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USING PATTERN MATCHING TO ASSESS GAMEPLAY

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Abstract: In this chapter we describe Analysis of Patterns in Time (APT) and how it can be used to analyze gameplay choices to provide evidence of a play-learner's understanding of concepts modeled in a game. APT is an empirical approach to observing and coding phenomena as mutually exclusive and exhaustive categories within classifications. These data form a temporal map of joint and sequential patterns. We examine the case of the online *Diffusion Simulation Game*. An algorithm calculates scores for gameplay data patterns and compares them with scores for patterns based on optimal strategies derived from the game's conceptual model. We discuss the results of using APT for analysis of game sessions for three play-learners. We describe how APT can be included as part of a serious game to conduct formative assessment and determine appropriate hints, coaching, or other forms of scaffolding during gameplay. We conclude by discussing APT methods for summative assessment.

Key words: pattern matching, gameplay strategies, assessment, models, scaffolding

1. INTRODUCTION

In this chapter, our goal is to illustrate the potential of Analysis of Patterns in Time (APT) as a way of measuring and analyzing play-learner interactions with a serious game, the *Diffusion Simulation Game* (DSG). First, we discuss APT and provide examples of a temporal map and APT queries. Next, we provide a brief overview of diffusion of innovations theory (DoI) and a description of the DSG. We then describe our procedure for applying APT to DSG play-learner data; we analyze temporal maps of multiple DSG games played by three different play-learners of varying proficiency, in order to illustrate how APT can detect patterns of play-learner moves and determine how consistent those patterns of play are with expert strategies based on DoI theory.

Finally, we discuss the potential of APT to measure what play-learners are learning over time as they interact with a simulation or game, and how such pattern analysis could be used by an intelligent agent in the game to determine appropriate hints, coaching, or other forms of scaffolding during gameplay to improve learning and performance.

2. OVERVIEW OF *MAPSAT*: MAP & ANALYZE PATTERNS & STRUCTURES ACROSS TIME

MAPSAT is a different approach to measurement and analysis of data, when compared to traditional methods. Compare these two sets of findings:

a. MAPSAT: Students in elementary schools are about 13 times more likely to be off-task during non-interactive classroom instruction, when compared with their engagement during interactive instruction.
b. Linear Models Approach (LMA): The amount of interactive classroom instruction predicts 32% of the variance in student task engagement, leaving 68% of the variance unexplained.

These results are based on the *same* classroom observation data (see Frick, 1990). What's the difference? The short answer: MAPSAT *measures the relation*. The LMA *relates the measures*.

We first discuss the traditional methods, which should be familiar to most readers. Next we address the theoretical background of MAPSAT, why and how it is different from the LMA, and why it is theoretically impossible to derive *a* from *b* above. We conclude with an example of a specific temporal map and then illustrate APT queries for counting patterns.

2.1 Traditional quantitative methods of measurement and analysis of data

In traditional quantitative research methods that are based on algebraic linear models, we typically obtain *separate measures of variables*, and then statistically analyze relations among measures (e.g., linear, curvilinear or logistic regression analysis). That is, we *relate measures*. This approach, which assumes linear and additive models, can result in aggregation aggravation—that is, obfuscation of important relationships due to assumptions in this approach (Frick, 1983, 1990; Frick, Myers, Thompson, & York, 2008).

In traditional measurement we aggregate units when we obtain a value for a variable. For example, we aggregate (count) the number of inches when we measure a person's height, or we count the number of pounds when we measure someone's weight. We repeat this process of *independent* aggregations for more persons' heights and weights. Then we attempt a statistical analysis of these sets of independent measures, such as correlation or linear regression. This kind of thinking stems from algebra, for example, $y = Bx + C$, where variable y is measured separately from variable x, and a *functional relationship is assumed* to exist between x and y, where B is the slope and C is a constant.

Specifically, imagine a spreadsheet of data. Normally each row in the spreadsheet would contain data on a single case, columns are for variable names, and in each cell a value for each variable is entered. See Table 1 for an example.

Table 1. Example of a typical spreadsheet for traditional quantitative analyses.

Case	**Gender**	**Height in Inches**	**Weight in Pounds**
1	male	70	200
2	female	60	120

Notice that a variable has a *single* value for each case, and these values are typically determined by separate measures for each case. In order to determine a relation between two variables, we would do a correlational analysis such as a Pearson Product Moment Correlation. This would be a statistical relation between separate measures, for example, between a person's height and his/her weight. It could also be an analysis of variance (ANOVA) to determine a statistical relationship between values of gender and height. Or we might perform a multiple regression analysis in order to predict a person's weight from knowledge of a person's gender and height.

2.2 Theoretical foundations of MAPSAT methods

While investigating the SIGGS theory model (Maccia & Maccia, 1966), Frick discovered that the measures of uncertainty in information theory were inadequate for predicting specific temporal patterns (Frick, 1983). SIGGS is grounded in *set* (S), *information* (I), *di-graph* (G) and *general systems* (GS) theories. SIGGS is a complex theory model with precise definitions of systems' dynamic and structural properties such as toput, strongness, adaptibility, stress, wholeness, and so forth. SIGGS was used to develop a theory of education, consisting of 201 hypotheses. Space does not permit further description here. See https://www.indiana.edu/~tedfrick/siggs.html.

In SIGGS, *information* is defined as a "characterization of occurrences" (Maccia & Maccia, 1966, p. 40), and in turn is further defined mathematically via set theory and probability theory (pp. 10-23, 40-53). Frick (1983) interpreted these occurrences as temporal events, characterized by classifications and categories used when observing empirical phenomena.

Determination of values of SIGGS properties of *feedin*, *feedout*, *feedthrough* and *feedback* requires measures of temporal patterns. More specifically *feedin* is defined as transmission of information (occurrences of elements) from *toput* at *time 1* to *input* at *time 2.* For example, the distribution of students who *apply* to various degree programs at a university in the spring are part of *toput*, and those students who are subsequently *admitted and attend* in the fall then become part of the *input* distribution of students in those degree programs in that particular education system. Similarly, *feedthrough* is defined in SIGGS as *feedin* followed later by *feedout*. For example, students matriculate (*feedin*), and later they graduate, drop out, or flunk out (*feedout—fromput* followed by *output*); this entire set of trajectories constitutes that system's student *feedthrough*.

In set theory, a *relation* is the Cartesian Product of two or more sets of elements. Such a relation consists of a set of ordered pairs of elements, or more generally, *tuples*. Each *n*-tuple characterizes a pattern—that is, a conjoining of elements. For example, a *4*-tuple characterizes the *feedthrough* of a particular student from *toput* at *time 1*, to *input* at *time 2*, to *fromput* at *time 3*, to *output* at *time 4*. One student might apply to a university music program (*toput*), be admitted as a music major (*input*), later change her major, completing a bachelor's degree in computer science (*fromput*), then get a good-paying job as a software engineer after graduation (*output*). Another *4*-tuple is characterized by a different student who applies for a computer science major, but instead gets admitted to a general studies program, later leaves the university with no degree, and then is employed in a low-paying job.

When occurrences of students moving through the university are mapped into categories of classifications which represent *4*-tuples, a *joint probability distribution* can be formed (from the Cartesian Product of *toput*, *input*, *fromput*, and *output* classifications which determine student *feedthrough* for the university). However, the *T* and *B* measures from information theory (Maccia & Maccia, 1966; Coombs, Dawes, & Tversky, 1970) do not provide specific predictions of temporal patterns (or trajectories); rather *T* and *B* coefficients are *measures of overall uncertainty* in the joint probability distributions of temporal occurrences. This is analogous to how an *F*-test in ANOVA indicates overall statistical significance, but does not tell us which contrasts are significant when there are more than two group means being compared.

Moreover, Frick (1983) subsequently proved mathematically that marginals (e.g., *toput*, *input*, *fromput*, *output*) of joint probability distributions cannot dependably predict cell values, that is, probabilities of conjoint occurrences of temporal events (e.g., *feedin*, *feedout*, *feedthrough*, *feedback*). He concludes:

> There is no unique solution to this set of equations [18 – 21, from the calculus of probability theory], since the determinate of the matrix of coefficients is zero.… The mathematical conclusion is that there is no way to uniquely determine the joint probability distribution given only the marginal probability distributions, except in a few special cases where the marginal probabilities are zeros and ones, or all equal. (p. 79)

Hence, the need for alternative methods was justified theoretically. APT was invented as such an alternative approach, which has been further developed into MAPSAT in recent years. Frick (1983, 1990) emphasized that the traditional approach taken to measurement in the LMA only uses marginal distributions, wherein variables are measured separately and then their relationships are estimated by statistical analysis (see section 2.1 above).

2.3 Pros and cons of MAPSAT methods

The primary advantage of using MAPSAT methods is that *researchers can detect relations (temporal or structural patterns) that cannot be revealed by the linear models approach*. This is because the LMA assumes a *functional* relationship between two or more variables that are measured separately. MAPSAT methods do not assume *functional* relations—that is, algebraic equations which are mathematical functions in the set-theoretic sense. In set theory, the difference between a *relation* and a *function* is clearly defined (e.g., see Coombs, Dawes, & Tversky, 1970, pp. 361-371).

The primary disadvantage of using MAPSAT methods is that *most researchers will first need to learn how to use them appropriately*. This is analogous to how one must learn about traditional measurement and statistics in order to use ANOVA, MANOVA, and linear/logistic regression methods. On the other hand, MAPSAT methods are much easier to learn and understand, since no complex mathematics, algebra, or statistics is required.

Use of MAPSAT methods requires a different approach to measurement of relations, since temporal and structural patterns are measured directly through observation of empirical phenomena. This requires development of a well-defined coding scheme that is related to research questions of interest. Then human observers must be trained to use the coding scheme. Subsequently they must observe and code empirical phenomena to obtain the temporal or structural maps needed for addressing research questions. Human judgment is normally required in order to discriminate phenomena observed and to use well-defined classifications and their respective categories when creating temporal or structural maps. This requires quantitative and performative intelligence, and in particular *instantial* "knowing that" and *performative* "knowing how" (see Frick, 1997, pp. 111-115). If such discrimination and skill can be accomplished by computers and related technologies, then software could be written which can classify and categorize empirical phenomena to create such maps—if this is possible and can be done reliably.

MAPSAT does not directly inform a researcher which patterns are highly predictable or not. Such patterns may be anticipated from theoretical expectations or research questions, or they may be discovered serendipitously by visual examination of temporal maps. MAPSAT queries of temporal maps must be performed in order to get measures of temporal relations, such as conditional probabilities of patterns or proportion time.

MAPSAT pattern *results* can be used with quantitative research methods such as the LMA so that generalizations can be made from a sample to a population (Frick, 1990). We illustrate MAPSAT for several cases in this chapter. Space does not permit illustration of inferential statistics with MAPSAT here. See Frick, Myers, Thompson, and York (2008) for descriptions of research studies using MAPSAT methods and statistical inference.

Finally, use of the LMA is appropriate when the goal of research is to discover or verify functional relationships—that is, characterized by algebraic equations. MAPSAT is appropriate for research whose goals are to discover or verify patterns that are ones that are not perfectly predictable (i.e., stochastic), in contrast to deterministic patterns where there is no uncertainty. See Frick (1983, 1990) for an in-depth discussion.

2.4 MAPSAT methods

In MAPSAT, we *measure relations* directly. This is not a play on words, but a significant paradigm change in conceptualizing research problems and how we collect and analyze data: *map relations* instead of *measure variables*, and then *analyze relation maps* instead of *statistically associating variables*. We call this alternative approach MAPSAT: Map & Analyze Patterns & Structures Across Time.

MAPSAT yields results from analysis of occurrences of categorical relations (i.e., *n*-tuples from a Cartesian Product in set theory), not a statistical analysis of separate measures of variables, results from which might yield a correlation coefficient or regression equation for describing a relationship. In MAPSAT, there are two approaches that can be taken. In the *Analysis of Patterns in Time* (APT) approach, we map *temporal* relations. In the *Analysis of Patterns in Configuration* (APC) approach, we construct a map of structural relations, called *affect-relations*, in a system.

Dynamic Bayesian Network Analysis (DBNA) is similar to APT (cf. Jensen & Nielsen, 2007). However, APT methods differ from DBNA in that *Bayes Theorem is not assumed in APT* nor used in computing conditional probabilities; rather relative frequencies of temporal sequences or proportion of time determine APT conditional probabilities. There are other differences as well, particularly concerning assumptions about measurement itself. For an in-depth discussion of differences among APT, Bayesian reasoning, and the Linear Models Approach, see Frick (1983, 1990). For brief descriptions of examples of empirical research studies that use APT methods, see Frick, Myers, Thompson and York (2008).

2.5 Fundamentals of APT

In APT we create a *temporal map* as the *basic unit of measure*. So, instead of putting a single value of a variable in a cell of a spreadsheet, imagine that *each spreadsheet cell contains another spreadsheet*. What is a temporal map in APT? Table 2 illustrates a temporal map that might be created by an amateur meteorologist.

Table 2. Temporal map from observation and coding of weather events, adapted from Frick (1990). This entire temporal configuration of event occurrences would be inserted into *one cell* in a spreadsheet and would replace a single cell value as illustrated in Table 1.

JTE	*Unix Epoch Time Started: Duration of JTE*	*Season of Year*	*Air Temperature (degrees F)*	*Barometric Pressure (p.s.i.)*	*Precipitation*	*Cloud Structure*
1	1417436508: dur. = 1470	{ Fall	{ 33	{ Above 30	{ Null	{ Cirrus
2	1417437978: dur. = 2277	|	|	{ Below 30	|	|
3	1417440255: dur. = 2554	|	|	|	|	{ Nimbus Stratus
4	1417442809: dur. = 794	|	|	|	{ Rain	|
5	1417443603: dur. = 1095	|	{ 32	|	|	|
6	1417444698: dur. = 477	|	|	|	{ Sleet	|
7	1417445175: dur. = 721	|	{ 31	|	|	|
8	1417445896: dur. = 1026	|	|	|	{ Snow	|
9	1417446922: dur. = 1207	|	{ 32	|	|	|
10	1417448129: dur. = 410	|	{ 33	|	|	|
11	1417448539: dur. = 442	|	|	|	{ Sleet	|
12	1417448981: dur. = 738	|	{ 34	|	|	|
13	1417449719: dur. = 2647	|	|	|	{ Rain	|
14	1417452366: dur. = 1325	|	|	|	{ Null	|
15	1417453691: dur. = 157	|	|	{ Above 30	|	|
16	1417453848: dur. = 780	|	{ 35	|	|	|
17	1417454628: dur. = 1464	|	|	|	|	{ Null
18	1417456092: dur. = 1	|	{ 36	|	|	|

There are 18 joint temporal events (JTEs) in the temporal map in Table 2. Each joint event is coded at some point in time. Cells in column 2 contain information about the Unix Epoch Time (elapsed seconds since Jan. 1, 1970), as well as the duration of the joint event (in seconds). There are 5 classifications indicated by columns: season of year, air temperature in degrees Fahrenheit, barometric pressure, precipitation and cloud structure.

Each singular temporal event (STE) is indicated in a cell. Every STE has associated with it the time it was coded, an event state (where a { indicates that there is a change in the classification value from what was coded earlier, and a | means that the previously coded event is continuing). For example, in JTE 4, precipitation changes to rain ({rain), while season continues to be fall, temperature continues to be 33 degrees, barometric pressure continues to be below 30 pounds per square inch (p.s.i.), and cloud structure continues as nimbus-stratus. At JTE 6, precipitation changes to sleet, while the states of the other classifications continue.

Classifications consist of mutually exclusive and exhaustive event value designations. For example, if precipitation is rain, then it cannot be sleet or snow at that point in time when observing weather on Dec. 1, 2014, at a specific location. The null value means that there is nothing relevant to the classification that can be coded at that point in time. Event values can be categories (nominal), ranks (ordinal), whole numbers (interval) or decimal numbers (ratio).

2.6 Examples of patterns and associated queries in APT

An APT query specifies a temporal pattern and returns results of matches found in the temporal map. This is what we mean by *measuring a relation* in APT. Results are reported below for both duration and frequency of pattern instances found in the temporal map illustrated in Table 2.

Pattern 1: APT Query for a 2-phrase sequential pattern

WHILE the FIRST Joint Temporal Event is true (Phrase 1):

Season of Year is in state *starting or continuing*, value = *Fall*

Barometric Pressure is in state *starting or continuing*, value = *Below 30*

Cloud Structure is in state *starting or continuing*, value = *Nimbus Stratus*

- Duration when Phrase 1 is True = 13,436 seconds (out of 19,584 seconds total). Proportion of Time = 0.68607
- Joint Event Frequency when Phrase 1 is True = 12 (out of 18 total joint temporal events). Proportion of JTEs = 0.66667

THEN while the NEXT Joint Temporal Event is true (Phrase 2):

Season of Year is in state *starting or continuing*, value = *Fall*

Barometric Pressure is in state *starting or continuing*, value = *Below 30*

Precipitation is in state *starting or continuing*, value = *Rain*

Cloud Structure is in state *starting or continuing*, value = *Nimbus Stratus*

- Duration when Phrase 2 is True = 4,086 seconds (out of 19,584 seconds total), given all prior phrases are true. Proportion of Time = 0.20864

- Joint Event Frequency when Phrase 2 is True = 3 (out of 18 total joint temporal events), given all prior phrases are true. Proportion of JTEs = 0.16667

- Conditional joint event *duration* when Phrase 2 is true, given all prior phrases are true = 0.30411 (4,086 out of 13,436 seconds (time units)).
- Conditional joint event *frequency* when Phrase 2 is true, given all prior phrases are true = 0.25000 (3 out of 12 joint temporal events).

This is a 2-phrase APT query for Pattern 1. Each phrase specifies the conditions which must be true for that phrase to be true (a match) in the temporal map. Furthermore, the second phrase will *not* be considered a match in the map unless (a) it occurs *after* the first phrase becomes true and (b) all conditions in both the first *and* second phrases remain true in the map. Based on the observations coded in the map in Table 2, the proportion of time that precipitation was rain is 0.304, given that it was first true that the season was fall, the barometric pressure was below 30 p.s.i. and cloud structure was nimbus stratus. Another way of stating this is that the likelihood of rain occurring at some point in time was 0.304 under these prior conditions.

Pattern 2: APT query for a 4-phrase sequential pattern

WHILE the FIRST Joint Temporal Event is true (Phrase 1):

Cloud Structure is in state *starting or continuing*, value = *Nimbus Stratus*

- Duration when Phrase 1 is True = 14,373 seconds (out of 19,584 seconds total). Proportion of Time = 0.73392
- Joint Event Frequency when Phrase 1 is True = 14 (out of 18 total joint temporal events). Proportion of JTEs = 0.77778

THEN while the NEXT Joint Temporal Event is true (Phrase 2):

Barometric Pressure is in state *starting or continuing*, value = *Below 30*

Cloud Structure is in state *starting or continuing*, value = *Nimbus Stratus*

- Duration when Phrase 2 is True = 12,111 seconds (out of 19,584 seconds total), given all prior phrases are true. Proportion of Time = 0.61841
- Joint Event Frequency when Phrase 2 is True = 11 (out of 18 total joint temporal events), given all prior phrases are true. Proportion of JTEs = 0.61111

- Conditional joint event *duration* when Phrase 2 is true, given all prior phrases are true = 0.84262 (12,111 out of 14,373 seconds (time units).
- Conditional joint event *frequency* when Phrase 2 is true, given all prior phrases are true = 0.78571 (11 out of 14 joint temporal events).

THEN while the NEXT Joint Temporal Event is true (Phrase 3):

Air Temperature is in state *starting or continuing*, value <= *32*

Barometric Pressure is in state *starting or continuing*, value = *Below 30*

Precipitation is in state *starting or continuing*, value = *Sleet*

Cloud Structure is in state *starting or continuing*, value = *Nimbus Stratus*

- Duration when Phrase 3 is True = 1,889 seconds (out of 19,584 seconds total), given all prior phrases are true. Proportion of Time = 0.09646
- Joint Event Frequency when Phrase 3 is True = 2 (out of 18 total joint temporal events), given all prior phrases are true. Proportion of JTEs = 0.11111

- Conditional joint event *duration* when Phrase 3 is true, given all prior phrases are true = 0.15597 (1,889 out of 12,111 seconds (time units).
- Conditional joint event *frequency* when Phrase 3 is true, given all prior phrases are true = 0.18182 (2 out of 11 joint temporal events).

THEN while the NEXT Joint Temporal Event is true (Phrase 4):

Air Temperature is in state *starting or continuing*, value <= *31*

Barometric Pressure is in state *starting or continuing*, value = *Below 30*

Precipitation is in state *starting or continuing*, value = *Snow*

Cloud Structure is in state *starting or continuing*, value = *Nimbus Stratus*

- Duration when Phrase 4 is True = 1,095 seconds (out of 19,584 seconds total), given all prior phrases are true. Proportion of Time = 0.05591
- Joint Event Frequency when Phrase 4 is True = 1 (out of 18 total joint temporal events), given all prior phrases are true. Proportion of JTEs = 0.05556

- Conditional joint event *duration* when Phrase 4 is true, given all prior phrases are true = 0.57967 (1,095 out of 1,889 seconds (time units)).
- Conditional joint event *frequency* when Phrase 4 is true, given all prior phrases are true = 0.50000 (1 out of 2 joint temporal events).

This 4-phrase query for Pattern 2 is more complex. First, cloud structure becomes nimbus-stratus, then second, barometric pressure becomes less than 30 p.s.i., then third, air temperature becomes less than or equal to 32 degrees and precipitation becomes sleet, then fourth, air temperature becomes less than or equal to 31 degrees and precipitation becomes snow. The likelihood of the fourth phrase being true is 0.58, given that the first three phrases become true in the order specified, and remain true.

Space does not permit description of matching and counting algorithms in APT. Nonetheless, it should be clear that complex combinations of events and event sequences can be counted by querying temporal maps.

The results of these two queries could be put into a spreadsheet, as can be seen in Table 3, which shows the pattern probabilities for three different temporal maps (maps 2 and 3 not shown here). The *pattern specified* in the query becomes the *variable* and the results of the APT measure of the pattern becomes the *value* that could be put into a spreadsheet cell in SPSS or Excel. One can, for example, then compute means and standard deviations on APT query results for each pattern and perform other statistical analyses of these pattern measures. For example, the statistical correlation between measures of Pattern 1 and 2 from these three temporal maps is highly negative (-0.86, meaning the *higher* the probability of Pattern 1 [when nimbus stratus clouds and p.s.i. < 30, then rain follows], the *lower* the probability of Pattern 2 [when nimbus stratus clouds, then p.s.i. < 30, then temp <= 32 F and sleet, then temp <=31 and snow follows]).

Table 3. Example of a spreadsheet with APT query results for temporal patterns as the variables. The value in each cell is a measure of the probability of the relation (pattern).

Map	**Pattern 1**	**Pattern 2**
1	0.30	0.58
2	0.25	0.67
3	0.40	0.56
Mean	0.317	0.603
(Standard Deviation)	0.076	0.059

In summary, in APT we measure relations directly by identifying and matching patterns in temporal maps. Note that, in this chapter, we focus on APT, and while we show how APT can be used to map and analyze temporal relations in the Diffusion Simulation Game (DSG), MAPSAT methods can be used for many kinds of research problems (see Frick, et al., 2008)

3. DIFFUSION OF INNOVATIONS THEORY AND THE DIFFUSION SIMULATION GAME

To illustrate how APT is used for serious games analytics, we will next examine data from several play-learners who played the DSG, a simulation game that models aspects of DoI theory. In order to be successful in the game, play-learners must apply DoI theory in appropriate and timely ways.

3.1 Diffusion of innovations theory

While working on his doctoral dissertation on the diffusion of agricultural innovations, Everett Rogers became convinced that the diffusion of innovations followed a general pattern regardless of the type of innovation or the culture in which it was spreading (Rogers, 2003). He began developing a general model of diffusion and published the first edition of his book, *Diffusion of Innovations*, in 1962. Each subsequent decade he published an updated edition as he reviewed the latest research and theoretical developments and refined the model. At the time of publication of the fifth edition (2003), Rogers estimated that there were about 5,200 publications on diffusion, with roughly 120 new diffusion publications each year.

Rogers defines "diffusion" as a social process "in which an innovation is communicated through certain channels over time among members of a social system" (p. 5). The goal of communication with respect to an innovation is to reduce uncertainty by sharing information and subjective evaluations of the innovation. Rogers' definition contains four main elements that are key to understanding the model, including

1. the nature and attributes of the innovation;
2. the communication channels through which information is disseminated;
3. the time required for individuals to make a decision regarding the adoption of the innovation;
4. the social system through which the innovation is diffused.

A detailed description of DoI theory is beyond the scope of this chapter. However, knowing a little about a few key aspects of the model will aid in understanding the simulation game that is the focus of this chapter's analysis.

A **communication channel** is "the means by which messages get from one individual to another" (Rogers, 2003, p. 18). *Mass media channels* enable a small number of people to spread their messages to a large audience. Mass media channels are generally effective in creating awareness about the existence of an innovation, especially among earlier adopters who tend to pay more attention to external sources of information. *Interpersonal channels* "involve a face-to-face exchange between two or more individuals" (p. 18). Interpersonal communication is less effective in creating awareness or interest in an innovation and more effective in persuading someone to try an innovation about which they are already aware, especially if the message is coming from someone who is "similar in socioeconomic status, education, or other important ways" (p. 18).

Based on decades of observation and research, Rogers developed a model of the **innovation-decision process**, which he defines as

> the process through which an individual (or other decision-making unit) passes from first knowledge of an innovation, to the formation of an attitude toward the innovation, to a decision to adopt or reject, to implementation and use of the new idea, and to confirmation of this decision (p. 20).

Rogers describes five stages in this process. In the first edition of his book (Rogers, 1962), these stages were: awareness, interest, appraisal, trial, and adoption. By the fifth edition (Rogers, 2003) these stages had become: knowledge, persuasion, decision, implementation, and confirmation—and he contends that they usually occur in this specific sequence unless, for example, the decision stage precedes the persuasion stage because adoption was declared mandatory by an authority figure.

Rogers categorizes the individuals who form a **social system** according to their *innovativeness*, which he defines as “the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than the other members of a system” (p. 22). The five categories range from *innovators*, who actively seek information about new ideas through relatively greater exposure to mass media and interpersonal networks that extend well beyond their local system, to *laggards*, who are the least connected to others in the system with many being near isolates, making them difficult to influence. *Early adopters* are of particular importance in the diffusion of an innovation because they have “the highest degree of opinion leadership in most systems” (p. 283), making them crucial in achieving a critical mass of adopters and influencing later adopters.

3.2 The Diffusion Simulation Game

The original DSG was conceived and created “in 1975-76 at Indiana University by an Instructional Development Center team composed of professor Michael Molenda and six IST [Instructional Systems Technology] graduate students, led by Patricia Young and Dale Johnson” (M. H. Molenda, personal communication, May 9, 2011). The board game was to be used during a day-long workshop, and Molenda and Rice (1979) reported that it underwent extensive formative evaluation and refinement to ensure that the affective and cognitive objectives were achieved. Among these objectives were the ability to classify individuals by adopter type and communication role (e.g., opinion leader) based on described attributes, to identify the stages of the innovation-decision process, and to select the most effective diffusion activities based on the available information.

In the DSG, the player takes on the role of a change agent whose task is to influence the principal and teachers at a junior high school to adopt peer tutoring. The player may gather information about each staff member and also view diagrams of professional and interpersonal networks.

The player may also choose from a variety of diffusion activities, some of which target a single individual or up to five people. For example, the player may use the “Talk To” activity to have a face-to-face discussion with one staff member; the “Print” activity to distribute written materials to as many as five staff members; or the “Local Mass Media” activity to influence those who pay attention to the mass media. Each activity requires from one to six weeks to complete, and the player has two academic years (72 weeks) to persuade as many staff members as possible to move through the stages of the innovation-decision process and adopt peer tutoring.

The results of a player’s choices are determined by an “algorithm board” (Molenda & Rice, 1979, p. 462) shown in Figure 1. The circled numbers in

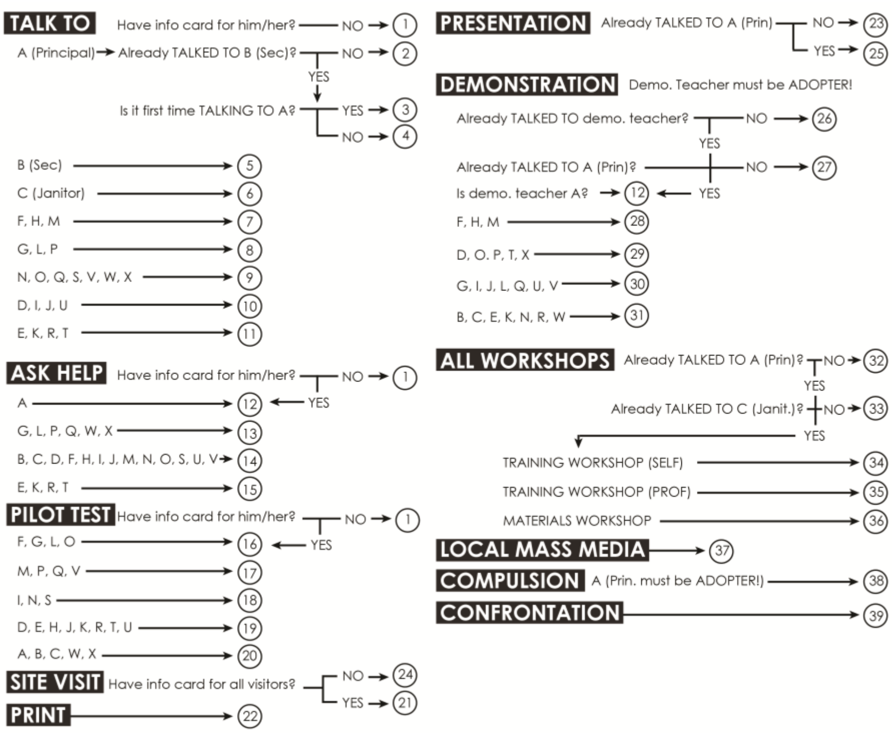

Figure 1. Algorithm board in the original Diffusion Simulation Game (Molenda & Rice, 1979).

Figure 1 indicate which group of feedback cards should be accessed, one of which is randomly selected. Based on the chosen activity, the affected staff members, and in many cases previously chosen activities, the game monitor consults the algorithm board to determine the outcome. For example, if the "Talk To" activity is selected along with one of the opinion leaders (represented in the game by the letters F, H, and M), the game monitor is instructed to refer to the card set represented by the number 7. This particular card set contains six cards, five of which provide positive feedback and reward points, such as:

> He/she listens attentively to your ideas and shares them with his/her out-of-school compatriots. GAIN 2 POINTS FOR HIM/HER and ONE POINT FOR EACH OF HIS/HER SOCIAL CONTACTS.

The sixth card also provides positive feedback but does not reward points:

> A potentially useful contact; if he/she adopts, a number of others will be favorably disposed. Unfortunately, this is the week his/her family was moving into a new home…no time for serious talk. May be worth trying again later. NO POINTS.

The slight possibility of unfavorable results for what should be effective strategies is meant to model the stochastic nature of dealing with human beings in the real world. One of the affective goals of the game is to foster appreciation for the difficulty of diffusing an innovation.

In 2002, Frick led a development team in the creation of the DSG as an online simulation game (Frick, Kim, Ludwig, & Huang, 2003). Figure 2 shows the interface for this online version, which was developed using HTML, CSS, and XML for information display and storage, and PHP for interaction programming. The latest version of the game may be accessed at https://www.indiana.edu/~simed/diffusion/.

In Figure 2, staff members (A-X) are listed on the left, with filled rectangles indicating each staff member's stage of adoption. Activities for getting information about staff members and diffusion activities are listed on the right. Elapsed time in weeks is shown on the top right. Vertical scrolling is typically required to see the entire game board in a Web browser.

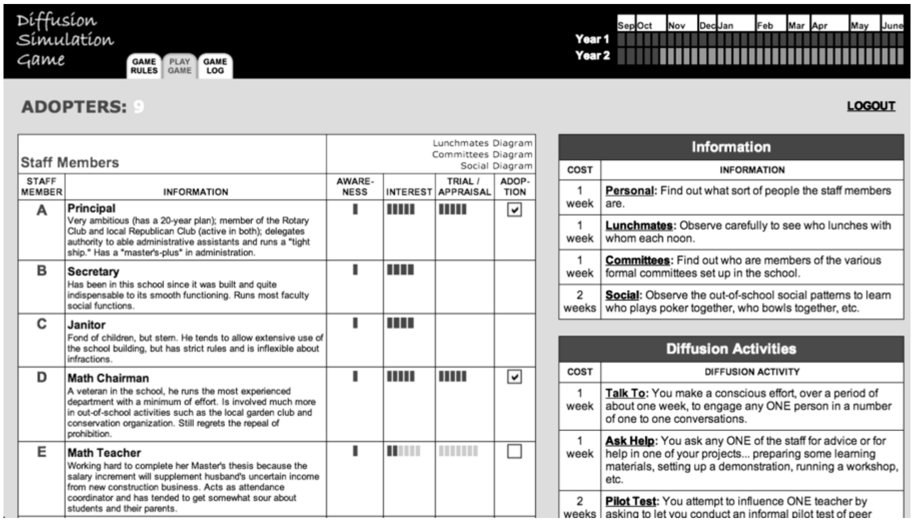

Figure 2. Partial image of the online *Diffusion Simulation Game.*

Since 2006, when Frick released a public version with anonymous login, data from more than 30,000 game sessions have been collected (through April, 2014).

4. APPLICATION OF *APT* TO *DSG* PLAY-LEARNER DATA

As with any designed learning experience, with serious games we must specify performance indicators of learning. Because the DSG uses DoI as its primary conceptual model, we began by identifying generalizations from *Diffusion of Innovations* (Rogers, 2003) that were applicable while playing the DSG. For example, Rogers says that mass media should be effective in spreading knowledge about an innovation, especially among innovators and early adopters. We then mapped these statements to actions that may be taken in the DSG, which involve combinations of activities, adopter types, and innovation-decision phases. Next we identified data associated with these actions and designed a database for data collection in which the columns are event classifications (e.g., activity selected, current stage in the innovation-decision process for each staff member) and the rows contain the relevant categories in each classification for each turn in a game.

We specified two general kinds of strategies. The first kind of strategy involved the selection of an activity available in the game at an appropriate time to influence staff members at particular stages of the innovation-decision process. Some activities, here referred to as *targeted* activities, require the selection of one or up to five staff members (targets). For example, the *Talk To* activity requires the selection of one staff member, while the *Site Visit* activity allows the selection of up to five staff members. The second kind of strategy involved the selection of particular staff members based on their attributes, which include adopter type, opinion leadership, and interpersonal relationships.

We specified nine strategies from DoI that should lead to success in the DSG, subsequently reviewed and confirmed by experts in DoI (Myers, 2012). Each of these strategies consisted of a pattern of joint occurrences of categories within the various classifications. To continue the example above, Strategy 3 says to use the Local Mass Media activity to gain points in the Awareness and Interest phases among earlier adopters. For details on the strategies, see Myers (2012, pp. 82-87).

In addition to the improvements to the DSG's computational model described above, we implemented a registration and login system to replace anonymous gameplay. This enabled us to associate multiple games with a single play-learner so that we could look for changes in patterns of strategy use over time. We also wrote a strategy scoring algorithm that analyzed the game state and assigned a score to each strategy based on the likelihood of its success in that turn. Strategy 3 would be assigned a high score if all or most of the earlier adopters needed points in the Awareness or Interest phases. Otherwise it would receive a low score and other strategies would have a higher probability of success.

Nearly two months after launching the revised DSG, we downloaded play-learner data for analysis. Of the 257 active play-learners, 240 gave us permission to use their data. We decided to examine only "finished" games, which we defined as achieving all 22 adopters or using all 72 available weeks. We found 109 play-learners had completed one or more games, while 27 had completed two or more games, and 14 had completed three or more games. From this sample, we selected three players to serve as illustrative examples with contrasting patterns here.

To simplify the APT queries, we recoded several variables into new APT classifications and categories. For example, the two measures of success in the game are the number of adopters achieved and the number of adoption points achieved. The number of points necessary to turn a particular staff member into an adopter depends largely on his or her adopter type, with innovators requiring as few as 5 points and laggards as many as 14 points. The points are distributed across the Awareness, Interest, and Trial phases that lead to Adoption. Obtaining all 22 adopters requires 220 points. When measuring success in the DSG, the number of points obtained is arguably a better metric than the number of adopters obtained. To understand this, imagine a game in which the player obtained 8 adopters while the rest of the staff members were still in the Awareness or Interest stages. Compare this with a game in which the player obtained only 5 adopters while the rest of the staff members had moved through Awareness and Interest and were in the Trial stage. Overall the latter player gained many more points toward adoption even though fewer adopters were obtained. We created a new APT classification named "Game Outcome" with the following categories based on final adoption points (see Table 4).

Table 4. Categories of game outcomes based on number of adoption points.

Game Outcome	**Adoption Points**
Maximally Successful	220
Highly Successful	166 – 219
Moderately Successful	146 – 165
Unsuccessful	0 - 145

Table 5 shows the APT classifications used in this study, along with a brief description of each.

Table 5. APT classifications for analysis of DSG play-learner data.

Classification	**Description**
Unix Epoch Time	A unique timestamp for each turn.
Player	The play-learner's identifier.
Game	The game identifier. Each player has multiple games for analysis.
Turn	The turn identifier for a game.
Activity	The DSG activity chosen by the play-learner for this turn.
Game Outcome	A category based on the number of adoption points, as described in Table 4.
Target Opinion Leader	"TRUE" if the person selected to engage in the turn's activity was an opinion leader. "FALSE" if the person selected was not an opinion leader. "NULL" if no person was selected.
Target Gatekeeper	"TRUE" if the person selected to engage in the turn's activity was a gatekeeper. "FALSE" if the person selected was not a gatekeeper. "NULL" if no person was selected.

Target Earlier Adopter	"TRUE" if the person selected to engage in the turn's activity was an innovator or early adopter. "FALSE" if the person selected was not an innovator or early adopter. "NULL" if no person was selected.
Target Social Connectedness	"TRUE" if the person selected to engage in the turn's activity had 10 or more interpersonal connections with other staff members. "FALSE" if the person selected had fewer than 10 connections. "NULL" if no person was selected.
Target Decision Phase	The target's phase in the innovation-decision process at the start of the turn: "NULL," "Awareness," "Interest," "Trial," or "Adoption."
Target Follower Interest	Based on the percentage of the target's followers who are in the Interest phase: "High" > 65%; "Medium" = 33% – 65%; "Low" = 1% - 32%; "None" = 0%.
Turn Rank	As described earlier, a score for every optimal strategy was calculated for each turn. These scores were then assigned a rank from 1 (Best) to 10 (Worst, when no optimal strategy was used). The value for Turn Rank is the rank of the strategy used for the turn.

The three players selected for this analysis all showed some improvement over time in Game Outcome. Player 1 played 4 games; the first 3 were Unsuccessful, and the last was Moderately Successful. Player 2 played 11 games; the first 2 were Unsuccessful, and the last 3 were Highly Successful. Player 3 played 6 games; the first was Unsuccessful, the fifth was Maximally Successful, and the others were Moderately to Highly Successful.

We ran an APT query for every strategy to calculate the frequency of that strategy in each game. Strategy 1 specifies targeting earlier adopters and opinion leaders, and Strategy 8 specifies targeting people with a large number of interpersonal connections. However, these strategies must be considered in the context of the activity chosen, for if the activity is not appropriate (e.g., an activity like Print that raises awareness and interest used with targets who are already in the Trial phase), it will be less successful. Therefore, for strategies that include targeted activities, we also ran queries to see how frequently desirable targets were selected. We ran similar queries to calculate when those strategies were ranked high (in the top three ranks) and low (in the bottom three ranks). In general, we expected that greater use of high-ranking strategies would increase the probability of success in the game.

As an example, let's look at Strategy 3, which says to use Local Mass Media and Print activities to gain points in the Awareness and Interest phases among earlier adopters. Let's focus on Local Mass Media, which is not a targeted activity. The scoring algorithm for this activity counts the number of earlier adopters who need points in Awareness or Interest and divides that by the total number of earlier adopters. Therefore, this activity's strategy score will be highly ranked when many earlier adopters need points in Awareness or Interest. Use of this activity when it is highly ranked should increase the probability of a successful game outcome.

We have set up our data so that each game is a separate APT map. The APT query tool returns counts and proportions for each map. The first APT query looks at overall use of this strategy by counting the number of turns in which Local Mass Media is used in proportion to the total number of turns. Here is an example result from one play-learner's map:

Pattern 3: Query Result for Player 1, Game 3

WHILE the FIRST Joint Temporal Event is true (Phrase 1):
Diffusion Activity is in state *starting or continuing*, value = *Local Mass Media*

- Duration when Phrase 1 is True = 2 moves (out of 59 DSG moves total). Proportion of Time = 0.03390
- Joint Event Frequency when Phrase 3 is True = 2 (out of 74 total joint temporal events). Proportion of JTEs = 0.02703

In this example, the play-learner used Local Mass Media in 2 out of 59 turns or 0.03390 (3.4%) of the time. Using this query, we find Player 1 did not use Local Mass Media in the first two games (both Unsuccessful games). In the third game (also Unsuccessful), Player 1 used the activity in 2 out of 59 turns, a proportion of 0.03390. In the fourth and final game, the activity was used in 2 out of 68 turns, a proportion of 0.02941.

The next APT query further limits the turns to those that had high ranking strategy scores, defined as a Turn Rank value of "Less than or equal to 3." To continue with the previous example result:

Pattern 4: Query Result for Player 1, Game 3

WHILE the FIRST Joint Temporal Event is true (Phrase 1):
Diffusion Activity is in state *starting or continuing*, value = *Local Mass Media*
Turn Rank is in state *starting or continuing*, value <= 3

- Duration when Phrase 1 is True = 1 moves (out of 59 DSG moves total). Proportion of Time = 0.02222

- Joint Event Frequency when Phrase 1 is True = 1 (out of 74 total joint temporal events). Proportion of JTEs = 0.01351

The final APT query (not shown for pattern 5) changes the Turn Rank value to "Greater than or equal to 6." Table 6 shows for all players and games (by game outcome) the proportions of Local Mass Media use overall (pattern 3), when its rank is high (pattern 4), and when its rank is low (pattern 5).

Table 6. Use of Local Mass Media activity by game outcome and strategy rank for turn. See Table 4 for definitions of **Un**successful, and **M**o**d**erately, **Hi**ghly and **M**a**x**imally Successful game outcomes.

Player 1	**Un**	**Un**	**Un**	**Md**						
Overall	0.00	0.00	0.03	0.03						
High	0.00	0.00	0.02	0.03						
Low	0.00	0.00	0.02	0.00						
Player 2	**Un**	**Un**	**Md**	**Hi**	**Md**	**Hi**	**Md**	**Un**	**Hi**	**Hi**	**Hi**
Overall	0.00	0.05	0.03	0.07	0.05	0.06	0.04	0.05	0.02	0.10	0.10
High	0.00	0.00	0.00	0.02	0.02	0.02	0.02	0.00	0.00	0.05	0.05
Low	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.02	0.02
Player 3	**Un**	**Hi**	**Md**	**Hi**	**Mx**	**Hi**					
Overall	0.02	0.07	0.10	0.10	0.05	0.09					
High	0.02	0.02	0.03	0.03	0.03	0.03					
Low	0.00	0.05	0.05	0.08	0.03	0.06					

Player 1 seems to gain in his understanding of the strategy regarding the use of Local Mass Media with earlier adopters who need points in the Awareness and Interest phases. By his final game (Moderately Successful), he used the strategy in 3% of his turns, always when it was highly ranked. Player 2 applied the strategy more sporadically; in her last two games she used it the most (10% of turns), but it had a low ranking for 2% of turns. Player 3 used the strategy relatively frequently, but the proportion of times when it was low ranking suggests that her timing was off and she needed to pay more attention to the innovation-decision phases of the earlier adopters.

For another example we will focus on Player 3's use of Strategy 2, which says to use the Personal Information and Talk To activities to establish empathy and rapport in order to understand a client's needs, sociocultural values and beliefs, and previous exposure to related ideas. We will focus on the Talk To activity, which is especially useful with gatekeepers, people who control access to resources and can create obstacles to the diffusion of an innovation. Here is an example of a query result for one of Player 3's games:

Pattern 6: Query Result for Player 3, Game 3

WHILE the FIRST Joint Temporal Event is true (Phrase 1):

Diffusion Activity is in state *starting or continuing*, value = *Talk To*

Target Gatekeeper is in state *starting or continuing*, value *True*

- Duration when Phrase 1 is True = 7 moves (out of 43 DSG moves total). Proportion of Time = 0.16279
- Joint Event Frequency when Phrase 1 is True = 7 (out of 82 total joint temporal events). Proportion of JTEs = 0.08537

Now let's compare all of Player 3's games, including proportions of use when the strategy is ranked high (pattern 7) and low (pattern 8) for all targets, and then for targeted gatekeepers (patterns 9-11). See Table 7.

Table 7. Use of Talk To activity by game outcome and strategy rank for turn.

Player 3	**Un**	**Hi**	**Md**	**Hi**	**Mx**	**Hi**
Overall	0.27	0.38	0.28	0.35	0.34	0.31
High Rank	0.00	0.26	0.21	0.23	0.29	0.28
Low Rank	0.16	0.02	0.00	0.00	0.00	0.00
w/Gatekeepers						
Overall	0.09	0.17	0.18	0.18	0.13	0.13
High Rank	0.00	0.14	0.13	0.13	0.13	0.13
Low Rank	0.02	0.02	0.00	0.00	0.00	0.00

In her first (Unsuccessful) game, she used the Talk To activity less than in subsequent games, and when she used it, it was never one of the high ranking strategies. Furthermore, she targeted gatekeepers less than in subsequent games.

As we saw in the weather example above, APT is not limited to single-phrase queries of temporal maps. Indeed, its power lies in querying sequences of complex patterns that are not easily found in database tables or spreadsheets.

The DSG promotes the use of Strategy 2 (the use of the Personal Information and Talk To activities to establish empathy and rapport) by requiring the play-learner to use the Personal Information activity on his first turn to gather information about five people. Furthermore, attempts to use some other activities are stymied if the Personal Information and Talk To activities have not been used with certain people, especially gatekeepers. For example, if an attempt is made to talk to the principal before talking to the principal's secretary, the game provides this feedback:

> STOP! The secretary says the principal is too busy to see you. You're not going to have access to him without her "approval." Have a talk with her.

Savvy players quickly learn from their mistake. The results of an APT query that looks for instances in which the play-learner first uses the Talk To activity with the principal, then with the secretary, then with the principal again is shown below. Note that the secretary is a gatekeeper, but the principal is the only staff member who is both a gatekeeper and an opinion leader.

Pattern 12: Query Result for Player 3, Game 1

WHILE the FIRST Joint Temporal Event is true (Phrase 1):

Diffusion Activity is in state *starting or continuing*, value = *Talk To*

Target Opinion Leader is in state *starting or continuing*, value = *True*

Target Gatekeeper is in state *starting or continuing*, value = *True*

- Duration when Phrase 1 is True = 2 DSG moves (out of 43 DSG moves total). Proportion of Time = 0.04651
- Joint Event Frequency when Phrase 1 is True = 2 (out of 86 total JTEs). Proportion of JTEs = 0.02326

THEN while the NEXT Joint Temporal Event is true (Phrase 2):

Diffusion Activity is in state *starting or continuing*, value = *Talk To*

Target Opinion Leader is in state *starting or continuing*, value = *False*

Target Gatekeeper is in state *starting or continuing*, value = *True*

- Duration when Phrase 2 is True = 1 DSG moves (out of 43 DSG moves total), given all prior phrases are true. Proportion of Time = 0.02326
- Joint Event Frequency when Phrase 2 is True = 1 (out of 86 total JTEs), given all prior phrases are true. Proportion of JTEs = 0.01163

- Conditional joint event *duration* when Phrase 2 is true, given all prior phrases are true = 0.50000 (1 out of 2 DSG moves (time units)).

- Conditional joint event *frequency* when Phrase 2 is true, given all prior phrases are true = 0.50000 (1 out of 2 JTEs).

THEN while the NEXT Joint Temporal Event is true (Phrase 3):
Diffusion Activity is in state *starting or continuing*, value = *Talk To*
Target Opinion Leader is in state *starting or continuing*, value = *True*
Target Gatekeeper is in state *starting or continuing*, value = *True*

- Duration when Phrase 3 is True = 1 DSG moves (out of 43 DSG moves total), given all prior phrases are true. Proportion of Time = 0.02326
- Joint Event Frequency when Phrase 3 is True = 1 (out of 86 total JTEs), given all prior phrases are true. Proportion of JTEs = 0.01163

- Conditional joint event *duration* when Phrase 3 is true, given all prior phrases are true = 1.00000 (1 out of 1 DSG moves (time units)).
- Conditional joint event *frequency* when Phrase 3 is true, given all prior phrases are true = 1.00000 (1 out of 1 JTEs).

This 3-phrase query for pattern 12 found that Player 3 made the mistake of approaching the principal before talking to the secretary once during her first game only. The results for pattern 12 in her remaining maps showed that she never made this mistake again.

5. USING APT FOR ASSESSMENT

5.1 Formative assessment during gameplay

In the examples above, we analyzed data from a serious game to demonstrate how APT can be used to find evidence of a play-learner's understanding and application of the theory underlying a simulation game. This information could be used by an instructor (or by the play-learner herself) after gameplay to identify misconceptions or gaps in understanding.

The approach we used to compare patterns of gameplay data with optimal strategies could be applied during gameplay to provide an instructional overlay (Myers & Reigeluth, *in press*; Reigeluth & Schwartz, 1989) that delivers appropriate hints, coaching, or other forms of scaffolding during gameplay to improve learning and performance. This instructional support could be requested by the play-learner who is struggling to determine the best course of action, or it could be supplied at the start of a turn as a hint or at the end of a turn as an explanation or prompt for reflection.

In the DSG, for example, the game engine could calculate optimal strategy scores for the turn in progress, and a virtual mentor could provide appropriate generalizations from DoI theory to help the play-learner see the connection between the theory and the game. Similar to the examples above, the game engine could also use APT queries on a play-learner's previous game maps to identify persistent misconceptions, which might be addressed at the start of a game. For example, in Table 6 we saw that Player 3 was consistently using Local Mass Media when it was a low-ranked strategy, indicating that she did not understand its usefulness in raising awareness and interest among earlier adopters. At the start of her next game, the game engine could identify this problem and provide relevant generalizations from Rogers (2003):

> Generalization 5-13: *Mass media channels are relatively more important at the knowledge stage, and interpersonal channels are relatively more important at the persuasion stage in the innovation-decision process* (p. 205).
>
> Generalization 7-22: *Earlier adopters have greater exposure to mass media communication channels than do later adopters* (p. 291).

5.2 Using APT for summative assessment

Serious game analytics need not be limited to formative assessment. Summative assessment is normally considered to be an evaluation of an entity across a sample of cases or situations in order to make an inference about a population of cases (Reigeluth & Frick, 1999; Scriven, 1967; Worthen & Sanders, 1987). For example, we might want to determine the *effectiveness* of the DSG in terms of student learning achievement—that is, do students appropriately apply principles from DoI theory to play it successfully? Or, we might be interested in *efficiency* of learning via the DSG—that is, how quickly can students learn through playing the DSG repeatedly until they achieve success? Alternatively, we might be interested in comparing two different versions of the DSG, such as one with coaching and one without coaching, to determine which is more effective or more efficient.

APT can be used to make inferences from a sample to a population of cases. In other words, APT can be used to make generalizations about a class of cases, if appropriate sampling strategies are employed. That is, we first analyze patterns *within* each case, and then average probabilities of these patterns *across* cases in order to avoid aggregation aggravation.

Probabilities of patterns resulting from APT queries are the measures of "variables" for each case (see Table 3). These measures can then be treated statistically in a normal manner to form means and standard deviations, and then subsequent analyses can be carried out (e.g., ANOVA, regression, factor, discriminant, cluster, Bayesian network, and other data mining approaches [e.g., see Jensen & Nielsen, 2007; Witten, Frank, & Hall, 2011]). A caveat is that data must be collected as temporal maps in order to make APT queries about patterns. Such patterns normally cannot be inferred from the way data are typically collected with separate measures of variables, as Frick (1983) proved mathematically (see Section 2.2 above).

With respect to network analysis (NA) methods for summative assessment, MAPSAT Analysis of Patterns in *Configurations* (APC) could be used. APC is based on mathematical di-graph theory, as are most NA methods (e.g., Brandes & Erlebach, 2005). Properties of di-graphs can be measured with APC that are typically *not* done in NA such as wholeness, vulnerability, interdependence, passive dependence, and strongness. Space does not permit further elaboration here. See Thompson (2008).

6. CONCLUDING REMARKS

In this chapter, we have described Analysis of Patterns in Time and demonstrated its effectiveness for serious games analytics. Games have tremendous potential as immersive learning experiences that challenge play-learners to apply their knowledge and skills to solve authentic, difficult problems in a safe environment. Designers of serious games have vast amounts of empirical data available that can be used to assess the learning trajectory of a play-learner. APT can turn these data into actionable assessments that lead to personalized scaffolds targeting an individual's misconceptions and gaps in knowledge and skills. APT can provide *unobtrusive* assessments for analyzing play-learner interactions with serious games, in contrast with methods such as direct observations, video recordings, surveys, questionnaires, interviews, and traditional tests of learning achievement.

While APT can be used for formative assessment of individual cases, as illustrated in this chapter, it can also be used for summative assessment and for research whose goal is to make generalizations based on statistical inferences from a sample to a population. For example, APT can be a valuable research tool for investigating the *effectiveness* of simulations, games, and other forms of instruction by showing the relationship between what students experience and what they are learning. Myers and Frick

(2015) are conducting such a study of the Diffusion Simulation Game to illustrate the use of APT for this purpose.

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