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Using Latent Transition Analysis in Nursing Research to Explore Change Over Time

Tonya J. Roberts, MS, RN[Research Assistant] and
School of Nursing, University of Wisconsin-Madison, Madison, Wisconsin

Sandra E. Ward, PhD, RN[Helen Denne Schulte Professor, Director]
Center for Patient-Centered Interventions, School of Nursing, University of Wisconsin-Madison,
Madison, Wisconsin

Abstract

Background—Latent transition analysis is a method of modeling change over time in categorical variables. It has been used in the social sciences for many years, but not in nursing research.

Objective—To illustrate the utility of latent transition analysis for nursing research by presenting a case example (a secondary analysis of data from a previously conducted randomized control trial testing the effectiveness of a tailored psychoeducational intervention to decrease patient-related attitudinal barriers to cancer pain management) and to understand for whom, and in what direction, the tailored intervention resulted in change with respect to attitudinal barriers and pain symptoms.

Method—The model was developed by (a) defining a class structure based on individuals' barrier patterns, (b) adding demographic predictors and distal pain outcomes, and (c) modeling and testing transitions across classes.

Results—There were two classes of individuals: Low Barriers and High Barriers. Older, less educated individuals were more likely to be in the High Barriers class at time 1. Individuals in either class did not have different pain outcomes at the end of the study. Of those individuals that transitioned across classes, those who received the intervention were statistically more likely to move in a favorable direction (to the Low Barriers class). Furthermore, there is evidence that some individuals in the control group had unfavorable outcomes.

Discussion—The results from the example provide useful information about for whom, and in what direction, the intervention resulted in change. Latent transition analysis is a valuable procedure for nurse researchers because it collapses large arrays of categorical data into meaningful patterns. It is a flexible modeling procedure with extensions allowing further understanding of a change process.

Keywords

Patient-centered nursing; nursing research methodology; pain

Correspondence: Tonya Roberts, K6/117-T CSC, 600 Highland Avenue, Madison, WI 53792-2455, 608-265-8569, tjbeal@wisc.edu.

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Measurement of change is a fundamental concern to nearly all scientific disciplines. Assessing change over time can provide information about a process, offer ways to predict or understand behavior, and test the effectiveness of an intervention. Furthermore, longitudinal studies allow exploration of the relationships between changes in outcome variables with changes in other important variables. Carefully designed longitudinal studies provide beginning evidence for inferences about causality when the study design is correlational and when there is solid evidence for causality in experimental trials.

Change has been studied in several ways in nursing research. One method gaining popularity is growth curve modeling. In a growth curve model, repeated measures for individuals are treated as trajectories whose properties (slope and intercept) can be modeled as a function of a number of variables (predictors, covariates, etc.; Duncan, Duncan, Strycker, Li, & Alpert, 1999). Growth curve models can answer questions about how individual trajectories vary based on a starting point and rate of change over time. Growth curve models are used typically to model change over time in continuous variables (Collins, 2006). However, not all outcomes of interest to nursing researchers are continuous in nature. Alternative methods that allow modeling of change over time in categorical outcomes are necessary as well.

Latent transition analysis (LTA) is a variant of latent class analysis used for modeling change over time in categorical variables. It is a person-oriented approach to analysis of stage-sequential dynamic latent variables; it is person-oriented because individuals are classified into subgroups, during latent class analysis, based on their item response patterns. In other words, an assumption is not made that relationships among variables hold for all individuals (Bergman & Magnusson, 1997; Bergman, Magnusson, & El-Khoury, 2003). Therefore, LTA is appropriate for answering questions about the types of individuals who change over time. Latent transition analysis is based on Markov chain models (Kaplan, 2008; Langeheine & van de Pol, 2002; van de Pol & de Leeuw, 1986) and is considered a model of stage-sequential dynamic latent variables because the movement of individuals in forward and backward directions across discrete stages is captured (Collins & Wugalter, 1992). Therefore, LTA can be used to answer questions about the direction in which individuals change. (See text, Supplemental Digital Content 1, which briefly describes the LTA mathematical model.)

Latent transition analysis can be appropriate in a variety of nursing studies. For example, it could be used for testing patient-centered interventions (e.g., determining for whom the intervention works best); understanding behavior or psychological change (e.g., alcohol use, attitudinal change); capturing developmental stages (e.g., Kubler-Ross stages of grief); or predicting symptom development (e.g., onset of puberty) or resolution (e.g., chronic pain). In each of these cases, patterns of categorical responses on the outcomes of interest (e.g., presence or absence of seven alcohol use behaviors) would be used to organize individuals into classes (e.g., never drinkers, sometimes drinkers, and abusers). Then changes in class membership over time are modeled (e.g., probability of becoming an alcohol abuser at time 2, given you are a never-drinker at time 1). In addition to the central questions that LTA can answer, extensions of LTA that include predictors and distal outcomes to the model are possible and enrich understanding of the change process (McGrath & Tschan, 2004).

This analysis has been used in social sciences for many years (Collins & Wugalter, 1992), but has not been used commonly by nursing researchers, but given the range of questions that LTA can answer, it is a useful technique for nurse researchers. The purpose of this paper is to illustrate the utility of LTA for exploring change over time for nursing researchers. A case example was developed based on data drawn from a previously conducted randomized controlled trial (RCT). The goal of the example was to demonstrate

how LTA can further understanding about for whom a tailored nursing intervention worked best, with respect to changing attitudes and resolving symptoms.

Method

Parent Study

The RCT was reviewed for human subjects protection and approved by the institutional review boards at both data collection sites (University of Wisconsin and Kansas University Medical Center). The RCT was a test of a tailored psychoeducational intervention in overcoming attitudinal barriers to optimal pain management for persons who called the Cancer Information Service and had moderate to severe cancer-related pain (Ward, Wang, Serlin, Peterson, & Murray, 2009).

A 3-group design was used in the study. In the control group, attitudinal barriers were not assessed at baseline because it was believed that asking about barriers could influence behavior. The single collection of data, at follow-up only for this group, precluded an assessment of change over time, and these participants were excluded from the present analysis. Participants from the remaining study groups, assessment only and assessment plus intervention, were included in the analysis because attitudinal barriers and pain outcomes were assessed for these participants at baseline and follow-up. Participants in the assessment-only group had data collected on attitudinal barriers and pain at time 1 and time 2 but did not receive the intervention. Participants in the assessment plus intervention group received the tailored intervention, corrective information for each attitudinal barrier present, to change their knowledge about the barrier. The assessment-only group will be referred to as the *control group* and the assessment plus intervention group will be referred to as the *intervention group* throughout the remainder of the paper.

Case Example

In the present case example, LTA was used to understand for whom and in what direction, the tailored attitudinal barrier intervention from the parent study changed attitudinal barriers and pain outcomes. The following research questions were addressed:

1. How many classes of participants are present, based on barrier patterns?
2. What characteristics predict who belongs to which barrier class at time 1?
3. Do individuals who belong to a particular barrier class have different pain outcomes at time 2?
4. Do individuals change barrier classes over time, and is the change more favorable for those individuals who received the intervention?

Sample

The sample included 791 participants from the original study. Descriptive statistics are outlined in Table 1. Participants were predominantly highly educated Caucasian females. The mean age was 55.7 years ($SD = 13.16$, range = 20–89).

Variables

Barriers—The short form of the Barriers Questionnaire II (BQII; Ward et. al., 2009) was used to assess barriers to pain management. Participants were asked whether they agree or disagree for each of 8 barriers. The barriers were: (a) fatalism about cancer pain management, (b) fear of addiction, (c) worry about developing tolerance, (d) concern about side effects, (e) fear of being a complainer, (f) worry about immune system damage, (g)

worry about masking changes in disease status, and (h) concern about distracting a physician from focusing on a cure. Participant response patterns to the items were used to determine latent classes for the LTA.

Demographics—Gender and age were collected. Race was a categorical variable (Caucasian, African American, or other race). An education variable was coded as less than high school, high school, and more than high school. These variables were used as predictors of class membership.

Pain severity—Three intensity items from the Brief Pain Inventory (BPI; Cleeland & Syrjala, 1992) were used to assess pain severity. Participants were asked to report their worst pain during the past week, least pain during the past week, and pain now. Response options for each item range from 0 to 10. An average of the three items was computed and used as a distal outcome.

Pain interference—The seven pain interference items from the BPI were used. The items address the extent to which pain interferes with daily functioning such as sleeping, walking, and working. Response options range from 0 to 10 and a mean of the seven items was used as a distal outcome.

Procedure

The LTA model was specified using a four-step process answering each of the research questions. Specifically, these steps were: (a) defining the latent class structure using latent class analysis, (b) predicting class membership by adding demographic predictors to the latent class model at time 1, (c) testing distal pain outcomes across latent classes at time 2, and (d) modeling and testing transition probabilities for change in class membership over time. (See text, Supplemental Digital Content 2, which provides more information regarding the LTA general procedure; see Collins & Lanza, 2010 and Nylund, 2007 for a detailed procedural discussion.)

Mplus versions 5.1 and 5.2 (Muthen & Muthen, 2007) were used to conduct the analysis using robust maximum likelihood estimation.

Results

Number of Classes Based on Barrier Patterns

The latent class structure was estimated for the control group at time 1, control group at time 2, intervention at time 1, and intervention at time 2. (See text, Supplemental Digital Content 3, which illustrates Mplus syntax for defining latent class structure.) A latent class structure of each of these groups was constructed to determine (a) whether, and how many, meaningful classes of individuals were in the sample and (b) if patterns in response probabilities and class proportions were similar across groups and consistent with theory.

A two-class solution (as opposed to a three- or four-class solution) was found to provide the best fit, based on interpretability and lowest Bayesian information criterion (BIC), for each of the four models. Only the results of the two-class solution will be described here. The response probabilities and class proportions for each model are shown in Table 2. The patterns of response probabilities are used to label the latent classes. The first class was labeled High Barriers because participants were more likely to agree than disagree to at least five of the eight barriers. The second class was labeled Low Barriers because participants were more likely to disagree than agree for at least five of the eight barriers.

A similar pattern in response probabilities is found across the four models. The class proportions are subsequently similar across the models with the exception of the proportions for the intervention group at time 2. In this group, there is a decreased proportion of participants in the High Barriers class and an increased proportion in the Low Barriers class. This finding is consistent with what would be expected if the intervention was successful.

Predictors of Barrier Class Membership at Time 1

The predictors of class membership at time 1 are shown in Table 3. (See text, Supplemental Digital Content 4, which illustrates Mplus syntax for LTA with predictors.) The odds ratios for age and more than a high school education are significant predictors of class membership at time 1 for both the control and intervention groups. The interpretation of these results is consistent with traditional logistic regression. For every year increase in age, participants have slightly greater odds of being in the High Barriers class at time 1 than in the Low Barriers class. Participants who have more than a high school education have 50–60% lower odds of being in the High Barriers class than in the Low Barriers class at time 1 than do those participants that have only a high school education.

Class Membership Predicting Pain Outcomes at Time 2

Distal outcomes often are added to longitudinal models to assess long-term outcomes of a change process. In LTA, these outcomes often are related to the last latent class variable model. Measures of pain, including severity and interference, were added as distal outcomes related to the last latent class variable. Then, a Wald test of the mean contrasts was conducted to determine whether there was a significant difference in pain outcomes across barrier classes at time 2. (See text, Supplemental Digital Content 5, which illustrates Mplus syntax for LTA with distal outcomes added). Specifically, mean pain severity at time 2 for the Low Barriers class and High Barriers class was compared, first for participants in the control group and then for participants in the intervention group. This is a total of two pain severity contrasts. Two contrasts of mean pain interference were tested similarly.

Results are shown in Table 4. None of the Wald tests were statistically significant for either the control or intervention groups. In other words, pain severity and pain interference did not differ significantly between the High Barriers and Low Barriers classes at time 2 in either the control group or the intervention group. Class membership does not predict pain outcomes at time 2. Separate models for the control and intervention groups preclude testing whether the lower severity and interference scores for the intervention group are significantly different from the control group scores. Only comparisons *within* group are possible.

Changing Class Membership Over Time – Intervention vs. Control Groups

Transition probabilities are represented in a matrix (Table 5) and provide information about an individual's latent status at time 2 given their latent status at time 1. (See text, Supplemental Digital Content 6, which illustrates Mplus syntax for modeling and testing transition probabilities across trial groups).

The results showed change over time in class membership for some participants. Transitions for the control group are described first. Most participants in the control group stayed in the same class from time 1 to time 2. In the control group, participants in the High Barriers class at time 1 had a 96.4% probability of remaining there at time 2. In the control group, participants who were in the Low Barriers class at time 1 had an 87.0% probability of remaining there at time 2. The probability (3.6%) that participants would move from the High Barriers class to the Low Barriers class by time 2 was not significantly different than

zero. Furthermore, there was a 13.0% probability that participants would transition from the Low Barriers class to the High Barriers class from time 1 to time 2.

Transition probabilities were somewhat different for participants in the intervention group. In the intervention group, participants had only a 59.5% probability of remaining in the High Barriers class from time 1 to time 2 and a 40.5% probability of transitioning from the High Barriers class to the Low Barriers class. Furthermore, intervention group participants who were in the Low Barriers class at time 1 had a nonsignificant probability of transitioning to the High Barriers group at time 2.

Two net effects of the intervention above the control on transition probabilities were tested for significant differences, namely for moving from the High Barriers class at time 1 to the Low Barriers class at time 2 and for staying in the Low Barriers class from time 1 to time 2. Only two effects need to be tested, because the other possibilities (Low Barriers to High Barriers and remaining in High Barriers) gave the same net effects, only in the opposite direction. The net effect of the intervention on moving favorably from the High Barriers class to the Low Barriers class ($.405 - .036 = .369$) was significant. The net effect of the intervention on remaining in the Low Barriers class over time ($.968 - .870 = .098$) was not significant.

In addition to testing the differences in transition probabilities between intervention and control groups, an estimate of effect size can be determined. An effect size in terms of an odds ratio can be calculated from the probabilities. Probabilities can be converted first into odds using the formula $p/1-p$ where p = probability. Then, these odds can be divided to produce an odds ratio. Using the probability of moving favorably (from the High Barriers class to the Low Barriers class), the probability .405 for the intervention group and .036 for the control group would be converted into the following odds: .6807 and .3830. Dividing these odds produces an odds ratio of 1.78. This odds ratio indicates that participants in the intervention group were nearly twice as likely to move favorably than those in the control group.

Discussion

The example illustrates how LTA can be used to understand for whom a tailored nursing intervention changed attitudinal barriers and pain outcomes, and in what direction. Specifically, individuals who have high attitudinal barriers or who belong to the High Barriers class initially respond particularly well to the intervention with respect to reduction in attitudinal barriers. However, the class to which individuals belonged at time 2 was not related to differences in pain symptoms. Furthermore, some individuals who have few attitudinal barriers, or belong to the Low Barriers class initially, acquire more barriers over time and transition to the High Barriers class. This was a significant occurrence for participants in the control group only. This finding indicates that assessment of attitudinal barriers alone may be sufficient to cause attitudinal change and in an adverse direction.

Advantages of Latent Transition Analysis

There are many advantages to using LTA to explore change over time. The most obvious is the ability to model change in categorical data. Latent transition analysis does not require multivariate normal data, and items do not have to be at a measurement level other than nominal (Collins & Lanza, 2010), making it particularly useful for several situations, including not just those where the phenomenon of interest is considered categorical in nature, but when data can only be captured categorically. Medical records, particularly narratives such as nursing notes, often do not lend themselves to continuous categorization of a phenomenon and can present an interesting challenge for data analysis. Latent transition

analysis could allow researchers to make qualitative distinctions in records on a given phenomenon which can then be used to classify individuals and their change over time. There may be other situations where the clinical situation dictates the need for categorical data collection, such as the surveying of patients with limited cognitive or physical capacity for understanding or making judgments on a continuous scale. For example, persons with dementia are often asked *yes* and *no* items in places, but cognitively intact individuals are asked to rate a similar item on a scale from 0 to 10.

Nurse researchers, with their interest in the delivery of holistic, patient-centered care, often are interested in knowing whether individuals are qualitatively different based on their patterns of responses on a phenomenon of interest. This is different than knowing, for example, that women have higher rates of depression than men. The difference lies in understanding whether there are qualitatively different patterns of depression that make women different from each other with respect to their actual experience of depression and its symptoms. Latent transition analysis is unique; it can be used to help understanding of the patterns in data and determine whether persons are qualitatively different from one another based on their responses. This is possible because it fundamentally rests on the latent class model that collapses large arrays of contingency table information into meaningful classes. In addition, LTA allows for measurement error so that individuals who do not map directly into a class are dealt with in a systematic way, rather than being removed for internal consistency as they might be when analyzing contingency table data (Collins, 2006).

Latent transition analysis is also useful for analyzing data from a range of study designs. The most common application of LTA has been in longitudinal survey designs. Using LTA with a survey design is beneficial when the aim is to describe change over time in categorical data and is particularly useful for modeling the transitions across multiple time points and/or large spans of time. The practical example in this presentation, however, demonstrates that LTA is also useful when testing causation such as in RCTs. The LTA procedures and output even allow calculation of common statistics of interests in RCTs such as effect size. Finally, LTA might be useful in longitudinal qualitative studies, where structured interviews are implemented and a common coding scheme is used to categorize the data, if the goal is to understand and quantify some type of qualitative change.

There are many extensions in latent transition modeling that make it an extremely versatile analysis procedure. Unlike simply analyzing crosstabs in a contingency table, LTA can be used to specify the kind of change that is theoretically important such as forward and backward, just forward, or just backward. For example, a transition probability can be constrained to zero if theory guiding the study indicates that reversals in movement across classes are not possible. As the example in this presentation has demonstrated, covariates and distal outcomes can be added and the possibility of modeling subpopulations is possible. Data sets with more items or more response options per item such as three- or four-point Likert options can be accommodated in LTA, as can more time points at which data were collected (Collins & Lanza, 2010).

Disadvantages of Latent Transition Analysis

One of the most unfortunate disadvantages of using LTA is the sample size requirement. Latent transition models require large sample sizes. Latent transition analysis models data from large contingency tables of responses and therefore requires sufficient sample size because sparse cells, or small cell counts, in the contingency table lead to unstable results. In other words, standard errors cannot be estimated reliably when cell sizes are near zero. This can happen when sample sizes are small, when one or more groups are small, when one of the latent classes has a very small prevalence, or when membership in one of the classes is essentially zero for some level of a covariate (Collins & Lanza, 2010). Therefore, sample

size needs for LTA are likely to be greater than 100, and even larger than that if executing a complex model (Collins & Wugalter, 1992).

While the setup, running, and interpretation of an LTA model can be straightforward for simple models, complex models may require assistance of statistical expertise. There are some aspects of latent transition modeling that can make the model setup and interpretation difficult. In cases where measurement invariance (the class structure stays the same across time) is not a reasonable assumption, constraints need to be placed in the model, and models with varying levels of constraints need to be tested against each other to determine which level of constraint is most appropriate (Collins & Lanza, 2010; Nylund, 2007). Models without full measurement invariance may also make interpretation of probabilities and comparison of groups across time difficult because the meaning of the classes changes over time (Collins & Lanza, 2010). Label switching (e.g., High Barriers group is class 1 for the control group but is class 2 for the intervention group) is another phenomenon that can make the setup and interpretation of a latent transition model difficult. This is particularly an issue when direct comparisons across groups are made. For example, reaching a conclusion about whether participants in the intervention or the control group reported in this presentation had a higher probability of transitioning favorably would have been difficult to make if the class labels had switched. To avoid label switching, starting values for each of the variables in each class must be determined and assigned carefully.

Finally, while using LTA does not rely on many of the stringent assumptions required by other statistical models (e.g., multivariate normal data in regression) and does not require adjustments when these assumptions are violated (e.g., using logistic regression rather than ordinary least squares regression for categorical data), using LTA does require one very important assumption: local independence. This means that observations *within* a latent class should be independent from one another. This does not mean that all observations in the dataset are independent from one another (Collins & Lanza, 2010).

Conclusions

Latent transition analysis is a statistical method for modeling change over time in categorical variables that could be useful in answering questions of importance to nurse researchers. This method of analysis is well-suited to answering questions where understanding in which direction change occurs for subgroups across discrete qualitative states is important. Useful information is provided when LTA is conducted because the procedures reduce large contingency tables of categorical observations into meaningful patterns that provide detailed information about for whom, and in what direction, change occurs over time.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Descriptive Statistics

	Control (<i>n</i> = 421)	Intervention(<i>n</i> = 370)
	<i>M (SD)</i>	<i>M (SD)</i>
Age, in years	55.7 (13.16)	55.13 (12.70)
	<i>n (%)</i>	<i>n (%)</i>
Gender		
Male	110 (25.6)	101 (26.1)
Female	319 (74.4)	286 (73.9)
Education		
< High school	40 (9.3)	43 (11.1)
High school	105 (24.5)	86 (22.2)
> High school	284 (66.0)	257 (66.4)
Race		
Caucasian	340 (78.9)	300 (76.7)
African American	53 (12.3)	60 (15.3)
Other	38 (8.8)	31 (7.9)
	<i>M (SD)</i>	<i>M (SD)</i>
T1 Barriers	4.28 (1.85)	4.13 (1.86)
T2 Barriers	3.90 (2.00)	2.98 (1.95)
T1 Pain Severity	3.63 (2.20)	3.65 (2.30)
T2 Pain Severity	3.44 (2.45)	3.32 (2.36)
T1 Pain Interference	5.03 (2.85)	4.87 (2.88)
T2 Pain Interference	4.69 (2.96)	4.48 (2.98)

Notes. T1 refers to data collected at time 1 and T2 refers to data collected at time 2.

Table 2

Response Probabilities and Class Proportions for Latent Class Structure

Latent class	Barriers								Class Proportions	X _{LR} ² (238)
	Barr 1	Barr 2	Barr 3	Barr 4	Barr 5	Barr 6	Barr 7	Barr 8		
Control Time 1										
HB	.11 ^a	.14	.75	.30	.23	.52	.17	.04	.48	215.92
LB	.26	.49	.91	.75	.83	.84	.73	.26	.52	
Control Time 2										
HB	.13	.13	.77	.41	.30	.50	.20	.03	.48	238.16
LB	.31	.64	.92	.79	.88	.87	.88	.33	.52	
Intervention Time 1										
HB	.06	.11	.80	.37	.29	.53	.16	.03	.46	210.38
LB	.27	.51	.93	.77	.79	.87	.74	.29	.54	
Intervention Time 2										
HB	.10	.21	.77	.35	.51	.51	.29	.03	.32	183.77
LB	.34	.83	.96	.86	.85	.92	.83	.49	.68	

Notes. Response probabilities are for disagreement with the barrier items. Barr = barrier, HB = High Barriers, LB = Low Barriers.

^aRead value (.11) as 11% of participants in the High Barriers class disagreed with barrier 1.

Table 3

Logistic Regression Coefficients and Odds Ratios for Predictors of Being in the High Barriers Class at Time 1

	Predictor	Coefficient	SE	Odds Ratio
Control	FEMALE	-.295	.310	.745
	AGE	.045	.011	1.046*
	AFRAMER	.708	.460	2.030
	OTHRACE	.164	.435	1.178
	LESSHS	-.333	.468	.717
	MOREHS	-.708	.300	.493*
Intervention	FEMALE	.344	.339	1.411
	AGE	.041	.014	1.042*
	AFRAMER	.318	.318	1.374
	OTHRACE	2.313	1.334	10.105
	LESSHS	.957	.619	2.604
	MOREHS	-.948	.432	.388*

Notes. The reference category is Caucasian for race comparisons and high school for education comparisons.

* significant results at $p < .05$

Table 4

Mean and Standard Error for Time 2 Pain Outcomes by Class

Class	Time 2 Pain Outcomes	
	Severity	Interference
	<i>M (SE)</i>	<i>M (SE)</i>
Control		
HB	2.63 (.193)	3.33 (.245)
LB	2.61 (.201)	3.73 (.269)
Intervention		
HB	2.76 (.366)	3.81 (.548)
LB	2.22 (.177)	2.93 (.232)

Notes. None of the contrasts across classes were significant at Bonferroni p -value = .25.

HB = High Barriers, LB = Low Barriers

Table 5

Transition Probabilities from Time 1 to Time 2

		Time 2			
		Control		Intervention	
		HB	LB	HB	LB
Time	HB	.964 ^a *	.036	.595 [*]	.405 [*]
1	LB	.130 ^b *	.870 [*]	.032	.968 [*]

Notes. HB = High Barriers, LB = Low Barriers

^aRead as 96.4% of participants who were in the High Barriers class at time 1 were predicted to remain in the High Barriers class at time 2.

^b13.0% of participants who were in the Low Barriers class at time 1 were predicted to transition to the High Barriers class at time 2.

* probabilities significantly different from 0 at $p < .05$