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Abstract: Background. Latent transition analysis (LTA) is a method of modeling change over time in categorical variables. Latent transition analysis has been used in the social sciences for many years but has not been employed in nursing research. Objectives. This paper illustrates the utility of LTA for nursing research by presenting a case example, a secondary analysis of data from a previously conducted RCT testing the effectiveness of a tailored psychoeducational intervention to decrease patient-related attitudinal barriers to cancer pain management. LTA was used to understand for whom, and in what direction, the tailored intervention resulted in change with respect to attitudinal barriers and pain symptoms. Methods. The LTA model was developed by a) defining a class structure based on individuals' barrier patterns, b) adding demographic predictors and distal pain outcomes, c) modeling and testing transitions across classes. Results. There were two classes of individuals, a Low Barriers class and a High Barriers class. 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. LTA is a valuable procedure for nursing researchers because it collapses large arrays of categorical data into meaningful patterns. LTA is a flexible modeling procedure with extensions that allow further understanding of a change process.

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

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Abstract

Background. Latent transition analysis (LTA) is a method of modeling change over time in categorical variables. Latent transition analysis has been used in the social sciences for many years but has not been employed in nursing research. **Objectives.** This paper illustrates the utility of LTA for nursing research by presenting a case example, a secondary analysis of data from a previously conducted RCT testing the effectiveness of a tailored psychoeducational intervention to decrease patient-related attitudinal barriers to cancer pain management. LTA was used to understand for whom, and in what direction, the tailored intervention resulted in change with respect to attitudinal barriers and pain symptoms. **Methods.** The LTA model was developed by a) defining a class structure based on individuals' barrier patterns, b) adding demographic predictors and distal pain outcomes, c) modeling and testing transitions across classes. **Results.** There were two classes of individuals, a Low Barriers class and a High Barriers class. 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. LTA is a valuable procedure for nursing researchers because it collapses large arrays of categorical data into meaningful patterns. LTA is a flexible modeling procedure with extensions that allow further understanding of a change process. **Key Words.** Patient-centered nursing, nursing research methodology, pain.

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

2 Measurement of change is a fundamental concern to nearly all scientific disciplines.

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

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

18 Latent transition analysis (LTA) is a variant of latent class analysis used for modeling
19 change over time in categorical variables. Latent transition analysis is a person-oriented
20 approach to analysis of stage-sequential dynamic latent variables. Latent transition analysis is
21 person-oriented because individuals are classified into subgroups, during latent class analysis,
22 based on their item response patterns. In other words, an assumption is not made that
23 relationships among variables hold for all individuals (Bergman, Magnusson, & El-Khoury, 2003;

1 Bergman & Magnussen, 1998). Therefore, LTA is appropriate for answering questions about the
2 types of individuals who change over time. Latent transition analysis is based on Markov chain
3 models (Kaplan, 2008; Langeheine & van de Pol, 2002; van de Pol & de Leeuw, 1986) and is
4 considered a model of stage-sequential dynamic latent variables because the movement of
5 individuals in both forward and backward directions across discrete stages is captured (Collins
6 & Wugalter, 1992). Therefore, LTA answers questions about the direction in which individuals
7 change. (See SDC 1 text for a brief description of the LTA mathematical model.)

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

20 LTA has been used in social sciences for many years (Collins & Wugalter, 1992), but has
21 been largely absent from nursing research. Given the range of questions that LTA can answer,
22 it is a useful technique for nurse researchers. The purpose of this paper is to illustrate the
23 utility of LTA for exploring change over time in topics found in nursing research. A case

1 example was developed based on data drawn from a previously conducted Randomized
2 Controlled Trial (RCT). The goal of the example was to demonstrate how LTA can further
3 understanding about for whom a tailored nursing intervention worked best, with respect to
4 changing attitudes and resolving symptoms.

5 **Methods**

6 **Parent Study**

7 The RCT was a test of a tailored psychoeducational intervention in overcoming
8 attitudinal barriers to optimal pain management for persons who called into the Cancer
9 Information Service and had moderate to severe cancer related pain (Ward, Wang, Serlin,
10 Peterson, & Murray, 2009). The study used a 3-group design. In the control group, attitudinal
11 barriers were not assessed at baseline as it was believed that merely asking about barriers
12 could influence behavior. The single collection of data, at followup only for this group,
13 precluded an assessment of change over time and these participants were subsequently
14 excluded from the present analysis. Participants from the remaining study groups, assessment
15 only and assessment plus intervention, were included in the present analysis as attitudinal
16 barriers and pain outcomes were assessed for these participants at baseline and followup.
17 Participants in the assessment only group had data collected on attitudinal barriers and pain at
18 time 1 and time 2 but did not receive the intervention. Participants in the assessment plus
19 intervention group received the tailored intervention, corrective information for each
20 attitudinal barrier present, to change their knowledge about the barrier. For ease in
21 understanding the assessment only group will be referred to as the control group and the
22 assessment plus intervention group will be referred to as the intervention group throughout
23 the remainder of the paper.

1 Case Example

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

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

11 Sample

12 The sample included 791 participants from the original study. See Table 1 for descriptive
13 statistics. Participants were predominantly highly educated Caucasian females. The mean (SD)
14 age was approximately 55.7 (13.16) years with a range of 20 to 89 years.

15 Variables

16 **Barriers.** The short form of the Barriers Questionnaire II (BQII) (Ward, et. al., 2009) was
17 used to assess barriers to pain management. Participants were asked whether they agree or
18 disagree for each of 8 barriers. The barriers include; 1) fatalism about cancer pain
19 management, 2) fear of addiction, 3) worry about developing tolerance, 4) concern about side
20 effects, 5) fear of being a complainer, 6) worry about immune system damage, 7) worry about
21 masking changes in disease status, and 8) concern about distracting a physician from focusing
22 on cure. Participant response patterns to the items were used to determine latent classes for
23 the LTA.

1 **Demographics.** Gender and age in years were collected. Race was a categorical variable
2 (Caucasian, African American, or Other Race). An education variable was also coded as less
3 than high school, high school, and more than high school. These variables were used as
4 predictors of class membership.

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

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

14 **Procedure**

15 The LTA model was specified using a four step process answering each of the research
16 questions. Specifically, these steps were 1) defining the latent class structure using latent class
17 analysis, 2) predicting class membership by adding demographic predictors to the latent class
18 model at time 1, 3) testing distal pain outcomes across latent classes at time 2, and 4) modeling
19 and testing transition probabilities for change in class membership over time. Mplus v5.1 and
20 v5.2 (Muthen & Muthen, 2007) were used to conduct the analysis using robust maximum
21 likelihood estimation.

22 **Results**

23 **Latent Class Structure**

1 The latent class structure was estimated for the control group at time 1, control group
2 at time 2, intervention at time 1, and intervention at time 2 (see SDC 2 text for an illustration of
3 Mplus syntax for defining latent class structure). A latent class structure of each of these
4 groups was constructed to determine; 1) whether, and how many, meaningful classes of
5 individuals were in the sample and 2) if patterns in response probabilities and class proportions
6 were similar across groups and consistent with theory.

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

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

21 **Predictors of Class Membership**

22 The predictors of class membership at time 1 are shown in Table 3 (see SDC 3 text for an
23 illustration of Mplus syntax for LTA with predictors). The odds ratios for age and more than a

1 high school education are significant predictors of class membership at time 1 for both the
2 control and intervention groups. The interpretation of these results is consistent with
3 traditional logistic regression. For every year increase in age, participants have slightly greater
4 odds of being in the High Barriers class at time 1 than in the Low Barriers class. Participants
5 who have more than a high school education have 50-60% lower odds of being in the High
6 Barriers class than in the Low Barriers class at time 1 than do those participants that have only a
7 high school education.

8 **Class Membership Influencing Pain Outcomes**

9 Distal outcomes are often added to longitudinal models to assess long term outcomes of
10 a change process. In LTA, these outcomes are often related to the last latent class variable
11 model. Measures of pain, including severity and interference, were added as distal outcomes
12 related to the last latent class variable. A Wald test of the mean contrasts was then conducted
13 to determine whether there was a significant difference in pain outcomes across barrier classes
14 at time 2 (see SDC 4 text for an illustration of Mplus syntax for LTA with distal outcomes added).
15 Specifically, mean pain severity at time 2 for the Low Barriers class and High Barriers class was
16 compared, first for participants in the control group and then for participants in the
17 intervention group. This is a total of two pain severity contrasts. Two contrasts of mean pain
18 interference were similarly tested.

19 Results are shown in Table 4. None of the Wald tests were statistically significant for
20 either the control or intervention groups. In other words, pain severity and pain interference
21 did not differ significantly between the High Barriers and Low Barriers classes at time 2 in either
22 the control group or the intervention group. Class membership does not predict pain outcomes
23 at time 2. Separate models for the control and intervention groups preclude testing whether

1 the lower severity and interference scores for the intervention group are significantly different
2 from the control group scores. Only comparisons *within* group are possible.

3 **Modeling and Testing Transition Probabilities**

4 Transition probabilities are represented in a matrix and provide information about an
5 individual's latent status at time 2 given their latent status at time 1 (see SDC 5 text for an
6 illustration of Mplus syntax for modeling and testing transition probabilities across trial groups).
7 Table 5 displays the probability matrix.

8 The results show change over time in class membership for some participants.
9 Transitions for the control group will be described first. Most participants in the control group
10 stayed in the same class from time 1 to time 2. In the control group, participants in the High
11 Barriers class at time 1 have a 96.4% probability of remaining there at time 2. In the control
12 group, participants who were in the Low Barriers class at time 1 have an 87.0% probability of
13 remaining there at time 2. The probability (3.6%) that participants will move from the High
14 Barriers class to the Low Barriers class by time 2 was not significantly different than zero.
15 Furthermore, there is a 13.0% probability that participants will transition from the Low Barriers
16 class to the High Barriers class from time 1 to time 2.

17 Transition probabilities are somewhat different for participants in the intervention
18 group. In the intervention group, participants have only a 59.5% probability of remaining in the
19 High Barriers class from time 1 to time 2 and a 40.5% probability of transitioning from the High
20 Barriers class to the Low Barriers class. Furthermore, intervention group participants who are
21 in the Low Barriers class at time 1 have a nonsignificant probability of transitioning to the High
22 Barriers group at time 2.

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

9 **Discussion**

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

20 Latent transition analysis provides useful information for researchers by reducing large
21 arrays of contingency table information into meaningful classes and then modeling the
22 probability of dynamic movement across these classes. In addition, LTA, unlike simply analyzing
23 crosstabs in a contingency table, can specify the kind of change that is theoretically important

1 such as forward and backward, just forward, or just backward. So, for example, a transition
2 probability can be constrained to zero if theory guiding the study indicates that reversals in
3 movement across classes are not possible. Finally, LTA allows for measurement error so that
4 individuals who do not map directly into a class are dealt with in a systematic way, rather than
5 being removed for internal consistency as they might be when analyzing contingency table data
6 (Collins, 2006). Data sets with more items or more response options per item such as three or
7 four point Likert options can be accommodated in LTA, as can more time points at which data
8 were collected (Collins & Lanza, 2010).

9 **Limitations of LTA**

10 Latent transition models require large sample sizes. Latent transition analysis models
11 data from large contingency tables of responses and subsequently requires sufficient sample
12 size as sparse cells, or small cell counts, in the contingency table lead to unstable results. In
13 other words, standard errors cannot be reliably estimated when cell sizes are near zero. This
14 can happen when sample sizes are small, when one or more groups are small, when one of the
15 latent classes has a very small prevalence, or when membership in one of the classes is
16 essentially zero for some level of a covariate (Collins & Lanza, 2010). Therefore, sample size
17 needs for LTA are likely to be greater than 100, and even larger than that if executing a complex
18 model (Collins & Wugalter, 1992).

19 On the other hand, LTA does not require multivariate normally distributed data. Items
20 do not have to be a measurement level other than nominal (Collins & Lanza, 2010). Latent
21 transition analysis relies on one fundamental assumption, local independence. This means that
22 observations *within* a latent class are independent from one another, hence *local*

1 independence. This does not mean that all observations in the dataset are independent from
2 one another (Collins & Lanza, 2010).

3 **Conclusions**

4 Latent transition analysis is a statistical method for modeling change over time in
5 categorical variables that could be very useful in answering questions of importance to nursing
6 researchers. Latent transition analysis is well-suited to answering questions where
7 understanding in which direction change occurs for subgroups across discrete qualitative states
8 is important. Latent transition analysis provides useful information by reducing large
9 contingency tables of categorical observations into meaningful patterns that provide detailed
10 information about for whom, and in what direction, change occurs over time.

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Table 1.

Descriptive statistics

Variable	Control (n=421)	Intervention (n=370)
	Mean (SD) or Frequency (%)	Mean (SD) or Frequency (%)
Age	55.7 (13.16)	55.13 (12.70)
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)
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)

Note. 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	χ^2_{LR} (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	

Note. Response probabilities are for disagreement with the barrier items. 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	S.E.	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*

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

*indicates significant results at $p < .05$.

Table 4.

Mean (M) and standard error (SE) for time 2 pain outcomes by class

Class	Time 2 Pain Outcomes	
	Severity	Interference
	M (SE)	M (SE)
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)

Note. None of the contrasts across classes were significant at Bonferroni p value = 0.25. 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 1	HB	.964 ^{a*}	.036	.595*	.405*
	LB	.130 ^{b*}	.870*	.032	.968*

Note. 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.

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

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