New Ways to Measure Systemic Change:
Map & Analyze Patterns & Structures Across Time

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Abstract

Map & Analyze Patterns & Structures Across Time (MAPSAT) is a new set of mapping tools that are appropriate for analyses of system dynamics and structure in education. MAPSAT consists of two complementary methodologies: Analysis of Patterns in Time (APT) and Analysis of Patterns in Configuration (APC). In APT, a researcher creates temporal maps by observing phenomena and coding sequential and simultaneous event changes with categories in classifications. In APC, a researcher creates maps that represent affect-relations among components of a system. These affect-relations indicate system structure during some period of time. Examples are provided which illustrate a wide range of applications of MAPSAT: patterns of teaching and student engagement in elementary schools; patterns of First Principles of Instruction, academic learning time, and student mastery in postsecondary education; sequential patterns of scaffolding in technology education of preservice teachers; structural properties of activity settings in a Montessori classroom; structural change in mentoring affect-relations when comparing an existing and new doctoral program; extension of curriculum maps to include structural relationships among academic standards, units of instruction, and student learning achievement; and design of a computer simulation of educational systems.

Background of the Problem

Research methods in education used for much of the 20th century were largely quantitative methods. Experimental and quasi-experimental designs were commonplace (e.g., Campbell & Stanley, 1966), and analytical techniques included ANOVA, regression analysis and their extensions. The basic problem was that this general linear models approach seldom yielded findings that could be directly linked to educational practice. Within-group and within-person variance was often large, typically obfuscating differences between groups that could be attributed to so-called treatments, practices or programs (Medley, 1977; 1979). Cronbach & Snow (1977) further extended ANOVA to deal with aptitude-treatment interactions (ATI), with hopes of reducing the within-group variance. But this, too, was seldom successful in yielding significant results.

In the 1970s and 80s, others began to explore alternative approaches that later became known as qualitative and case study methodology (cf. Guba & Lincoln, 1985; Stake, 1995; Yin, 2003). Qualitative methods have become widely used in educational research in the past two decades. One clear advantage of qualitative methods is that rich details of individual cases can give readers helpful insight into and understanding of the educational phenomena investigated. The unavoidable dilemma that often accompanies this approach is lack of justification for generalizability of findings. When samples are purposive and small, generalizability in the sense of making inferences from sample to population is seriously compromised. Indeed, respected books on qualitative methods avoid the term 'generalizability' and instead employ the notion of 'transfer' – i.e., results of what was found in this particular investigation *may* transfer to other similar situations the reader encounters (cf. Merriam, 1997). Mixed methods approaches have become more popular in recent years (Creswell, 2003), in which strengths of both qualitative and quantitative approaches have been utilized.

Is there an alternative that bridges qualitative, quantitative and mixed methods? We believe so. The first author explored in the 1970s pattern analysis methods that later became known as Analysis of Patterns in Time (Frick, 1983; 1990). In the late 1990s, he began collaborating with Kenneth Thompson, who was working on systems theory in which structural and dynamic properties of systems were put forth (cf. Thompson, 2005a; 2008d). Thompson's work with Axiomatic Theories of Intentional Systems (ATIS) and ATIS Graph Theory led to new ways of measuring system *structure* (cf. Thompson, 2008c), which were complementary to temporal pattern analysis for measuring system dynamics. The combined approach was called Analysis of Patterns in Time and Configuration (APT&C) (e.g., see Frick, An & Koh, 2006). As we further developed this methodology, it became clear that what was common to both approaches and different from traditional qualitative and quantitative approaches was the notion of *mapping* the patterns, analyzing the maps, and realizing that structural change across time is also part of this approach. Thus, in 2007, we changed the nomenclature to MAPSAT: Map & Analyze Patterns & Structures Across Time.

What is MAPSAT?

MAPSAT is a new set of relation mapping and analysis methods. MAPSAT contains two methodologies: Analysis of Patterns in Time (APT) and Analysis of Patterns in Configuration (APC). APT detects *temporal* relations that linear statistical models cannot, nor can Bayesian networks. APC measures *structural* properties that are determined from axiomatic theory, unlike social network analysis (SNA). APC can measure hyper-graphs of multiple affect-relation sets, setting it apart from other forms of network analysis. Both APT and APC have mathematical foundations in graph theory.

In traditional quantitative research methods that are based on algebraic linear models, we typically obtain separate measures of variables, and then we statistically analyze relations among measures. That is, we *relate measures*. Alternatively, we could *measure relations* directly. This is not a play on words, but a significant conceptual shift in thinking about research problems and how we collect and analyze data.

Frick (1990) invented a procedure called Analysis of Patterns in Time (APT) in order to map temporal relations. Phenomena are observed and coded with categories in classifications. The resulting temporal maps are then queried for temporal sequences of events. For example, Frick (1990) found that if interactive (direct) instruction was occurring, the likelihood of student engagement was very high

(*APTprob* = 0.97). However, when non-interactive (non-direct) instruction was occurring, then students were engaged much less (*APTprob* = .57). Regression analysis of the same data was only able to predict 33 percent of the variance in student engagement.

Thompson (2005b; 2008d) has developed Axiomatic Theories of Intentional Systems (ATIS). ATIS Graph Theory provides us a way to measure 17 structural properties of systems that include strongness, flexibility, interdependence, wholeness and vulnerability This approach is called Analysis of Patterns in Configurations (APC). A recent study of a Montessori classroom indicated that some structural properties were markedly different in two different types of learning settings: head problems and morning work period. In the latter, for example, there was much more *interdependence* with respect to affect-relation sets for *choice of learning activities* and *guidance of learning* (Frick & Koh, 2007).

How is MAPSAT different from traditional methods of measurement and analysis? MAPSAT differs from regression methods in that these latter methods assume some kind of mathematical function for modeling a relation. In these traditional methods, variables are measured separately and then statistical association is attempted according to the function assumed (e.g., linear, curvilinear, logistic). In MAPSAT, relations themselves are mapped directly, and then later different types of patterns are counted during analysis. MAPSAT is a *logical* analysis of relations, not a statistical analysis of separate measures.

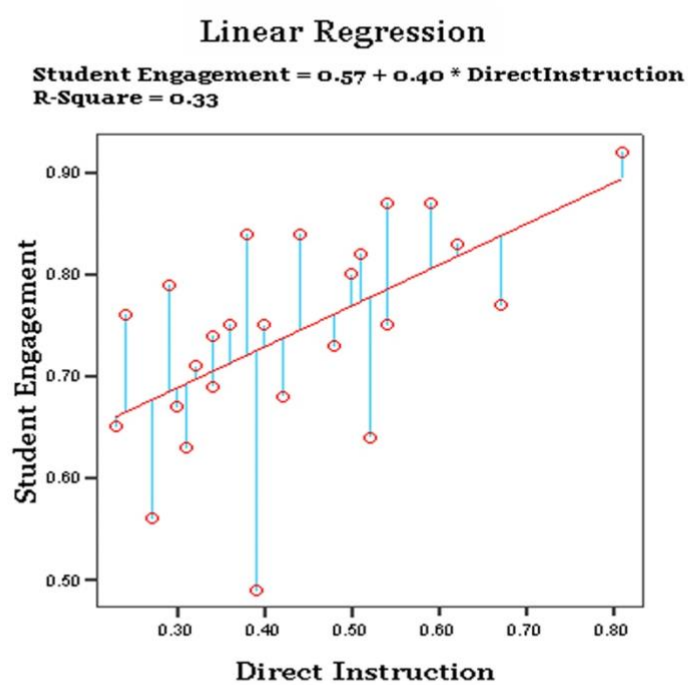
MAPSAT is a form of network measurement and analysis. More specifically, Bayesian Network Analysis (BNA) and Social Network Analysis (SNA) are similar to MAPSAT in that they are types of network analysis and are grounded in mathematical digraph theory (Thompson, 2008c; Jensen & Nielsen, 2007; Brandes & Erlebach, 2005). These three approaches to network analysis are more closely related, compared with extant methods of measurement and regression analysis described above. While MAPSAT APC methods and SNA do have common aims, the advantages of MAPSAT are its theory basis (ATIS) and ability to measure structural properties of hyper-graphs of multiple sets of affect-relations.

An Example: Analysis of Patterns in Time (APT) and Academic Learning Time

In the first major study to compare APT with linear models (Frick, 1990), 25 mildly handicapped children were observed throughout the day in their elementary school classroom learning environments in central and southern Indiana. Each child was observed between 8 and 10 hours across multiple days over a semester. These environments ranged from self-contained classrooms for special education students to regular classrooms in which the mildly handicapped children were included. Trained classroom observers coded the kinds of academic learning activities provided, and within each reading and mathematics activity the behaviors of target students and instruction made available to the student were coded at one-minute intervals. During data analysis, student behaviors at each time sampling point were collapsed into two categories: engagement and non-engagement. Similarly, instructional behaviors at each sampling point were collapsed into two categories: direct (interactive) instruction and non-direct (non-interactive) instruction.

Linear models approach. As can be seen in Figure 1, if the data are analyzed with the linear models approach, student engagement can be predicted by a regression equation. Approximately 33 percent of the variance in student engagement can be accounted for by the amount of direct instruction provided. While this finding shows that there is a statistically significant positive relationship ($p < 0.05$) that is moderate in size, there is still a great deal of uncertainty (67 percent of the variance is not predictable). Notice that the vertical lines (blue) indicate the distances between the data points and the regression line (red), indicating *errors* in prediction. The relationship between direct instruction and engagement is represented by a function for a line. In this example, the function for the line is: EN = 0.57 + 0.40DI. Each data point represents the overall proportion of engagement for a particular student, paired with the overall proportion of direct instruction provided to that student. Engagement is aggregated *separately* from direct instruction for each case, so there is one overall engagement score for a student and one overall direct instruction score. Thus, there are 25 data pairs from which the regression equation is estimated. In Table 1, the left two columns contain p(DI) and p(EN) for each student. For example, for student 1 p(DI) = 0.50 and p(EN) = 0.80, which is one of the x,y data pairs in Figure 1.

Figure 1. The linear models approach to analyzing a relation



APT analysis

The same data were analyzed from an APT perspective. From this perspective data are aggregated differently. The *joint occurrences* of student engagement and instruction were counted in order to form probabilities or proportions. For example, for student 1, the *probability* of (DI & EN) = 0.46; *p*(DI & NE) = 0.04; *p*(EN | DI) = 0.92; and *p*(EN | ND) = 0.67. These joint and conditional probability estimates for this student were based on nearly 500 data points where the joint occurrences of instruction and engagement were observed and coded. Similar probabilities were estimated for the remaining 24 systems, and then the probabilities were averaged. Thus, there were nearly 15,000 data points representing the joint occurrences of direct instruction and engagement in the 25 systems. See Table 1.

Table 1. Temporal Relationships: Joint Occurrences of Direct Instruction (DI), Student Engagement (EN), Non-direct Instruction (ND), and Student Non-engagement (NE) in Columns 3 - 6; Conditional Occurrences in Columns 7 - 8.

p(DI)	*p*(EN)	*p*(DI & EN)	*p*(DI & NE)	*p*(ND & EN)	*p*(ND & NE)	*p*(EN|DI)	*p*(EN|ND)
0.50	0.80	0.46	0.04	0.34	0.16	0.92	0.67
0.39	0.49	0.37	0.02	0.12	0.49	0.95	0.20
0.27	0.56	0.26	0.01	0.30	0.43	0.97	0.41
0.34	0.69	0.34	0.00	0.35	0.31	1.00	0.53
0.48	0.73	0.47	0.01	0.25	0.26	0.98	0.49
0.40	0.75	0.39	0.01	0.35	0.25	0.98	0.59
Etc.	Etc.	Etc.	Etc.	Etc.	Etc.	Etc.	Etc.
Mean *(SD)*	***Mean*** *(SD)*	***Mean*** *(SD)*	***Mean*** *(SD)*	***Mean*** *(SD)*	***Mean*** *(SD)*	***Mean*** *(SD)*	***Mean*** *(SD)*
0.432 (0.144)	**0.741** (0.101)	**0.416** (0.139)	**0.015** (0.010)	**0.324** (0.114)	**0.243** (0.104)	**0.967** (0.029)	**0.573** (0.142)

As can be seen in the two far-right columns in Table 1, conditional probabilities for student engagement during direct instruction and non-direct instruction are presented. The mean probability of student engagement during direct instruction is very high (0.967). Students are about 1.7 times more likely to be engaged during direct instruction than during non-direct instruction (0.967/0.573). Another way to look at this is the likelihood of non-engagement during non-direct instruction. Students are about 12.9 times more likely to be off-task during non-direct instruction ((1 – 0.573) /(1 – 0.967)). These patterns are very clear and consistent across 25 different systems. When teachers interacted with those target students either individually or in groups that included those students, they were very likely to be on-task. These probability ratios (odds) are *in principle* no different than the odds of getting some kind of cancer later in life being between 5 and 10 times greater for heavy smokers, when compared with non-smokers (Kumar, Abbas & Fausto, 2005). This temporal relationship is not necessarily causal, but nonetheless is a predictable pattern.

An Example: Analysis of Patterns in Time (APT) of Course Evaluation Data

A recent study was completed by Frick, et al. (2008), in which APT was used to analyze relationships among scales derived from a course evaluation instrument on Teaching and Learning

Quality (TALQ). In this study, 464 college students completed the TALQ instrument in 12 university classes in business, philosophy, history, kinesiology, social work, informatics, nursing, and health, physical education and recreation. Unlike the Frick (1990) study, in which approximately 500 samples of teacher and student behavior were collected for each system, in the TALQ study there was just one set of measures for each case. In Table 2, results are shown for frequencies and percentages of patterns in college classrooms.

Table 2. Data from Frick et al. (2008) study for the APT Query: If Agreement on First Principles = ? and Agreement on Successful Engagement = ?, then Student Mastery = ?

	Agreement on First Principles							
	No				Yes			
	Agreement on Successful Engagement				Agreement on Successful Engagement			
	No		Yes		No		Yes	
	Instructor Rating of Student Mastery		Instructor Rating of Student Mastery		Instructor Rating of Student Mastery		Instructor Rating of Student Mastery	
	Count	%	Count	%	Count	%	Count	%
Low (0-5)	15	31.9%	1	5.6%	1	2.3%	2	1.4%
Medium (6-8)	29	61.7%	12	66.7%	41	95.3%	112	75.7%
High (8.5-10)	3	6.4%	5	27.8%	1	2.3%	34	23.0%
Total	47	100.0%	18	100.0%	43	100.0%	148	100.0%

For example, it can be seen from the APT query, 'If Agreement on First Principles is No and if Agreement on Successful Engagement is No, then Instructor Rating of Student Mastery is Low?', this pattern occurred in 15 out of 47 cases, for a probability estimate of 0.319. On the other hand, for the query, 'If Agreement on First Principles is Yes and if Agreement on Successful Engagement is Yes, then Instructor Rating of Student Mastery is Low?', this pattern occurred in just 2 out of 148 cases, for a probability estimate of 0.014. Thus, it can be seen that when students did *not* agree that First Principles of Instruction occurred in their classes *nor* were they successfully engaged, then the likelihood of being rated as a low master by their instructor is much greater than when students *did* agree that First Principles and successful engagement (ALT) had occurred. The ratio of these probabilities, 0.319 divided by 0.014, is 22.8. Thus, students in this study were about 23 times more likely to be rated at a low mastery level of course objectives when First Principles and ALT were perceived to be largely absent in a course, compared with when both were present. Similarly, students were about 3.6 times more likely to be rated as high masters, when both First Principles and ALT were present compared with their absence, according to student ratings on TALQ scales (Frick et al., 2008).

These relationships are nonlinear. In fact, we have no way to calculate a tri-variate correlation to measure a 3-way association such as we have with these APT queries. If we do a linear regression in order to predict the student mastery level from a combination of First Principles and ALT, only 8 percent of student mastery is predicted by student successful engagement. While this relationship is highly statistically significant, what is noteworthy is that First Principles of Instruction does *not* contribute significantly to the prediction of student mastery in this linear model! The reason for this is based on the assumptions for regression analysis: a linear, additive model. No such assumption is made in APT. In Table 2, it is patent that presence and absence of First Principles and ALT do appear to make a big difference when predicting low and high mastery levels, as described above. On the other hand, medium levels of mastery are less dependent on the presence versus absence of First Principles and ALT (0.953/0.667 = 1.43), or odds of about 1.4 to 1. These patterns are obfuscated by traditional linear models, whereas they are quite clear in an APT analysis. Frick (1983) proved mathematically that APT can predict patterns that the linear models approach cannot. The Frick (1990) and Frick et al. (2008) studies clearly illustrate this fact empirically.

Examples of Temporal Maps, APT Queries and Computations

Sequential patterns (frequency but not duration). Koh (2008) investigated how teachers in educational technology classes used scaffolding strategies. Scaffolding is one of the strategies that is often discussed in problem-based learning methods, as well as in instructional design for complex learning (cf. van Merriënboer & Kirschner, 2007; van Merriënboer, Clark and de Croock, 2002). She videotaped university classes for about 27 hours. She then coded the videotapes using the classifications which are the column headings in Map 1. To protect identities of students, their names have been changed to capital letters (C, H, L and M in this sample extracted from one of the classes she observed).

Map 1. Coding Example adapted from Joyce Koh's dissertation (2008), p. 38. Cell entries have been highlighted in green to indicate instances of the pattern: If student interaction is Tech Help, then instructor interaction is Show N Tell?

Temporal Order	Instructional Activity	From	To	Student interactions	Instructor interactions	Resources	Equipment
1	Lab	Instructor	C	Null	progress check	Project/ Assignment descriptions	Student computer terminal
2					Show N Tell		
3		C	Instructor	clarify task			
4		Instructor	C		Direction maintenance		
5		C	Instructor	tech help			
6		Instructor	C		Show N Tell		
7		C	Instructor	Clarify content			
8		Instructor	C		Direction maintenance		
9					Frustration Control		
10					Direction maintenance		
11		M	Instructor	can't hear			
12		Instructor	M		can't hear		
13		L	Instructor	tech help			
14		Instructor	L		progress check		
15					Show N Tell		
16		H	Instructor	Tech help			
17		Instructor	H		progress check		
18		H	Instructor	Share content			
19		Instructor	H		Show N Tell		
20		L	Instructor	tech help			
21		Instructor	L		Show N Tell		

A particular pattern has been highlighted in Map 1 for purposes of illustration. Koh (2008) was interested in mapping the temporal sequences but not durations of events, so there is no classification for date and time in Map 1. Each time a new event is observed, a new row is added; thus sequence in time runs from top to bottom of the temporal map. When an event is observed in one classification, it is assumed to continue until another relevant event is observed. For example, the Instructional Activity was initially coded as Lab, and that activity did not change during the observation, while 13 Instructor Interactions were observed.

The coded instructional sequences were also used to make APT queries about the joint probabilities of categories within and between classifications. For example, to find out how instructors responded to student requests for Tech Help, the following APT query could be set-up:

IF Student Interaction = *Tech Help*, THEN Instructor Interaction = *Show and Tell* ?

Using the information in Map 1, it can be seen that there were 4 instances of student requests for *Tech Help*. Given that *Tech Help* was true, it was followed 3 times by *Show and Tell* and 2 times by Progress *Check*. Therefore, if students asked for *Tech Help*, the probability of this instructor responding by *Show and Tell* was 3/5 = 0.60. The symbol ⍰ has been added to the map to show where the pattern is true, and the symbol ⍰ was added to show where the pattern is false in the map.

Sequential patterns (both frequency and duration). Map 2 illustrates a temporal configuration when both frequency of events and their duration are of interest in APT. This map has also been highlighted in colors in order to illustrate an APT query and results.

Map 2. Example of a temporal map with highlighting for the APT query: If target student is Mona and instruction is direct, then student engagement is on-task? Green areas represent where the pattern is true, while pink areas indicate that the pattern is false.

Clock Time	Target Student	Instruction	Student Engagement
9:01	Mona	Direct	Off-task
9:02			
9:03			On-task
9:04			
9:05			
9:06			Off-task
9:07			On-task
9:08		Non-Direct	
9:09			
9:10			
9:11			Off-task
9:12			
9:13	Null	Null	Null

Query for Map 2:

IF target student IS Mona

AND instruction IS direct,

THEN student engagement IS on-task?

Query Results from Map 2:

Cumulative duration = (9:06 – 9:03) + (9:08 – 9:07) = 4 minutes

Cumulative frequency = 2

Likelihood = 2 out of 4 = 0.50

Proportion time = 4 minutes out of 7 = 0.57

Space does not permit further elaboration here. However, this example shows the need for MAPSAT software to allow entry of codes and times, as well as to do the tabulation of event frequencies and accumulation of durations in order to obtain results of APT queries.

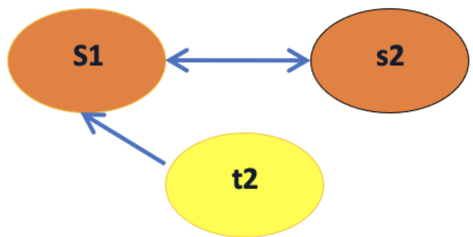
MAPSAT: Analysis of Patterns in Configurations (APC)

While APT is useful in coding and analyzing system dynamics (temporal sequences and changes), it does not capture system structure or structural changes. Thompson (2005a, 2005b) provided the significant insight that APT could be extended to characterize *structure* or configuration of educational systems, in addition to characterizing system *dynamics* – or processes in education – as APT was designed originally to do. Configural patterns characterize *structures* in education – i.e., how education is organized, or relations between parts. Axiomatic Theories of Intentional Systems (ATIS) provides the theoretical foundation for *quantitative* measures of system structure required by APC (Thompson, 2005a; 2005b; 2008c). These measures include: complexity, hierarchical order, heterarchical order, compactness, centrality, flexibility, active dependence, passive dependence, independence, interdependence, strongness, unilateralness, weakness, wholeness, and vulnerability.

ATIS is a systems theory that predicts relationships among system properties, both structural and dynamic. There are over 200 axioms and theorems in ATIS. For example, #106 predicts: *If system strongness increases, then toput increases*. See Thompson (2008a; 2008d) for further details and Frick and Thompson (2008) for examples of axioms relevant to systemic change in education

Structural relations are denoted in APC by system components that are connected by 'affect-relations.' For example, in Map 3, the 'support' affect-relation is depicted. 'Affect-relation' is used in the sense of a verb—e .g., *x* affects *y*[1]. The affect-relation set with respect to *Support*: {(*s1*,*s2*)(*s2*,*s1*)(*t2*,*s1*)} is another way of characterizing what is illustrated in the digraph (directed graph) in Map

Map 3. Example of 'support' affect-relations



3. During the observation of this small system, student *s1* supports *s2*; *s2* supports *s1*; and teacher *t2* supports *s1*. This configuration persists over some period of time and represents system structure with respect to the 'support' affect-relation.

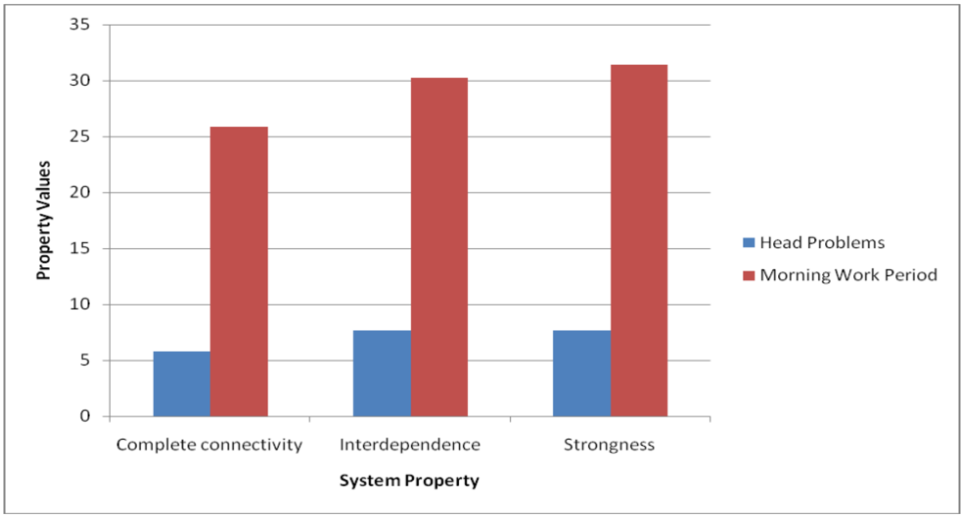
Frick and Koh (2007) explored in a case study how classroom structures support student autonomy in a Montessori classroom. Ten one-hour observations were conducted in April, 2006, in an upper elementary Montessori classroom located in southern Indiana. It had twenty-eight students, ages 10-12, a Montessori-certified head teacher and two assistant teachers.

Data on interactions between teachers, students and classroom resources were collected through ethnographic field notes. The constant comparative method (Creswell, 1998) was used to identify common interaction patterns and classroom activity structures. Digraphs were constructed based on these observations and field notes for two distinctly different kinds of activity settings: *Head problems* and the *Morning Work Period*. During *Head Problems*, all the students were expected to solve mathematics problems on a worksheet prepared by the teacher for that day that was distributed to the entire class

[1] Affect-relations are not about feelings or emotions—i.e., when 'affect' is used as a noun.

(typically lasting about 45 minutes). On the other hand, during *Morning Work Period* (typically lasting 3 hours), students were individually free to choose Montessori *Works* and engage in learning associated with those *Works* for as long as they wanted. Then a student could choose another work, etc. During the *Morning Work Period* students were often seen to be helping each other, many times working in twosomes or threesomes on the same activity; other students would individually meet with one of the teachers who would provide feedback on previously completed works. Figure 3 illustrates three ATIS

Figure 3. Structural properties for 'support' affect-relation in Montessori classroom during Head Problems and Morning Work Period (from Frick and Koh, 2007)



property measures that contrast the different activity structures typical in this Montessori classroom. It can be seen that there was much more ‘complete connectivity’, ‘interdependence’ and ‘strongness’ of the structure for ‘support’ affect-relations during the *Morning Work Period*, when contrasted with the *Head Problems* activity. How were these structural property measures obtained? These measures are defined in ATIS Graph Theory (Thompson, 2008c). Examples of these definitions are provided below:

$\mathcal{M}$: **Completeness measure**, $\mathcal{M}({}_{CC}\mathfrak{S})$, $=_{df}$ a measure of pair-wise directed component affect-relations.

$$\mathcal{M}({}_{CC}\mathfrak{S}) =_{df} \{[\textstyle\sum_{i=1,\ldots,n}\log_2(\prod_{j=1,\ldots,m}|\ell(\mathfrak{e}) \mid \mathfrak{e} = (u,v) \supset \exists\mathfrak{e}'[\mathfrak{e}' = (v,u)] \wedge \ell(\mathfrak{e}) \geq 1|_j)_i] \div \mathbf{C}\} \times 100$$

$\mathcal{M}$: **Interdependentness measure**, ${}_N\mathbb{S}$, $=_{df}$ a measure of components that are both initiating and receiving.

$$\mathcal{M}({}_N\mathbb{S}) =_{df} \{[\textstyle\sum_{i=1,\ldots,n}(\log_2\prod_{j=1,\ldots,m}|\ \mathsf{u} \mid \mathsf{u}\in{}_I\boldsymbol{E} \wedge \mathsf{u}\in{}_T\boldsymbol{E}\ |_j)_i] \div \mathbf{C}\} \times 100$$

$\mathcal{M}$: **Strongness measure**, ${}_S\mathbb{S}$, $=_{df}$ a measure of the shortest path between components.

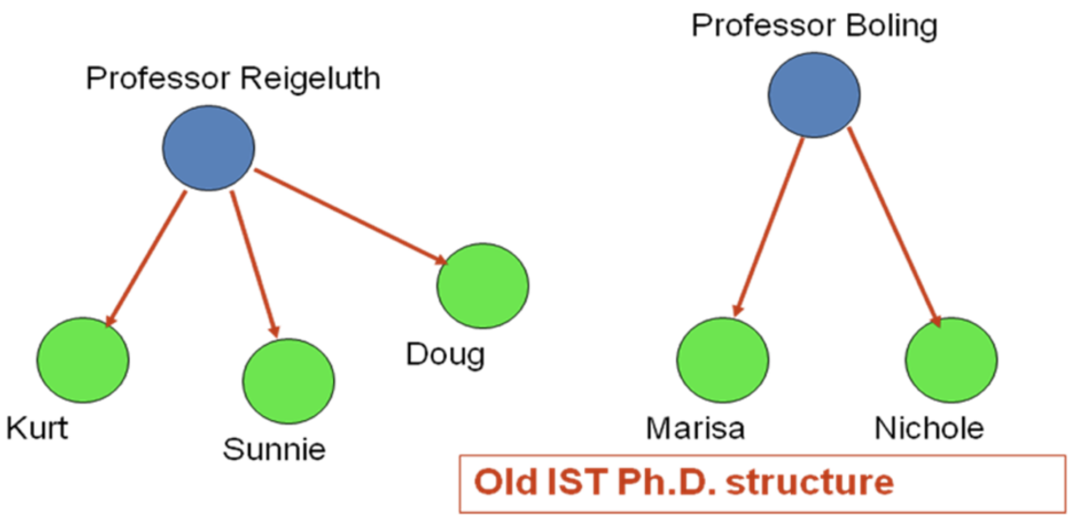
$$\mathcal{M}({}_S\mathbb{S}) =_{df} \{[\log_2\textstyle\sum_{i=1,\ldots,n}(\prod_{j=1,\ldots,m}(|\ \ell(e) \mid \ell(e) = \ell^{\min}(e)|_j)_i] \div \mathbf{C}\} \times 100$$

Space does not permit elaboration of these measures here; however, it is important to note that these measures were created such that they are consistent with ATIS axioms. Predicate calculus is used to define system properties and their measures. See the ATIS Glossary (Thompson, 2008b).

Example of Measuring Structural Change in a System

The Instructional Systems Technology (IST) Department at Indiana University has changed its Ph.D. program in order to give students more experience in doing research and to provide more faculty and peer mentoring. Maps 4 and 5 depict the differences in structure with respect to the 'mentoring' affect-relation. These maps are provided for purpose of illustration here, and so do not include all faculty and Ph.D. students in the IST program. By visual inspection, it is clear that more mentoring appears to be going on in the new Ph.D. structure, depicted by the red arrows in the digraphs. Table 4 shows the results of the structural measures, using results from MAPSAT software developed by Frick, Myers and York (2008). This example shows that, in the new doctoral program, the structure of mentoring affect-relations is more complex, flexible, interdependent and strong than the old program. The new program is also less vulnerable with respect to mentoring affect-relations. The number of components remains unchanged, but the structure has changed. See Thompson (2008c) for definitions of structural properties and their respective measures.

Map 4. Structure of 'mentors' affect-relation in old Ph.D. program, e.g., Professor Boling mentors Marisa and Nichole.



Map 5. Structure of 'mentors' affect-relation for new Ph.D. program

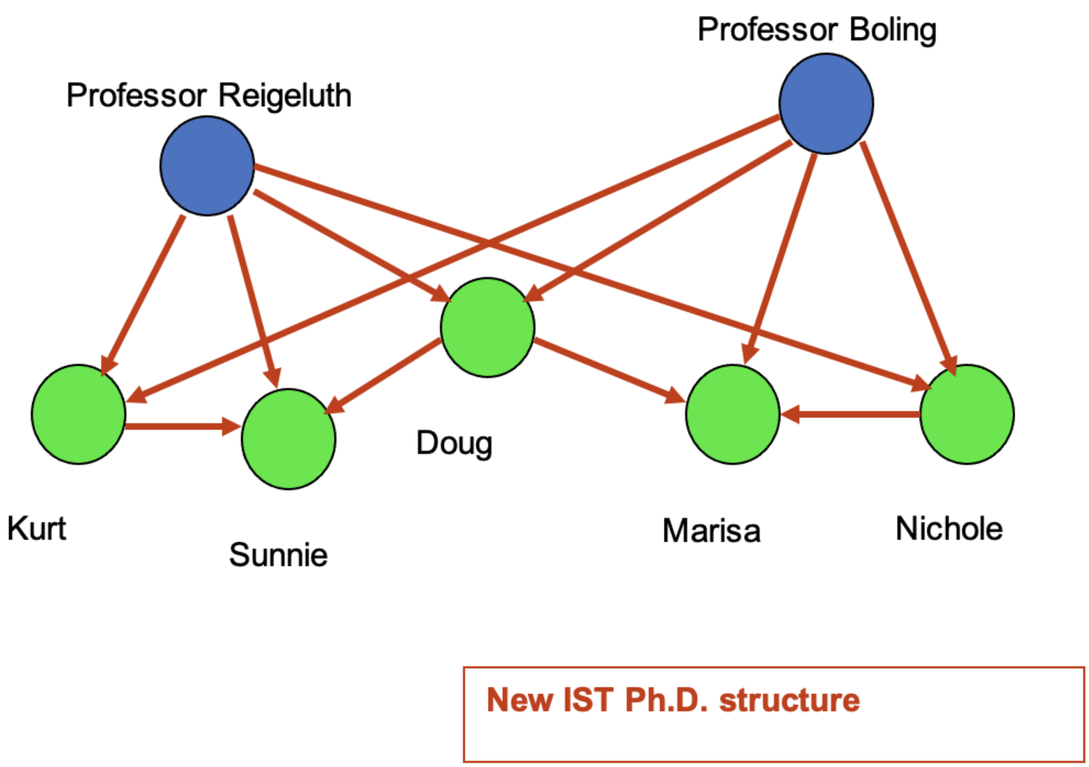


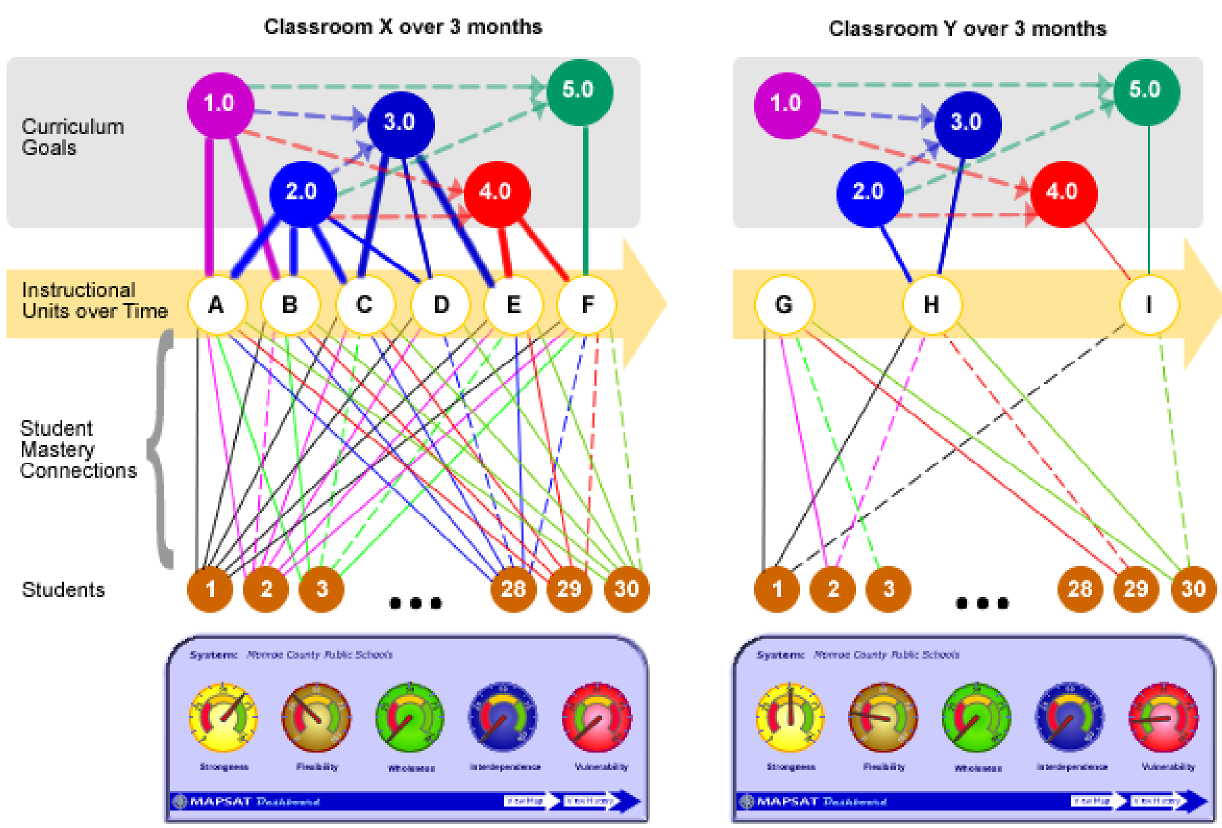
Table 3. Comparison of structural property values in old vs. new IST Ph.D. programs

ATIS Structural Property	*Old IST Ph.D Structure*	*New IST Ph.D. Structure*
Active Dependence	18.81	36.34
Complexity	5	14
Flexibility	0	44.90
Interdependence	0	37.62
Size	7	7
Strongness	18.81	89.80
Vulnerability	36.38	0

An Example of Extending Curriculum Mapping with MAPSAT APC

Heidi Hayes Jacobs (2004) is recognized as a pioneer in curriculum mapping, although this idea has been around for at least 20 years. Map 6 illustrates how a curriculum map is extended by goals that are linked to each other, to instructional units, and indirectly to students.

Map 6. Maps of two different classrooms, with MAPSAT Curriculum Dashboards illustrating different structure property values for strongness, flexibility, wholeness and vulnerability.



Assume that Goals 1 to 5 are important goals for students to achieve that prepare them for careers in science, technology, engineering and mathematics (STEM). Furthermore, notice that these goals are not independent but instead related to each other. For example, Goal 2 is prerequisite and supportive of Goals 3, 4 and 5.

Notice also that the curriculum *goal* maps for Classroom *X* and *Y* are *identical*, as can be seen in the gray shaded areas in the top part of Map 6. However, the remaining connectedness in the two classrooms is quite different. Classroom *X* is more *strongly connected* than is *Y*, even though they have identical curriculum goal structures. In the map of Classroom *X*, more students have mastered objectives in the instructional units, and those units in turn are more connected to the curriculum goal structure—when compared with Classroom *Y*'s map.

The maps in Map 6 go beyond what typical curriculum maps represent. Notice that these maps also include instructional units (IUs) that each classroom has completed over a period of 3 months, and the linkages of those IUs to each curriculum goal. For example in Classroom *X*, note that Goal 1 is supported by IUs *A* and *B*, and that Goal 2 is supported by IUs *A, B, C* and *D*. Alternatively, in Classroom *Y*, Goal 1 is not supported by any instructional unit, and Goal 2 is supported by *H* only. Finally, note how students in each classroom are connected to each instructional unit. A solid line indicates that that student has mastered the learning objectives in the instructional unit, whereas a dashed line indicates partial mastery. No line between a student and an IU means that the student failed to master objectives of that unit.

The MAPSAT Dashboard. Imagine for a moment that a school has an electronic dashboard that shows measures of properties of their *Student-Instructional Unit-Curriculum* maps for all classrooms and students in the school. Similar to how maps for classrooms are represented in Map 6, maps for an entire school could be measured. School principals, teachers, students and their parents could "see" how their school is doing at any time. A computer dashboard is analogous to the cockpit instrument panel that a pilot uses to fly an airplane. The instrument panel tells the pilot about important indicators such as the plane's heading, airspeed, and status of landing gear.

If a school system's curriculum goal structures are designed to help prepare high school students for STEM careers, then *the MAPSAT Curriculum Dashboard provides metrics about the connectivity of classroom instruction and student learning to those STEM-related goals.* Structures that have greater strongness, flexibility, interdependence and wholeness and with less vulnerability will better prepare students for STEM careers. The MAPSAT Dashboard will provide indicators of the effectiveness of STEM career preparation in a high school by measuring the *structure* of its curriculum, instruction and student learning.

Potential for Use of MAPSAT in Simulating Educational Systems

Learning to teach is an example of complex learning. We are designing a digital simulation that will allow preservice teachers to experiment with and practice providing individualized instruction for learners. Briefly, given a group of virtual students and specific academic goals, the teacher must select instructional activities that are effective, efficient, and engaging—i.e., take into consideration the student's interests, prior knowledge, and zone of proximal development; make best use of human and technological resources; and adhere to First Principles of Instruction (cf. Merrill, Barclay & van Schaak, 2008; van Merriënboer, Clark & de Croock, 2002). The simulation requires the teacher to perform the whole task initially in its simplest form, with one academic goal and one to three virtual students. Once the teacher achieves mastery at this level, more goals and students are added, requiring greater skill in grouping students for activities and utilizing technology.

We anticipate using MAPSAT in this simulation in two ways. First, as with the Curriculum Dashboard, MAPSAT's APC can be used to calculate the effectiveness of the teacher's decisions based on the property values for the virtual classroom. A teacher who is making good choices in matching students and instructional activities will have a classroom system with above average values for strongness, interdependence, and wholeness. Second, the teacher's decisions can be analyzed using MAPSAT's APT.

For example, particular sequences may be queried during the simulation and when found may trigger feedback to help the teacher identify and correct misperceptions. An APT map may also be generated for use in post-simulation debriefing to help the teacher see decision patterns and devise new strategies for subsequent sessions.

Summary

In this brief report we have attempted to provide an overview of a new way of measuring systems relations and systems change by providing a number of examples of MAPSAT research applications. We are in the process of developing computer software in order to facilitate the use of MAPSAT methods by other researchers. We believe that MAPSAT has great potential for helping researchers to better understand systemic change in education, as well as to evaluate instructional strategies and theories and complex learning. MAPSAT provides a different mindset for quantifying and examining relationships among phenomena. MAPSAT provides rigor in how patterns are identified and analyzed in educational systems.

References

Brandes, U. & Erlebach (Eds.) (2005). *Network analysis: Methodological foundations*. Berlin: Springer-Verlag.

Campbell, D. & Stanley, J. (1966). *Experimental and quasi-experimental designs for research*. Chicago: Rand McNally.

Creswell, J. W. (1998). *Qualitative inquiry and research design*. Thousand Oaks, CA: Sage Publications.

Creswell, J. W. (2003). *Research design: Qualitative, quantitative and mixed methods approaches* (2^{nd} ed.). Thousand Oaks, CA: Sage Publications.

Cronbach, L. & Snow, R. (1977). *Aptitudes and instructional methods: A handbook for research on interactions*. New York: Irvington.

Frick, T. (1983). Non-metric temporal path analysis: An alternative to the linear models approach for verification of stochastic educational relations. Bloomington, IN: Ph.D. dissertation. Retrieved June 3, 2008: https://tedfrick.sitehost.iu.edu/ntpa/ .

Frick, T. (1990). Analysis of patterns in time (APT): A method of recording and quantifying temporal relations in education. *American Educational Research Journal, 27*(1), 180-204.

Frick, T., An, J. & Koh, J. (2006). Patterns in Education: Linking Theory to Practice. In M. Simonson (Ed.), Proceedings of the Association for Educational Communication and Technology, Dallas, TX. Retrieved June 3, 2008: https://tedfrick.sitehost.iu.edu/aect2006/patterns.pdf .

Frick, T., Chadha, R.,Watson, C., Zlatskovksy, E., Green, P., & Chen, Z. (2008). Improving course evaluation to improve instruction and complex learning in higher education. Paper presented at the 2008 AECT Research Symposium, Bloomington, IN.

Frick, T. & Koh, J. (2007). Self-Regulation, Autonomy, and Expertise Development in Problem-Based or Design-Based Learning Environments. Paper presented at the 2007 American Educational Research Conference, Chicago, IL. Retrieved June 3, 2008: https://tedfrick.sitehost.iu.edu/montessori_AERA_2007.pdf.

Frick, T., Myers, R. & York, S. (2008). MAPSAT software: Map & Analyze Patterns & Structures Across Time. Bloomington, IN: Indiana University School of Education, Department of Instructional Systems Technology.

Frick, T. & Thompson, K. (2008). Predicting education system outcomes: A scientific approach. In M. Orey, V. J. McClendon & R.M. Branch (Eds.), *Educational Media and Technology Yearbook 2008* (Vol. 33). Westport, CT: Libraries Unlimited, 62-76.

Guba, E. & Lincoln, Y. (1985). *Naturalistic inquiry*. Newbury Park, CA: Sage.

Jacobs, H. H. (2004). *Getting results with curriculum mapping*. Alexandria, VA: Association for Supervision and Curriculum Development.

Jensen, F. & Nielsen, T. (2007). *Bayesian networks and decision graphs* (2nd Ed.). NY: Springer.

Koh, J. (2008). *The use of scaffolding in introductory technology skills introduction for preservice teachers*. Unpublished doctoral dissertation, Bloomington, IN: Indiana University Graduate School.

Kumar, V., Abbas, A., Fausto, N., (2005). *Robbins and Cotran pathologic basis of disease* (7th edition). Philadelphia: Elsevier/Saunders.

Medley, D. (1977). *Teacher competence and teacher effectiveness: A review of process-product research*. Washington, DC: American Association of Colleges for Teacher Education.

Medley, D. (1979). The effectiveness of teachers. In P. L. Peterson & H. Walberg (Eds), *Research in Teaching: Concepts, Findings, and Implications*. Berkeley, CA: McCutchan, 11-27.

Merriam, S. (1997). *Qualitative research and case study applications in education*. San Francisco: Jossey Bass.

Merrill, M. D., Barclay, M., & van Schaak, A. (2008). Prescriptive principles for instructional design. In J. M. Spector, M. D. Merrill, J. van Merriënboer & M. F. Driscoll (Eds.), *Handbook of research on educational communications and technology* (3rd ed.). New York: Lawrence Erlbaum Associates, 173-184.

Stake, R. (1995). *The art of case study research*. Thousand Oaks, CA: Sage.

Thompson, K. R. (2005a). "General system" defined for A-GSBT. *Scientific Inquiry Journal, 7*(1), 1-12. Retrieved July 4, 2007: https://aptfrick.sitehost.iu.edu/reports/SIJ-THOMPSON-1.pdf .

Thompson, K. R. (2005b). Axiomatic theories of intentional systems: Methodology of theory construction. *Scientific Inquiry Journal, 7*(1), 13-24. Retrieved July 4, 2007: https://aptfrick.sitehost.iu.edu/reports/SIJ-THOMPSON-2.pdf .

Thompson, K. R. (2008a). ATIS: Axiomatic Theories of Intentional Systems. Columbus, OH: System-Predictive Technologies. Retrieved June 3, 2008: https://aptac.sitehost.iu.edu/glossary/atisTheory.html .

Thompson, K. R. (2008b). ATIS glossary. Columbus, OH: System-Predictive Technologies. Retrieved June 3, 2008: https://aptac.sitehost.iu.edu/glossary/ .

Thompson, K. R. (2008c). ATIS graph theory. Columbus, OH: System-Predictive Technologies. Retrieved June 3, 2008: https://aptfrick.sitehost.iu.edu/reports/11ATISgraphtheory.pdf .

Thompson, K. R. (2008d). ATIS reports. Columbus, OH: System-Predictive Technologies. Retrieved June 3, 2008: https://aptfrick.sitehost.iu.edu/reports/ .

van Merriënboer, J. J. G. & Kirschner, P. A. (2007). *Ten steps to complex learning: A systematic approach to four-component instructional design*. Hillsdale, NJ: Lawrence Erlbaum Associates.

van Merriënboer, J. J. G., Clark, R. E., & de Croock, M. B. M. (2002). Blueprints for complex learning: The 4C/ID model. *Education Technology Research & Development*, *50*(2), 39-64.

Yin, R. (2003). *Case study research: Design and methods*. Thousand Oaks, CA: Sage.