Latent Transition Modeling for Categorical Latent Variables: An Application Using Longitudinal Resilience Data*

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Abstract

This study aims to illustrate how the latent transition modeling might be applied to identify qualitative change patterns in longitudinal assessment settings. Using the data collected on three measurement occasions, we examine whether and to what extent resilience latent class memberships of pre-service teachers changed over time. First, latent class models are tested for all time points separately, revealing that a 4-class model is the best fitting model (Resilience, Competence, Maladaptation, and Vulnerability). Next, latent transition model alternatives are tested, leading to the conclusion that the transition model with stationary probabilities provides the best fit. The results show that individuals with the statuses of Vulnerability and Competence have the highest probabilities of maintaining the same status compared to others and that the highest transition probabilities occur from the status of Resilience to Competence and from Maladaptation to Vulnerability. These findings suggest that individuals with sufficient coping skills might have the status of Resilience and move toward Competence, while those lacking coping skills might have the status of Maladaptation and move toward Vulnerability with the absence or decrease of adversity. A discussion is provided highlighting the usefulness of the latent transition modeling when it is suspected that latent class memberships of subjects could be sensitive to change over time.

Keywords: Assessment, Categorical Latent Variable, Latent Transition Analysis, Longitudinal

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INTRODUCTION

Psychological constructs that cannot be directly observed are often referred to as latent variables and are labeled as static or dynamic, depending on how prone they are to change over time (Collins & Flaherty, 2002). In the study of dynamic variables, it is of critical importance that longitudinal assessment designs are utilized to help support the validity of the inferences to be made (Baltes & Nesselroade, 1979; Collins, 1991; Maxwell & Cole, 2007; Schoenberg, 2008). The repeated data in a longitudinal design allow for the simultaneous evaluation of intra-individual change and inter-individual differences (Wu et al., 2013). With longitudinal research, it is possible to study whether changes occur in the construct over time, what patterns of change are observed, and whether other variables affect those patterns (e.g., Lanza et al., 2003). The design of longitudinal studies is critical for the meaning of inferences related to the construct of interest. The researchers (Collins, 2006; Ployhart & Vandenberg, 2010; Wang et al., 2017) highlight the necessity of examination of the theoretical background of the construct, design of an application procedure reflecting the nature of change in the construct (e.g., the number of measurement occasions and measures), selection of an appropriate statistical model, and integration of all these components.

Statistical models, which are expected to be compatible with the research design, can be classified according to whether the latent variable is continuous or categorical (Muthén, 2007). Continuous variables reflect quantitative differences between individuals along one or more continua, while categorical variables reflect qualitative differences between groups (Ruscio & Ruscio, 2008). In longitudinal models, this distinction is combined with the notion of change, and quantitative change can be modeled when latent variables are taken as continuous. In contrast, qualitative change can be modeled when latent variables are taken as categorical. The former reflects a change occurring in some degree/amount (e.g., decrease or increase in scores of a listening test), and the latter reflects a change occurring in a form/type (e.g., change in reading strategies) (Shaffer & Kipp, 2013). For continuous latent variables, we might use conventional psychometric models such as structural equation models (SEMs) in cross-sectional study settings or growth analysis where the continuous latent variables reflect individual differences in development over time (Muthén, 2007). For categorical latent variables, we might use latent class analysis (LCA) (Lazarsfeld & Henry, 1968) in cross-sectional study settings or latent transition analysis (LTA) (Collins & Wugalter, 1992; Langeheine, 1988) in longitudinal settings. The LTA, a generalization of LCA, allows to model the change patterns in individuals' subgroups (classes) defining dynamic categorical latent variables (Wang & Chan, 2011).

While the methodologies and applications for modeling change are relatively familiar to researchers when variables of interest are presumed to be measured on a continuous scale (e.g. latent growth curve model), a need still remains for studies providing methodologies and applications suited for research involving variables measured on a categorical scale (e.g., Sorgente et al., 2019; Wang & Chan, 2011). Considering the discrete latent constructs in social sciences (e.g., attachment styles, problem-solving strategies), studies modeling categorical variables will have great potential in forming and testing various theories or hypotheses (Yu, 2013). The present study addresses that methodological gap by focusing on the application of LTA and illustrating a multi-step modeling strategy formulated for researchers interested in modeling qualitative changes that can only be quantified using categorical variables. Presented together with a brief overview, the approach illustrated here is capable of resolving potential issues that may arise while using LTA. Integrating LTA into the analysis of repeated assessment data, we provided an example applying this approach to 3-wave data collected during a longitudinal study investigating patterns of changes in pre-service teachers' resilience and experienced adversity levels over time.

Resilience shows the what extent individuals cope with and adapt to adversity or stressful situations (Vella & Pai, 2019). The present study considers this construct as a dynamic (Tusaie & Dyer, 2004) and categorical latent variable. Categories of the variable were evaluated in the light of groups (Resilient, Competent, Maladaptive, and Vulnerable) suggested by Masten and her colleagues (Masten, 2015; Masten & Tellegen, 2012; Masten et al., 1999; Masten et al., 2004). When making inferences about the resilience of individuals, two components need to be taken into account: adversity (difficulty/risk/stress) and adaptation (IJntema et al., 2019; Vella & Pai, 2019). Although resilience measures should consider these two components, they generally do not involve the assessment of specific person-situation interactions and allow only one-time measurement. IJntema et al. (2019) emphasize current measures' limitations in reflecting the dynamic nature of resilience. Therefore, we designed a longitudinal measurement model allowing us to monitor individuals' experienced adversity and resilience in their current situation.

In this study, using data collected within a longitudinal measurement design, we identified the potential resilience classes of pre-service teachers. Then, we examined the probabilities of transitioning between those classes over a period of time. The research questions are as follows: (1) Are there classes with specific response patterns of resilience for each time point? (2) Do individuals' resilience classes vary between time points? (3) What transition patterns can be identified between resilience classes?

METHOD

Research Design

In this study, a longitudinal panel design was used. This design uses a study group with the same individuals at each measurement point (Menard, 2008).

Participants and Data Collection

The data were collected from a group of pre-service teachers in Türkiye (n = 360) who volunteered to complete a measure at three different time points at 4-week intervals over the course of an academic semester. The mean age of participants was 21.38 (SD_{age} = 2.64); 74.2% were female, while 12.5% were male. The measurement tool was designed considering the results of a previous study (Akbas & Kahraman, 2019). The measure was composed of self-report items related to adversity exposure and perceived resilience. Items related to adversity exposure were as follows: "Facing problems/adversity" (*A1*) and "Facing severe adversity" (*A2*). Items related to perceived resilience were as follows: "Coping with problems/adversity" (*R1*), "Feeling challenged" (*R2*), and "Feeling resilient" (*R3*). The items were coded dichotomously (0 = Low, 1 = High). The measure was administered via an online platform using only participant numbers to protect the privacy of the respondents. All respondents signed a consent form at the beginning of data collection.

Data Analysis

Latent Transition Analysis

In LTA, measurement models are defined for each measurement occasion by using LCA models, and changes in class memberships over time are modeled based on the relationships between latent variables (structural models) (Wang & Wang, 2012). For instance, in an LTA model with 3-time points, LCA models (C_1, C_2, C_3) can be constructed for each time point, and then autoregressive relationships ($C_1 \rightarrow C_2$, $C_2 \rightarrow C_3$) between the latent variables can be defined (Nylund, 2007).

The mathematical model of LTA is presented below in terms of three measurement occasions and three indicators (items) of the latent class variable on each occasion. For simplicity, the example and representation here were adapted from Collins et al. (2002) by excluding the exogenous static variable. Let us assume response categories for the items are as follows: $i, i', i'' = 1, ..., I$ for the first item $j, j', j'' = 1,..., J$ for the second item, and $k, k', k'' = 1,..., K$ for the third item. Here, i, j, and k represent responses at the first time point; i', j', and k' at the second time; and i'', j'', and k'' at the third time. Let us define $p, q, r = 1,..., S$ latent statuses (denoting dynamic latent classes), where p refers to status in the first time point, q refers to status in the second time point, and r refers to status in the third time point. If y = $\{i, j, k, i', j', k', i'', j'', k''\}$ denotes a particular response pattern for the current example, then the proportion of individuals with this pattern can be shown as following (adapted from Collins et al., 2002):

$$P(Y = y) = \sum_{p=1}^{S}\sum_{q=1}^{S}\sum_{r=1}^{S} \delta_p\, \rho_{i|p}\, \rho_{j|p}\, \rho_{k|p}\, \tau_{q|p}\, \rho_{i'|q}\, \rho_{j'|q}\, \rho_{k'|q}\, \tau_{r|q}\, \rho_{i''|r}\, \rho_{j''|r}\, \rho_{k''|r}$$

Here, δ_p stands for the proportion in status ‘*p’* at the first time point;

$\rho_{i|p}$ stands for the probability of response ‘*i*’ to the first item in the first time point conditioned on membership in status ‘*p*’ at the first time point; and

$\tau_{q|p}$ stands for the probability of being in status ‘*q*’ at the second time point conditioned on membership in status ‘*p*’ at the first time point.

As shown in the formula above, three sets of parameters are estimated in LTA: (1) latent status prevalences, (2) item-response probabilities, and (3) transition probabilities (Collins & Lanza, 2010). Latent status prevalences (δ) denote the proportion of the population in latent statuses, while item-response probabilities (ρ) denote the probability of a specific response for an indicator conditional on status membership (Lanza et al., 2003). These two parameters are direct counterparts in LCA and are estimated separately for each time point if there is no constraint, but transition probabilities (τ) are a type of parameter specific to LTA and indicate how change happens between latent statuses (Collins & Lanza, 2010).

Data Analysis Steps

The multi-step modeling strategy was conducted in five consecutively executed steps (Nylund, 2007; Ryoo et al., 2018):

Step 0: Studying descriptive statistics. The proportions of individuals for the observed variables were calculated for each time point and then compared across time points.

Step 1: Testing LCA models for each time point. LCA models starting from the model with one class up to the model with five classes were separately evaluated for all time points to determine the latent class structure underlying the data, even though it was assumed that the latent variable had four categories. The fit indices of all models for each time point were examined, and the model with the best fit was chosen. The following indices and criteria were used to evaluate model fit: AIC (the Akaike Information Criterion) (Akaike, 1987) and BIC (the Bayesian Information Criterion) (Schwarz, 1978), with lower values signifying better fit (Masyn, 2013; Nylund et al., 2007); VLMR-LRT (the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test) (Lo, Mendell & Rubin, 2001; Vuong, 1989), and BLRT (Bootstrap Likelihood Ratio Test) (McLachlan & Peel, 2000), with significant *p* values implying that the *K* class model had better fit than the *K-1* class model (Nylund-Gibson & Choi, 2018); and the Likelihood Ratio Chi-square (χ^2) Test, with non-significant *p* values indicating model-data fit. After model selection, the assumption of local independence, which implies that observed variables conditional on the latent classes are independent (Magidson & Vermunt, 2004), was tested using standardized bivariate residuals (<1.96).

Step 2: Exploring transitions based on cross-sectional results. Based on the class membership probabilities estimated in Step 1, individuals were assigned to the identified classes based on their highest latent class probabilities at each time point. Cross-tables were then constructed to examine the observed transitions between these measurement points.

Step 3: Examining measurement invariance assumption. Two models (non-invariance and full-invariance) were tested to ensure that the measurement invariance assumption was met. In the non-invariance model, item-response probabilities were estimated freely for all time points, while in the full-invariance model, they were constrained to be equal. If the assumption holds, it can be said that latent classes have the same meaning for all time points, and direct inferences can be made regarding the change (Collins & Lanza, 2010; Nylund, 2007).

Step 4: Testing LTA models and exploring transitions. The four LTA model alternatives given in Figure 1 were evaluated: (1) a model involving only first-order (lag-1) effects, (2) a model involving first-order (lag-1) effects where the transition probabilities were restricted to be equal between time points, (3) a model involving both first-order (lag-1) and second-order (lag-2) effects, (4) a model involving a second-order latent variable with two latent classes (mover-stayer), in which the transition probability parameters for the "mover" class are freely estimated while the probabilities for the "stayer" class are constrained to being a unit matrix. The model-data fit was evaluated using the AIC, BIC (Collins & Lanza, 2010), and Likelihood Ratio Test (Nylund, 2007), which are suggested for model evaluation in LTA. Finally, the parameters estimated by the model providing the best fit were summarized and interpreted in the context of the theoretical framework.

For LCA and LTA, Mplus 7.0 was used (Muthén & Muthén, 1998-2012). This program can deal with missing data among the observed variables using FIML (Full Information Maximum Likelihood) (Nylund, 2007). And, it is sufficient for analysis to have data even at a single measurement point (Wang & Wang, 2012).

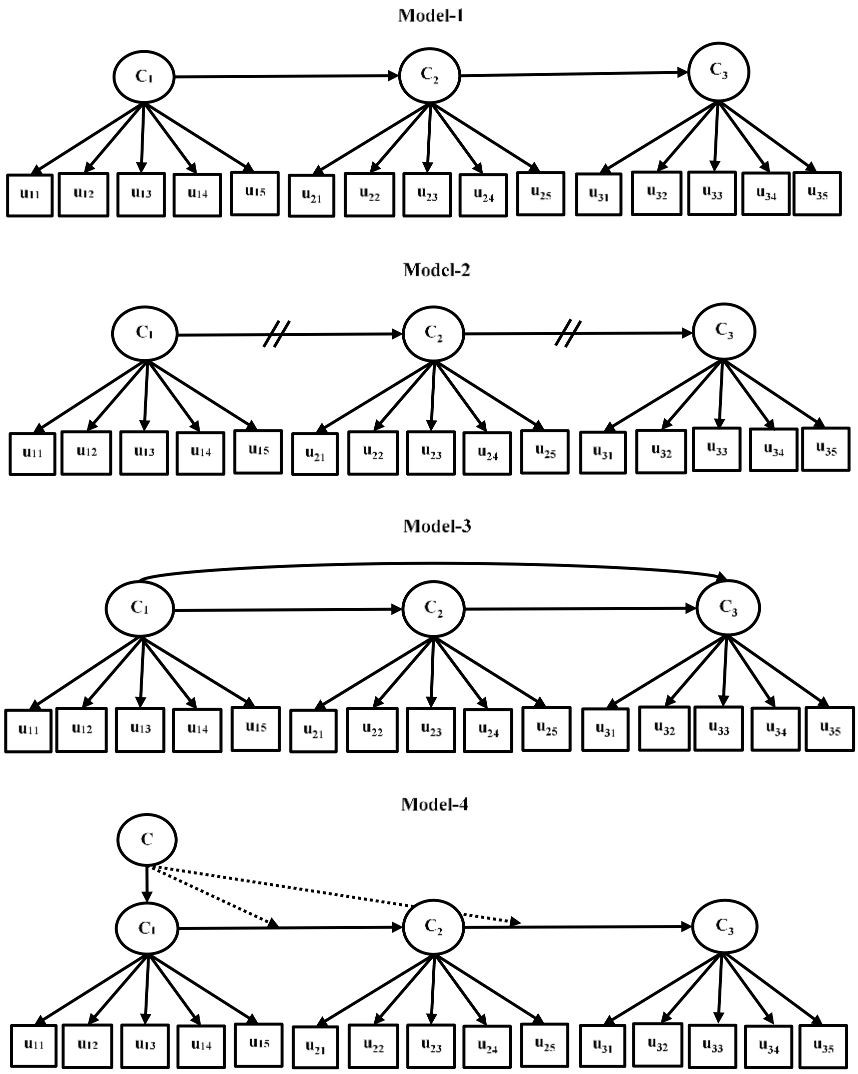

Figure 1. LTA models

Note. C represents categorical latent variables and u represents categorical observed variables.

RESULTS

Step 0: Descriptive statistics. The proportions of individuals in the "High" category for item *A1* were .17, .30, and .21 for the 3-time points, respectively, while they were .07, .11, and .10 for item *A2*. These proportions were .35, .31, and .23 for item *R1*; .66, .68, and .60 for item *R2*; and .76, .74, and .66 for item *R3*. Accordingly, it can be said that the distribution of individuals into categories was similar across the time points. The proportions of missing data were .18, .14, and .20 for item *A1*; .18, .14, and .20 for item *A2*; and .16, .13, and .19 for item *R1* for the time points, respectively. There were no missing data for items *R2* and *R3*.

Step 1: LCA models for each time point. The model fit indices (Table 1) indicated that the 4-class model was most plausible for the first time point (T_1). Specifically, it was seen that the models with 3, 4, and 5 classes fit the data well (LR χ^2 p>.01), and the 3-class model had the smallest BIC while the 4-class model had the smallest BIC. The VLMR-LRT and BLRT values showed that the 4-class model improved the model fit compared to the 3-class but the 5-class model did not improve the fit compared to the 4-class. In the other time points, T_2 and T_3, the 4-class model was also chosen, considering not only the model fit indices but also the parsimony and interpretability of the model. For the selected models, the standardized bivariate residuals for each time point were less than 1.96, showing that the local independence assumption was met.

After model selection, estimations for the conditional item-response probabilities were examined and it was observed that the latent classes had different response probability patterns in each data wave in terms of the items related to adversity (*A*) and resilience (*R*) (Appendix A). In alignment with the hypothesis derived from the theoretical framework, the four latent classes were labeled as *Resilience*, *Competence*, *Maladaptation*, and *Vulnerability* after an in-depth analysis of the individuals' item-response patterns as estimated by the LCA models.

Table 1. Fit indices for LCA models

	Models				
	1-class	2-class	3-class	4-class	5-class
T_1					
AIC/BIC	1757.91/ 1777.34	1665.34/ 1708.08	1604.44/ 1670.51	1602.39/ 1691.77	1610.63/ 1723.33
LR χ^2 (df), *p*	198.29 (25), .00	93.18 (20), .00	20.28 (14), .12	6.26 (7), .51	3.05 (1), .08
VLMR-LRT, p/ BLRT, *p*	-	104.58, .00/ 104.58, .00	72.89, .00/ 72.89, .00	14.05, .01/ 14.05, .00	3.76, .33/ 3.76, .67
T_2					
AIC/BIC	1920.83/ 1940.26	1833.60/ 1876.35	1759.94/ 1826.00	1756.93/ 1846.31	1767.37/ 1880.07
LR χ^2 (df), *p*	202.13 (26), .00	102.90 (20), .00	17.24 (14), .24	2.23 (8), .97	.68 (2), .71
VLMR-LRT, p/ BLRT, *p*	-	99.23, .00/ 99.23, .00	85.66, .00/ 85.66, .00	15.01, .11/ 15.01, .00	1.56, .53/ 1.56, .67
T_3					
AIC/BIC	1848.03/ 1867.46	1731.33/ 1774.08	1660.05/ 1726.12	1641.94/ 1731.32	1637.72/ 1750.42
LR χ^2 (df), *p*	261.16 (26), .00	132.46 (20), .00	49.18 (14), .00	19.07 (8), .01	2.85 (2), .24
VLMR-LRT, p/ BLRT, *p*	-	128.70, .00/ 128.70, .00	83.28, .00/ 83.28, .00	30.11, .01/ 30.11, .00	16.22, .00/ 16.22, .00

Note. df = degrees of freedom

Step 2: Transitions based on cross-sectional results. Based on the cross-tables of class membership assignments (Appendix B), it was observed that the proportions of individuals staying in specific classes (e.g., *Competence*) were higher compared to others. The proportions of individuals moving between specific classes (e.g., from *Maladaptation* to *Vulnerability*) were higher than others, indicating various transition patterns in the data.

Step 3: Measurement invariance assumption. The fit indices of the non-invariance and full-invariance models showed that the assumption of measurement invariance was met for the current data (non-invariance model AIC = 5001.85, BIC = 5269.99; full-invariance model AIC = 4959.14, BIC = 5071.84; $\Delta\chi^2(40) = 36.52$, $p>.05$). Hence, it was concluded that characteristics or meaning of the latent classes were equivalent for all time points.

Step 4: LTA models and transition probabilities. Based on the fit indices of the LTA model alternatives (Table 2), it was observed that the model with the smallest BIC was Model-2, while that with the smallest AIC was Model-3. However, in the estimation of Model-3, a warning message was received, stating that the parameter estimations might not be trustworthy for some reason. When nested Model-1 and Model-2 were compared, a significant difference was found, but Model-2 was chosen as the final model because it was more parsimonious and did not reveal any estimation problems.

Table 2. Fit indices for LTA models

	Model-1	Model-2	Model-3	Model-4
AIC	4816.40	4819.94	4808.17	4812.57
BIC	4999.05	4955.95	5025.79	5010.76
Log-likelihood	-2361.20	-2374.97	-2348.08	-2355.28
#p	47	35	56	51
c	.98	1.10	.89	1.03
cd	.63		--	--
TRd, *p*	43.67, .00		--	--

Note. #p = Number of parameters, c = Scaling correction factor, cd = Difference test scaling correction, TRd = Chi-square difference test

The parameter estimations of Model-2 are presented in Table 3. Statuses were labeled based on a joint evaluation of the theoretical model and the conditional item-response probabilities estimated equally for all times. The first status, with high probabilities for both the adversity (*A*) and resilience (*R*) items, was labeled as *Resilience*, while the second status, which had low probabilities for adversity items and high probabilities for resilience items, was labeled as *Competence*. The third status, with high probabilities for adversity items and low probabilities for resilience items, was labeled as *Maladaptation*, while the fourth status, with low probabilities for both groups of items, was labeled as *Vulnerability*.

Table 3. Item-response probabilities and latent status prevalences estimated for Model-2

	Statuses			
	Resilience	Competence	Maladaptation	Vulnerability
Items	Item-response probabilities			
A1	1.00	.00	1.00	.09
A2	.42	.00	.54	.00
R1	.52	.44	.09	.12
R2	.83	.85	.18	.21
R3	.90	.94	.00	.33
Time points	Latent status prevalences			
T_1	.14	.61	.05	.20
T_2	.20	.48	.08	.25
T_3	.19	.43	.09	.28

Note. Item-response probabilities are presented for the response category “High.”

The latent status prevalences (Table 3) indicated that the proportions for the *Resilience*, *Maladaptation*, and *Vulnerability* statuses were similar for all time points and the proportions for the *Maladaptation* status were low. For *Competence*, it was observed that the proportion of individuals with this status at time T_1 was higher than at other time points and higher than the proportions of the other statuses.

Table 4. Transition probabilities estimated for Model-2

		T+1			
		Resilience	Competence	Maladaptation	Vulnerability
T	Resilience	.41	.46	.00	.13
	Competence	.22	.64	.03	.11
	Maladaptation	.04	.17	.34	.45
	Vulnerability	.01	.10	.20	.69

Note. One set of transition probabilities was estimated because of equality constraints.

The transition probabilities (Table 4) showed that individuals with statuses reflecting low levels of adversity (statuses of *Vulnerability* and *Competence*) tended to stay in the same status over time. In contrast, individuals with statuses reflecting high levels of adversity (statuses of *Maladaptation* and *Resilience*) tended to move toward other statuses. The probabilities of transitioning from *Resilience* (with high adversity and resilience) to *Competence* (with low adversity and high resilience) and from *Maladaptation* (with high adversity and low resilience) to *Vulnerability* (with low adversity and resilience) were higher compared to other transition probabilities.

DISCUSSION

The purpose of the current study was to illustrate an application of LTA using 3-wave resilience data where latent class memberships were estimated for a group of pre-service teachers. The results showed that the model with four classes had the best fit. These latent classes were interpreted in line with a theoretical model proposing that individuals can be divided into groups characterized by their experienced adversity and adaptability levels (Masten, 2015; Masten & Tellegen, 2012; Masten et al., 1999; Masten et al., 2004). LTA model alternatives were tested to model the transitions among these classes and it was observed that the best fitting model was the one with equal transition probabilities between time points. As a result, it was concluded that individuals were more likely to maintain the statuses of *Competence* and *Vulnerability* (low adversity). In contrast, individuals with the status of *Resilience* (high adversity, high resilience) and *Maladaptation* (high adversity, low resilience) had a tendency to move toward statuses with the same level of resilience but lower adversity. Presenting detailed information at the individual level, these findings provide insights into practical and theoretical terms by raising additional questions, such as what are the factors affecting the transition patterns and how these patterns affect other characteristics of individuals.

While this paper's primary focus has been to provide a brief overview and an application of LTA, the results were also helpful in compiling a meaningful narrative that was later shared with a group of participants (n=12) who agreed to participate in a follow-up study. The majority of these participants confirmed that the findings presented to them about their predicted class memberships and transition patterns were reasonably accurate. The results showing that intra- and inter-individual differences existed in terms of resilience offer a reflection of how to model repeated data obtained with a longitudinal design and interpret the findings when the construct of interest is prone to change and can be considered categorical.

It should be noted here that the inferences made in this study are subject to a number of limitations due to the use of a relatively small sample, few items, and a temporal design with a limited number of measurement occasions. A temporal design with 3-time points at 4-week intervals was used in this study. Although the ideal approach is to plan a temporal design as suggested by the theoretical model (Collins, 2006), this may not always be possible due to the lack of logistical resources. Among resilience studies, there are examples of research in which data were collected over 3 months to 2-6 years (Cosco et al., 2017). However, it has been stated that collecting data at closer and more frequent time points might be a more effective way to capture change (Collins & Lanza, 2010; Timmons & Preacher, 2015). In addition, in the present study, five indicator variables were used, which were related to experienced adversity and perceived resilience. One reason for this was that there might be model definition problems if the number of items is high in LTA. The other reason was the limitations of the current resilience measures while collecting repeated data. Hence, it is of utmost importance that the inferences presented here about these pre-service teachers' resilience transition patterns not be taken as inferences to be generalized to pre-service teachers at large.

We only tested four versions of LTA models here, but various extensions of these models can be formulated. For example, higher-order effects might be added using data from more time points, specific transition probabilities might be constrained (e.g., setting some to 0) to test hypotheses about change, various groups (e.g., gender) might be compared concerning transition patterns, and other measurement models might be used (e.g., DINA model (Li et al., 2016)). By incorporating auxiliary variables into the models, the features of the individuals forming the classes and the results of class membership could be examined in more detail (Nylund-Gibson et al., 2014).

This study has presented an illustrative example of LTA modeling that can be used to obtain in-depth information for studies in which qualitative individual differences and changes related to such constructs are of interest. The information provided by the models proposed here is of a quality that can potentially meet the needs of researchers studying individual differences by placing individuals at the center of their research studies (Molenaar, 2004; Raufelder et al., 2013). The information gained at the individual level might be helpful for monitoring individuals, designing tailored prevention and intervention programs (Beck et al., 2010), or evaluating such existing programs' short- and long-term effectiveness for specific subgroups (Lanza et al., 2003). Researchers in psychology and education interested in evaluating individuals' developmental processes may take advantage of the LTA by utilizing person-centered approaches and longitudinal assessment designs that can be used to discover time-sensitive qualitative individual differences.

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APPENDIX A

Item-response probability estimations for each time point

Items	Classes			
	Class-1	Class-2	Class-3	Class-4
	T_1			
A1	1.00	.00	1.00	.25
A2	.52	.00	1.00	.00
R1	.53	.51	.14	.09
R2	.94	.80	.01	.10
R3	.80	.92	.00	.27
	T_2			
A1	1.00	.15	1.00	.00
A2	.50	.00	.37	.00
R1	.49	.50	.05	.12
R2	.81	.94	.19	.29
R3	.86	.98	.07	.46
	T_3			
A1	1.00	.00	1.00	.22
A2	.34	.00	1.00	.00
R1	.52	.29	.09	.15
R2	.75	.80	.27	.07
R3	1.00	.89	.00	.02

Note. Item-response probabilities are presented for the response category "High."

APPENDIX B

Cross tabulation of class membership assignments based on results of Step-1

		T_2				
		Resilience	Competence	Maladaptation	Vulnerability	Total
T_1	Resilience	.43	.43	.03	.13	1.00 (*n*=40)
	Competence	.24	.47	.05	.24	1.00 (*n*=257)
	Maladaptation	.00	.00	.33	.67	1.00 (*n*=6)
	Vulnerability	.07	.32	.19	.42	1.00 (*n*=57)
		T_3				
		Resilience	Competence	Maladaptation	Vulnerability	Total
T_2	Resilience	.27	.59	.02	.12	1.00 (*n*=82)
	Competence	.11	.76	.03	.11	1.00 (*n*=157)
	Maladaptation	.04	.35	.19	.42	1.00 (*n*=26)
	Vulnerability	.02	.45	.11	.42	1.00 (*n*=95)