast amount of modeling opportunities. As mentioned

Figure 3

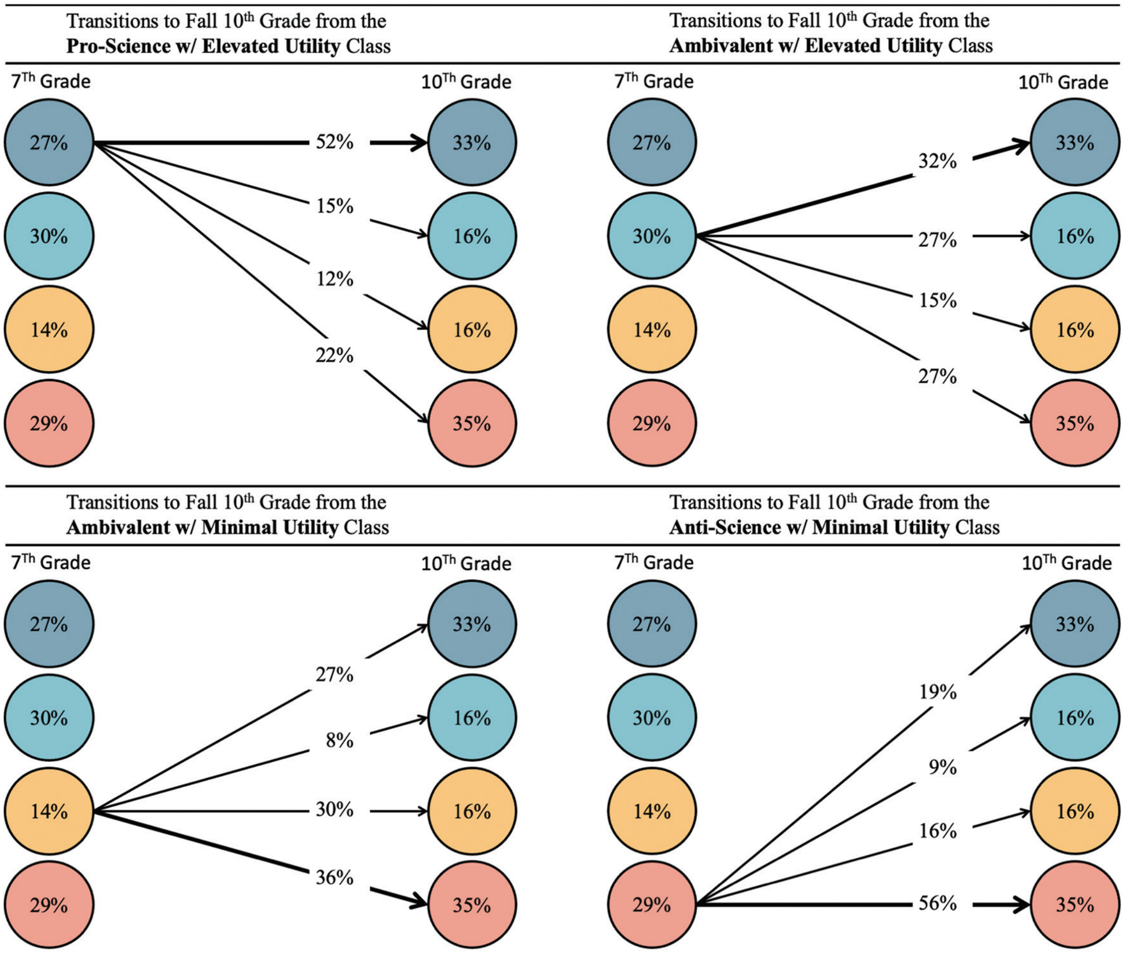
Probability Plot of the Four-Class Solution for the Fall Seventh Grade and Fall 10th Grade (Top Panel) and Four-Class Solution for the Invariance of (Bottom Panel) Science Attitudes



Note. See the online article for the color version of this figure.

previously, LTAs are typically conducted with longitudinal data; however, they do not have to be, as is the case with co-occurrence (Jeon et al., 2017) models. These models open another perspective on the joint distribution of heterogeneity. Additionally, the inclusion of covariates and outcomes can help to understand patterns better. Another extension would be to use retrospective data in an LTA. Spikol et al. (2019) used retrospective parents' report data on their child's autism-related behaviors prior to age 3 and postage 3 in what

Figure 4
Visual Representation of the Transition Probabilities for Each Class, Conditioned on Seventh Grade Latent Classes



Note. Arrows in bold indicates the highest transition probability. See the online article for the color version of this figure.

they called a "quasi-LTA" (p. 709) to examine how parent reports may predict autism behavior in later childhood.

The LTA model is most traditionally applied with LCA as the measurement model at each time point, but the LTA framework, in general, is not limited to LCA; in fact, LPAs are estimated as the measurement model at each time point (e.g., Ciarrochi et al., 2017; Moore et al., 2019). Furthermore, LTAs can be extended for use with *different* mixture models as measurement model for each latent variable; for example, instead of using two LCAs, Nylund-Gibson et al. (2014) conducted an LTA with two *different* mixture models: an LCA and a growth mixture model. Further extensions of the LTA model like this could be utilized.

Other possible extensions include multilevel LTAs and associative LTAs (Bray et al., 2010). Multilevel LTA (Cho et al., 2013) is a recent extensions of the LTA model. The multilevel LTA model allows for a Markov process to be specified at the individual level and at the grouping level. Consider, for example, a context where children are nested within classrooms, and researchers are modeling heterogeneity in victimization experiences in youth. The multilevel LTA model would specify a Markov process for the individual (Level 1) and how the individual transitions among the latent classes of victimization, while also modeling the change in the composition of the classrooms over time (Level 2). Although possible, there are few examples of the multilevel LTA model found in the literature.

The associative LTA model (ALTA; Flaherty, 2008; Bray et al., 2010) incorporates LTA across two longitudinal processes. The ALTA model is similar to the parallel process growth model (e.g., Bollen & Curran, 2006) in that it simultaneously models two dynamic processes, allowing them to have interrelations across the two LTA domains. The example provided by Bray et al. (2010) modeled the association between alcohol use and sexual behavior and the change over time in class membership. The specification of the LTA model in the larger latent variable framework allows for the possibility of a wide variety of models and extensions.

The RI-LTA model (Muthén & Asparouhov, 2020) is a more recent addition to the LTA family. The individual level random intercept factor captures stable, trait-like variability across time,

Table 3
Final Class Counts and Proportions for the Latent Class Patterns Based on Estimated Posterior Probabilities

Latent class pattern			
Seventh grade class	10th grade latent class	*n*	%
1	1	437.03	.14
1	2	121.23	.04
1	3	96.74	.03
1	4	179.19	.06
2	1	293.88	.10
2	2	245.37	.08
2	3	136.05	.04
2	4	244.36	.08
3	1	116.82	.04
3	2	35.19	.01
3	3	132.53	.04
3	4	156.29	.05
4	1	174.44	.06
4	2	81.70	.03
4	3	139.59	.05
4	4	501.61	.16

Note. The label refers to Latent Class 1 = proscience with elevated utility; Latent Class 2 = ambivalent with elevated utility; Latent Class 3 = ambivalent with minimal utility; Latent Class 4 = antiscience with minimal utility.

which results in transition probabilities that are free from stable trait influence. Muthén and Asparouhov (2020) show that this model may more accurately describe the movement among the classes over time. Specifically, the RI-LTA model uses a latent variable, either continuous (factor) or categorical (groups), to capture variation at the individual level. Given the recency of this model, there are still opportunities to better understand under what conditions the LTA is sufficient (e.g., when the random intercept does not add further understanding such as in the applied example in this article) and how the random intercept influences the specification of the measurement and structural parts of the LTA model. It may be the case that the RI-LTA model provides little additional information in some contexts, such as LTAs with two time points or in models that have observed variables that are primarily state-like. In these contexts, LTA (without the RI component) may be sufficient and more parsimonious. In our review of 53 published LTA articles using the Web of Science database, we found that 51% articles had only two time points, thus two-time point LTA makes up a significant portion of the published LTA applications. Understanding the benefit of RI-LTA in these contexts is important to fully understand its utility in the larger LTA framework. For more on the RI-LTA and its specification, see the Mplus website (specifically web talks No. 1 and 2 at www.statmodel.com) for examples.

Conclusion

The flexible utility of LTA, demonstrated throughout, has highlighted the utility of this modeling approach to address research questions that are applicable to a broad range of social science research. In this article, we introduced the fundamentals of the LTA model; however, the modeling possibilities are quite varied and could provide important insight into future avenues to extend the LTA method. There is a need to create measures that are designed to be used in a mixture modeling context. As these modeling approaches become more commonly applied, we will hopefully begin to design studies that propose LTA as the analytic technique, and thus design measures tailored for this approach.

The utility of LTA in a wide range of modeling contexts has increased the applications of LTA in many different disciplines. Because the LTA model is part of the larger family of mixture modeling, developments of best practice (e.g., enumeration, reporting, and variance specification) remain areas of research, which will contribute to our understanding of the strengths and limits of this modeling approach. A standard for best practices for specifying and estimating LTA models is still under development.

New developments in the family of LTA models may change the landscape of its use in the future, as demonstrated with the recent proposal of the RI-LTA model (Muthén & Asparouhov, 2020). Simulation studies can help us better understand different aspects of this model; for example, in what contexts we should be concerned with invariance or partial measurement invariance in the context of RI-LTA. When continuous or categorical random effects are needed given varying LTA conditions, and at what point in the modeling process the random intercepts should be included (e.g., before enumeration or after, before invariance testing or after). In our example, the categorical RI-LTA model and noninvariance RI-LTA model would not converge on a stable solution, because of identification issues and the log likelihood value not being replicated, respectively. In contrast, the invariant RI-LTA model with continuous intercept did show slight improvement of fit on two of the three considered fit indices. However, this model did not result in significant factor loadings (only one out of five was significant), and transition probabilities were not different across the two models. This result indicates that the value added of the RI-LTA is not seen in this example with only two time points. The model with measurement invariance would not converge for this example, so we were not able to fully compare all model specifications.

For methodologists and applied researchers, it is important, albeit difficult, to stay informed about the current best practices that the field has established. As we understand more about the specification and theoretical implications of LTA models, it is important that we share this knowledge with other methodologists as well as applied researchers using these models and come to

Table 4
Model Fit for the LTA and RI-LTA Models, With and Without Measurement Invariance

Model	NPAR	LL	BIC	SABIC	Test (*df*)	χ^2(*P*-value)
1. LTA (noninvariant)	55	−14,447.71	29,336.88	29,162.13		
2. LTA (invariance)	35	−14,458.24	29,197.40	29,086.19	1 vs **2** (15)	18.23† (.57)
3. RI-LTA (invariance)	40	−14,442.02	29,205.10	29,078.00		

Note. LTA = latent transition analysis; RI-LTA = random intercept LTA model. Bold indicated the selected model. † Satorra-Bentler adjusted LRT.

Table 5

Transition Probabilities of the Unconditional Latent Transition Analysis and Random Intercepts Latent Transition Models

Model	Class	Proscience with elevated utility	Ambivalent with elevated utility	Ambivalent with minimal utility	Antiscience with minimal utility
Fall 7th grade		Fall 10th grade			
LTA	Proscience with elevated utility	**.52**	.15	.12	.22
	Ambivalent with elevated utility	.32	**.27**	.15	.27
	Ambivalent with minimal utility	.27	.08	**.30**	.36
	Antiscience with minimal utility	.19	.09	.16	**.56**
Fall 7th grade		Fall 10th grade			
RI-LTA	Proscience with elevated utility	**.51**	.14	.14	.21
	Ambivalent with elevated utility	.33	**.25**	.18	.24
	Ambivalent with minimal utility	.25	.09	**.31**	.35
	Antiscience with minimal utility	.18	.10	.18	**.54**

Note. LTA = latent transition analysis; RI-LTA = random intercept LTA model. Bolded values along the diagonal indicate transition probabilities that describe stability.

consensus about its use. This article is intended to help provide some groundwork for the use of this modeling approach in social science research.

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