Latent Transition in Geospatial Thinking and Reasoning

For Tectonics Understanding

Qiong Fu[1], Alec M. Bodzin[1], and Everett V. Smith[2]

1. Lehigh University

2. University of Illinois at Chicago

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Abstract

We developed and optimized a series of Web GIS investigations that use features designed to promote middle school students' geospatial thinking skills and enhance their tectonics learning. In the current methodological study, we employed latent transition analysis (LTA) with a binary covariate (gender and then track) to characterize transitions over time (pretest to posttest) in tectonics learning. Data from 1,124 students of four urban middle schools included a pre- and posttest tectonics and geospatial thinking and reasoning achievement measure. Advantages of modeling academic profiles as a categorical latent variable, as well as its implications for science instruction, are discussed as compared with common mean-comparison methods (paired-sample *t* test and mixed ANOVA).

Keywords: latent transition analysis, urban middle level students, geospatial thinking

Geospatial Thinking and Reasoning

Geospatial thinking, a subset of spatial thinking, is a skill that necessitates knowledge about space, the ability to use tools of representation properly, and reasoning skills (National

Research Council [NRC], 2006). Geospatial reasoning skills provide a means for manipulating, interpreting, and explaining structured information and are involved in higher-order cognitive processes that include solving problems or making decisions. One potential method for teaching geospatial thinking and reasoning is through spatially-enabled learning technologies, such as Geographic Information Systems (GIS) (Battersby, Golledge, & Marsh, 2006), which may enhance science curriculum learning by adding an emphasis on geographic space, visualization, scale, representation, and spatial thinking and reasoning skills.

We developed a series of Web GIS investigations that use features designed to promote middle-level students' geospatial thinking skills and enhance tectonics learning. The investigations use a geospatial learning approach that builds on our previous curriculum design work with geospatial technologies. The design approach incorporates a framework, design principles, an instructional model for the development and implementation of learning activities with spatially-enabled learning technologies, and educative materials (Davis & Krajcik, 2005) to support teacher enactment. The Web GIS interface was designed for middle school learners using JavaScript programming with APIs. It is compatible with computers and mobile learning devices (such as iPads, other tablet devices, and smart phones) that are rapidly appearing in schools. We developed a series of unique learning tools and features designed to help promote geospatial thinking skills and enhance tectonics learning with the Web GIS learning activities.

We also developed an assessment for the pretest taken before, and posttest taken after, the enactment of the Web GIS investigations. The assessment was optimized based on both classical and iterative Rasch analyses findings from two previous administrations, with the final version comprising 15 tectonics content items and 19 items that measure geospatial thinking and reasoning skills as they apply to tectonics concepts. Students' responses for each test item were scored one for the correct and zero for incorrect responses. This study focuses on the geospatial subscale. The findings from our previous studies provide support that geospatial thinking and reasoning related to a science content area can be learned, can be taught formally to students in an urban middle level school, and can be supported by appropriately designed learning activities with Web GIS (see Bodzin, 2011; Bodzin, Fu, Peffer, & Kulo, 2013; Bodzin, Fu, Kulo, & Peffer, in press).

Objectives and Study Approach

In our previous studies, we employed statistical procedures such as paired-sample *t* tests to compare mean differences between pretest and posttest, or mixed-design ANOVA to compare mean differences over time and between subgroups of a covariate (e.g., gender). It should be noted that paired-sample *t* test compares the means for the entire sample over time, ignoring possible subgroup differences in growth trajectories that may even cancel out each other. Similarly, mixed design ANOVA assumes uniform growth trends within each subsample of the covariate. In reality, however, distinct underlying subgroups (latent classes) may exist at each time and students are likely to move over time from a bottom- to a top-performance group, and vice versa. Therefore, the objective of this study is to explore the sample heterogeneity and obtain a dynamic picture for middle-level students' transition across time in tectonics learning. For the purpose of evaluating the utility of our self-developed Web GIS investigations in students' tectonics learning, the downward movement probabilities in this study were restricted at zero. That is, our primary interest is how many students benefited from the designed learning activities with Web GIS and moved upward. Moreover, it seems to make sense to assume zero probabilities for students to move downward in their geospatial reasoning and thinking skills.

We employed a latent variable approach named latent transition analysis (LTA; Collins & Lanza, 2010; Muthén & Asparouhov, 2011; Nylund, 2007; Reboussin, Reboussin, Liang, & Anthony, 1998). The LTA model has two advantages over *t* tests or ANOVA: (1) Latent variable models estimate and remove measurement error, and (2) Estimation of LTA is based on response patterns in the contingency table from the number of items.

The research questions include (1) Are there distinct subgroups of students within the sample based on their patterns of responses to the pre-posttest questions? (2) Is there change between latent classes membership across time? Did the change probabilities differ between gender or between academic tracks?

Theoretical Framework

The theoretical framework is derived from latent class theory (Goodman, 1974; Lazarsfeld & Henry, 1968) for measuring categorical latent variables, describing stage-sequential development, and capturing initial status and transitions over time. Latent variable models differ in whether both latent and observed variables are categorical or continuous (Collins & Lanza, 2010). When the observed variables are categorical (e.g., Likert-scale rating data or dichotomous test data), an item response theory (IRT) approach would yield a continuous latent variable whereas latent class analysis (LCA) would model a categorical latent variable for the underlying unobserved subgroups (i.e., latent classes) in a population. The LTA model is an extension of LCA for longitudinal data with at least two time points to characterize change (transition) over time and further with a covariate influencing the latent transition probabilities. LTA has been mostly applied in social, behavioral, and health research and in some academic profiles for at-risk students.

Methods

Participants

In total, 1,124 grade-8 students (51% being male) learning Earth and space science in four urban schools in the northeast region of the United States participated in the Web GIS tectonics investigations during the 2012-2013 academic school year. Among them, 1068 students completed the pretest, 1081 students the posttest, 1025 students both pre- and posttests. The majority of the students were from low-income households. The local school districts stipulated that the students were grouped into six ranked tracks based on their previous PSSA mathematics test scores for the purpose of placing students to different science classes at the beginning of the school year; 33% were assigned to the top track (Track 1). The 12 teachers attended two days of professional development to become acquainted with the Web GIS tectonics investigations.

Data Analysis

Before LTA was conducted in Mplus version 7 (Muthén & Muthén, 1998-2013), we started from the following analyses in SPSS version 21 as a base for comparison with the LTA results: (1) paired-sample *t* test for checking the mean difference between pretest and posttest; (2) mixed-design ANOVA from pretest to posttest between gender groups; and (3) mixed-design ANOVA from pretest to posttest between tracks. To simplify the analysis but at the cost of statistical information, the six tracks were merged into two (Track 1 versus other tracks combined). Note that paired-sample *t* test was actually not necessary because the findings would be similar to the mixed-ANOVA findings for the main effect of time, ignoring gender or track.

After comparing model fit information between 2-class and 3-class LCA models for the pretest and posttest separately, we decided on the 2-class LTA model for each time point with a binary covariate (gender or dichotomous track, separately) influencing the latent transition probabilities. The Mplus syntax using a probability parameterization (rather than a logit parameterization) is attached in the appendix. The probability of moving downward is fixed at zero, assuming no decline in students' geospatial reasoning and thinking skills. The same set of latent class indicators (i.e., the 19 geospatial test items) were measured at two time points (pretest and posttest). The model assumes measurement invariance by fixing the thresholds equal across time for the 19 items. The default estimator in Mplus for this type of analysis is maximum likelihood with robust standard errors. The Mplus output for LTA includes latent class membership probabilities, latent class membership, item-response probabilities (usually fixed equal over time, assuming measure invariance), and transition probabilities conditional on latent classes within each subgroup of the covariate.

Results and Conclusions

Descriptive statistics for geospatial pre- and posttest total scores across gender and track groups are summarized in Tables 1 and 2.

--------------------------------------Insert Table 1 and Table 2 About Here------------------------------------

Paired-sample *t* test revealed a significant difference between the pretest (Mean (SD) = 9.61 (3.73)) and the posttest (Mean (SD) = 13.71 (3.84)), $p < .001$. The effect size was large, Cohen's $d = 1.08$, calculated by dividing the difference between posttest and pretest mean scores by the pooled standard deviation (square root of the average of the squared standard deviations; Cohen, 1988).

Mixed-design ANOVA from pretest to posttest between gender groups (see Table 3) found (1) statistically significant gain from pretest to posttest (ignoring gender), $F(1, 1023) = 1566.89$, $p < .001$, $\eta^2_{partial} = .61$; (2) a non- or marginally-significant mean difference between gender (ignoring time), $F(1, 1023) = 3.41$, $p = .065$, $\eta^2_{partial} = .003$; and (3) differential growth with significantly higher gain over time for male than for female students, $F(1, 1023) = 7.62$, $p = .006$, $\eta^2_{partial} = .007$.

The results for mixed-design ANOVA from pretest to posttest between tracks (see Table 4) indicated (1) statistically significant gain from pretest to posttest (ignoring track), $F(1, 1023) = 1462.67$, $p < .001$, $\eta^2_{partial} = .59$; (2) a significant mean difference between tracks (ignoring time), $F(1, 1023) = 438.36$, $p < .001$, $\eta^2_{partial} = .30$; and (3) differential growth pattern across track groups with a small effect size, $F(1, 1023) = 4.30$, $p = .038$, $\eta^2_{partial} = .004$.

------------------------------------Insert Table 3 and Table 4 About Here-----------------------------------

The LTA with gender (see Table 5) indicated that, among the male students, based on the estimated conditional probabilities for the class variables (available from Tech 15 in Mplus version 7), 23 percent of the boys were predicted to stay in the same class from the pretest to the posttest (Stayers for C1). They were the top male performers based on their total correct responses on both tests (Table 6). By contrast, the majority class (Class 2 or low-performance group) on the pretest split into two subgroups on the posttest: the probability for them was 0.34 to stay in the low-performance group and 0.66 to move to the top-performance group. Among the female students, 19 percent of the girls were predicted to stay in the same class from the pretest to the posttest (Stayers or top-performers on both tests). By contrast, the majority class (low-performance group) on the pretest split into two subgroups on the posttest: the probability for them was 0.43 to stay in their group and 0.57 to move to the top-performance group. The frequency counts and proportions based on the posterior most-likely class membership are similar to those based on the estimated conditional probabilities for the class variables.

-------------------------------------Insert Table 5 and Table 6 About Here-----------------------------------

The LTA with the dichotomous track (the original Track 1 versus the other tracks combined; see Table 7) indicated that, among the Track 1 students (33% of the entire sample), based on the estimated conditional probabilities, 43 percent were predicted to stay in the top-performer class on both tests (Table 8). By contrast, the low-performance class on the pretest split into two subgroups on the posttest: the probability for them was only 0.03 to stay and 0.97 to move up to the top class. In the tracks-2-to-6-combined group (67% of the entire sample), 8% of the students remained in their top-performer class from posttest to posttest, but among the 92% in the low-performance group on the pretest, the probability was 0.51 to stay and 0.49 to move up to the top class on the posttest.

Both LTA with dichotomous covariates indicate that a substantial proportion of students in the low-performance latent class at the pretest time were predicted to move up to the top class at the posttest time.

-------------------------------------Insert Table 7 and Table 8 About Here-----------------------------------

Significance and limitations of the study

The findings provide support that a majority of students with lower geospatial thinking and reasoning skills at the beginning of the curriculum implementation enhanced their geospatial skills to a level commensurate to those with higher geospatial skills by the end of the curriculum implementation. This has implications for equity issues in science education; well-designed Web GIS tectonics investigations may be more helpful for lower geospatial ability level students to apply spatial thinking and reasoning skills to tectonics concepts.

The latent class membership on the geospatial pretest may be more appropriate for the science class placement than the previous PSSA mathematics test scores in the current practice.

However, it does not seem realistic for schools to wait so long till the pretest results come out after the school year started. When the classes are set for the entire school year, the dynamic, rather than stationary, latent class transition by the end of school year as we found in this study implies that science teachers should have the flexibility of moving students up to an advanced class. In terms of research methodology, the class transition analysis from pretest to posttest offers an alternative statistical method for data with at least two time points. The information adds insight about the individual moving profiles based on the item-level responses, which would not be possible to detect from paired-sample *t* test or mixed-design ANOVA.

The LTA model for two time points with a binary covariate may be extended for more time points and non-zero probabilities of moving downward. The limitations with the LTA are obvious: a bigger sample size is needed each latent class with the subgroup of a covariate. To ensure the identification of the model but at the cost of statistical information, we merged the six tracks into two with arbitrary cut between Track 1 and lower tracks. Theoretically, both covariates (gender and tracks) should be included in a single LTA model. However, given our sample size and the interpretability of the results, we included each covariate separately.

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Table 1

Descriptive statistics for geospatial pre- and posttest total scores across gender

	Gender	Mean	*SD*	*N*
Pretest Total	Male	9.66	3.79	520
	Female	9.56	3.68	505
	Total	9.61	3.73	1025
Posttest Total	Male	14.04	3.69	520
	Female	13.36	3.97	505
	Total	13.71	3.84	1025

Table 2

Descriptive statistics for geospatial pre- and posttest total scores across tracks

	Tracks	Mean	*SD*	*N*
Pretest Total	Track1	12.03	3.05	353
	Tracks2-6	8.34	3.42	672
	Total	9.61	3.73	1025
Posttest Total	Track1	16.43	1.94	353
	Tracks2-6	12.28	3.82	672
	Total	13.71	3.84	1025

Table 3

Mixed-design ANOVA from pretest to posttest between gender groups

Source		*df*	Mean Square	*F*	*p* value	Partial Eta Squared
Within-Subjects Contrasts	time	1	17171.01	1566.89	< .001	0.605
	time * Gender	1	83.51	7.62	0.006	0.007
	Error(time)	1023	10.96			
Between-Subjects Effects	Gender	1	39.47	3.41	0.065	0.003
	Error	1023	11.56			

Table 4

Mixed-design ANOVA from pretest to posttest between tracks

Source		*df*	Mean Square	*F*	*p* value	Partial Eta Squared
Within-Subjects Contrasts	time	1	16080.80	1462.67	< .001	0.588
	time * Track	1	47.24	4.30	0.038	0.004
	Error(time)	1023	10.99			
Between-Subjects Effects	Track	1	3560.06	438.36	< .001	0.300
	Error	1023	8.12			

Note. Time includes pretest and posttest. Track includes upper track versus all other tracks combined.

Table 5

Estimated conditional probabilities for the pre-post latent classes between gender

Group (proportion of the entire sample)	Latent class for Pretest (proportion of the subsample)	Latent class for Posttest	
		1	2
Male (.51)	1 (.23)	1.00	0.00
	2 (.77)	0.66	0.34
Female (.49)	1 (.19)	1.00	0.00
	2 (.81)	0.57	0.43

Table 6

Means and standard deviations of pre- and posttest total for latent classes between gender

Gender	Latent class for Pretest	Latent class for Posttest	Pretest_total		Posttest_total		Latent class label (N = 1025)
			Mean	*SD*	Mean	*SD*	
Male	Class 1	Class 1	14.58	1.53	16.74	1.53	Stayers, high-performers (121)
	Class 2	Class 1	9.10	2.56	15.40	1.96	Movers from low to top (**269**)
		Class 2	6.26	2.64	8.72	2.33	Stayers, low-performers (130)
Female	Class 1	Class 1	14.75	1.54	16.64	1.78	Stayers, high-performers (95)
	Class 2	Class 1	9.43	2.55	15.37	1.85	Movers from low to top (**240**)
		Class 2	6.84	2.68	8.71	2.60	Stayers, low-performers (170)

Table 7

Estimated conditional probabilities for the pre-post latent classes between tracks

Group (proportion of the entire sample)	Latent class for Pretest (proportion of the subsample)	Latent class for Posttest	
		1	2
Track 1 (.33)	1 (.43)	1.00	0.00
	2 (.57)	0.97	0.03
Tracks 2~6 (.67)	1 (.08)	1.00	0.00
	2 (.92)	0.49	0.51

Table 8

Means and standard deviations of pre- and posttest total for latent classes between tracks

Tracks	Latent class for Pretest	Latent class for Posttest	Pretest_total		Posttest_total		Latent class label (N = 1025)
			Mean	*SD*	Mean	*SD*	
1	Class 1	Class 1	14.90	1.57	17.18	1.34	Stayers, high-performers (148)
	Class 2	Class 1	10.00	2.00	16.04	1.90	Movers from low to top **(200)**
		Class 2	8.60	1.52	9.80	1.10	Stayers, low-performers (5)
2~6	Class 1	Class 1	14.50	1.28	16.00	1.60	Stayers, high-performers (50)
	Class 2	Class 1	9.24	2.69	15.16	1.68	Movers from low to top **(303)**
		Class 2	6.51	2.73	8.96	2.58	Stayers, low-performers **(**319**)**