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Volume 15 Article 7

2017

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Recommended Citation

Jostad, Jeremy; Sibthorp, Jim; Butner, Jonathan E.; Rochelle, Shannon; and Gookin, John (2017) "Using Dynamical Systems Theory in Outdoor Adventure Education Research," *Research in Outdoor Education*: Vol. 15 , Article 7.
DOI: 10.1353/roe.2017.0005
Available at: https://digitalcommons.cortland.edu/reseoutded/vol15/iss1/7

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Cover Page Footnote

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Research in Outdoor Education 2017, Vol. 15, pp. 93–113

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Abstract

A challenge of studying outdoor adventure education (OAE) is the multifaceted nature of these programs. There are multiple components in OAE, such as students, instructors, or the environment that can influence the development of student learning outcomes. When conducting quantitative studies, researchers have limited ability to control these influences because of the natural setting of such programs, hindering many of the most common quantitative research designs. To address these challenges in OAE reserach, this article demonstrates the use of a dynamical systems theory (DST) approach of modeling quantitative data. The foundations, assumptions, and descriptors used to explain DST phenomena are introduced. Methodological considerations and an example analysis are presented.

Keywords: social, group, dynamic

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When Tim arrived for his outdoor adventure education (OAE) course he was very nervous and anxious. This was the first time he had been away from home for weeks at a time and the first time he had gone backpacking. Tim had always struggled to find friends at home and now he was in a group with 11 students he had never met prior to this course. Feelings of isolation crept up inside of him but he was motivated to learn as much as possible, not only about the wilderness but about himself.

The first couple days of Tim's course were a challenge as he was required to learn the basic technical skills of the course, in addition to trying to get to know everyone. After the first three days of the course he struggled to develop social connections with his tent group because they did not share his interests and were not from the area where he lived. He felt as though he connected best with another student on the course, Jake, but they had not hung out with each other very much because there was so much to learn and so many tasks to complete. One of the instructors had developed good rapport with Tim by checking in every day and showing concern for Tim's well-being. The relationship with his instructor was very helpful at the beginning of the course and helped him persevere through the social challenges of the course. On day seven of the course the group changed tent groups and Tim was now in a group with Jake. Tim was able to develop an extremely close relationship with Jake and the others in his tent group after spending more time with them. Tim's experience changed dramatically when he was finally able to "connect" to other students on his course.

As illustrated in the vignette above, there are many factors that can and do influence how students on OAE courses change and develop. In Tim's case, the focus is on the social system and how Tim does or does not connect with other students on his course. However, the specific outcome is less important than the premise that a multitude of factors both drive and impede change in OAE. The complex relationships between the student, the others in the group, and the environment in which these experiences take place, create a challenge to studying OAE phenomena. To explain student behavior through the traditional social psychological paradigm, that is, testing and modeling behavior as a linear "cause and effect" relationship between two variables provides a very limited scope of understanding. Behavior is rarely, if ever, a linear and independent relationship between two variables; rather, the complexity of behavior is a result of the interdependency between the self, environment, and others (Lerner, 2002). Understanding the how and why of OAE remains challenging because of the multifaceted

DOI: 10.1353/roe.2017.0005

nature of the programs, participants, instructors, and the physical environment (Ewert & Sibthorp, 2014).

Outdoor adventure education programs are comprised of multiple components that interact over multiple time scales to contribute to the learning and experience of a student (McKenzie, 2000; Sibthorp & Jostad, 2014; Walsh & Golins, 1976). For example, OAE programs offer different and sometimes multiple activities, stress different outcomes, and implement their programs with different approaches. These simple nuances, while seemingly minor, can have vast influences on the outcomes of a student. Students who participate in OAE courses also come from a variety of backgrounds with different goals for the course. Some may have participated in past backcountry experiences, whereas others may have never spent a night in a tent. Instructors play a central role and influence a multitude of aspects within an OAE course (Brown, 2002; Shooter, Paisley, & Sibthorp, 2008). The remoteness and challenge the physical environment can impose on participants also contribute to the variety of influences on every course. One way to better explain the complex nature of OAE may be through the use of dynamical systems theory (DST).

Dynamical systems theory recognizes that phenomena are comprised of multiple interconnected parts that continually interact with one another to produce emergent phenomena (Kelso, 1995). The goal of DST is not to measure every part of the system and determine the type of influence it may produce, but rather to examine the patterned behavior of a system over time (Wiese, Vallacher, & Strawinska, 2010). While the field of psychology has seen a growth of DST studies in areas ranging from motor development to familial interactions and identity (e.g., Lichtwarck-Aschoff, van Geert, Bosma, & Kunnen, 2008; Magnavita, 2012; Thelen & Smith, 2006), there have been few studies within the context of OAE (e.g., Williams, 2013) that have measured or modeled behavior with such a framework. Due to the multifaceted nature and complexity of influential factors within OAE programs, this theoretical framework deserves attention. Therefore, the purpose of this paper is to explain the theoretical foundations of DST and provide a data-based example of *one* modeling technique that can be employed by researchers.

Dynamical Systems Theory

Dynamical systems theory has deep roots in social psychology and has long been used to describe phenomena; however, recent advances in mathematics and statistical programs have provided the ability to track changes in systems more accurately. The term 'dynamical systems', in its most elementary form, refers to the mathematical formulation of change within a system over time. Dynamical systems models are composed of mathematical equations that describe time-based systems and the changes that occur within these systems (Granic, Hollenstein, Dishion, & Patterson, 2003). Furthermore, dynamical systems posit that contextual factors, the parts that comprise the system, also influence the change in the system. Observing this change and understanding the components that influence the temporal patterning within a system are of central importance.

This type of thinking is different than traditional approaches in three fundamental ways (McGrath, 1997). First, the focus of research is on the entire system and not directed on single variable effects, which provides a macro perspective on the phenomena of interest. Second, the state of the system is reflected in the emergence of system level phenomena that are influenced through micro level interactions. Third, the goal of DST is to understand the trajectory of the system, or in other words, the spatio-temporal dance of the system. Therefore, DST seeks to measure and model this change in systems through a language of space and time.

A DST perspective recognizes that there are multiple aspects that influence how Tim connects with other students on the course and that this changes over time. Rather than trying to focus on one or two variables that influence how Tim connects to other students, such as his personality or goals for the course, DST asserts that the focus should be to understand the unfolding of the macroscopic behavior. Therefore, the development of how Tim socially connects to others in his group is of interest.

There is a vast array of DST literature and a multitude of new research that uses DST as the theoretical foundation. For a good summary of DST and examples of how the theory might be used in social psychology see the following authors (Abraham & Shaw, 1992; DiDonato, England, Martin, & Amazeen, 2013; Hollenstein, 2011; Lewis, 2000; Thelen & Smith, 2006; Vallacher & Nowak, 1994, 1997). The following section will discuss some of the foundational assumptions of DST.

Foundational Assumptions

To begin an understanding of DST some of the foundational assumptions must be described. These assumptions guide how phenomena are conceptualized and the types of tools that might be used to analyze dynamical systems.

DOI: 10.1353/roe.2017.0005

Emergence and self-organization. Two of the main assumptions of dynamical systems are emergence and self-organization. Emergence suggests that the interaction of the lower order parts of a system produce a pattern of behavior that is new or different than that which existed prior (Wiese et al., 2010). That is, the individual parts of the system interact in such a way to produce something qualitatively different than the parts alone. This new emergent behavior of the system is a spontaneous product of self-organization.

Self-organization is the way in which the parts of the system interact with one another to produce emergent global behavior (DiDonato, et al., 2013). Self-organization does not have a causal agent requiring the parts to interact in a particular way, rather, the process is spontaneous (DiDonato et al., 2013). Considering Tim's experience, there are many different aspects that influence how he socially connects with others on his course. However, these connections cannot be explained solely by his sex or age (the parts of the system), rather it is through the interaction of multiple parts (age, sex, personality, interests) that leads to the emergence of this feeling of connection with others. Rather than measuring all of these parts, the focus should be on the behavior of the system (development of connection) over time.

Sensitivity to initial conditions. An important concept in dynamical systems theory is the notion that non-linear dynamical systems are sensitive to initial conditions. As the goal of DST is identifying the emergent patterns of a system over time, small differences in initial conditions or measurements can lead to vast differences in long-term predictions (Mitchell, 2008; Spencer & Perone, 2008). Not only does this assumption reiterate the importance of accurate measurements, but it provides a foundation of how data can be analyzed. If initial states of the system can provide information about future trajectories of the system, then it is possible to use these current states as predictors for the future. For example, the level of connection Tim feels at home with his peers can be seen as the initial conditions. If he struggles to connect with his peers at home he may feel this at the beginning of the course. His lack of connection at the beginning of the course may ultimately hinder his ability to develop a strong, or stable, connection with others by the end of the course.

Stability. Another key assumption is that systems generate stable patterns. System theorists assume that all systems are open systems, constant "energy" comes into and out of the system over time. This notion recognizes that systems are constantly changing and may vary from one moment to the next, but particular types of stability occur in order for the system to be most efficient. However, there is constantly energy that disturbs this stability, which is known as a perturbation. Perturbations are the micro changes within a system from all of the interconnected parts (Butner, Gagnon, Guess, Lessard, & Story, 2015). These perturbations can tell us about the stability of a system but are not modeled within the system.

There is a level of connection with the group that Tim feels most comfortable with and he naturally gravitates toward this level of connection throughout the course. However, there are many aspects of the course that may move him away from this particular state, such as the number of students in the group or the challenges of the day. These aspects of the course represent perturbations that move Tim around his stable state.

These assumptions provide the foundation of how DST phenomena are conceptualized, and thus, guides how systems are described and modeled. The following is a description of common terms used to depict dynamical systems.

Describing Dynamical Systems

There are some terms used to describe dynamical systems that are necessary for understanding how dynamical systems operate. These include order parameters, control parameters, attractors, repellers, and phase transitions.

Order Parameter

One of the crucial elements in defining the system is identifying the system level variable of interest known as an order parameter. Order parameters represent the emergent behavior of the system that is of interest (Thelen & Smith, 2006). To some extent, order parameters are similar to dependent variables in social psychological research; however, order parameters differ from dependent variables in two main respects. First, while dependent variables are described or explained by predictor variables (e.g., independent variables), order parameters provide an understanding of the system in relation to their change over time (Vallacher & Nowak, 1997). That is, order parameter values are determined by the previous measured moments in time. As discussed earlier, given that we know the initial values or states of a system, predicting future values is possible. A second difference between order parameters and dependent variables is that they must uniquely describe overall systematic conditions that evolve and change over time (Vallacher & Nowak, 1997). Therefore, order parameters must have the ability to change over time and not be static. There are a number of phenomena that can be considered order parameters in OAE, such as the development of self-efficacy, prosocial behaviors, and learning. In the above example, the way Tim connects to other students may be considered an order parameter because how he connects with others is a phenomenon that is influenced by its previous states and changes over time.

Control Parameter

As order parameters can be likened to dependent variables in classical methodology terms, control parameters can be likened to independent or moderator variables. Control parameters are those that influence or change the trajectory of the order parameter; they do not necessarily control the system but are a parameter in which the trajectory of the system is sensitive (Thelen & Smith, 2006). Control parameters are often recognized as the catalyst that moves the system from one state to another. Researchers can identify control parameters based on the parameters they believe can produce change. Therefore, control parameters are different than independent or moderator variables because they predict qualitative change as opposed to a stable current value of a parameter. While many parameters within a system may have some quantitative influence on the order parameter, typically only a few will be able to develop noteworthy qualitative change. For example, the level of connection Tim feels with other students may be influenced by how his goals for the course differ from others in his group. These differing/conflicting goals may be so prominent that they create a qualitative change in his trajectory of connection with others. It may be possible for him to feel connected to others in the group, but after realizing that his motives (to develop leadership skills) differ from those of his peers (to hang out), he could feel isolated and not well connected. Therefore, Tim's goals may act as a control parameter because they may move him to a higher or lower state of connection that are qualitatively different from one another. As Vallacher and Nowak (1997) note, "describing the effect of such a variable is clearly more enlightening about the system than is describing the effect of variables that produce only quantitative effects" (p. 79). The way that DST describes the influence that control parameters have on order parameters is through attractors and repellers.

Attractors and Repellers

Attractors and repellers are critical elements in understanding dynamical systems because they provide a measure of stability for the system. Attractors and repellers represent different states within the phase space.

The phase space is specified by measured coordinates that represent the location and trajectory of the order parameter through time (Abraham & Shaw, 1992; Nowak & Lewenstein, 1994). This space can be represented through multiple dimensions, but the most common are one-dimensional, two-dimensional, and three-dimensional space. The movement or trajectory of the order parameter within this phase space represents the stability of the dynamical system.

Attractors are a given location or area within the phase space where the trajectory of the order parameter slows and converges into a more stable state (Thelen & Smith, 2006). While there are multiple types of attractors in varying degrees of complexity (see Nowak & Lewenstien, 1994), for the introductory purpose of this paper, only fixed point attractors will be discussed.

Fixed point attractors occur when trajectories of the system converge on one point, regardless of the initial starting point (Thelen & Smith, 2006). One of the easiest ways to illustrate this concept is by considering different basins (attractors) that a ball (order parameter) may fall into or come to rest, given the different dimensions of the system (see Figure 1). The deeper the well, the stronger the fixed point attractor. This is a fixed point attractor because once the ball falls into a particular basin it will always gravitate toward the bottom of the basin (Figure 1 theoretically shows two fixed point attractors, one for each basin). A stronger attractor will show more stability (the first basin in Figure 1) whereas a weaker attractor will show less stability (the second basin in Figure 1). These stable states are where the order parameter gravitates given the expected combinations of control parameters on the system.

It is possible that Tim may connect with Jake better than any other person in his group. When Tim is feeling lonely or missing his family, Jake provides the understanding he needs to feel connected to the group. Tim also prefers to be around Jake when he is feeling good about the group. This is an example of fixed point attractors because Tim's feeling of connection stabilizes when he is with Jake.

Repellers are areas within the phase space from which the order parameter tends to move away. Repellers are often found between two attractors. If we consider Figure 1, the area between the two attractors can be viewed as a repeller because the ball will always move away from the top of the well. Repellers represent unstable areas of the state space where order parameters do not gravitate. Kelso (1995) suggests that instabilities provide three aspects of understanding to the system. First, they demarcate behavioral patterns by providing an awareness of stability changes between the

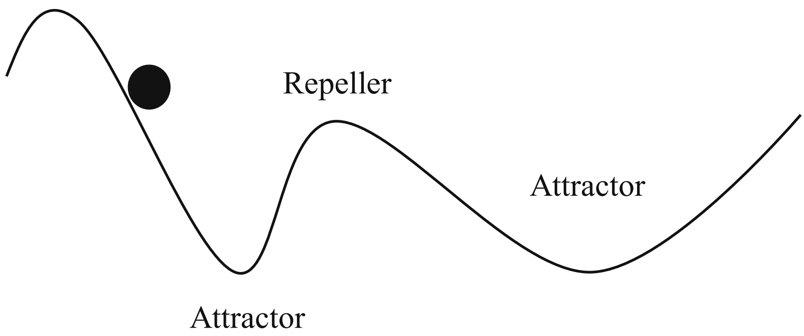

Figure 1 Basins of attraction. Visual representation of attractors and repellers.

attractor basins. Second, instabilities provide a way to model the order parameter behavior and see how the control parameters move the system through the phase space. Third, instabilities provide a way to anticipate future pattern changes and the length of time it takes for a system to recover from a perturbation. Recognizing these areas of instability within a given phase space is important in understanding the qualitative changes of the order parameter.

Phase Transitions

Phase transitions refer to the qualitative shift or change that occurs in the order parameter due to changes in the control parameter (DiDonato et al., 2013). This change brings about something qualitatively different than before and serves as a transition from one attractor state to the next. For example, stronger connections with others on OAE courses can result from shared challenging experiences. Low levels of challenge on a course may represent one attractor basin and a level of connection between students that is represented by superficial teamwork. Increasing the level of challenge and providing more opportunities for challenge can create a transition into a new attractor state of connection. This new attractor state may be represented by students communicating, supporting one another, and problem solving. The ideas described above are the foundations to understanding how dynamical systems are conceptualized and described. The next section will describe and demonstrate one approach of how dynamical systems can be measured and modeled.

Modeling Dynamical Systems

A variety of tools can be used to measure and model dynamical systems (topology, state space grids, non-differential equations, STELLA), and each serves to answer/inform different research questions. For example, topology is a graphical representation of differential equations via maps (see Butner et al., 2015). State space grids are another graphical approach that uses ordinal data and displays the data on two dimensions (see Hollenstein, 2007). Another approach is through the use of simulations with software such as STELLA (see Wells, Ruddell, & Paisley, 2006). Many of the tools can be quite complex, but a simple set of tools can be used for many common research questions. The following will provide an example of how to use regression techniques to model a dynamical system in OAE research.

Data Collection

One of the difficult aspects of collecting DST data in OAE is the requirement of repeated measures over time. For the data to be meaningful, it necessitates at least three time points and needs to show change in the order parameter. Collecting data more frequently is preferred as this provides a better description of the system over time. However, it is important to consider the time and rate at which the phenomena in a study develop. For example, if trying to understand the development of social connections, measurements should be administered early and frequently in the course when social connections are most likely to change.

Data-based Example

Data for this example of modeling were collected from two semester courses from the National Outdoor Leadership School (NOLS) for the first nine days of courses in 2015. The two semester courses were 87 days in length, but because the variable of study was sense of belonging and rations were 9 days in length, the most appropriate time to collect the data was at the beginning of the course. Both courses began with a three-day wilderness medicine section before beginning a backpacking section in the Rocky Mountains. A total of 24 students, 17 males and 7 females with a mean age of 20.2 years, completed questionnaires the first nine days of the course. The students completed the questionnaires at the end of each day in an area away from other students. Students on these courses did not know each other prior to this trip so the beginning of the course provided a great opportunity to see the development of sense of belonging.

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DOI: 10.1353/roe.2017.0005

Order Parameters and Control Parameters. Sibthorp and Jostad (2014) developed a model of the social system using a systems theoretical framework. Their model recognized many of the main components in the social system and how they might interact with one another. Using this model as a framework, sense of belonging was the order parameter that was measured using the ten-item Feeling of Social Belonging Scale (Richer & Vallerand, 1998). The scale consists of two dimensions of belonging (acceptance and intimacy) and both show strong reliability (.89 and .91).

Two variables were used as the control parameters in this study. Goal conflict represented the goal component of the Sibthorp and Jostad (2014) model. Goal conflict describes the extent to which students felt they want similar outcomes as others on the course. This was measured with one item that was written by the authors and had been used in previous research. The question specifically asked "I want different things in this course than others in the group." Instructor support represented the instructor component of the model and is defined as the level of care and support an instructor provides toward the students. Instructor support was measured using a modified four item sub-scale of the Classroom Life Scale (Johnson, Johnson, Buckman, & Richards, 1985). All questions on the questionnaire were 7-point Likert-type questions.

Analysis: Change as Outcome Model. Because dynamical systems are fundamentally interested in change, change becomes the outcome variable in the data (Butner et al., 2015). One way to create a change value is to make a lead variable and then compute a difference score for each individual. A difference score can be computed by subtracting the value of the present state of the system from the next time point (the lead). This simple difference score represents a first order derivative of velocity, which suggests how fast the order parameter is changing. Because DST assumes that the given value of an order parameter at time one will provide information on the future trajectories of the system, the current value of a student's sense of belonging can be used to predict its own change. This initial prediction is the baseline model in a DST analysis because it depicts the underlying pattern of the order parameter. This baseline model represents the trajectory of the order parameter without any influence of control parameters. These notions, while somewhat different than traditional methods, align with how systems are conceptualized. That is, time has been built into the data, rather than using time as a predictor variable as in traditional growth models. A graphical representation is provided in Figure 2 by viewing the change of sense of belonging as the outcome variable and the present value as the predictor variable. From this simple graph, the notions of stability and attractors can also be extrapolated.

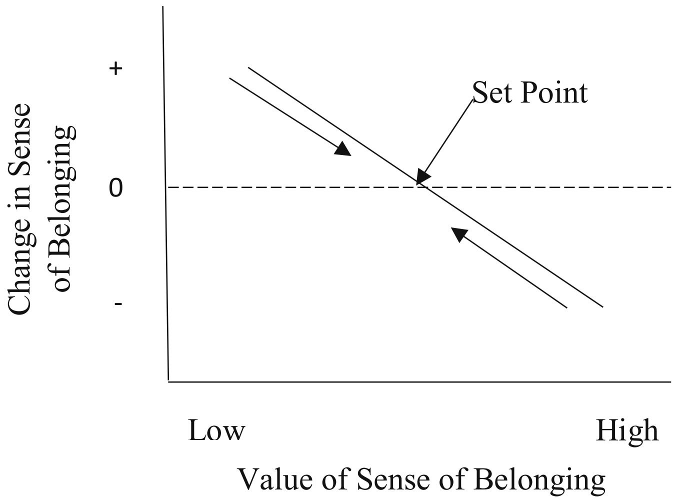

Figure 2 Attractors. Graphical representation of an attractor.

The value of sense of belonging is shown on the x-axis and the change in sense of belonging on the y-axis. The dashed line in the graph represents an area of no change and this has a special name called the *set point*. The set point is the specific measured location and value within the phase space from which behavior is depicted because it represents the point of no change, or stability (Butner et al., 2015). If the negative sloping line represented the data of a time series for a single individual, then this graph would represent an attractor because all points within this graph would converge on the set point over time. If the current value of sense of belonging (on the x-axis) is higher than the set point (further to the right), this student would have negative change (y-axis). This means that the future value (or change) for this student would decrease over time. That is, when a student's sense of belonging is higher than the set point, it tends to decrease or "attract" toward its set point. When the current value of sense of belonging resides below the set point (further to the left on the x-axis), change will be positive and the student will be drawn toward the set point. Fundamentally, negative sloping lines represent attractors. On the contrary, positive sloping lines represent repellers because when the current value of sense of belonging is higher (further to the right on the x-axis) than the set point, change is positive, and thus, individuals will have higher values in the future and move farther away from the set point (see Figure 3). This graph provides information about what value of sense of belonging people are attracted toward and shows the strength of this

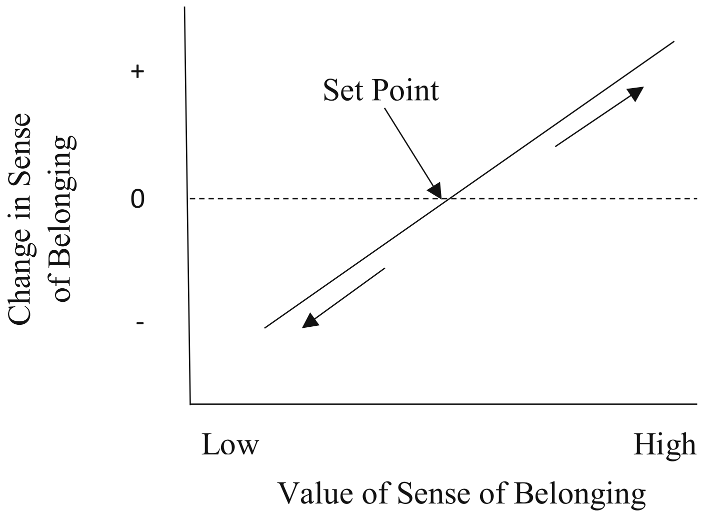

Figure 3 Repellers. Graphical representation of a repeller.

attraction. A steeper slope shows a stronger attractor or repeller, whereas a slope that is less steep shows a weaker attraction or repulsion.

When the data are conceptualized in these terms, it is possible to identify points or areas of attraction and the rate at which students move toward these states; however, these notions can be measured with relatively simple equations. When looking at a single time series of data for one person, it is possible to measure set points, attractors, and repellers using the following regression equation:

$$X_{t+1} — X_t = b_0 + b_1 (X_t) + e$$

The $X_{t+1} — X_t$ represents the change that is occurring in sense of belonging from the student's present value to their future value. The b_0 represents the y intercept and the $b_1 (X_t)$ represents the slope of the equation given a value of X. The set point and strength of attraction or repulsiveness of the system can be calculated through the above equation. By setting change to zero (because the set point represents no change), the set point can be measured within the system by the equation:

$$X = -b_0 / b_1$$

The regression model will provide a slope ($b_{1,}$ the attraction or repulsion) and intercept value ($-b_0$), which can then be plugged into the above equation

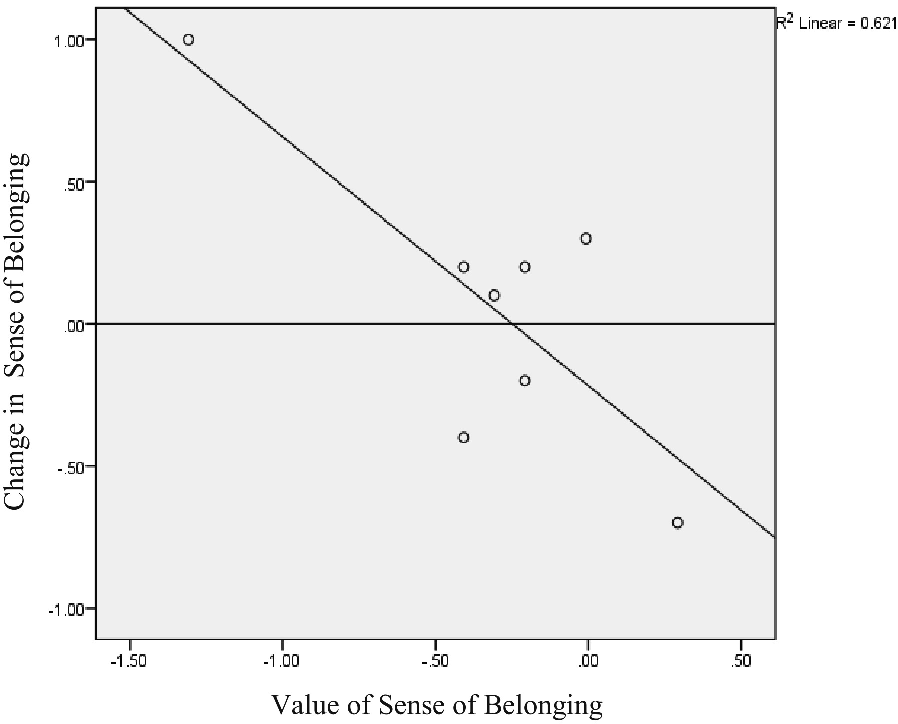

Figure 4 Attractor with data. Tim's relationship between current sense of belonging and change.

to determine the value of the set point. Whether the slope is an attractor or repeller can be determined by the sign of the slope (positive or negative) and the strength of the slope is indicated by the value of the coefficient.

To illustrate how this works using a single time series from these data, Figure 4 shows a graph of Tim with his current level of sense of belonging (on the x-axis) predicting his change (on the y-axis). The graph suggests attractive behavior due to the negative sloping line. The set point can be computed using the equation above with the slope of -0.88 and a constant value of -0.22 (all predictor variables have been grand mean centered). This particular model shows an attractor (-0.88) with a set point value of -0.25, which is approximately what is shown from the graph. Also interesting is the fact that this equation alone accounts for 62% of the variance in Tim's change in sense of belonging. So far an explanation of how an order parameter predicts its own change has been presented, but of interest is how control parameters "control" the system.

Another piece which can be added to this equation is a control parameter that may alter the trajectory of the system. For example, a difference in goals (goal conflict) between students on the course may alter their sense of belonging in two ways. Control parameters can alter both the location of the set point and the strength of attraction or repulsion. If a control parameter is added as a main effect, it has the ability to only change the set point of the equation, but not the slope (Butner et al., 2015). However, if an interaction term is added to the equation, the potential of changing the set point and the strength of attraction or repulsion is possible (Butner et al., 2015). That is, by adding an interaction between the value of sense of belonging and "goal conflict," it is possible not only to change the set point, but change the strength (slope) of an attractor or repeller. Multilevel modeling can be used to expand this notion beyond a single time series.

Change as Outcome Models with Multilevel Modeling. The change of one person is rarely of interest to social scientists; rather, measuring multiple people is often the goal. Multilevel models provide the ability to model variables that are non-independent and can handle missing data (Raudenbush & Bryk, 2002). The same steps as above can be used to create the lead and change variables.

Figure 5 shows a linear plot for all students over the nine days with change in sense of belonging as the outcome and the current value of sense of belonging as the predictor. This graph suggests a fixed point attractor exists at approximately a value of 0.5 and shows that 15% of the variance can be explained by this equation. Using the values of the intercept and the slope, it is possible to mathematically calculate the set point. The slope in this model has a value of -0.38 and an intercept of 0.11. According to the equation mentioned above, the set point can be determined by dividing the intercept by the slope (–(0.11)/-0.38), which equals 0.29. The strength of this set point can be determined by looking at the value of the slope, which in this equation is -0.38. These values are somewhat different than what Tim's data showed. Tim had a much lower set point and showed stronger attractive behavior than the average student, which could have been a result of his difficulties at the beginning of the course.

Due to the nature of this population and the construct, it is feasible that students may vary in their set points and in their slopes. That is, students may have different set points and may move toward those set points at different rates. To understand if this exists, variance components on the intercept and slopes were modeled. In this example, both were significant ($p < .01$).

In order to understand why people may differ on the variance components, control parameters were added to the model. First, the level one

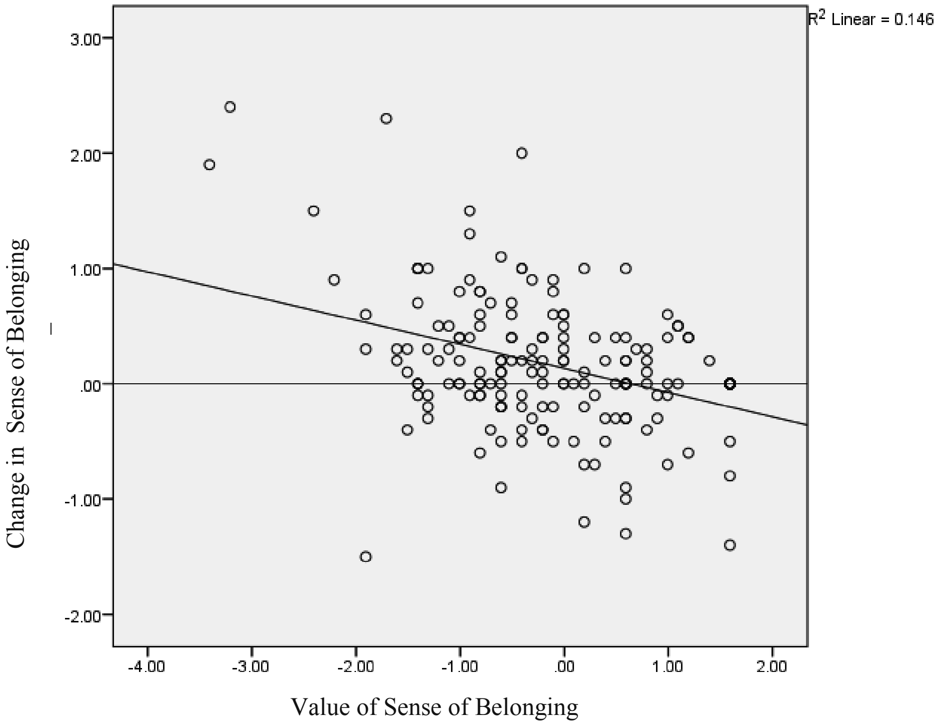

Figure 5 Attractor with data for all students. The average relationship between current sense of belonging and change.

control parameter of goal conflict was added both as a main effect and an interaction. According to this model, there was not a significant main effect but there was a significant interaction (ß = -0.05, $p < .05$), which suggests that for every one unit increase in daily goal conflict, the slope of a student's change becomes more attractive by 0.05 units. That is, students who have more goal conflict with others tend to gravitate toward the attractor faster. This change in the slope also makes it more stable, and thus more difficult to change from. The set point in this model did not significantly change.

To put these results in context, these data suggest that on days when the average student in Tim's group had higher levels of goal conflict, the rate at which students moved toward their set points in belonging increased. This increase in the slope indicates that the average student's set point is more stable, which makes it more resistant to perturbations, but also more difficult to change. If for example, they wanted to increase their sense of belonging, goal conflict makes it more difficult for them to make this change.

Instructor support, a level two predictor, was also modeled as a main effect and an interaction. This model showed a significant main effect ($\beta = 0.20$, $p = .01$) but did not show a significant interaction. This result suggests that for every one unit increase in instructor support, the student increased their level of sense of belonging by 0.20 units. That is, students who felt more support from their instructors had higher levels of belonging.

To calculate the effect size of this model, the predicted and residual values were saved from the model and then aggregated by the standard deviation (see Snijders & Bosker, 1999 for more information). Using this approach, this DST model accounted for 43% of the variance in the change of sense of belonging. The following section provides a further description to understand and conceptualize DST results.

Understanding Example DST Results. The focus of DST is not to advocate for cause and effect relationships, but to track the temporal patterns of phenomena and understand what components within the system can alter this pattern. The first part of this analysis, predicting change by the current value of sense of belonging, acts as a baseline model. From this, it is possible to determine the stable (attractors) areas within the system and how a student moves (changes) toward those stable points. In our example, the attractor existed above the zero point, meaning a student's level of sense of belonging tended to stabilize 0.29 units above the average of all students. Therefore, when students had lower values of sense of belonging they gradually moved toward the set point over time. The slope of this equation serves to show how fast students move toward this stable state and acts as a marker for the strength of the attractor.

The control parameters were used to explain if components of the system influence the temporal pattern of the order parameter. The significant interaction of goal conflict and sense of belonging showed that this control parameter increases the rate at which a student moves toward the attractor state on a daily basis. That is, the current level of sense of belonging moderates the relationship between daily goal conflict and change in sense of belonging. In addition, this interaction suggests that the attractor is more stable when goal conflict exists, meaning it is more difficult for students to change their level of belonging once it gravitates toward the attractor. The second control parameter was instructor support. When students felt they had greater support from their instructors over the entire nine days they also felt a greater sense of belonging.

Applying these findings to Tim's experience can help understand how goal conflict acts as a control parameter. The change in slope suggests that goal conflict makes him move toward the attractor faster and makes it more difficult for Tim to change his level of belonging once he has reached the attractor state. The instructor support control parameter also suggests Tim increases his sense of belonging when feeling supported by his instructors.

Implications for Professional Practice

An understanding of DST does not only provide the researcher another tool to better comprehend human behavior, but DST can also help practitioners recognize the components and processes of change that a client may experience in their program. The beauty of looking through the DST lens is that there is simply not one aspect of the program that creates change or growth, but there are a multitude of components that interact to create this change over time (Wiese et al., 2010). If practitioners use a DST lens they are better able to identify the components that might create change (control parameters) and may be able to leverage how this change influences their clients. Furthermore, DST requires practitioners to look at their programs holistically and understand the "big picture." Having this perspective on programs can be beneficial for new and veteran staff.

Researchers and practitioners should not be discouraged by unfamiliar language or seemingly complicated statistics if they want to implement DST into their profession. Many people are already familiar with the ideas introduced in this paper through their understanding of ecological systems and how different parts of a system can create change over time. To begin your DST thinking, first identify all of the components within your system. Second, identify the component you are trying to better understand or measure (i.e. order parameter). Third, identify the main components within the system that might influence (i.e. control parameters) the component you want to understand. Finally, track the trajectory of change within the component of interest. Tracking this change can be done quantitatively with robust and complicated statistics, or with relatively simple statistics. However, tracking this change can also be done qualitatively for those who do not want to use statistics. All of the ideas provided in this paper can be used by practitioners and researchers by simply understanding the basics of how dynamical systems operate.

DOI: 10.1353/roe.2017.0005

Conclusion

The purpose of this article was to show how DST can be used as a theoretical and methodological tool in OAE research. While a variety of tools and resources can be used to analyze dynamical systems, this paper illustrated *one* approach that uses familiar statistical analyses and equations. Ultimately, using a DST framework requires an adjustment of how phenomena are viewed and understood. Rather than seeking cause and effect relationships, the first step may need to be a step back, by focusing on observing a system over time. In order to understand the processes of OAE programs, a theory is needed that helps to understand the process of change, and DST provides one way to accomplish this task.

Tim's experience on an OAE course is incredibly important to understand, however, his experience occurs in a dynamic and complex setting consisting of multiple interacting parts. In order to truly advance the understanding of what occurs during OAE programs, researchers need to recognize and acknowledge multiple variables that influence outcomes in OAE (Scrutton & Beames, 2015). Dynamical systems theory provides a platform to take on these challenges, which can help understand the development of many outcomes participants may gain from their OAE experiences.

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