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Testing the Degree of Cross-Sectional and Longitudinal Dependence Between Two Discrete Dynamic Processes

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Abstract

Developmental research often involves studying change across 2 or more processes or constructs simultaneously. A natural question in this work is whether change in these 2 processes is related or independent. Associative latent transition analysis (ALTA) was designed to test hypotheses about the degree to which change in 2 discrete latent variables is related. The ALTA model is a type of latent class model, which is a categorical latent variable model based on categorical indicators. In the ALTA approach, level and change on 1 variable is predicted by level and change in another. Two types of hypotheses are discussed: (a) broad hypotheses of dependence between the 2 discrete latent variables and (b) targeted hypotheses comparing specific patterns of change between levels of the discrete variables. Both types of hypotheses are tested via nested model comparisons. Analyses of relations between psychological state and substance use illustrate the model. Recent psychological state and recent substance use were found to be associated cross-sectionally and longitudinally, implying that change in recent substance use was related to change in recent psychological state.

Keywords

developmental methods; analysis of change; latent class analysis; categorical data

Developmental research often involves studying change across two or more processes or constructs simultaneously. A natural question concerning two changing constructs is whether change in those two processes is related? That is, as development (or more broadly, change) in one domain progresses, is development in another domain related? For example, are changes in one domain of cognitive development associated with changes in another? It is possible that both cognitive domains are developing independently, or that change in one domain spurs change in the other. Cross-sectional research cannot reveal temporal effects like those just described. The example presented here examines whether changes in recent psychological state predict changes in recent substance use, but the methods are applicable broadly to research examining change in two constructs.

Research on associated change may focus on broad patterns of association between the two constructs or on more narrowly focused associations. As an example of a broad hypothesis, consider examining whether change across all levels of substance use is associated with (or predicted by) change across levels or states of psychological state. One could think of this as conceptually similar to an omnibus *F* test in an analysis of variance where many possible patterns of differences can lead to a conclusion of some difference. In a context where two

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dynamic processes are under study, one might think of this broad hypothesis as whether overall there are any associations in change and stability between the constructs.

In contrast, hypotheses about associations between two changing constructs may also be quite precise. For example, one could examine differences in the rates of two specific changes in substance use between people with two different patterns of change in psychological state over time. These more precise or targeted hypotheses may be thought of as similar to specific planned comparisons in an experimental study. Both broadly and narrowly focused research questions are addressed here.

Note that in the example above, the research questions were phrased in terms of change among states or levels. The approach presented here follows from a perspective of looking at discrete categories (including subgroups in a population and applicable to stage theories) exemplified by the latent class model (Goodman, 1974; McCutcheon, 1987). The work presented here is also rooted in latent variable and measurement error perspectives from psychometrics.

Quantitative and Qualitative Change

Before discussing the latent class model, I briefly consider two statistical and conceptual approaches to the study of change. This discussion is not exhaustive but intended to contrast two orientations toward the analysis of change. One of the most common approaches to the analysis of change is growth curve or multilevel modeling (Bryk & Raudenbush, 1992). These are models of quantitative or continuous change (i.e., change is modeled as a matter of degree or amount of a characteristic). The cross-domain growth model (Sayer & Willett, 1998) is appropriate for modeling associations between two quantitative constructs. In cross-domain growth models, the individuals' growth curves of one characteristic are used to predict those individuals' growth curves for another characteristic. For example, individual trajectories of reading ability over the grade school years could be used to predict those individuals' trajectories of writing ability.

On the other hand, qualitative models allow changes in the nature or quality of a characteristic. Models of qualitative change can allow differences in degree of a characteristic, but unlike models of continuous growth, they may also allow new states or characteristics to emerge. Stage models of development are excellent examples of qualitative change. Latent transition (Collins, Hyatt, & Graham, 2000) and latent Markov (Langeheine, 1994) models are two models for qualitative change. The approach described in this article, associative latent transition analysis (ALTA), is analogous to the cross-domain growth model but for qualitative change.

This article focuses on understanding the degree and patterning of association between two changing latent categorical variables. As will be shown, a very detailed picture of development emerges from ALTA. Before I discuss the ALTA model, however, I briefly present the latent class and latent transition models. In the interest of space, many details and issues around the use of these models are not discussed. References to more thorough presentations of this background material are provided.

Latent Class and Latent Transition Models

The latent class model is a statistical approach to identify unobservable subgroups or types of observations in a population and belongs to a broad class of models, known as *mixture models* (McLachlan & Peel, 2000; Titterton, Smith, & Makov, 1985). It accounts for heterogeneity in data by identifying homogeneous subgroups. The latent class model was originally developed in sociology. One of the early applications tested whether two classes

of people (universalistic vs. particularistic values) could account for a set of responses to survey items (Goodman, 1974; Lazarsfeld & Henry, 1968). Since that initial work, the latent class model has been applied to many research areas. Stern, Arcus, Kagan, Rubin, and Snidman (1995) presented a latent class analysis of infant temperament. In this work, several measures of temperament are given to a sample of infants and then it is determined whether a small number of latent classes (corresponding to different temperament types) can account for the observed relations among the items.

In applications of the latent class model, the class variable is unobservable, just as a factor is in factor analysis. But whereas the factor model assumes a continuous latent variable, the latent class model assumes a categorical latent variable. The latent class variable is inferred from patterns of responses to measured items, again similar to how a factor is inferred from covariation among measured items.

The latent class model was originally developed for categorical data (though it has been broadened to other types of indicators; e.g., Flaherty, 2003; Moustaki, 1996). Consider four yes/no items. The latent class model attempts to account for the observed response patterns. A response pattern is the set of responses to the individual items. Four binary items yield 16 separate response patterns (2^4); two examples are (a) no, no, no, no or (b) yes, no, no, yes. For the analysis, *no* might be coded as 1 and *yes* as 2.

The latent class model includes two types of parameters (i.e., population values), both of which are probabilities. Please note that probabilities may be interpreted as a probability for an individual or as a proportion for a sample or population. I use both terms throughout this article because both can be preferable at different times. The first are the latent class proportions. These parameters describe the distribution of the latent classes in the populations. Consider an analysis looking at two levels of psychological state: one positive and one negative. The latent class proportions indicate how many people are expected to be in the positive latent class and what proportion are in the negative latent class.

The other parameter type in a latent class model is a response probability. These parameters are conceptually similar to factor loadings in factor analysis, in as much as they guide the interpretation of the latent classes. To continue with the positive and negative psychological state classes, people in one class may be expected to report positive psychological states. Correspondingly, members of the negative class may be unlikely to endorse items indicating positive psychological state.

The response probabilities are the probability of making a particular response given that one is a member of a particular latent class. If a response probability for the positive latent class were 0.9, then that would mean that someone in that class is 90% likely to reply affirmatively to that item. Notice that these same people are also 10% likely to reply negatively to that same item. The latent class model incorporates measurement error via the response probabilities and allows one to assess psychometric reliability (Biemer, Woltmann, Raglin, & Hill, 2001; Clogg & Manning, 1996; Flaherty, 2002). Response probabilities near 1.0 denote a high correspondence between class membership and endorsement of the characteristic measured by the item. On the other hand, for binary items, response probabilities near 0.5 (i.e., chance) indicate no relation between class membership and the item.

Latent Class Model Assumptions

The latent class model is a nonparametric model with relatively few assumptions. There are three primary assumptions of the latent class model. First, it is assumed that the latent classes are mutually exclusive and, second, that they are exhaustive. That is, every person in

the population is expected to be a member of one and only one latent class. The third assumption is referred to as conditional independence and concerns the relations between items once the latent class variable is included in the analysis. Conditional independence means that the items are assumed to be statistically independent once one takes the latent class variable into account. That is, all the association between items is assumed to be due to the latent class variables. This assumption can also be tested (Hagenaars, 1988).

Parameter Restrictions

Parameter restrictions are commonly employed in latent class models (Flaherty, 2002; Formann, 1985). Two types of parameter restrictions are parameter fixing and equality constraints. Fixing a parameter to a value means that the parameter is not estimated. Equality constraints force two or more estimates to be equal to a single shared value. In longitudinal models, one common use of equality constraints is to make the response probabilities equal over time. This ensures that the latent classes have the same interpretation over time. Hypotheses regarding associated change between two latent class variables are tested with equality constraints as well.

Latent Class Model Fit and Selection

As a simple measurement model, the fit of the latent class model must be evaluated. Conceptually, this is identical to assessing the fit of a confirmatory factor model (Bollen, 1989). In fact, fit and assessment in the latent class model are very similar to factor analysis and structural equation modeling (SEM) in many ways. Model fit can be assessed with the G^2 or Pearson's X^2 statistic (sometimes referred to as the χ^2 statistic), as with other categorical data approaches (Agresti, 1990). Both of these fit statistics are compared to the model degrees of freedom (df). The df is the number of response patterns minus one and minus the number of estimates. These statistics quantify the overall fit of the model estimates to the data.

Nested model comparisons are another type of fit assessment. Nested model comparisons are typically used to check whether model restrictions are acceptable; again, just as with confirmatory factor analysis and SEM. Generally, nested models are models that have specific restrictions on estimates that are unrestricted in the larger model. For example, in confirmatory factor analysis, a model with factor loadings constrained to be equal across groups is nested within a model where those factor loadings can differ across groups. The decision to accept a simpler model over a more complex model is based on the likelihood ratio test; that is

$$\Delta G^2 = \frac{G^2_{restricted} - G^2_{full}}{df_{restricted} - df_{full}}$$

Latent Transition Analysis

Latent class analysis was originally developed with static (i.e., unchanging) latent variables in mind. Longitudinal research focuses on dynamic latent variables, that is, latent variables that change systematically over time (e.g., Collins & Cliff, 1990). Latent transition or latent Markov analysis (LTA; Graham, Collins, Wugalter, Chung, & Hansen, 1991; Langeheine & van de Pol, 2002) are longitudinal versions of the latent class model. In these models, people may change among latent classes over time. The response probabilities play the same role in these longitudinal models as they do in the basic latent class model. That is, they model the relations between items and the latent class variable. However, rather than simply estimating

latent class proportions, these longitudinal models estimate an initial set of latent class proportions and transition probabilities. The transition probabilities describe how people change among the latent classes.

Continuing the example of classes of psychological state, the initial latent class probabilities would describe how a sample was distributed among the latent classes at Time 1. The transition probabilities would describe change and stability across assessments. One example might be the probability of changing from Time 1 positive psychological state to Time 2 negative psychological state. Another corresponds to stability—the probability of being in the positive state at both Times 1 and 2. Corresponding transition probabilities for people starting out in the negative latent class would also be estimated.

There is a vast literature on the latent class and related models. The focus of this article is on using the ALTA model to investigate cross-sectional and longitudinal associations between two dynamic latent class variables. As such, much of the background and detail regarding latent class and latent transition models has been omitted. McCutcheon (1987) is a thorough introduction to the latent class model and Lanza, Flaherty, and Collins (2003) cover both latent class and latent transition models. Goodman (1974) and Clogg (1995) provide more statistical treatments of the latent class model.

ALTA

The latent transition model was developed to extend the latent class model to address longitudinal research questions. Similarly, the associative latent transition model is an extension in so much as it is designed to address research questions about dependence between two changing categorical latent variables.

The latent class model includes two types of parameters: latent class probabilities and response probabilities. For the latent transition model, the latent class probabilities of the latent class model are split into two sets of parameters: initial class probabilities and transition probabilities. The ALTA model further refines the parameters in the latent class and latent transition models. The ALTA model includes both a predictor latent class variable (X) and a dependent latent class variable (Y), and latent class membership for the Y variable is conditional on X latent class membership. However, the ALTA model also allows earlier latent class memberships (both X and Y) to affect subsequent latent class memberships. This results in a sort of bidirectionality of effects. The ALTA model includes the following parameters: (a) the initial distribution of X (α s), (b) the initial distribution of Y conditional on initial level of X (β s), (c) the subsequent distribution of X conditional on previous levels of X and Y (ϵ s), and (d) the subsequent distribution of Y conditional on the previous and concurrent levels of X and the previous level of Y (η s).

Consider two constructs: recent psychological state and recent substance use. There has been a long interest in examining relations between psychological state variables and substance use (Mason, Hitchings, & Spoth's, 2007, study includes a brief recent review of this issue). I use ALTA to describe change and stability in recent psychological state and how that change and stability is associated with change in recent substance use.

Figure 1 contains a diagram that illustrates how individuals may change over time in the ALTA model described in this article. It is not a graphical representation of the statistical model, as found in structural equation models (Bollen, 1989). Rather, it is a conceptual diagram of the latent classes people may occupy and how people may change among them for both latent class variables.

In Figure 1, arrows denote how people can move among the latent classes. (They do not represent correlations or specific parameters.) Someone can move through several latent classes between measurement assessments. Figure 1 shows the allowable paths through the latent class memberships. For example, if someone was in the *no use* latent class at Time 1 and in the *past year alcohol* latent class at Time 2, one would expect that individual to have occupied the *tried alcohol* latent class at some point, even though it was not observed. Double headed arrows in Figure 1 indicate that people can move forward or backward among the classes, and change over time can occur between the levels of both X and Y in this model. The arrow from *recent psychological state* to *recent substance use* denotes that substance use is the dependent latent class variable. I use this diagram to describe the parameters in the ALTA model.

One can think of the ALTA parameters as a nested structure. The goal is to describe how class memberships in one categorical variable are associated with the class memberships of the other variable. The α s are the outermost set and describe the distribution of the X classes at Time 1. From Figure 1, the α s correspond to the membership probabilities for each of the three recent psychological state latent classes at Time 1 (top). The β s are the next set and they describe the distribution of the Y classes at Time 1 for every level of X at Time 1. (The distribution of Y is conditional on X .) Continuing with the figure, the β s are the probabilities of membership in each of the substance use classes at Time 1 within each of the three levels of Time 1 recent psychological state.

The next set of parameters are the ϵ s, and these are the first longitudinal parameters. The ϵ s are the distribution of X at Time t for every combination of X and Y at Time $t - 1$. These parameters model change in the X variable. Referring again to Figure 1, the ϵ s are the Time 2 (or later) probabilities of recent psychological state class membership given where an individual was on both psychological state and substance use previously. For example, one ϵ parameter is the probability of being in the positive psychological state latent class at Time 2, given that at Time 1, one was a member of both the positive psychological state and *no substance use* classes. Further, these parameters could be used to compare whether people in a common psychological state latent class but different substance use classes at Time 1 were more or less likely to be in a different psychological state latent class by Time 2.

The final parameters to consider are the η s. These describe the distribution of the Y latent class variable, taking into account (i.e., conditional on) current X class membership and the previous time points' X and Y memberships. That is, the η s reflect how change in the Y variable is related to change on X . In Figure 1, the η s are the probabilities of membership in each substance use class at Time 2, conditional on the Time 2 psychological state class and the pair of Time 1 class memberships for psychological state and substance use. For example, η parameters would show whether people who were in the positive psychological state at both times and *no use* at Time 1 were more likely to also report no use than those who had changed to negative psychological state at Time 2.

The ALTA model also includes response probabilities, just as the latent class and latent transition models do. These probabilities are interpreted and evaluated exactly as described above. The notation and a more precise description of the ALTA model is given in the online Appendix. The model is also described in detail in Flaherty (2007).

Using Parameter Restrictions to Test for Dependence Between X and Y

In this section, procedures for using equality constraints to test broad hypotheses of association between the latent class variables in ALTA are presented. Testing more specific hypotheses is illustrated in the Results section.

Four models of overall association will be described: independence, cross-sectional, longitudinal, and full association. The independence model stipulates that the two variables are statistically independent. Change may occur on X and/or Y but that change is not associated between the latent class variables. The independence model is specified with three sets of equality constraints. First, the β s are constrained to be equal across all levels of the Time 1 X variable. In the example, this means that the probability of substance use class membership does not depend on recent psychological state class membership. Second, the ϵ s are constrained to be equal across all levels of the previous time's Y latent class variable. Continuing the example, this restriction implies that time t psychological state class only depends on time $t - 1$ psychological state class and not at all on time $t - 1$ substance use class. Third, the η s are constrained to be equal across all levels of times $t - 1$ and t of the X latent class variable. In the example, this would mean that time t substance use class only depends on time $t - 1$ substance use class, and not on times $t - 1$ or t psychological state class membership. These three broad patterns of constraints together impose independence between the two latent class variables. Were the independence model to fit, it would imply that there were not class membership associations (cross-sectionally or longitudinally) across the X and Y variables. By comparing an independence model to a less restrictive model with a nested model test, one can decide whether the independence model fits about as well as the less restrictive model.

Cross-sectional and longitudinal association allow partial association between the latent class variables. Cross-sectional association includes the equality constraints on the ϵ s and η s but no constraints on the β s (1 above). This implies that substance use latent class memberships depend on concurrent psychological state latent class. Longitudinal association does not include constraints in ϵ s and η s but does impose constraints on the β s. The longitudinal association model implies that there are no cross-sectional associations but that someone's class memberships for both psychological state and substance use at later time points depends on their pair of initial latent class memberships. The full association model does not impose any broad set of constraints on any of the sets of estimates. These broad patterns of parameter restrictions are also described precisely in the online Appendix.

These models can also incorporate additional types of parameter restrictions. For example, if some transitions are illogical (e.g., changing from a latent class involving recent drunkenness to a latent class characterized by never having tried alcohol), the corresponding parameters can be fixed to zero.

Empirical Illustration

In order to illustrate the ALTA model and the process of testing for different patterns of dependence between X and Y , the analysis of associations between recent psychological state and recent substance use in a sample of U.S. students is presented. In these models, recent psychological state will be treated as the predictor (X) and recent substance use as Y . This choice was made following from the self-medication hypothesis of substance use (Khantzian, 1985). It suggests that substance use is an effort to relieve aversive psychological states. I use ALTA to examine overall whether recent substance use class membership and change therein are associated with class memberships for recent psychological state. The ALTA estimates will also be used to make specific comparisons such as whether particular combinations of recent psychological state are associated with increased or decreased levels of recent substance use.

Method

Study Participants

The National Longitudinal Study of Adolescent Health (subsequently referred to as *Add Health*) is a nationally representative sample of U.S. students in Grades 7–12 (Harris et al., 2003). The sample was first surveyed in 1994 and again in 1995. Results presented here are based on the Add Health public use data files. The initial sample size available in the public use data is 6,504, and 4,834 were successfully reinterviewed. These data are nearly equally split by gender (48% male). The sample is approximately 66% White, 25% African American, 1% Native American, and 4% Asian or Pacific Islander. Ethnic background for about 5% of the sample was coded as other. Approximately 12% of the sample indicated Hispanic origin. Additionally, about 17% of the sample had a household income below \$16,000 a year. All 6,504 respondents are included in this work.

Measures

Psychological state and substance use were both modeled using dichotomous variables. Two composite items for psychological state were used at each measurement occasion. One summarized 15 items measuring negative feelings and experiences over the past week, and the other summarized 4 items measuring past week positive feelings and experiences. Two examples of items measuring recent negative experiences are “You felt depressed” and “People were unfriendly to you.” Examples of items measuring recent positive feelings are “You felt hopeful about the future” and “You felt happy.” Each of the raw items had scores between 0 and 3, where a 0 = *never or rarely*, 1 = *sometimes*, 2 = *a lot of the time*, and 3 = *most or all of the time*. If the highest reported score across all the negative valence items was a 2 or 3, that person was coded as having negative feelings or experiences that past week. Similarly, if a person reported a 2 or 3 for the positive items, that person was coded as having positive feelings or experience that past week.

Five measures of recent use of alcohol and marijuana were used for the substance use classes. The first item asked whether the respondent had ever tried alcohol outside of the family. The second item inquired about any alcohol use in the past 12 months. The third item asked whether the respondent had been drunk or engaged in binge drinking (i.e., five or more drinks in a row). The fourth item concerned any past use of marijuana, and the fifth item asked about any marijuana use in the past 30 days. Unfortunately, each of these items was worded slightly differently at both measurement occasions. At the first measurement occasion, items began with the phrase “Have you ever ...?” At the second assessment, those items began with the phrase “Since the last interview ...?” Due to this difference in wording, the latent classes only reflect recent substance use, not lifetime use.

All but one of the items were coded such that a 1 denoted a no or absence and a 2 denoted a yes or presence. The positive feelings/experiences item was reverse coded so that a 1 denoted positive feelings and a 2 denoted the absence of positive feelings/experiences.

Analytic Strategy

Prior to fitting an ALTA model, individual LTA models were fit to the psychological state and substance use data separately. These LTA models had two purposes. The first was to determine the number of classes necessary to model each construct. The suitable number of latent classes for psychological state and substance use was chosen by examining model fit and interpretability. These LTA models included longitudinal restrictions on each of the measurement estimates so that the latent classes had the same meaning over measurement occasions.

The second purpose of the separate LTA models was to attempt to simplify the measurement structure further. Upon choosing the number of latent classes, I fit a series of models with additional parameter restrictions among the response probabilities. One or two parameter restrictions were tested at a time, and the decision to accept the restricted model was based on nested model comparisons. These procedures were similar to those described in Flaherty (2002). Upon establishing the individual LTA models, I fit a series of ALTA models testing the broad hypotheses of association.

For the ALTA models, maximum likelihood estimates were obtained from an expectation-maximization algorithm (Dempster, Laird, & Rubin, 1977; McLachlan & Krishnan, 1997) written in Fortran 90.¹ Missing data were handled via multiple imputation (Schafer, 1997), as implemented in S+ (Mathsoft, 1999). Results were averaged across three imputed data sets. A version of the ALTA software that handles missing data is under development.

Results

LTA Models

Prior to discussing the ALTA model results, the single LTA analyses are briefly summarized. Due to space considerations, these models are only summarized here.² The psychological state model consisted of three latent classes describing overall recent emotional state: positive, neither, and negative, with individuals in the neither latent class reporting few positive or negative emotional experiences. With equality constraints, only two response probabilities were estimated. Members of the positive latent class had a probability of 0.78 of saying no recent negative experiences and were certain to indicate some recent positive experiences (response probability = 1.0.). The neither latent class had a probability of 0.78 of indicating no recent negative or positive experiences. The negative latent class had the reverse pattern of the positive latent class; that is, they were certain to endorse recent negative experiences and had a probability of 0.78 of indicating no recent positive experiences.

The substance use model consisted of six latent classes: no use, tried marijuana, tried alcohol, past 12 month alcohol use, alcohol with drunk/binge, drunk and marijuana. Overall, the substance use latent classes were well-defined. Most of the high values of the response probabilities ranged from 0.85 to 1.0. Tried marijuana latent class members were 27% likely to indicate having tried alcohol and were 86% likely to indicate ever trying marijuana but were 57% likely to indicate recent marijuana use. So, although this class is labeled *tried marijuana*, some of that marijuana use may have occurred recently, and under a third of the members may have tried alcohol as well. But marijuana use appears the defining feature of this class, hence the label. Members of the drunk and marijuana latent class were 66% likely to endorse past 30-day marijuana use and had high probabilities of responding affirmatively to all the other use items (0.85–0.95). Equality constraints were used among the response probabilities where logical and where nested model comparisons did not indicate significant misfit. For example, the probability of indicating not being drunk or binge drinking was constrained to be equal across no use, tried marijuana, tried alcohol, and past 12 month alcohol use (constrained estimate = 0.98). Similarly, the probability of endorsing drunkenness or binge drinking was constrained to be equal across the alcohol with drunk/binge and drunk and marijuana latent classes (constrained estimate = 0.85). For a discussion of measurement quality in the latent class model see, Clogg and Manning (1996) and Flaherty (2002).

¹The program is freely available from Brian P. Flaherty.

²Full results of the LTA and ALTA models are available from Brian P. Flaherty.

Fitting and Comparing ALTA Models

Four ALTA models were fit to the psychological state and substance use latent variables together, based on the individual LTA models for psychological state and substance use just described. The four models fit corresponded to the independence, cross-sectional, longitudinal, and full association parameter restrictions described above and summarized in the online Appendix. Goodness-of-fit results appear in Table 1.

The cross-sectional model provides an improvement in fit over the independence model ($\Delta df = 10$, $\Delta G^2 = 1479.4$), suggesting that the two latent variables are not independent at Time 1. The longitudinal model also provides an improvement in fit over the independence model ($\Delta df = 299$, $\Delta G^2 = 4585.8$), suggesting that the two latent variables are related longitudinally. The full association model fits significantly better than both the cross-sectional model ($\Delta df = 299$, $\Delta G^2 = 4615.3$) and the longitudinal model ($\Delta df = 10$, $\Delta G^2 = 1508.9$). Taken together, these results indicate that psychological state and substance use are related both cross-sectionally and longitudinally.

Selected Results

Next, a few selected results from the full association model are presented to illustrate the ALTA model parameters and the testing of specific hypotheses. The α estimates describe the unconditional distribution of the sample across the psychological state latent classes. Interestingly, the most prevalent latent class switched between the measurement occasions. At Wave 1, the positive latent class contained 46% of the sample, with 19% and 35% in the neither and negative latent classes, respectively. By Wave 2, 46% of the sample was in the negative latent class, with 42% and 12% in the positive and neither latent classes, respectively.

The β estimates describe the distribution of the substance use latent classes, conditional on concurrent psychological state.

Table 2 shows that members of the positive latent class at Time 1 were most likely to be in the tried marijuana latent class or the no use latent class. People in the neither latent class were fairly evenly distributed across the substance use latent classes but were least likely to be in the no use latent class. Those in the negative latent class were most likely to be in the most advanced latent class, drunk and marijuana.

Recall that the model comparisons above showed that cross-sectional independence of the latent variables was rejected. However Table 2 shows that the distribution of substance use latent classes is much more similar for the neither and negative psychological state latent classes, than for the positive latent class. This post hoc observation can be tested by imposing equality constraints on the β s for the neither and negative latent classes only. Comparison with the full association model produces a G^2 difference of 174.2 with five degrees of freedom, which is significant. This suggests that despite the apparent similarity, the distribution of concurrent substance use is not the same for the neither and negative latent classes.

The ϵ estimates describe the distribution of Time 2 psychological state conditional on the pair of Time 1 latent class memberships (see Table 3). The table shows, for example, that people in the positive and no use latent classes at Time 1 are most likely to also be in the positive latent class at Time 2. However, someone in the positive and drunk latent classes at Time 1 is about 20% less likely to be in the positive latent class at Time 2.

An interesting overall pattern emerges in Table 3. Those who were in the positive psychological state at Time 1 and who either did not engage in substance use or engaged at a low level appear more likely to be in the positive psychological state at Time 2.

Greater levels of Time 1 substance use appear associated with an increasing likelihood of a transition from Time 1 positive psychological state to one of the other psychological state latent classes. Those who were in the neither psychological state at Time 1 were most likely to move to a different psychological state at Time 2, with some variability across Time 1 substance use. The negative psychological state showed the most stability, with individuals in this state most likely to be there at Time 2 irrespective of Time 1 substance use latent class. (Stability refers to a high probability of reporting the same psychological state latent class at adjacent time points, even though between assessments people could have changed latent class memberships several times.)

It appears from Table 3 that for those in the negative psychological state latent class at Time 1, Time 2 psychological state latent class may be independent of Time 1 substance use latent class. This post hoc hypothesis was tested by setting $\varepsilon_{d|Negative,c} = \varepsilon_{d|Negative}$, where c denotes the Time 1 substance use latent class and d denotes the Time 2 psychological state latent class. That is, Time 2 psychological state is independent of Time 1 substance use for those in the negative psychological state at Time 1. The difference in the G^2 values between this constrained model and the full association model was 64.25 with 10 degrees of freedom, which is significant. Even though the patterns of ε estimates for those starting in the negative latent class appear similar, they cannot be constrained to be equal across substance use latent classes.

The η estimates quantify relations between change in psychological state and change in substance use. Table 4 contains a subset of the η estimates from the full association model.

As the first illustration of these parameters, consider how people may change from one pair of latent classes at Time 1. The η estimates can be used to compare how a change in one latent class variable is associated with change on the other. For example, look at how people who began in the positive psychological state and no use latent classes have changed by Time 2. Figure 2 shows the distribution of Time 2 substance use latent classes among these individuals, given their Time 2 psychological state membership. (The values in Figure 2 are the first three rows of Table 4.)

For those in either the positive or negative psychological states at Time 2, the no use latent class was the most prevalent substance use latent class. However, the probability of membership in the no use latent class was quite different for these two groups of people (72% vs. 32%, respectively). If instead a person changed to the neither psychological state at Time 2, then he or she was most likely to be in the past 12 month alcohol latent class (59%).

Like the ε s, the η s can be used to compare stability of and movement between latent classes, where stability again refers to a high probability of membership in the same latent class at adjacent times. In contrast to LTA, which can be used to examine stability in or movement among latent class memberships for a single latent variable, the ALTA model can be used to examine stability and change in Y conditional on stability and change in X .

For example, consider individuals who are in the same psychological state latent class at both times. It is possible to compare the probability of substance use transitions across three stability subgroups: those who are in the positive, neither, or negative psychological state latent class at both times. Figure 3 illustrates transitions for two selected Time 1 latent classes: try marijuana (top row) and try alcohol (bottom row).

An overall pattern is evident in Figure 3. Those who are in the positive psychological state at both times are more likely to remain in their Time 1 substance use latent class. Those in the other two psychological states are less likely to remain in the same substance use latent class and are more likely to move to a more advanced substance use state. Those in the neither psychological state are particularly likely to move into latent class with recent drunk/binge drinking. Thus, it appears that stability in the positive latent class is related to less substance use, and stability in the neither psychological state is related to increasing substance use.

Now compare the findings for those who were in the positive psychological state latent class at both times, reviewed above, to results for those who moved from the positive psychological state at Time 1 to the neither psychological state at Time 2. Whereas those who were in the positive psychological state at both times were most likely also to be in the same substance use latent class at both times, those who moved to the neither psychological state show a greatly increased probability of more advanced substance use. Those who at Time 1 were in the try marijuana latent class had only a 28% probability of being there at Time 2 and a 42% probability of moving into the drunk latent class. (These values are in the fifth row of Table 4.) Those who at Time 1 were in the try alcohol latent class had only a 16% probability of being there at Time 2 and a 53% probability of moving to the drunk and marijuana latent class. (These values are in the eighth row of Table 4.) Thus, movement from the positive to the neither psychological state appears to be associated with a substantially increased risk of substance use advancement, as compared with those whose membership in the positive psychological state is more stable.

Discussion

This article illustrates two model fitting approaches for studying developmental change using a latent class model referred to as the *associative latent transition model*. The model is motivated by the desire to study contingent change between two categorical latent constructs. First, through the use of broad patterns of equality constraints, it is possible to test whether change over time in two latent class variables appears related in general. Second, fine-grained examinations of linked change through the targeted use of equality constraints and model comparisons are also described.

The ALTA approach was illustrated with an analysis of the association between psychological state and substance use in the Add Health data. The analysis indicated that a model incorporating both cross-sectional and longitudinal associations was necessary to model these data. The empirical example shows that the ALTA model presents a rich descriptive picture of change and stability in the sample and allows researchers to test complex hypotheses of contingent change. This illustration did not compare change across multiple groups, for example, age groups or gender, in order to keep the presentation manageable, but such subgroup comparisons are possible with the model.

While the Add Health data provide a rich empirical illustration for the ALTA model, these data are not perfect. The biggest data limitation was already noted—the substance use items do not measure lifetime use. They are nonredundant measures of recent use. As such, one cannot truly take advantage of the latent class model's ability to model measurement error. Furthermore, had the substance use items measured lifetime use, the size of the model reported here could have been reduced by eliminating illogical transitions (e.g., going from the drunk latent class to a never tried alcohol latent class). Additionally, the past week time scale of the psychological state variables is short compared to the longer time span of the recent substance use variables. This is a difficulty to the extent that the week prior to the survey was atypical. But if the past week was a typical week, then it may be a reasonable proxy.

Use and Applications

The ALTA model may be used to study relations between two dynamic or developmental processes operationalized as latent class variables. The conditional nature of the ALTA model lends itself to testing models where one construct is expected to precede the other. This would apply in experimental research where a treatment condition is expected to affect a mediator that in turn is expected to change an outcome. (For discussion of a stage-sequential view of mediation, see Collins, Graham, & Flaherty, 1998.) This type of research is wide ranging, with examples including maternal interventions aimed at maternal and child health and well-being (e.g., Yilmaz, Karacan, Yoney, & Yilmaz, 2006), early childhood socialization (e.g., Hustedt & Raver, 2002), and the prevention of cognitive decline among Alzheimer's patients (e.g., Arkin, 2007).

However, the ALTA model can also be used in nonexperimental research as done here. In these situations, the choice of a predictor variable should be based on theory and/or hypotheses. For example, ALTA could be used to study parent-child relations or socialization and how aspects of those constructs are associated with school engagement, achievement, or peer group affiliation.

Comparison With Other Approaches

The focus of this article has been to suggest the ALTA model as a way of conceptualizing and testing specific hypotheses about change over time. The ALTA model was designed to make estimates of contingent change easily interpretable and hypotheses about contingent change easily testable. ALTA is closely related to other latent class models that have previously appeared in the scientific literature. Like most other latent class models, it is subsumed under very general categorical models such as the one presented by Hagenaars (1998). Vermunt, Langeheine, and Bock-enholt (1999) presented a similar longitudinal model where static and time-varying discrete measured covariates predict a single changing discrete latent variable (i.e., a latent transition or latent Markov model). This approach would be akin to treating psychological state as an error-free covariate in the analyses presented here. Vermunt et al. noted in their discussion that it would be possible to add an error model to the time-varying covariate. ALTA explores that extension.

It is also worth comparing the ALTA model with other related models of change. These include cross-lagged models (Burkholder & Harlow, 2003), binary variable growth curves (Guo & Zhao, 2000), and cross-domain growth modeling (Sayer & Willett, 1998). One immediate difference between all three of these models and ALTA is that they are models of quantitative or continuous change.

Cross-lagged models—Cross-lagged models are longitudinal models in which two variables predict each other over time. Most simply, scores from time t on a variable X predict scores on a variable Y at time $t + 1$. Similarly, scores for Y at time t are used to predict scores for X at time $t + 1$. These models allow bidirectional lagged relations between X and Y .

There are a few important differences between cross-lagged models and ALTA. In cross-lagged models, one variable is not designated as dependent or conditional on the other. In the ALTA model, one variable is specified as conditional on the other. Both approaches can be useful depending on the specific research questions.

Another important difference between ALTA and a cross-lagged model is that cross-lagged models do not model association between change. In a cross-lagged model, X is predictive of a subsequent Y and vice versa, but change on Y is not predicted by change on X . That is, X

scores at Time 1 predict Y scores at Time 2, but there is no function of X scores at Time 1 and Time 2 to predict a function of Y scores. On the other hand, the ALTA model explicitly includes parameters that capture how change on Y is associated with change in X .

Last, cross-lagged models are correlational models. Like regression models in general, the regression coefficients describe relations in the sample overall. But these regression coefficients do not necessarily describe individual change or development. On the other hand, the ALTA model is closer to describing individual behavior. People with a particular set of class memberships have associated probabilities of subsequent class memberships. For example, people who were members of the positive psychological state and no use at Time 1 and negative psychological state at Time 2 were 20% likely to have changed to past 12 month alcohol use. That estimate is describing how particular individuals were expected to change.

Categorical variable growth curve models—Growth curve models have been extended to categorical responses, called *generalized linear mixed models* (Agresti, Booth, Hobert, & Caffo, 2000; Diggle, Liang, & Zeger, 1994). These approaches model the probability of the response categories over time. One key difference between these models and ALTA is that they typically only model change on a single response over time, whereas ALTA is for two dynamic categorical variables. Furthermore, growth curve models are fundamentally manifest variable models. They do not model measurement error explicitly as a latent class or factor model can. Last, as mentioned above, categorical variable growth models are essentially continuous models of change. The probability of a response category is modeled as a smooth function of time. In the ALTA model, as well as latent transition models, movement among the classes need not be a smooth function of time.

Above, the ALTA model was said to be “closer” to intraindividual change than cross-lagged models. But growth models are true models of intraindividual change. An individual’s predicted trajectory summarizes that person’s development over the time of the study. The ALTA model only characterizes individual development for adjacent time points. It is not a complete description of individual development for more than two times. In order to completely capture individual development, latent transition and ALTA models need to take all past class memberships into account when predicting membership at time t . (The number of past occasions used to predict a current state is referred to as the *order of the process*. ALTA is a first-order process.)

Cross-domain growth models—In cross-domain growth curve analysis, estimates for one trajectory are correlated with the estimates for another trajectory. This analysis yields a reasonably small set of estimates to interpret. For example, the slope of the first trajectory may be predictive of the slope of the second, and this correlation between trajectory slopes is assumed to hold across all levels of the characteristics being modeled.

In contrast, the ALTA model makes no assumptions about effects being constant across levels of one construct. On one hand, this is good because those effects may not be constant. For example, the effect of changing from positive to neither was different on the basis of whether an individual started in tried marijuana or tried alcohol. The ALTA model estimates those effects separately. The cost of this is a large model with many estimates. Furthermore, the interpretation is more detailed. One must take account of the chain of class memberships a single estimate entails. This level of detail similarly has costs and benefits. A cost is complication. A benefit is that a very detailed picture of developmental change may emerge. Finally, it should be noted that by using equality constraints, the model size can be reduced greatly and concepts like the constancy of effects across levels of the predictor latent class variable can be tested.

Limitations

ALTA models are generally complex with potentially many parameter estimates. However, implementation considerations for ALTA are essentially the same as those associated with other large latent class models, such as LTA. The factors affecting statistical power in latent class models are very similar to those that affect factor and component analysis. In general, the more highly saturated and well-defined a model is, the smaller the sample size necessary to fit the model. In factor analysis, this corresponds to large factor loadings and well-defined factors (i.e., simple structure). In latent class models, this corresponds to patterns of responses that are clearly associated with latent class membership (e.g., see Flaherty, 2002).

Another consideration is contingency table sparseness, indicated by the average expected cell frequency N/k , where N is the overall sample size and k is the number of cells in the contingency table. Large latent class models such as ALTA usually involve several variables measured at several times, often resulting in very large contingency tables. The example presented in this article involved seven variables measured at two times, resulting in a contingency table with $2^{14} = 16,384$ cells. With a sample size of 6,504 $N/k =$ approximately 0.4. Generally, N/k less than about 5 is considered sparse (Read & Cressie, 1988). There are two potential implications of contingency table sparseness. One is that there may be estimation problems, including failure to converge or other breakdown of the estimation procedure. However, large latent class models are surprisingly robust to such problems (Collins & Tracy, 1997; Collins, Wugalter, & Fidler, 1996), particularly those that are well-defined and have good saturation. The other implication is that the distribution of the goodness-of-fit statistic, G^2 , is no longer well approximated by the χ^2 distribution, as mentioned above. This affects tests of the relative fit of nested models involving the difference G^2 , as were presented here, less than tests of absolute fit. Future work on ALTA will include approaches to absolute fit testing.

The current version of the ALTA software does not provide standard errors. Where appropriate, hypothesis testing can be conducted via nested models, as demonstrated above. Standard errors can also be obtained via bootstrapping (Efron & Tibshirani, 1993).

Other software programs like Mx (Neale, Boker, Xie, & Maes, 2003), *ℓem* (Vermunt, 1997), or Mplus (Muthén & Muthén, 1998) may also be able to fit ALTA models, although because the ALTA software is more specialized it is easier to use for this application.

Despite these limitations, ALTA has some significant strengths. As was demonstrated here, using the ALTA approach can enable the investigator to draw meaningful conclusions from a very large contingency table. Although it might be possible to construct classes logically based on manifest data, rather than using the model and estimation procedures described here, it is difficult to know what to do with response patterns that do not map directly onto one of the classes. In the ALTA model, as in other latent class models, the probabilistic nature of the model allows one to model the entire table, including such response patterns.

But the most important strength of ALTA is conceptual. It was demonstrated above how to use ALTA to model psychological state and substance use as dynamic latent variables and how to fit models of relations between these two dynamic latent variables. There are scientifically important questions about contingent variables and linked developmental change in many domains in the behavioral sciences. Furthermore, as developmental knowledge increases, these sorts of questions can be expected to increase correspondingly. The ALTA model provides a clear yet detailed means of investigating these questions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

Diagram showing the paths by which people may change among the latent classes for both variables in the associative latent transition analysis (ALTA) model. Also shown are which latent class variable is predicted by the other.

Figure 2.

Change in substance use latent class conditional on change in psychological state for those starting in the positive and no use latent classes. NoUse = No use; TryMJ = tried marijuana; TryAlc = tried alcohol; 12moAlc = past 12 month alcohol use; Drunk = alcohol with drunk/ binge; DrnkMJ = drunk and marijuana.

Figure 3.

Comparison of stability of Time 1 tried alcohol and tried marijuana classes for people who remained in the same psychological state latent classes at both times. The legend refers to both plots. NoUse = No use; TryMJ = tried marijuana; TryAlc = tried alcohol; 12moAlc = past 12 month alcohol use; Drunk = alcohol with drunk/binge; DrnkMJ = drunk and marijuana.

Table 1

Goodness of Fit of Associative Latent Transition Analysis Models

Model	Number of parameters	G^2	df
Independence	29	13,083.4	16354
Cross-sectional	39	11,604.0	16344
Longitudinal	328	8,497.6	16055
Full	338	6,988.7	16045

Table 2

Time 1 β Estimates

Psychological state	Substance use				
	No use	Tried marijuana	Tried alcohol	Past 12 month alcohol use	Alcohol with drunk/binge
Positive	0.30	0.44	0.17	0.01	0.03
Neither	0.10	0.20	0.11	0.20	0.22
Negative	0.15	0.17	0.14	0.10	0.18
					0.25

Note. Substance use latent class membership (columns) is conditional on psychological state latent class (rows).

Table 3The ε Estimates

Time 1 substance use	Time 2		
	Positive	Neither	Negative
Time 1 positive			
No use	0.76	0.09	0.15
Tried marijuana	0.72	0.10	0.18
Tried alcohol	0.64	0.12	0.24
Past 12 month alcohol use	0.41	0.09	0.50
Alcohol with drunk/binge	0.56	0.05	0.40
Drunk and marijuana	0.41	0.12	0.47
Time 1 neither			
No use	0.42	0.19	0.39
Tried marijuana	0.52	0.23	0.26
Tried alcohol	0.56	0.19	0.25
Past 12 month alcohol use	0.34	0.24	0.42
Alcohol with drunk/binge	0.41	0.31	0.28
Drunk and marijuana	0.35	0.19	0.46
Time 1 negative			
No use	0.21	0.05	0.74
Tried marijuana	0.24	0.08	0.68
Tried alcohol	0.29	0.05	0.66
Past 12 month alcohol use	0.18	0.03	0.79
Alcohol with drunk/binge	0.23	0.02	0.75
Drunk and marijuana	0.26	0.03	0.72
Drunk and marijuana	0.26	0.03	0.72

Note. The columns of the table are Time 2 psychological state, which are conditional on Time 1 psychological state and Time 1 substance use class (the rows).

Table 4

Selected η Estimates

Time 2 psychological state	Time 2 substance use				
	No use	Tried marijuana	Tried alcohol	Past 12 month alcohol use	Alcohol with drunk/binge
Time 1 positive psychological state and no use					
Positive	0.72	0.18	0.04	0.02	0.03
Neither	0.12	0.03	0.01	0.59	0.25
Negative	0.32	0.14	0.00	0.20	0.17
Time 1 positive psychological state and tried marijuana					
Positive	0.22	0.63	0.06	0.02	0.03
Neither	0.03	0.28	0.04	0.19	0.42
Negative	0.17	0.17	0.17	0.09	0.22
Time 1 positive psychological state and tried alcohol					
Positive	0.00	0.24	0.65	0.01	0.04
Neither	0.04	0.03	0.16	0.00	0.25
Negative	0.00	0.12	0.32	0.13	0.19

Note. The columns of the table are Time 2 substance use, which are conditional on Time 1 psychological state, Time 1 substance use, and Time 2 psychological state (the rows).