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Modeling Behavior as Dynamic Sequential States: Introduction to the Special Issue

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Abstract

This special issue of *Evaluation and The Health Professions* focuses on applications and extensions of latent transition analysis (LTA), a longitudinal parameterization of the latent class (LC) model. LTA is a model of discrete or qualitative change over time among potentially complex states (e.g., patterns of recent drug use or abuse experiences), commonly referred to as latent classes, latent profiles, or latent statuses. Frequently, researchers will distinguish the term "classes" for cross-sectional studies and with LTA use "statuses" to indicate the concept of "dynamic change" with individuals shifting in their response patterns and associated statuses over time. It goes without saying that LTA models are underutilized, although quite flexible. This special issue showcases articles that apply LTA and extend the capabilities of this approach to modeling discrete change in new ways.

Keywords

dynamic sequential states, latent transition analysis, developmental studies, modeling change states, latent class analysis

This special issue of *Evaluation and The Health Professions* focuses on applications and extensions of latent transition analysis (LTA; Collins & Lanza, 2010; Collins & Wugalter, 1992), a longitudinal parameterization of the latent class (LC) model (Goodman, 1974; McCutcheon, 1987). LTA is a model of discrete or qualitative change over time among potentially complex states (e.g., patterns of recent drug use or abuse experiences), commonly referred to as latent classes, latent profiles, or latent statuses. Frequently, researchers will distinguish the term "classes" for cross-sectional studies and with LTA use "statuses" to indicate the concept of "dynamic change" with individuals shifting in their response patterns and associated statuses over time. It goes without saying that LTA models are underutilized, although quite flexible. This special issue showcases articles that apply LTA and extend the capabilities of this approach to modeling discrete change in new ways.[1]

Overview of LCA and LTA

The LC model contains a categorical latent variable analogous to the continuous latent variables of factor analysis. In factor analysis (Gorsuch, 1983), one postulates one or more latent continuous dimensions that explain/account for the covariance among the items. Similarly, one or more LC variables may be postulated to account for the bivariate associations among a set of measured variables. Whereas dimensions (usually associated with factor analysis models) organize people/observations from lowest to highest, LC variables are typically nominal, with no inherent ordering (see Croon, 1990, for ordered classes). Latent classes may differ both by degree, as well as qualitatively. Thus, we commonly speak of patterns or unique configurations of behavior (or responses) when discussing latent classes. In essence, the difference between one class and another emphasizes the unique "composition" of behavior for individuals that are members of the class.

Latent class models were initially developed in sociology (Lazarsfeld & Henry, 1968). These models identify homogeneous subgroups (i.e., classes) of observations in a parent population. Classes are latent, because they are not directly observable. We infer both the latent class structure of the population, as well as individual's likely class membership from the data. Latent class models entail relatively few assumptions. One assumption is that the proposed number of classes are exhaustive and mutually exclusive, meaning everyone in the population is a member of one and only one class. Like other basic measurement models, the latent class model also depends on an assumption of conditional or local independence. This means that the categorical latent variable (usually denoted by "C") alone accounts for or explains the associations between all the item pairs; there are no residual associations between items once we take the categorical latent variable into account. Restated, once we know someone's latent class membership, their item responses are statistically independent.

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The latent class model includes two types of parameters: latent class proportions and conditional response probabilities. The latent class proportions are the expected proportion of the parent population that is estimated to be in a specific class. The conditional response probabilities are the expected probability that a member of a specific class will make a specific response. As an example, Bray et al. (2021) have a latent class they label *Experimental Reasons* (for using marijuana). At the first timepoint in their data, this class comprises nearly 20% of the population. Members of this class have a predicted probability of saying “Yes” to a question about using marijuana to “see what it is like” of 0.86, or 86%. This can be interpreted as members of this class are expected to say “Yes” to this question 86% of the time. In contrast, members of this class are only approximately 10% likely to respond “Yes” to a question about using marijuana to relax. However, members of the class labeled *Escape + Coping Reasons* are 95% likely to say “Yes” to the question about using marijuana to relax. Latent class labels are derived by examining the conditional response probabilities to identify characteristics that help capture unique descriptive features of members of the class. This interpretation is conceptually similar to interpreting factors based upon factor loadings.

The latent transition model includes the two parameter sets described above, but also adds transition probabilities. These parameters capture the likelihood of moving from one status to another over time and thus give the procedure the name “stage-sequential models.” Once estimated, the transition probabilities are usually presented in a rectangular format with the diagonals indicating the probability of “staying” in a particular status over time and the off-diagonals indicating the probability of moving from one status to another. Where development is expected to remain fairly stable over time (and members of one status are unlikely to move to a different status) the diagonals are likely to be high in magnitude (i.e., .85). In the case where diagonals are moderately low (i.e., .15) there is likely to be considerable movement to one or more statuses over time.

Measurement

Up until this point, we have provided a brief overview of the mechanics of LC models. The LC model is a measurement model, seeking to explain item responses in terms of a more parsimonious representation (there could be as many classes as there are response patterns). As mentioned, the latent class model was initially developed for understanding the structure underlying multi-way frequency tables. For instance, in a model with four questions, each with binary responses “Yes” and “No,” there are 2^4 possible response profiles (YYYY, YYYN, YYNY, . . . , NNNN). This is the data analyzed in LC and LTA models. In confirmatory factor analysis and structural equation models (Hayduk, 1987), the data covariance matrix contains all the necessary information. In latent class and latent transition models, a cross-tabulation of all measured items (as demonstrated with the four sample items presented above) is the parallel data structure needed for the analysis.

Time Scale and Treatment

Longitudinal data, such as panel surveys (Lazarsfeld, 1940) or health promotion interventions with follow-ups conducted once each year for 3 years, are readily amenable to analysis with LTA (e.g., Spoth et al., 1999). There are many applications that use LTA to analyze prospective data. Examples of how this technique can be applied are found in education emphasizing developmental studies of motivation (Gillet et al., 2017), in medical research with studies of psychiatric comorbidity (McElroy et al., 2017), occupational studies of job insecurity and mental health (Elst et al., 2018), naturalistic studies emphasizing the developmental progression of substance use (Clendennen et al., 2019), and longitudinal studies of functional impairment in individuals exposed to community-based treatment (Stephens et al., 2009). In all of these examples, the latent class and latent transition models are probability models, although one can parameterize them as log-linear models (Bray et al., 2010). Traditionally, with intervention or longitudinal follow-up studies, measurements are typically widely spaced, for example, students assessed in school where they participated in an intervention can be assessed annually either each fall or each spring. In studies that employ this type of assessment protocol, measurements are assumed to have been collected at a common time or period. To illustrate, Griffin et al. (2021) use data collected in seventh grade, again in the 10th grade, and then again as young adults (23–26). These data are referred to as discrete time data with the intent of mapping change over time in the configuration of skills between these formative developmental years.

While panel studies are typical applications, this special issue includes three applications that treat time atypically. Lange et al. (2021) take a continuous time perspective. Rather than respondents measured at uniform discrete time points, the approach used by these authors allows respondents to have different numbers of assessments with different spacing, akin to survival analysis (Hosmer et al., 2011). However, unlike survival analysis, the response assessed in Lange et al. is a latent state representing cancer or no cancer. In contrast, Lee et al. (2021) do not model transitions per se, but rather collapse high frequency latent class combinations across time into a reduced set they refer to as latent profiles, common sets of latent class memberships over time. Voglesmeier et al. (2021) also adopt a continuous time LTA approach to intensive longitudinal data (Schafer & Walls, 2006), such as data produced by experience sampling (Larson & Csikszentmihalyi, 1983) or ecological momentary assessment (Shiffman et al., 2008).

Models of Change

Continuous models of change, such as growth curve models (Rogosa et al., 1982) typically model change over-time capturing development as a smooth function of time, although these models have grown to include discontinuities, as observed in regression discontinuity designs (see Imbens & Lemieux, 2008, for an example, and also see Deza, 2015) and piecewise growth models with discontinuous slopes (e.g., Chou et al., 2004; Li et al., 2001). In the typical growth model, parameters are obtained reflecting the intercept (starting point before growth) and slope (rate of growth over time). Additional parameters include variance terms reflecting dispersion in the slope (inter-individual differences in the rate of growth) and intercept (not everyone starts at the same point). Growth for the group as a whole is then modeled over time using mean change from one point in time to another for as many timepoints that data is collected. When the individual points representing means are connected over time, it portrays a "trajectory" or curve capturing developmental change.

In contrast, models of discrete change treat change and development as state changes, not as a smooth function (i.e., trajectory). States, which are the focus of discrete sequential models of change, represent a particular configuration of behavior, skills, cognitions or functioning that are determined based on the response probabilities associated with each class or status. Members of one state are uniquely different from another in the composition of their behavior (conditional response probabilities are used to distinguish states and class enumeration is based on several model fit indices). For instance, a state could represent youth that only drink alcohol but endorse using no other drug. Over time a subset of these youth may progress in their use of substances to use alcohol and cigarettes, or alcohol and marijuana. The different states are qualitatively distinct based on the unique patterns or "composition" of behaviors (Lanza et al., 2010; Maldonado-Molina & Lanza, 2010). Additional examples of states may include degree of alcohol consumption and associated symptomatology with one state containing individuals that are moderate drinkers with few symptoms of abuse or dependence whereas another state can include high-risk or heavy drinkers with profound symptoms of abuse or dependence (Guo et al., 2000).

Introducing Covariates

In many cases, researchers wish to identify predictors of class membership or transitions between latent statuses. The intent of using covariates or explanatory variables is to help characterize members of a particular class as part of structural validation. In addition to being distinguished based on their conditional response probabilities, other demographic, personality, familial, or contextual factors may be associated with class or status membership. The introduction of covariates into a LCA or LTA model raises an important issue. The probabilistic nature of these models makes it possible for the covariate to influence within-class response distributions (i.e., the measurement model has to be re-estimated with the introduction of each covariate). In other words, introduction of covariates could potentially shift the class membership profile. Vermunt (2010, and 2021) addressed this issue and provided an alternative means of estimating class membership in the presence of both categorical and continuous covariates. Subsequently, Nylund-Gibson et al. (2014) provided an exposition of this approach including how to model distal outcomes (consequences predicted by class membership) using educational data on kindergarten readiness. Asparouhov and Muthén (2014) then pointed to the imperfect nature of prior classify-analyze approaches and showed how a more robust stepwise approach can be integrated into statistical modeling programs like Mplus (Muthén & Muthén, 1998–2012) as part of an auxiliary command for a mixture model (R3STEP).

In the Mplus framework, the LC model is first estimated with class enumeration based on penalty-based model fit indices, with consideration of latent class separation and homogeneity. Individuals are then assigned to their respective classes using posterior class membership probabilities, which are then fixed (accounting for measurement error). The model is then configured as a multinomial logistic regression predicting class membership from explanatory measures (covariates) while accounting for possible "classification error" that arises given the probabilistic nature of LCA/LTA techniques (log ratios or threshold parameters are attenuated for measurement error given the LC indicators are fallible). This procedure can be extended to the LTA model with measurement invariance and positing covariate effects.

With these modeling caveats in mind, the articles in this special issue plough headfirst into the issues of modeling dynamic sequential change, using different formats to showcase the use of these intriguing techniques. The issue is divided between articles that showcase the methodological features of either LTA and those that implement these techniques to illustrate their application in different "evaluation" and health-related settings. In all of these instances, the focus rests with modeling discrete dynamic change as exemplified by the LTA framework. In the first article Bray, Bruglund, Evans-Polce, and Patrick provide an overview of LTA and then use it to examine stability and change among classes of *reasons for marijuana use* in a nationally representative sample of young adults. They first use LCA to identify classes of respondents with similar patterns of reasons for marijuana use. They do this separately by measurement occasion and find five distinct classes at both times. The authors then model transitions among these classes using LTA. Following this, they examine the ability of several covariates to predict baseline class membership, as well as predict transitions, the latter capturing the influence of covariates on movement between statuses (i.e., reasons for marijuana use) at the two time points.

Griffin, Scheier, Komarc, and Botvin examine latent statuses of self-management skills, as well as transitions between statuses from seventh grade to 10th grade in a large school-based sample. The type of skills they include are integral to how youth manage their emotions (affective) and reduce stress, engage in self-talk to reinforce themselves (cognitive) and control their behavior (self-control). Taken as a whole, these skills are benchmarks of adult role socialization and protective against early-stage drug use (Griffin et al., 2001, 2002). The authors examine whether discrete change in cognitive and affective self-management skills influences later alcohol use. This etiology/consequence study emphasizes skills that are the core active ingredients of a drug prevention program (Botvin & Griffin, 2015; Life Skills Training), although the authors' analyses are restricted to untreated control youth not exposed to the intervention. The study represents an extension of prior work that modeled growth in self-management skills (Griffin et al., 2015). In the current study, the focus rests more with empirically confirming the "complexion" of self-management skills and determining whether status membership influences young adult alcohol use. Their findings show that youth who deteriorate in their self-management skills are at greater risk for subsequent alcohol use as young adults.

Lange et al., as mentioned above, take a different approach to modeling behavior change as part of a study on cancer risk prediction. They grapple with the issue of prostate cancer diagnosis, which as they point out, can be flawed for several reasons. One of the more important considerations is that a host of risk factors can influence diagnosis, some obfuscating important signals of cancer (i.e., differential detection) and causing spurious (attenuate or inflate) associations. In addition, the various screening tests used for diagnosis are themselves inaccurate at times lacking perfect sensitivity and specificity. The authors propose to model the association of relevant risk factors (i.e., family history and race) and "onset" of cancer, to avoid what they term as "detection bias" that can occur in routine cancer screening (e.g., biopsies are fallible). To do this, they posit a two-class latent disease model consisting of (unobserved) cancer onset or not with imperfect diagnostic tests as the class indicators. As they suggest, this strategy "decouples" the latent disease onset from the diagnostic process, the latter which is rife with error. In addition, rather than model transitions between fixed time-points, as is customary with LTA applications, the authors model transitions in continuous time with a latent binary state. This approach produces standard "hazard ratios" for disease onset corresponding to covariate effects over time.

Lee, Kim, Leatherdale, and Chung, approach discrete change over time by assembling "profiles" of latent statuses over time to model youth alcohol use embedded in a multilevel framework. In their nested or hierarchical model, students' behavior forms the basis of Level I indicators while aggregate school behavior forms the basis of Level II indicators. The assumption in this framework is that the behavior of students within a school will share closer resemblance compared to students from different schools (i.e., clustering), perhaps because of contextual (i.e., socioeconomic or cultural) influences in addition to social contagion and peer socialization (e.g., Scheier et al., 2002). Neglecting the influence of clustering can bias standard errors (and increase Type I errors) as some variance in individual behavior can be attributed to the larger cluster unit (i.e., schools). They use this multi-level framework, which controls for the intraclass correlation, to investigate sequential drinking patterns in a 9-year study of youth health behaviors conducted with 64 Canadian schools. The cross-sectional models identify distinct patterns of consumption including non-drinkers, ever lifetime, and binge drinkers. The sequential models reveal non-drinkers who stay, light drinkers who advance in their consumption patterns, and heavy drinkers who also advance over time. At the school level (assessing contextual factors that can influence individual-level drinking) they identify low-use (composed primarily of non-drinkers who remained so) and high-use schools (composed primarily of binge drinkers that advance in their consumption patterns over time), subgroups that would not have otherwise been noted using only an individual-level model. They also conditioned the level I model on race and gender, to assess the importance of these socializing influences as well as condition the level II model on alcohol retail density to assess neighborhood contextual effects. Their findings give pause and consideration to the application of prevention programs focusing not only on the individual's behavior (i.e., disrupting early-stage alcohol use to prevent drug progression) but also school-based climate programs that can target the social ecology of drinking including correcting misperceptions (i.e., norms) that underage drinking is socially tolerated.

Voglesmeier et al. (2021) apply LC and LTA to within-day dynamics of adolescent affective well-being. One goal of this work is to examine and test different measurement structures in different contexts. At some times or in some contexts, the associations between items may be different: item-factor associations may vary. Measurement invariance (Meredith, 1993) refers to the extent a factor structure is similar over time and/or across groups. Mistakenly assuming measurement invariance across contexts likely biases results in unpredictable ways. Additionally, this approach misrepresents the stability of psychological constructs. Rather, Vogelsmeier et al. propose a latent transition model in which the latent states are characterized by different item to latent-variable associations, i.e. measurement models. Additionally, Vogelsmeier et al. develop this model for ordinal indicators, so the measurement model is an item-response model (Embretson & Reise, 2013). Item-response models are measurement models similar to factor analysis, in that they posit a continuous underlying dimension, however, the measured items are categorical. These authors demonstrate this model in a sample of 250 adolescents measured in three 1-week bursts over a period of about 9 months. They present a model with two latent states corresponding to two different two-factor measurement models. As a final step, Vogelsmeier et al. classify the transitions over the three assessments into classes representing common transition patterns over the three waves, similar to Lee et al. (2021). Vogelsmeier et al. 2021 describe emerging emotional stability among some of these adolescents, as well as contextual effects on the affect factor structure.

It gives us great pleasure to assemble the different articles in this special issue. They are at once comprehensive, illustrative, and insightful. The articles are rigorous in their demonstration of new modeling techniques and promising in terms of their utility. For the articles proposing new methods and new angles on data analysis, there will be a lag between when these techniques are presented to the scientific community and then find their way into canned statistical programs, or discussion boards hinting of their possibility. In either case, readers of this special issue get to digest these novel applications, map their current and future work to these techniques for what they can reveal about latent dynamic change and perhaps use these techniques to learn more about hidden features of their own data.

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Note

1. Although we emphasized "latent Markov models" in the call for papers and reinforced the value of this approach to the various special issue contributors, the LTA framework and Markov model are similar in mathematical form and application. Readers are referred to Kaplan (2008), who provides an excellent discussion of manifest Markov chain models and latent Markov models for studying stage-sequential development.

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