DISSERTATION

DYNAMIC SYSTEMS THEORY AND THE PROCESS OF ADOLESCENT DEVELOPMENTAL CHANGE

Submitted by

G. Kurt Moore

School of Education

In partial fulfillment of the requirements

For the Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer, 2005

COLORADO STATE UNIVERSITY

COLORADO STATE UNIVERSITY

July 13, 2005

WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY GEOFFREY KURT MOORE ENTITLED DYNAMIC SYSTEMS THEORY AND THE PROCESS OF ADOLESCENT DEVELOPMENTAL CHANGE BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

Committee on Graduate Work

James H. Banning

Kevin P. Lyness

Adviser, Sharon K. Anderson

Co-Adviser, Laurie A. Carlson

Department Head/Director, Jean P. Lehmann

ABSTRACT OF DISSERTATION

DYNAMIC SYSTEMS THEORY AND THE PROCESS OF
ADOLESCENT DEVELOPMENTAL CHANGE

How do humans learn, change, and grow? This broad question has driven research in the disciplines of education, human development, and psychology for the past century. Microdevelopmental research studies report that periods of high variability are a typical precursor to gains in learning and development; Dynamic Systems Theory (DST) draws on chaos and complexity theories to explain this phenomenon as a normal, and indeed necessary, part of emergent change processes. This study explores the accuracy and applicability of DST predictions when applied to a long-term therapeutic change process.

This study analyzed archival behavioral rating scores on a randomized group of 31 high-risk adolescent males during their stays at a residential treatment center. These participants were scored every hour of every waking day for periods ranging from five to fifty-eight weeks. This data set provided a rare example of microdevelopmental measurements spread out over a macrodevelopmental period. The guiding research problem for this study was: are the observed behavioral fluctuations among these adolescent participants consistent with the features predicted by DST? Q-sorts of score graphs combined with a case-by-case qualitative analysis supported this proposition. In addition, fuzzy set analysis was used to find necessary and sufficient causes for these participants' positive or negative discharges from treatment.

For the participants in this study, the change process usually displayed the bifurcation patterns predicted by DST. The complex causal combination of percentage of weeks displaying variance and time required to make adequate progress was almost always necessary and sufficient to predict the type of bifurcation and discharge status, as was the causal combination of percentage of weeks displaying variance and estimated size of the Zone of Proximal Development. DST predicts that the farther and faster a system changes, the more variance it will display. This was evident; cases making larger amounts of progress usually required more time and displayed more variance. Rapid gain was generally accompanied by more variance, while slow gain almost always displayed less variance.

This study provides support for some of the predictions of Dynamic Systems Theory and suggests a few modifications, especially regarding cases where the change effort fails.

G. Kurt Moore
School of Education
Colorado State University
Fort Collins, CO 80523
Summer, 2005

ACKNOWLEDGEMENTS

I am both grateful for and humbled by the patient enthusiasm shown by my committee members. Drs. Anderson, Banning, Carlson, and Lyness have inspired me to a career in academia, and have faithfully executed the task with which I charged them. My advisor Dr. Sharon Anderson went far beyond any reasonable expectations, and deserves special thanks. Dr. Paul van Geert offered invaluable encouragement and advice early in the process. Dr. Charles Ragin provided quick assistance with his excellent fsQCA software. I am indebted to the superb thinkers whose eloquent writings have guided this study, including Drs. Esther Thelen, Marc Lewis, Richard Lerner, Kurt Fischer, and the immortal Gregory Bateson.

My family and friends have been remarkably tolerant, sustaining me through this long project that, I am sure, seemed pointlessly arcane. They are more important than they realize. Dr. James Kagan, Kim Bappe, Mike Ruttenberg, Ally, Alix, Ana, Bob, Sis… you all deserve thanks. Sara deserves a medal for her patience and love.

Finally, without the inspiration, guidance, prodding, and daily support of my parents, Dr. Gene and Mrs. June Moore, I would never have accomplished anything worthwhile at all. Thank you, folks!

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

> If learning is a class of short-term changes leading to new knowledge and skill, and development is a class of long-term changes leading to new knowledge and skill, researchers should be able to use a framework for change in knowledge and skill to analyze both learning and development…
>
> Kurt Fischer & Nina Granott (1995, p.303)

How do humans learn, change, and grow? This broad question has driven research in the disciplines of education, human development, and psychology for the past century. That century of research and theorizing has yielded definitions of change (Gottlieb, 1992; Skinner, 1974), stages of change (Erikson, 1950; Piaget, 1951; Prochaska, 1992), and types of change (Argyris, 1999; Watzlawick, Weakland, & Fisch, 1974), but few concrete explanations of how change really occurs. Theorists (Lewin, 1952; Piaget, 1951; Vygotsky, 1978) have posited logical, if vague, processes of learning and development, without being able to empirically document actual change mechanisms. At a very practical level, we want to know when to teach what, how to know whether our efforts are working, and what to consider normal progress. "The proliferation of incompatible theories and theoretical families is as daunting to developmentalists as to the educators and practitioners we are trying to reach" (Lewis, 2000, p. 36). The European and American education systems have predominantly relied on pre- and post-intervention testing to guide curriculum design, and this tradition still influences educators and policymakers in the form of school accountability measures and the No

Child Left Behind Act (2002). Learning and development theories have generally been derived from similar cross-sectional, static observations; these studies provide snapshots of change products, without illuminating the process (Granott & Parziale, 2002). Observers can see that change has occurred, but they can only guess at exactly how it happened.

Explanatory guesses (theories) are shaped and constrained by the linguistic, cultural, and metaphorical discourses from which they emerge (Foucault, 1971; Pepper, 1942). These differing philosophical worldviews have resulted in vastly different explanations of learning and development, and are difficult to reconcile. Mechanistic, organismic, contextualist, nativist, and constructivist perspectives all contribute to an understanding of human change processes; "yet the incommensurate metaphors or perspectives from which they derive make them very difficult to calibrate with each other. Thus, no integrated account can be fashioned by combining them" (Lewis, 2000, pp. 37-38). In sum, the human sciences have lacked not only appropriate methods to adequately examine the change process, but also a sufficiently useful metatheory from which to attempt coherent explanations.

A research approach named the *microgenetic method* (Siegler & Crowley, 1991), which examines change while it is occurring, can offer useful data about the change process. A newer interdisciplinary, metatheoretical framework called *Dynamic Systems Theory* (DST) (Lewis, 2000; Thelen & Smith, 1994, 1998, 2003; van Geert, 1991, 1994, 1998) might offer a solution to the theory problem. Microdevelopmental research studies report that periods of high variability are typical precursors to gains in learning and development; DST explains this phenomenon as a normal, and indeed necessary, part of the change process. This study attempts to notice, analyze, and better understand periods of variability within individual behaviors during a developmental change process.

> Despite its elusiveness, prediction remains a major goal of science; Freud
>
> appeared to be cognizant of the fact that retrospective prediction was much easier than prospective prediction ... his belief about the complexity involved in the development of maladaptive as well as normal behavior made him skeptical about the ability to predict outcome (Lewis, 2000, p. 17).

Struggling to predict, science attempts to at least identify processes as they occur:

> It is relatively easy to identify a learner as having been "in transition" after a task has been mastered—the learner who made progress on the task was in transition, whereas the learner who failed to make progress was not. However, such a *post hoc* measure is of limited use, both for experimenters interested in exploring the process of change, and for teachers interested in identifying learners who might be in a transitional period and therefore particularly receptive to instruction. We need a measure of transition that is not after-the-fact, and that has the potential to capture change as it is occurring (Goldin-Meadow & Alibali, 2002, p. 81).

Because researchers tend to find what they expect, and to operate within limited worldviews (Kuhn, 1962), answers before the 1970s usually conformed to steady-state gradualism (Bijou & Baer, 1961; Skinner, 1938). Generalized, universal processes were privileged over local, varying results. For years, theorists and researchers have observed perturbations in learning and development (Muenzinger, 1938; Tolman, 1932) and have debated their meaning. For the most part, these disturbances were mathematically minimized; linear analytic techniques emphasized smoothed-out learning and growth curves. When data for groups of subjects are pooled, fluctuations are dampened by temporal variations. Steenbeek and van Geert (2002) note, "In psychology, the almost universal inclination toward taking averages within and between subjects has led to an unfortunate neglect of an important source of information about processes of change, namely variation" (p 172). Recent studies, informed by catastrophe (Thom, 1972), chaos

(Prigogine & Stengers, 1984), and nonlinear dynamic systems theories (Thelen & Smith, 1994, 1998; van Geert, 1991, 1994), attend to intraindividual variation (Stadler, Vetter, Haynes, & Kruse, 1995; Fischer & Yan, 2002). In the discipline of human development, there has been a recent increase in the study of short-term change, called *microdevelopment* or *microgenesis*. When closely observed, "...people show great variation in their activities. Understanding how cognitive development and learning occur in adults and children requires focusing on this variability and finding the sources of order within it" (Yan & Fischer, 2002). This phenomenon of variability, or fluctuation, leading to profound change had been familiar to psychotherapists for many years: "... second-order change is always in the nature of a discontinuity or a logical jump" (Watzlawick, Weakland, & Fisch, 1974, p. 12).

Purpose Statement

In my work as an adolescent psychotherapist, I have noticed definite change-process patterns among my clients. They often go through a "roller coaster" of emotion and behavior during periods of intense change. During other periods, these clients are more stable. I have come to believe that these successive periods of fluctuation and stability are typical mechanisms of human change. This has been so clear as to have inspired me to draw a crude graph that describes the typical behavior patterns displayed by clients in residential treatment (see Figure 1.1, The Saxophone Curve). Peers and clients have examined this graph and agreed with its fundamental verity. One of my mentors, Dr. James Kagan (an adolescent psychiatrist), has suggested a critical need for a study of this apparent phenomenon.

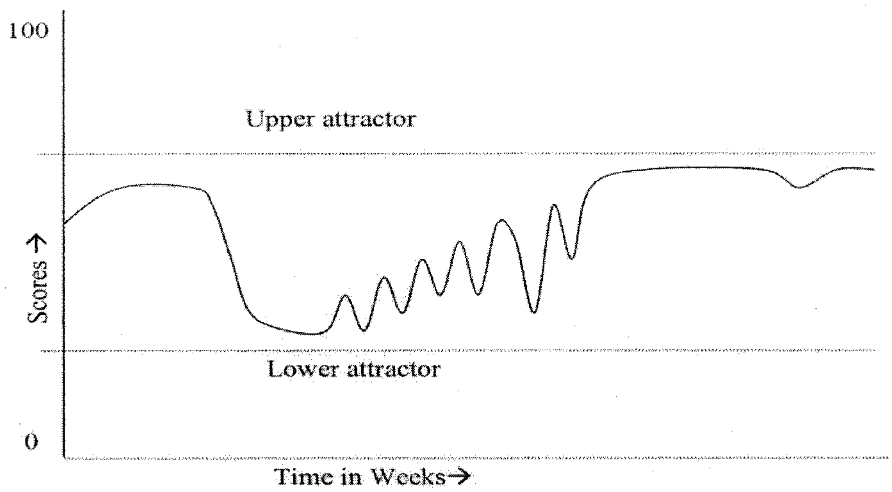

Figure 1.1 The "Saxophone Curve"

This rough chart based on my observations shows similarities to a graph that details evolving changes in the complexity of computerized artificial creatures (programs) operating within a competitive environment (Adami, Ofria, & Collier, 2003, p. 4466). The vertical axis represents increasing complexity versus the horizontal axis's increase in time:

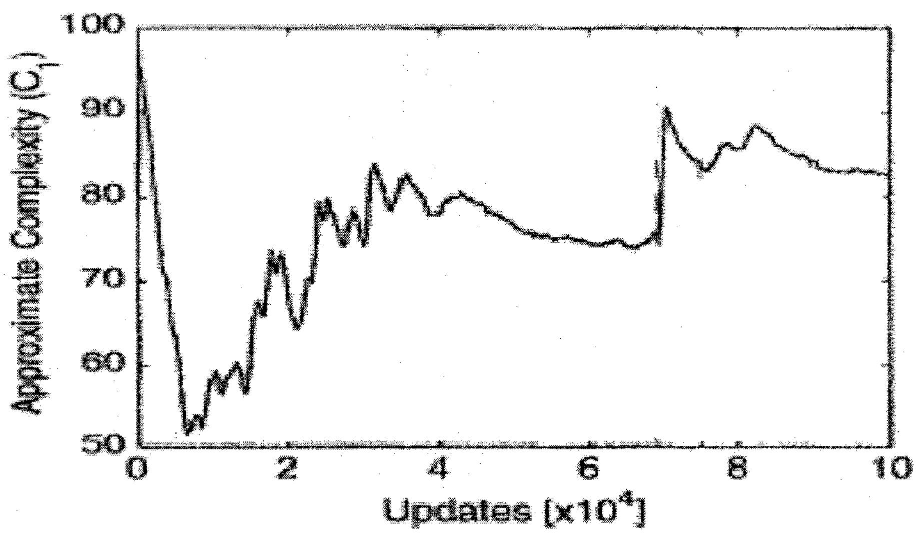

Figure 1.2 Increase in complexity, from Adami, Ofria, & Collier, (2003)

This interesting confluence of anecdotal and empirical evidence, with an apparently commensurate theory, provided the impetus for this study.

Need or Significance

A decent and growing body of empirical evidence describes the characteristics of complex change in open systems (Fischer & Yan, 2002; Stadler, Vetter, Haynes, & Kruse, 1995; Thelen & Ulrich, 1991; van Geert, 1991, 1993, 1998). A wealth of theoretical, and a paucity of empirical, evidence describes complex change in individuals. Individuals are too perversely idiosyncratic to be the focus of most empirical studies. Data are awash in noise. Focusing on changes within groups, where patterns are more easily discerned, is easier (Steenbeek & van Geert, 2002). This focus on groups increases statistical clarity, but it decreases the specific power of theory-based hypotheses. This study will use Dynamic Systems Theory to explain individual behavioral development.

This microdevelopmental research approach (the study of individuals in the process of change) continues to yield data supportive of nonlinear systems theory. "Most important perhaps, these studies provide a clear indication of what the change process is not—a simple transition from one mode of operation to another" (Kuhn, 1995, p.133). Individuals display variance in performance measures before they restabilize at higher levels of development.

In this study, I propose to explore the individual change process in a more empirical manner, using numerical, multiobserver, longitudinal behavior-rating scores. I will attempt to identify and categorize any patterns in the data. I will then examine any found patterns for their "fit" with Dynamic Systems Theory.

Statement of the Research Problem

Are the observed behavioral fluctuations among these adolescent participants consistent with the features predicted by Dynamic Systems Theory?

If "there is nothing as practical as a good theory" (Lewin, 1943), then I propose to evaluate the utility of Dynamic Systems Theory. Can this theory describe, explain, or even predict features of the change process? Could it allow educators, change agents, and clinicians a useful tool? Or is it merely another vague piece of "epistobabble" (Lask, 1987)?

Definition of Terms

Accommodation: Adapting one's schemas/paradigms/worldviews to the world outside one's self. Changing the structures by which one perceives or behaves (Piaget, 1927). Qualitative, irreversible change (Bateson, 1979). *See also* Second-order Change.

Adaptation: A feature of an organism whereby it seemingly improves its ability to fit into its environment and way of life. The process of achieving that fit (Bateson, 1979, p. 227).

Assimilation: Adaptation of the perceived outside world into one's existing schemas/paradigms/worldview. Fitting events into a preexisting system, or pattern (Piaget, 1927). Quantitative, reversible change (Bateson, 1979). *See also* First-order change.

Attractor: Roughly, a portrait of a system's stable behavior over time (Goerner, 1994). An attractor describes a stable pattern. Examples of attractors include paradigms, beliefs, values, and habits. Also called a *limit cycle.*

Behaviorism: A theoretical perspective that explains the behaviors of living systems as learned responses to external stimuli.

Bifurcation: "A …transformation from one type of behavior to a qualitatively different type of behavior" (Goerner, 1994, p.40). This transformation can involve an increase in adaptive organization. It also can mark the destruction of the system.

Change: A difference that is noticeable.

Chaos Theory: A set of ideas used to describe the behaviors of nonlinear, dynamic, interactive systems. A search for the order that can be found within seemingly random phenomena.

Complexity Theory: A set of ideas for the study of the behavior of complex systems. *Complexity* is also used to describe the degrees of complex organization within systems; for example, the cognitive complexity of an individual mind as it develops.

Development: The process of self-organization (Lewis, in Granott & Parziale, 2002). Behaviorists argue that development is synonymous with learning; most theorists regard development as qualitatively different from, yet interdependent with, learning. Some theorists say that development simply occurs, while learning is an active effort.

Disorder: Used here in the medical sense of illness; an ailment of body or mind.

Emergence: The idea that increased adaptive complexity and order unfold from previous, simpler systems.

First-order change: A quantitative change that does not alter a system's current structure. An assimilation of information into existing beliefs or rule systems.

Fluctuation: A disturbance or oscillation. A variation.

Fuzzy Logic: An analytic method based on the idea that exact measurement is often less useful than approximations.

Fuzzy Sets: Used in fuzzy logic analysis to allow distinctions between degrees of membership in a set.

Gestalt Theory: The theoretical perspective that explains the brain's construction of perception and meaning via structure creation.

Learning: The process of acquiring new knowledge; a change in understanding. "Modern research has made it clear that learning processes share all of the complexity, organization, structure, and internal dynamics once attributed to development" (Kuhn, 1995, p. 138).

Linearity: The relationships among two or more variables is linear if a change in the value of one variable produces a corresponding change in the others. The relationship(s) can be graphed as straight lines. The traditional science of statistics is based on linear prediction.

Macrodevelopment: Related to long-term changes.

Mesodevelopment: Related to medium-term changes; hypothesized to mediate the effects of microdevelopment on the individual's macrodevelopment, which includes personality.

Microdevelopment: Related to short-term changes.

Microdevelopmental range: The distance between upper and lower attractors between which an individual learner's performance varies during a short time period (Yan & Fischer, 2002).

Microgenesis: A synonym for microdevelopment. The microgenetic method is a research approach that closely observes learning/development processes in individuals.

Nonlinearity: The relationships among variables are nonlinear if their effects on each other are not of corresponding size. The relationship(s) cannot be graphed as straight lines. There may be large effects in one region and none in another. For example, Goerner (1994) notes that the dosage of aspirin has a nonlinear relationship with headache relief: "Eight aspirin do not reduce a headache 8 times as much as one aspirin" (p. 16).

Ontogeny: The process of development of the individual organism.

Recovery: Used here in the Twelve-Step sense, as in recuperation from addiction. To make the profound, second-order change from morbid addiction to enjoyable abstinence.

Score: Specified number in a numerical rating system. In this study, *scores* refer to the observed behavior ratings of the residents at a treatment center.

Second-order change: A qualitative change in a system's structure. An accommodation to new information. A change in the rules by which a system functions.

Self-organization: The process whereby a structure or pattern emerges within a system, without external direction. For example, the traditional village marketplace can be described as a self-organizing system for the exchange of goods.

Stability: The characteristic that a system, once functioning in a certain way, tends to maintain its structure. Open, dynamic, systems are often best able to maintain a stable structure by adapting to changing external conditions.

Stochastic: "Greek, *stochazein*, to shoot with a bow at a target; that is, to scatter events in a partially random manner, some of which achieve a preferred outcome. If a sequence of events combines a random component with a selective process so that only certain outcomes of the random are allowed to endure, that sequence is said to be stochastic" (Bateson, 1979, p. 230). This explanation can be regarded as a systems-theory definition of thinking, adaptation, and evolution.

Telos: A final goal, or endpoint.

Treatment: Used here in the therapeutic sense: "cure, healing, medication, nursing, remedy, therapy" (*Oxford English Dictionary*, 2000).

Variability: "A description of the differences between scores in a distribution. If all the scores in a distribution are the same, there is no variability. If the scores in a distribution are all different and widely spaced, the variability would be high" (Gliner & Morgan, 2000, p. 425).

Vicarious trial-and-error (VTE): A term coined by Karl Muenzinger and Evelyn Gentry (1930), defined as "a facing into one alley before the other one, whether right or wrong, was entered" (Muenzinger, 1938, p. 77). "Although first used to label choice-point behavior of rats prior to spatial or nonspatial discriminative responses, the term *VTE* has subsequently been extended to vacillatory behavior in other learning situations and today refers to oscillating behavior of various types of subjects at points of choice in a wide range of learning situations" (Stadler et al, 1996, p.163).

Zone of Proximal Development (ZPD): "The … distance between the actual developmental level as determined by independent problem-solving and the level of potential development as determined through problem-solving under adult guidance or in collaboration with more capable peers" (Vygotsky, 1978, p.86). This can be conceived of as a longer-term version of the microdevelopmental range.

Study Delimitations

For reasons of efficiency and expedience, this study is delimited to a small group of adolescent males who are under considerable pressure to make numerous significant changes within a year or less. This study will examine a very small population of age-limited (15-year-old to 19-year-old) males from one western state in the United States of America. Racially, the study will be limited to Caucasian, Hispanic, African-American, Native American, and mixed descendants of the above. In addition, the participants are, by nature of their ages, embroiled in a period of intense development; adolescence is normally associated with intense change, at both brain and behavioral levels (Jaffe, 2000; Lerner & Castellino, 2002). I have chosen this study sample because it allows intensive observation and processing within an existing system devoted to adaptive change, which, in turn, allows close analysis with minimal disruption.

This study does not intend to differentiate between induced or chosen change, nor between short-term and lasting change. It will focus only on the process of adaptive change. From an adaptive perspective, change needs to be only "just good enough" to facilitate survival. Indeed, in a rapidly changing environment, it is the ability to change, rather than the duration of the change, that matters.

Study Limitations

The primary participants represent a tiny percentage of the general population, in that they have sufficient personal, family, and/or legal problems to necessitate their removal from home and school for an extended (6-month to 12-month) period. These adolescents have a long-term pattern of maladaptive behaviors.

This study also assumes that positive change (defined here as learning that produces adaptive behavior) can be equated with an observable—at least, temporary and at most, permanent—alteration in an individual's neural system, such that he increases his chances for survival within contemporary mainstream society.

Researcher's Perspective

I am a licensed counselor; I practice psychotherapy with adolescents and their families. I am a teacher and a student, the oldest child of a pathologist and a psychiatric nurse. I am fascinated with change and stability, with health and illness, and with survival and extinction. I firmly believe in the human potential for adaptation. This synopsis briefly describes my "initial conditions."

During the course of my graduate studies, I have found an affinity with both quantitative and qualitative research paradigms; I believe in the value of both approaches, and this study begins as a mixed-methods project. Just as the greatest human mind can be destroyed by a simple virus, our beautiful theoretical constructs are easy prey for contradictory information. I see no necessary conflict among research traditions. "Here as elsewhere knowledge is obtained from a multiplicity of views rather than from the determined application of a preferred ideology" (Feyerabend, 1993, p. 37). Humans want to know, and there are diverse ways of knowing. I do believe that our most useful concepts are complex and evolving. In that spirit, I hope that this dissertation will contribute to our changing portrait of human life.

The denial of complexity is the beginning of tyranny.
—Anonymous

CHAPTER 2: LITERATURE REVIEW

This study searches for theoretical explanations of an existing data set. After a review of the literature, I believe that nonlinear Dynamic Systems Theory best explains the observed development/learning processes among the research subjects. Therefore, a review of systems theory, and the scientific paradigms that have contributed to it, seems appropriate. Because scientific paradigms extend into different disciplines and are usually derived from the traditional "hard" scientific disciplines of physics and chemistry, a "genealogy" of worldviews is tempting to lovers of methodology and the history of science. This literature review will skirt deeper investigations of these topics and will focus instead on the uses of Dynamic Systems Theory in social science.

Systems

A *system* can be defined as a group of entities in which the actions of any single entity affects, and can be affected by, the other entities within the group (von Bertalanffy, 1968). *Closed systems* are those that function in isolation from their environment. *Open systems* interact with their environment, which consists of other systems. "Every living organism is essentially an open system" (von Bertalanffy, 1968, p. 39). An atom is a system; the behaviors of each particle act to create, define, and control the system of particles that we call an atom. Elements are different from each other because they have different configurations of subatomic particles. Organic cells are systems, bounded by membranes. Groups of cells constitute specific tissues, which are again grouped into organs. This process of upward organization, ever increasing in complexity and size, extends all the way to solar systems and galaxies. Gravitational forces affect and control the orbits of moons, planets, and suns. From a systems perspective, the known universe can be understood as a vast collection of nested, interacting systems. "The living organism is a hierarchical order of open systems" (Bertalanffy, 1968 p.160).

When this perspective is applied to humans, it provides some interesting lenses through which to view and understand our behaviors. Individual humans—themselves elaborate organic systems—operate within family, work, community, cultural, ecological, and economic systems. Uri Bronfenbrenner (1979) identified levels of systems as *microsystems, mesosystems, exosystems,* and *macrosystems*. The immediate familial individuals we see face-to-face every day comprise our microsystems. The interactions among our microsystems comprise our mesosystems. Our communities and cultures comprise our exosystems, in that those entities affect us, even though we might never encounter them in person. Larger economic and historical contexts comprise macrosystems. All of these systems shape and constrain individuals. Language systems and discourses (Foucault, 1970) create and limit individual minds. While an individual affects the systems within which she operates, the scale and homeostatic pressures of the larger systems tend to limit this influence. These dynamics apply equally to cancerous cells, ideas, political revolutions, and hurricanes. Systems theory has generated "a basic re-orientation in scientific thinking" (von Bertalanffy, 1968, p. 5), and has shaped almost all modern theorization in the social sciences, including individual and family psychotherapy (Bateson et al., 1956; Haley, 1959; Minuchin, 1974; Selvini-Palazzoli, Boscolo, Cecchin & Prata, 1978; Watzlawick et al., 1974).

Mechanistic Theories

Explanatory guesses (theories) are shaped and constrained by the linguistic, cultural, and metaphorical discourses from which they emerge (Pepper, 1942; Foucault, 1978). These philosophical models have resulted in very different explanations of learning and development. *Mechanistic theories*, based on the metaphor of system-as-machine, conclude that "the human is inherently passive; his or her activity results from the action of external forces, ones placed *on* the person through environmental stimulation or *in* the person through genetic inheritance" (Lerner, 2002, p. 53). Just as one can deduce the set of rules governing a machine's behaviors from an analysis of its parts and products, one can similarly reduce and discover the phenomenon of human change. An example of this worldview is found in the classic academic joke that "all psychology is really just biology; all biology is really just chemistry; all chemistry is really just physics, and all physics is really just math." Mechanistic theories "have been valuable for modeling the rule-based regularities in development, especially those that are common to human and nonhuman information-processing" (Lewis, 2000, p. 37). Change is thus viewed as the continuous product of function. Cybernetics, the study of closed systems (Ashby, 1960, 1966; Wiener, 1948), has elaborated on the concepts of feedback and homeostasis. Ashby (1960) titled one of his chapters "Dynamic Systems" and introduced it with the statement

> We take as basic the assumptions that the organism is mechanistic in nature, that it is composed of parts, that the behavior of the whole is the outcome of the compounded actions of the parts, that organisms change their behavior by learning, and that they change it so that the later behavior is better adapted to their environment than the earlier. (p.12)

Although more recent Dynamic Systems theorists disagree with Ashby's mechanistic assumptions, his concept of learning as adaptive change strongly influences the present study. The mechanistic cybernetic view of systems influenced the "Milan Group" of family therapy theorists, who emphasized the value of new information as feedback, stimulating a system to "autocorrect" (Selvini-Palazzoli et al., 1978), achieving a new and more adaptive state of homeostasis.

Organismic Theories

Organismic theories are based on a metaphor of system-as-flowering plant, in which the whole is qualitatively different from the sum of its parts. Different rules and processes are found at different levels of a system's organization; thus, a higher level process "cannot be understood, since it does not exist, at the lower level" (Lerner, 2002, p. 59). The seed does not contain a miniature flower. Rather, the flower's form unfolds from earlier, different forms of stems and leaves and buds. This metaphor can be applied to learning and developmental processes, and allows conceptions of discontinuous changes, such as stage-shifts (Lewis, 2000). The organismic metaphor implies a "goal for development: To achieve the form the organism is inherently destined to take" (Lerner, 2002, p. 61). Changes unfold in a predetermined sequence, toward a telos (predetermined final goal). A rose bush, given the necessary inputs at the correct times, will ultimately produce roses. A human embryo will, in the same way, produce a reproductively fit, mature adult. Change is thus viewed as unidirectional, progressive, and teleological. Within any one level of an open system, however, development follows similar systemic processes. Plant leaves, as systems, not only function according to the rules and patterns common to all leaves, but also display the same mechanisms of feedback and homeostasis-seeking as do roots and flowers. This combination of within-form continuity and between-form discontinuity is the basis for Piaget's, Erikson's, Freud's, and Kohlberg's stage theories.

Piaget

Observing his own children, the revered Swiss developmental theorist Jean Piaget noticed that they went through stages of mental development (Piaget, 1947). He postulated the Sensorimotor stage, starting in infancy, during which as humans we develop the basic ability to touch, feel, and manipulate our environments. Starting around the age of 2, as we acquire language, we enter the Preoperational stage. We learn to use symbols and words to represent the external world. Perception rules over logical thought. During this stage, children cannot grasp ideas such as conservation of size, reversibility, and deductive logic. During the Concrete stages, usually starting around age 7, we learn to describe and predict our world in concrete ways. Numbers, names, and logic skills develop. As we move into the Abstract stages, generally between ages 11 to 14, we become better able to extend our concepts via metaphor, connecting ideas and events in more complex ways (Piaget, 1951; Flavell, 1963).

Piaget hypothesized that within any stage, we are in a continuous process of interaction with our environment. He is credited with the first elucidation of the concept of *constructionism*—the idea that the learner actively constructs cognitive structures, as opposed to passively absorbing them from teachers.

Piaget started his career as a biologist, and this background structured his approach to developmental psychology. He believed that cognition is simply one example of a biological system; "Digestion, respiration, and circulation are also examples of biological systems. Intelligence… is a biological system… governed by the laws that govern any other biological system" (Lerner, 2002, p.373). He sought to identify and classify the processes by which humans mentally adapt to their environments. As we encounter new events/objects (affordances), we attempt to fit them into our existing knowledge structures (assimilation). If affordances are beyond these current structures, we are forced to change our structures (accommodation).

> In summary, the major developmental mechanism of adaptation that occurs in the forms of actions and experiences involves a synchronic dialogue between a conservative mechanism consolidating the present state of development (assimilation) and a progressive mechanism preparing and establishing a future state of development (accommodation). (van Geert, 1998, p. 637)

As our structures increase in complexity via this dialectical process, we progress to higher stages of cognitive ability. A temporary state of stability, during which the system's activity is in successful balance with its environment, is termed *equilibrium* (Lerner, 2002). "Development takes the form of a journey through successive levels of equilibrium, that is, stages" (van Geert, 1998, p.636).

In many ways, assimilation is similar to first-order change, and accommodation describes second-order change. Context is important, as well; learning/change within one structure may not influence other structures. For example, consider the cases of autistic savants, who may be able to perform incredibly complex abstract levels of thought in mathematics or art, yet who are unable to operate beyond rudimentary concrete levels in other domains of thought (Sacks, 1985).

Contextualist Theories

Contextualist theories are based on a concept of system-in-history. Systems move through a stream of events; each event affects, and is affected by, this interaction. The level of analysis thus moves beyond the individual organism to its interactions. Vygotsky can be considered a forefather of contextualism.

Vygotsky

Lev Vygotsky has been described as the Mozart of psychology, because of his incredible brilliance and early death from tuberculosis. During the early years of the 20th century, before, during, and after the Soviet revolution, Vygotsky studied and wrote about the ways in which humans learn and develop. His works were largely unavailable in the West until 1968 because of Stalinist repression, the Cold War, and lack of translation.

Vygotsky (1978) recognized the primacy of social interaction and language. Traveling through a variety of Soviet/Asian ethnic groups, he noticed that children in all cultures first learn to speak aloud, and then internalize this speaking as thought. Deaf children do the same thing with sign language. He conceptualized *scaffolding*—the necessity for leaping to more complex ideas on previously constructed platforms. He theorized the Zone of Proximal Development (ZPD), describing it as the distance between a learner's current level of knowledge and the highest potential level of knowledge that the learner could currently apprehend given instruction. He also noted that the ZPD varies among individuals, and is in a constant state of movement. Vygotsky asserted the importance of the relationship between teacher and learner. He described this relationship as an apprenticeship, wherein the learner watches and emulates the teacher, eventually equaling or surpassing the teacher. Throughout his works, Vygotsky emphasized the dynamic, social, process-oriented nature of learning/development. He asserted the primacy of culture (context) as the driving factor in human development.

Change thus becomes the norm, and changes ripple through time in every direction. Contextualism finds "environmental causation, sudden interruptions, and individual differences in timing" (Lewis, 2000, p. 37). Contextualism, applied to human change/development theory (Lerner, 1991; Lerner & Ford, 1992), produces rich concepts of the change process.

Dynamic Systems Theory

Dynamic Systems Theory evolves from mechanistic, organismic, and contextualist systems theories. This theory incorporates their perspectives into a commensurate explanation of the learning and change processes of living systems. DST posits that

1. Forms and patterns create one another via self-organizing processes; structure emerges and, thus, must neither be the result of preordained internal (genetic, organismic) instructions, nor be produced strictly by external (environmental, mechanistic) pressures.
2. Self-organizing systems tend to become more complex. They do so to increase their adaptive success. More sophisticated systems generally have more tools and options available to handle environmental pressures.
3. Systems reorganize via discontinuous, abrupt changes, characterized by instability and high variability. These phase transitions (bifurcations) are unpredictable and nonlinear.
4. Self-organizing systems are, paradoxically, highly sensitive and highly stable. They are able to exist at the edge of chaos, thus maintaining an extreme sensitivity to environmental information. They simultaneously

are prone to maintain stability (homeostasis) and strive to assimilate feedback into their existing structures (Lewis, 2000, p. 39).

DST thus offers a way to incorporate mechanistic, organismic, and contextualist concepts, bridging the incommensurate gaps between and among them.

Because living systems—that is, humans—are in constant interaction with other systems, they face disruptions. Here, disruption may be viewed as any contextual event that disturbs a system's equilibrium, or homeostatic state. Life is a process of continual disruption. We face constant discrepancies between our current states and the ones we need to attain. But living systems must maintain their organization because disorganization threatens the survival of a system. Death/entropy is the ultimate disorganization (Ford & Lerner, 1992).

"All stability, change, and development in humans must be, therefore, a product of processes that deal with disruptions or discrepancies by maintaining, restoring, or creating coherent organization" (Ford & Lerner, 1992, p.172). So processes have evolved for continually maintaining, restoring, and creating coherent intraperson and person-environment patterns of organization.

A system can deal with disorganizing forces in only three ways: It can maintain the current systemic organization by avoiding disruption, by restoring this organization after the disruption passes, or by changing the systemic organization to a new form, either gradually or suddenly. Change occurs either "by evolution or revolution." These two strategies are analogous to other change theories: By temporarily changing, but then returning to the old organization, the system is exhibiting *first-order change* (Watzlawick, Weakland, & Fisch, 1974). Enduring change in the system's organization can be described as *second-order change* (Watzlawick et al., 1974). This deep change can be either incremental (gradually leading to a new organization) or transformational (rapid, dramatic change—i.e., a flash of insight, or a religious awakening). Furthermore, these change patterns approximate the 3 types of bifurcations—changes—described in Chaos Theory (Prigogine & Stengers, 1984).

Chaos Theory

Chaos Theory (Prigogine & Stengers, 1984) predicts that open systems will exhibit a degree of instability at bifurcation points. "Movement from one orderly regime to another necessarily spans a phase of relative disorder" (Lewis, 2000, p. 39). Chaos Theory describes three general types of bifurcations: *subtle, abrupt,* and *implosive.* In a subtle bifurcation, the system makes minimal adaptations without displaying dramatic fluctuations. In an abrupt bifurcation, the system will display noticeable, unpredictable fluctuations and will reorganize at a more adaptive, higher level of complexity. In an implosive bifurcation, the system will not successfully make the leap to a more adaptive level of complexity; it will instead implode (or explode), perhaps surviving by reorganizing at a lower level of complexity. Chaos Theory also predicts that greater amounts of systemic change will be associated with more extreme fluctuations, although not in a linear relationship.

While studying computer models of weather systems in an attempt to improve meteorological prediction, Edward Lorenz (1963) found that minute changes in variables produced enormous differences in outcomes. The weather patterns were extremely sensitive to initial conditions; temperature, wind speed, pressure, and humidity differences of less than one thousandth of 1% caused wildly different results. From these frustrating attempts to linearize nonlinear systems came the quote, "A butterfly stirring the air today in Peking can transform storm systems next month in New York" (Gleick, 1987). These perplexing mathematical studies were the foundation of Chaos Theory, hereafter called *nonlinear Dynamic Systems Theory*, or *DST*. DST suggests that, although patterns are likely to emerge within open systems, predicting exactly when, where, and how they will look is impossible. In nature, and in human activities, chaotic/nonlinear systems are the norm. Trees will grow branches, but no one can predict their exact patterns. Humans will generally learn to speak, but no one can predict exactly when, or what the first three words will be. Nonlinear systems theory recognizes the impossibility of precise prediction and control, but it emphasizes the importance of emergent, self-organizing patterns. The phrase "tends to" becomes vital. Probability replaces certainty.

For example, we know that a child placed in an affordance-rich environment (Gibson, 1969) will tend to learn/develop more quickly and deeply than a child in a deprived environment. This does not predict or guarantee individual results, but a pattern is evident. When a family undertakes a course of family therapy, introducing new information and behaviors into their system, the family members will tend to improve their functioning. No one, however, can accurately predict the outcome for any one family. This uncertainty has been terrifically frustrating for social scientists, who have traditionally modeled their research on the physical sciences. There is no room for "tends to" in chemistry.

Variability and Second-Order Learning

A wealth of both scientific and folk data exists for the rocky road to profound learning and change:

- It is always darkest before the dawn.
- It will get worse before it gets better.
- If you aren't falling down, you aren't learning.
- No pain, no gain.

In their article "Nonlinear Phenomena in Learning Processes," Stadler, Vetter, Haynes and Kruse (in Pribram & King, 1996) assert that we can examine the theory of self-organization in the learning of complex systems using three empirical hypotheses focused on variability:

1. When measured over a sufficiently long time, with nearly constant learning effort and linear increase of task difficulty, learning processes will show characteristic nonlinearities in performance (phase transitions).
2. The stability of some parameters of the performance will break down at the end of each phase of stagnation (critical fluctuations). In contradiction to naïve expectation, one hypothesis should be that at the end of the highly optimized performance the rate of errors increases.
3. Again in contradiction to naïve expectation, the learner will also show a significant increase in sensitivity to disturbances at the end of this phase of optimized performance (critical slowing down) (p. 159).

Stadler et al. (1996) reexamine archival behaviorist studies (mostly from before World War II) as a way to test the above three hypotheses. The researchers found considerable support for the hypotheses, not only in the data, but also in the observations and theorizations of early behaviorists. When faced with choice points in a maze, rats often displayed twitching, uncertain behaviors. Researchers described these fluctuating pauses as *vicarious trial-and-error* (VTE); they hypothesized that the rats were visually running the maze inside their brains, exploring possible outcomes before physically moving forward (Tolman, 1932). The University of Colorado's Karl Muenzinger noted that "We have also found invariably that in a difficult discrimination the frequency of VTE is higher than in an easier one" (1938, p. 81).

Recently, Yan & Fischer (2002) have studied adults who are learning to use computer software. They describe a similar group of three patterns in this process:

1. Each person's performance levels vary within a range between upper and lower attractors during dynamic construction of a skill.
2. Performance moves through different pathways from a novice pattern to a transitional pattern characterized by scalloping (repeated building up and collapse of complex performance) to an expert pattern. Social scaffolding plays an important role in moving a learner toward the upper attractor.
3. Each person functions at diverse levels depending on demands of the task, domain, background, scaffolding, and capacity and thus shows asynchrony in level, not simple consistency. Tasks and situations attract specific skill levels that are often below people's highest capacities (Yan & Fischer, 2002, p. 141).

Chaos, Variability, and Development

Within the developmental psychology discipline, researchers are moving from a preoccupation with the products of stable stages to a closer analysis of intraindividual variability. Granott (2002) states that "researchers who adopt a process-oriented approach view variability as a characteristic developmental attribute," and that "variability does not only characterize transitional states in children's development, but rather seems to be a general characteristic of human behavior, prevailing within a person as well as between persons" (p. 214). This points to a potentially significant interdisciplinary union.

Van Geert (1994) reexamined Vygotsky's concept of a Zone of Proximal Development (ZPD) from a DST perspective. He found evidence for strong congruence between the idea of the ZPD and the functions of Chaos Theory, extending the concept to mathematical formulations. Van Geert interprets the ZPD as the "region between a learner's actual and potential performance levels" (p.347). He hints that these levels function as attractors, and that the distance between them can be measured and optimized.

Some of the most influential microdevelopmental/dynamic systems research has been published by Esther Thelen. She studied the development of human infant limb movement; "What began as a way of understanding movement has become a way of understanding many aspects of human behavior and its development" (Thelen & Bates, 2003, p. 383). Thelen and Bates found that infants did not develop in an organismic, genetically determined manner. Rather,

> Such physical and biological structures literally "self-organize" to form patterns; that is, the individual parts, none of which contain any program

> or blueprints, produce a more complex organization *as a result of their interrelations*. Thus, when the many, heterogeneous elements that produce movements—nerves, muscles, joints, metabolic processes—cooperate together in a task, they cohere together in a way that is more complex than the sum of the parts…. (p. 381)

This is the foundational process Dynamic Systems Theory posits. Thelen and Bates further assert that

> The key metric of such dynamic systems is their stability, or the strength of the 'attractors' of their patterns. When patterns self-organize, they settle into preferred states, which can either be quite stable, or unstable and easily perturbed. When patterns are stable, the elements cohere and resist change. For patterns to change, the system must lose stability; internal or external components can reorganize into a new and more stable state….
>
> Patterns change only at critical values, and then they do so rather suddenly, without intermediate patterns. Experimental studies of other rhythmical movements have documented that system change is preceded by loss of stability indexed through increased fluctuations or variability in the system components… (2003, p. 381)

Thus, the change process is characterized by a loss of stability, a period of heightened variability, and then reorganization as a more complex, stable system.

Strengths and Weaknesses of Extant Literature

Most currently publishing researchers in the microdevelopmental field—for example, Thelen, Grannot, Parziale, van Geert—are cautious about making grand leaps of theory from the existing data. They are also careful to not oversimplify or overgeneralize their findings. Most of their studies display strong experimental or quasiexperimental designs, albeit with small *n*s. The difficulties inherent in repeated measures of cognitive processes—test/retest issues, ecological validity, interrater reliability, and so on—are generally spoken to and minimized. In Fisher and Yan's above-described study involving teaching statistical software, the design effort was exemplary. The campus computer lab was familiar to the students, the process was transparent, the task real and useful. Because the task involved clearly measurable mathematical skills, measurement error was minimized. The researchers' analysis was simple and clear, as well. They did not pool participant data but kept them separate, in accordance with the idea of intraindividual variability; and they graphed the data for comparisons.

Many of the authors seeking to apply chaos/Complexity Theory to human behavior do not share this caution. For example, a psychologist in Wyoming (Butz, 1993, 1997) has written several books in which he fits individual and family psychotherapy into Chaos Theory—that is, he describes habits and personality as attractors. Butz makes some convincing arguments, and his works are useful for practitioners seeking new ways to understand their craft; there is little to no empirical evidence, however, for these assertions. Again, this lack of empirical evidence is a common feature of much of the literature that relates chaos/Complexity Theory to human activity, and this limitation is probably one reason Dr. van Geert has instructed me to use the term *nonlinear Dynamic Systems Theory* in my dissertation.

One of the most challenging gaps in the literature concerns the relationship between short-term microdevelopmental and long-term macrodevelopmental processes. *Microdevelopment: Transition Processes in Development and Learning* (2002), edited by Grannot and Parziale, hypothesizes change as a fractal process, meaning that micro- and macro-level processes follow the same patterns. This idea, drawn from chaos, complexity, and systems theories, holds that events tend to unfold in similar patterns, regardless of scale. Although there are many supporting examples in the physical and biological sciences (developing capillaries and bronchioles resemble rivers and tree branches and snowflake designs, for instance), there is little or no research evidence for the exact processes of adaptive human change. The question becomes much more complicated when applied to the most complicated structures yet discovered: the human brain. With more synaptic connections than there are stars in the known universe, an individual brain's development presents a challenging topic for study. Despite the intensive work being done on determining how the human brain operates, large gaps in our understanding remain. One glaring question is "By what exact processes do humans learn and change?"

Because thought is as yet invisible, learning/change can be assessed only via visible changes in behavior. This is where I hope that the present study can make a small contribution. By extending microdevelopmental measurements and methods over a longer time scale, with a decently large *n* (30 +), this study might be able to illuminate some features of the change process. If these data support the predictions of Dynamic Systems/Chaos Theory, then the fractal relationship between microdevelopment and macrodevelopment should be apparent.

CHAPTER THREE: METHODS

The exploration of nonlinear dynamic systems requires some specific methods. As Gilgen (1995) notes in the preface to *Chaos Theory in Psychology,*

> ...rather than reducing the intricacies of a complex situation via experimental restrictions or statistical manipulations, one could design research projects that revealed the patterns of change that define the system ...we generally deal with complexity by restricting the options of our subjects and taking out of play things we cannot control via experimental designs. Descriptive statistics reduce the inherent complexities of group data via means, standard deviations, or other summarizing values; and inferential statistics give us information about the likelihood that the variables singled out for study had the predicted effect. In other words, we deal mostly with complexity by trying to reduce, or neutralize, aspects of it (pp. xv-xvi).

The method described above is reasonable when one is attempting to test the efficacy of a surgical procedure or a specific educational intervention. Traditional analytical methods used in education, development, and psychology stem from efforts in these social sciences to emulate "the methods and analytic techniques of mechanistic, 19th-century physical sciences. This paradigm is inappropriate for the study of self-organizing, active, reactive, interactive, and adaptive organisms" (Granic & Hollenstein, 2003, p. 643).

Researchers of human behavior need to "remember...that the fundamental goal of modeling or analyzing a self-organizing system is to understand a *pattern* of dynamic behavior. Hypotheses must be built around such a pattern" (Barton, 1994, p.12). In this study, using archival data of adolescent boys over a 1-month to 12-month period, I will look for patterns and examine the explanatory/predictive utility of Dynamic Systems Theory in the context of the adaptive change process in adolescent males.

Rationale for This Study

Dr. Paul van Geert (2002) from the University of Groningen in Holland has published studies in which he analyzes microdevelopmental data from numerous statistical approaches. He states that "longitudinal data sets with dense measurements are ideally suited for applying the concept of fuzzy score ranges" (p. 335). The present study certainly fits this description. "The fuzzy set approach allows simultaneous description of individual differences, developmental levels, and the pathways of development" (Moore & Dixon, 1991, p. 458).

Philosophical Assumptions

Humans are not easily understood and measured; test scores are snapshots at best. Observational data are fuzzy by nature: Was the child "annoyed," "angry," "enraged," or "frightened"? Charles Ragin (1987, 2000), a sociologist, has applied fuzzy-logic analysis to political science and sociologic data, with impressive results. Events that are, by their very nature, unmeasurable (at least accurately) by mathematical scales can still be described and analyzed logically. This premise applies to most activity in the social sciences: "... in view of the nature of the causes, psychological properties such as skills, abilities, knowledge or concepts are properties that apply to persons in a fuzzy way" (van Geert, 2002, p. 322).

Furthermore,

> ...repeated testing, for instance in a microdevelopmental design, almost unequivocally hints at a *range* of successive scores, with an upper and a

> lower bound. This range may show properties of a normal distribution around a mean or it may not do so. But even if there exists something like a normal distribution, it is not automatically the case that its central tendency (in the limit) is the true value, whereas all other values boil down to deviations due to measurement errors (van Geert, 2002, pp 321-322).

Standard statistical analysis will treat variance as error, even though this variance is usually an intrinsic and hence important part of the subject's characteristics. Van Geert has stated that

> ...the causes of developing performance are in fact a fuzzy and distributed set. Variability across time is one of the indicators of this fuzziness, which is not a matter of error or unsystematic variance but an inherent property of the developing and functioning person (p. 341).

While the behavioral scores used in this study (and in most studies in the social sciences) are, by their very nature, subjective, this does not mean that they are useless for or immune to quantitative analysis. This data demands, instead, an *appropriate* analysis.

Research Design

As previously mentioned, I will look for patterns of change in this archival data. One theory for explaining change is Dynamic Systems Theory (DST). Granic and Hollenstein (2003, pp. 647-649) describe an emerging research process informed by the principles of DST. They credit Thelen and Smith (1994, 1998) and Thelen and Ulrich (1991) with the delineation of these six steps:

1. *Identify the collective variable of interest.*

   "A collective variable must be an observable phenomenon (not a construct or latent variable) that captures the coordination of the elements of a multidimensional system" (Granic & Hollenstein, 2003, p. 647). For this study, the observed phenomenon of heightened behavioral variability has been identified as the collective variable of interest.

2. *Describe the attractors for the system.*

   "This involves mapping the real-time trajectory of the collective variable in various contexts across different developmental periods and identifying its relative stability... High stability indicates an attractor state" (Granic & Hollenstein, 2003, p.647). For this study, the attractors can be described as stable lowest and highest states, determined by visual examination of each case's graphs. The distance between these attractors may provide a useful measurement of the amount and type of change that an individual has achieved.

3. *Map the individual developmental trajectories of the collective variable.*

   "This step requires collecting observations at many time points in a longitudinal design (also see Fogel, 1993)... Then, developmental profiles can be graphed on a case by case basis and the similarities and differences among profiles can be described" (Granic & Hollenstein, 2003, p.648). This is one of the more persuasive reasons for using this archival data source; intensive observations have already been made and graphed for the individual subjects. The collective variable of interest and attractor states can be gleaned from these data, and the cases can now be studied and analyzed.

4. *Identify phase transitions in development.*

   "...transitions in development are characterized by increased variability, a breakdown of stable patterns, and the emergence of new forms ... transition periods are critical to mark because it is at this stage that researchers have access to, and may manipulate, mechanisms underlying change" (Granic & Hollenstein, 2003, p. 648). For this study, I am seeking to identify transition periods and to ascertain whether the hypothesized relationship between phase transitions and change does exist. If it does, then it may be possible to improve process-type assessments and interventions:

> Clinical interventions may have their greatest impact if they are targeted at these "sensitive periods." Also, interventions may *induce* a phase transition, which may be one compelling way to characterize treatment progress... For example, treatment progress, operationalized as a destabilization of the system, may be tested by examining the observed amplitude of oppositional outbursts. Evidence for a clinically induced phase transition may include an increase in the standard deviations of the amplitude of outbursts and a decrease in *within-subject* correlations between, for instance, different contexts and the occurrence of oppositional behavior (Granic & Hollenstein, 2003, p. 648).

The potential applications of this research will be discussed at greater length in chapter five. For this study, the focus remains on an oft-hypothesized, but underproven, link between increased variability and adaptive change.

5. *Identify control parameters.*

This step presents difficulties in a study of the present type. Because I am using archival data based on observation, there are no manipulated variables. However, the treatment program itself, in which all of the subjects have participated, imposes the control parameters. In the present study, the observed behavior changes can be regarded as responses to the manipulations of environmental and social parameters.

> In DS language, control parameters are the "agents of change." The purpose of tracking the collective variables across different contexts and developmental transition points is to ultimately

> identify the mechanisms underlying processes of change … this step is the most difficult because psychological systems are incredibly complex and the problem of identifying one or very few causal mechanisms that can be manipulated to test their impact on the system is often insoluble. Moreover, a control parameter may not always be something that *can* be manipulated (e.g., socioeconomic status, parental depression). Nevertheless, DS researchers urge us to at least keep the concept in mind for future studies, after careful microlevel observations have been completed (Granic & Hollenstein, 2003, pp. 648-649).

The implications of this idea, and suggestions for future studies, will be discussed in chapter five.

6. *Manipulate control parameters to experimentally generate phase transitions.*

   This step is not attempted in the present study. If the results suggest significant relationships between phase transitions, adaptive change, and predictable outcomes, then future studies can address specific interventions via experimental manipulation.

Participants

This study examines a small population of age-limited (15-year-old to 19-year-old) males from one western state in the United States of America. Racially, the study will be limited to Caucasian, Hispanic, African-American, Native American, and mixed descendants of the above. In addition, the participants are, by nature of their ages, embroiled in a period of intense development; adolescence is normally associated with intense change, at both brain and behavioral levels (Jaffe, 2000; Lerner & Castellino, 2002). Adolescence has been called "an exemplary ontogenetic period within which to study the developmental systems involved in human regulatory processes" (Lerner, Lerner, Stefanis & Apfel, 2001, p.11). I have chosen this study sample because it allows intensive observation and processing within an existing system devoted to adaptive change, allowing close analysis with minimal disruption.

There are two primary reasons for using archival data. First, in keeping with the above statement by Gilgen (1995), I will not attempt to reduce the complexity of the change process by isolating or manipulating variables. Second, there are ethical challenges inherent to working with a population of vulnerable adolescents. Legally prescribed change is already enough of an ethical morass, especially when it is administered by privileged members of the dominant culture. To interfere with this treatment process for any reason other than the long-term well-being of the clients seems to me unethical. Therefore, I will not study any current clients, and I will examine the score patterns only of past clients who are no longer under any form of legal or personal duress to comply. I will thus avoid even unconscious attempts to influence their behaviors or scores.

Location

The archival data is drawn from participants in a residential treatment program located in a mid-size city in the Rocky Mountain area. All data are pulled from the records of one program over a two-year period, during which there was no significant change in the program's structure.

Measures

For an example of the raw score sheets from which the measures are derived and a deeper explanation of the scoring process, see Appendix A. These score sheets are kept with other records of a client's stay in treatment in a secure facility for a minimum of three years after his discharge.

Procedures

This study will begin with the collection of archival behavioral rating scores on a large (n >30) randomized group of high-risk adolescent males during their stays at a residential treatment center. The behavior scores were not generated for the purpose of this or any other study; they were used to provide feedback, to gauge progress, and to determine privileges. This group provides a large, consistent sample of carefully observed adolescents whose behavior is scored while they are involved in profound learning/change processes. The participants are scored on their observed behaviors 24 hours a day, every day, during their stay in a residential treatment center. The average successful stay lasts between 6 months and 12 months. Scoring is done by a large (20 person to 30 person) group of staff members, consisting mostly of teachers and counselors. Scores are discussed among raters and are adjusted by group members if they are believed to be too extreme. Scores are reported as percentage points out of a possible 100. This method is not a claim for numerical exactness; daily averages for a stable client display a typical random/error variance of up to 5%; in other words, two raters may easily disagree by 5 percentage points. Weekly averages are more highly esteemed as accurately reflecting an individual's genuine behaviors, generally displaying an error/variance rate of less than 5%. A convenience-sampled group of 15 clients displayed a mean variation of 5.5% during a one-week period, ranging from a minimum of 2% ($n = 2$) to a maximum of 25% ($n = 1$). Indeed, at this treatment center, there has traditionally been a tendency to regress to the mean. An average performance is rated a

70%; most scores fall between 60% and 80%. For this study, the focus will be on *patterns* of scores; therefore, their *trueness* is less important than their *utility*. There is no objective standard with which to compare this scoring system. At the most basic level, the scores reflect the adult observers' assessments of the (mostly unwilling) subjects' adaptation to cultural expectations. The concept of inter-rater reliability depends on an acceptance of the assumptions of true-score theory, which holds that any measured score is a combination of a "real" score plus some quantity of random, fluctuating error. Furthermore, the true score is assumed to be unrelated to the error.

Reliability and Validity

For this study, and for any developmental studies focused on variance, the assumption of a single true score is dangerous. The focus here is not on any measurement of long-term outcomes or on group comparisons. It is, simply, an attempt to understand patterns. When scores are drawn on a bar graph, are any patterns evident? If so, do these patterns fit with the three general types of bifurcations: subtle, abrupt, and implosive? Is there any relationship between fluctuating scores (weekly averages displaying variance above 6%) and periods of adaptive change? Finally, is there a relationship between this variance and the subjects' successful completion of the treatment program?

Given the nature of the data, I believe that the use of fuzzy-set analysis will yield more valid results than traditional statistical analysis.

> In the hands of a social scientist… a fuzzy set can be seen as a fine-grained, continuous measure that has been carefully calibrated using substantive and theoretical knowledge relevant to set membership... Fuzzy sets are especially valuable in the back-and-forth between theory

> and data analysis precisely because they are heavily infused with theoretical and substantive knowledge (Ragin, 2000, p. 7).

Data Analysis

To answer research question one, I employed Q-sorts. Research questions two and three were addressed via an informed qualitative evaluation. Research question four was addressed using fuzzy logic and fuzzy sets. First described by the Iranian-American mathematician Lohfti Zadeh (1965), fuzzy logic is a tool that emulates the way humans actually reason about the world. "Fuzzy logic mimics the remarkable ability of the human mind to summarize data and focus on decision-relevant information" (Zadeh, 1994, p.49). For example: We do not observe a furry creature across the room and calculate a bell curve and confidence intervals about what species it could be. We instead decide whether it fits more into the category of "dog" or the category of "cat." If we are certain that it is a dog, we ascribe it full membership in the category (set) called "dog." We can mathematically describe this certainty (however fuzzy) as "1," and its cat-likeness as "0." If, however, we cannot tell for sure whether it is feline or canine, but we know it is one of the two, we could say that it is .5 cat and .5 dog; it is not half-dog and half-cat; rather, it displays characteristics of both groups. Then, using Boolean logic and truth tables, we can analyze numerous variables: size, color, shape, ears, and so on, and calculate a reasonable estimate of what the creature in fact is. This process seems to be the way humans think, and fuzzy logic is being used extensively in the development of artificial-intelligence and neural-network simulations.

How does this method apply to the analysis of learning/change? Van Geert (2002) and others (Ragin, 1987, 2000) have pointed out some of the inherent challenges associated with developmental, psychological, and educational data, and the value of fuzzy analytic techniques:

> …fuzzy logic enables us to quantify linguistic qualifiers such as "highly" or "weakly" in terms of prototypical degree-of-membership functions and to specify decision nets that allow us to simplify complex predictive relationships between measured variables and possible outcomes (van Geert, 2002, p. 329, in Granott & Parziale, eds.).

To apply this fuzzy-set method to the current dissertation, I can identify whether or not a person displays variance in behavioral scores beyond the norm. For this sample, a weekly variance of 5% or 6% seems to be average. I can further describe a subject's variance as "none," "a little, but below average," "average," "above average," "quite a lot," or "huge." I can assign evenly-spaced, ranked numerical values to these fuzzy, but very natural and real, descriptors; for example, 0.0, .17, .33, .5, .67, .83, and 1.0. Unlike multiple regression, fuzzy analysis does not attempt exact numerical formulas, but it does attempt to build logical statements. For example, if the value of A exceeds .5, but B does not, then a large value C tends to result. If both A and B exceed .5, then a different value of C seems to be a recurring pattern. These Boolean algorithms allow researchers to identify necessary and sufficient causes, and to highlight common patterns. Fuzzy logic relies, in the beginning, on a subjective—but transparent—decision-making process wherein groups are chosen and defined, and in which participant data is then placed and rated. Any subsequent reviewers can disagree with set assignments and reanalyze the data.

While examining the data, I will study the following independent and dependent variables. The independent variable of amount of progress, the difference between the case's low and high weekly averages, will be considered variable A. For fuzzy-set assignment, possible values include the following: 0 = none (no or negative progress); .17

= negligible gain; .33 = moderate gain; .5 = average gain (to be determined from an analysis of all cases used); .67 = marked gain; .83 = large gain; and 1.0 = extreme gain.

The independent variable of percentage of weeks the case displays variance will be labeled as variable B. For fuzzy-set assignment, possible values include the following: 0 = none; .17 = few; .33 = below average; .5 = average; .67 = above average; .83 = a large percentage; and 1.0 = extreme percentage of weeks with variance.

The independent variable of time, weeks taken to move from the case's low average (stable state) to high average, will be identified as variable C. This variable will be defined based on an analysis of all cases used. This number will probably range from 4 weeks to 48 weeks.

Dependent Variable

The dependent variable, named D, describes the bifurcation type. With which (Q-sorted) group does the case best fit? The bifurcation type, or pattern, might be valued, for example, as follows: 0.0 = totally subtle (no change); .17 = subtle change; .33 = some chaos; .5 = chaotic change; .67 = between chaotic and implosive; .83 = eventually implosive; and 1.0 = immediate implosion.

Algorithm

The resulting algorithm can be mathematically described as

A (0-1) + B (0-1) + C (0-1) = D (0-1).

In summary, I planned to address the research problem via these four research questions: first, when scores are drawn on a bar graph, are any patterns evident? This will be determined via Q-sorts. Second, if any patterns to the data are evident, do these patterns fit with the three general types of bifurcations: subtle, abrupt, and implosive? Third, for the individual cases in the sample, is there evidence that periods of increased variance precede upward progress? Finally, for the sample group of subjects, is there a causal, predictive relationship between the amounts of variance each case displays, their bifurcation patterns, and their positive or negative discharges from the treatment program? In addition, I planned to assess the utility of DST. If the predictions of Dynamic Systems Theory hold true, these data should show the following:

A. For a progression between attractors that are close together, there should be less variance than for cases in which the change is from attractors that are farther apart.

B. Sudden progress should be accompanied by more variance than gradual change.

Lastly, I will report these findings, discuss the implications, and suggest directions for further research.

CHAPTER 4: RESULTS

I presented this research problem in chapter 1: Are the observed behavioral fluctuations among these adolescent participants consistent with the features predicted by Dynamic Systems Theory? Dynamic Systems Theory (DST) describes an approach to the study of living systems that derives from physics and biology.

To thoroughly explore this problem, I presented four research questions in chapter 3. First, when scores are drawn on a bar graph, are any patterns evident? Second, if any patterns to the data are evident, do these patterns fit with the three general types of bifurcations: subtle, abrupt, and implosive? Third, for the individual cases in the sample, is there evidence that periods of increased variance precede upward progress? Finally, for the sample group of subjects, is there a causal, predictive relationship between the percentage of weeks with significant variance each case displays, their bifurcation patterns, and their positive or negative discharges from the treatment program?

To answer the fourth question, I would explore the fuzzy algorithm A + B + C = D to see whether any of the independent variables, or any complex combination of them, was necessary or sufficient to predict the dependant variable D (type of bifurcation). In addition, I proposed to explore whether these data support two predictions derived from DST. According to DST, these data should show that, for a progression between attractors that are close together, there should be less variance than for cases in which the change is from attractors that are farther apart. Furthermore, sudden progress should be accompanied by more variance than gradual change.

I proposed to first examine this archival score data, looking for patterns via a Q-sort analysis of the graphed data; I would use Prigogine and Stenger's (1984) three types of bifurcations (subtle, abrupt, and implosive) as a guide to group subjects by their similarity to these patterns. If there seemed to be more than three dominant patterns, I would describe them. If there were no clear types of patterns among the sample data, then there would be no reason for further analysis. Second, I planned to quantify the independent and dependent variables by assigning fuzzy set values for each case. I could then analyze these values using fuzzy logic to see whether the fourth research question and the two predictions of DST held true.

The treatment center reported that 133 cases met the criteria (correct date range of stay, complete set of score records) for inclusion. Using a random-number generator (www.randomizer.org), I selected 35 cases as the study sample in the hope of obtaining at least 30 usable cases. Personnel at the treatment center copied the score sheets for these cases and delivered 35 file folders that contained the detailed weekly score sheets and a page listing detailed treatment outcomes.

A careful screening of these data indicated that four cases featured scrambled or sufficient missing scores to render them unusable, and I thus excluded those cases, leaving an *n* of 31. In six of the remaining cases, the reported treatment outcomes did not seem to match the score trends. I asked the treatment center to double-check these, and they reported that two were indeed incorrect. The data analysis incorporates all six, including these two with corrected outcomes.

Research Question 1

The first research question related to whether there were any evident patterns among these data when scores were drawn on a bar graph. I hand-graphed each of the usable 31 sample cases to create a visual chart. This visual presentation allowed for effective Q-sorting. For each week, lowest and highest daily scores were plotted, thus showing the range (variance) and overall trends. These graphs did not indicate treatment outcomes, so that the Q-sorters would not be influenced by this information. Here is an example of a graph:

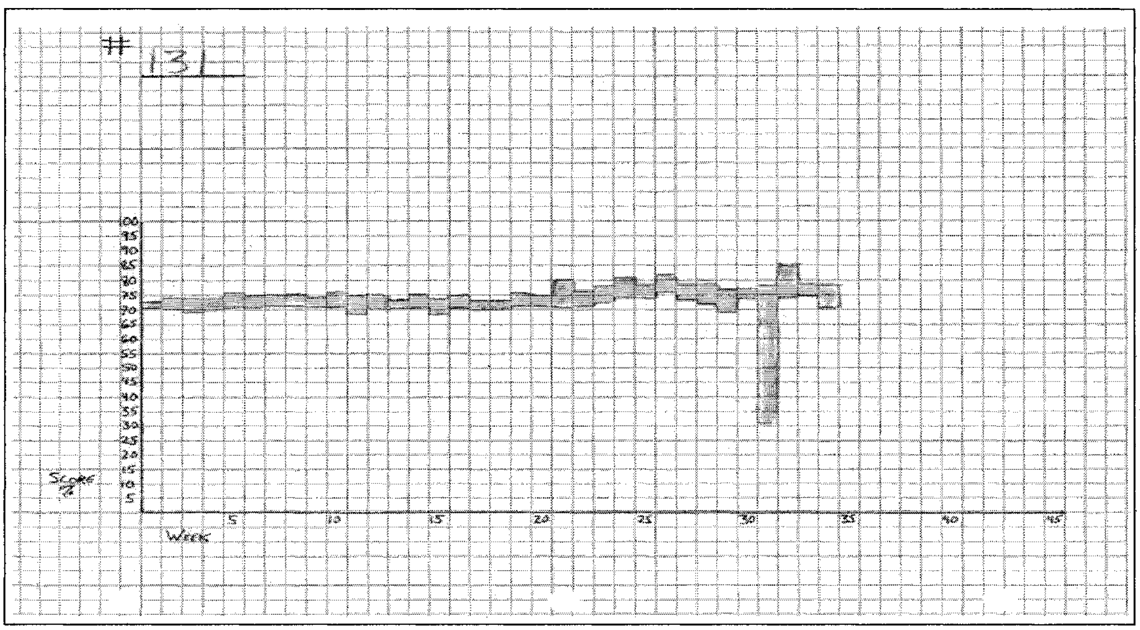

Figure 4.1 Sample Q-Sort Graph Showing Range (Variance) and Overall Trends of Client Behavior Rating Scores

Q-Sorts

I showed two people with minimal knowledge of this research project the stack of 31 graphs. I also did a sort. I explained that the vertical axis represented scores, while the horizontal axis represented time. I then instructed them to sort the 31 graphs into similar piles; this was the only direction I gave. Both asked, "How many piles?" I answered, "As many as seems appropriate."

Sorter A separated the graphs into three groups:

1. Group 1. "Upward tending with mostly smooth variation."

   Case #s: 10, 31, 42, 49, 50, 62, 64, 65, 71, 77, 91, 107, 111, 114, 123, 127, 128, 131

2. Group 2. "Downward trending, more variance."

   Case #s: 8, 57, 59, 61, 72, 76, 87, 97, 98, 113

3. Group 3. "Large variance, brief stay."

   Case #s: 13, 48, 70

This sorter commented, "Some cases seemed like they were in between the categories, or combined different types at different stages."

Sorter B created six groups. This sorter did not name or describe any of the groups.

1. Group 1. Case #s:71, 72
2. Group 2. Case #s:13, 48, 70
3. Group 3. Case #s:31, 50, 59, 64, 77, 87, 97, 98
4. Group 4. Case #s:8, 49, 57, 61, 111, 113, 114, 127
5. Group 5. Case #s:65, 76, 91, 107, 123, 128, 131
6. Group 6. Case #s:10, 42, 62

This sorter commented, "The ones that stuck it out longer had fewer ups and downs. The ones that were about a half-page (*between 20 weeks and 30 weeks)* had similar ups and downs."

Sorter C (this researcher) created 6 groups:

1. Group 1. "Very little variance, very little change".

   Case #s: 76, 91, 123, 131

2. Group 2. "Some variance, upward-climbing scores."

   Case #s: 107, 127, 128

3. Group 3. "Average-looking variance, upward-tending scores."

   Case #s: 10, 49, 65, 77

4. Group 4. "Above-average variance, upward-tending scores."

   Case #s: 8, 31, 42, 50, 62, 64, 71, 111

5. Group 5. "Considerable variance, downward-tending scores."

   Case #s: 13, 57, 59, 61, 72, 87, 98, 113, 114

6. Group 6. "High variance, downward-tending scores, short stay."

   Case #s: 48, 70, 97

In summary, these Q-sort results indicate that there are noticeable differences between cases, and that there are distinctive patterns to these data. Although these sorters picked different characteristics to group on, they demonstrated that there are indeed clear groups. Without clear criteria for group membership, distinguishing between categories is difficult; a quick visual inspection of a graph cannot provide the same precision as mathematical analysis. However, these Q-sort data do support further exploration.

Research Question 2

The second research question was "If there are any evident patterns to the data, do these patterns fit with the three general types of bifurcations: subtle, abrupt, and implosive?" Prigogine & Stenger (1984) describe a subtle bifurcation as a system's smooth movement between attractors. Subtle bifurcations display no, or minimal, fluctuation. Abrupt bifurcations involve sudden, chaotic changes accompanied by fluctuations in the system's behavior or performance. Implosive bifurcations involve more fluctuation than the system can tolerate, and the system "implodes," either retreating to the original attractor or falling into severe disorganization.

Based on the Q-sorts and my own evaluation, I concluded that there is enough agreement, and enough difference, between various groupings of patterns to support this idea. Some of the cases displayed two or even all three of the hypothesized bifurcation types. For example, case #65 looked like a completely subtle bifurcator for the first three months of his stay, with little variance and no change; at week 14, he began a more chaotic period of progress, leading to a positive discharge. Another case, #114, moved from healthy chaos to a brief period of smooth stability, and then suddenly into an implosion. Enough of this sample fit the hypothesis well enough to justify further analysis. Based on an informed evaluation, it appeared that 5 (16%) of the 31 cases fit the subtle/smooth bifurcation pattern. At least 16 (52%) of these cases fit into the abrupt pattern, and another 6 (19%) seemed to be implosive. The remaining 4 (13%) showed features of two or all three patterns. This sample group provided several examples of each bifurcation pattern, and thus merited further exploration.

Research Question 3

Dynamic Systems Theory predicts that individual learning/development often occurs in sudden, chaotic leaps, rather than in smooth curves. The third research question addressed this prediction: For the individual cases in the sample, is there evidence that periods of increased variance precede progress?

I answered this question via a case-by-case analysis, judging whether periods of heightened variance were indeed followed by periods of higher scores and reduced variance. For the whole sample group, I addressed this question with a fuzzy-logic analysis, to determine whether a complex causal relationship between amounts of variance, amounts of change, and the time taken to make this change was necessary and/or sufficient to predict the discharge status at the end of treatment.

To explore individual differences, I analyzed each of the 31 clients' data sets. I gave a general description of the client's stay in treatment, including the eventual outcome (discharge type—positive or negative, as reported by the treatment center) and the client's total length of stay, in weeks.

I gave a numerical explanation of the client's amount of progress, the time it took to make this change, and the percentage of weeks of his stay that showed significant (greater than 6%) variance. An analysis of the entire sample indicated that, of the cases that did not show 100% of their weeks in extreme variance, 51.6% (approximately half) of their weeks displayed score ranges of more than six percentage points. Those cases in which 100% of their weeks displayed considerable variance were excluded from this calculation of average variance because their inclusion would seriously skew the results upward. Therefore, weekly score ranges greater than six points were rated as displaying significant variance. This variable showed a range from 8% to 100%. I estimated a client's upper and lower score attractors, and, thus, his probable Zone of Proximal Development. I visually estimated this zone; I looked for the lowest and highest tendencies of the client's fluctuating scores, remembering that learners often circle around these attractors. These numbers were not necessarily actual scores, but, rather, tendencies. For this sample group, the mean, median, and mode size for this Zone of Proximal Development is 15 percentage points. Given the above attributes, I judged how well each client's real change pattern fit the bifurcation models of Dynamic Systems Theory. The case-by-case analysis follows, grouped by apparent bifurcation type. Cases fitting the subtle bifurcation pattern are first, followed by those fitting abrupt, and then implosive. Finally, those cases that appear to fit into two or all three bifurcation patterns are described. For each case, a Q-Sort Graph depicts the client's range (variance) and overall trends of behavior rating scores during the time the client was in residential treatment.

Subtle

Case #76

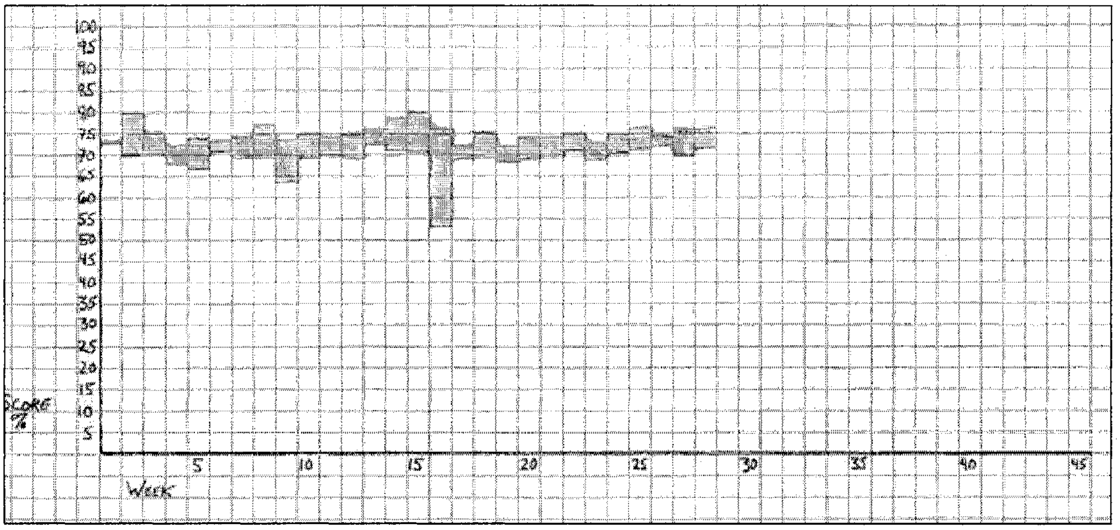

Figure 4.2 Score Graph for Case #76

This client's stay in residential treatment lasted 28 weeks and led to a negative discharge. He lost 6 points on his average weekly score from his highest to lowest average weekly scores, taking only 1 week (between weeks 15 and 16) to do so; in other words, his best week immediately preceded his worst. He displayed a minimal amount of variation, with only 26% of his weeks showing significant variance.

This client's lower attractor seemed to hover around 68, while his upper attractor approximated 77. This difference of only 9 points reflects a below-average Zone of Proximal Development for this sample group. This case fits the predicted pattern of a subtle bifurcation leading to an unsuccessful change attempt; there was too little variation and too little change.

Case #91

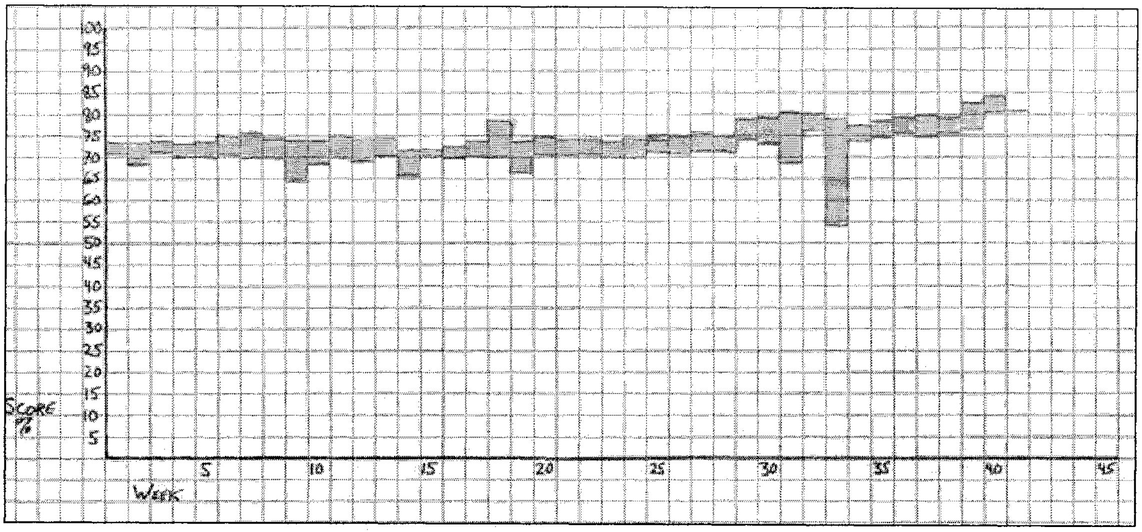

Figure 4.3 Score Graph for Case #91

This client remained in residential treatment for 41 weeks and received a positive discharge. He took only 26 weeks to gain 14 points, with only 13% of his weeks showing significant variance. His lower attractor seemed to cycle around 67, while his upper attractor approximated 80. This difference of 13 points reflects a slightly below-average Zone of Proximal Development for this sample group.

This case displayed only a few weeks of high variance followed by weeks of improved scores, fitting the hypothesized pattern for successful subtle change. The client's initial scores were quite high (70+), so he can be regarded as needing only minimal improvement. This case illustrates an example of a client with higher social skills who did not require abrupt change; in other words, his Zone of Proximal Development (the distance between his lower and upper attractors) was comfortably narrow for the time he took to make this bifurcation.

Case #107

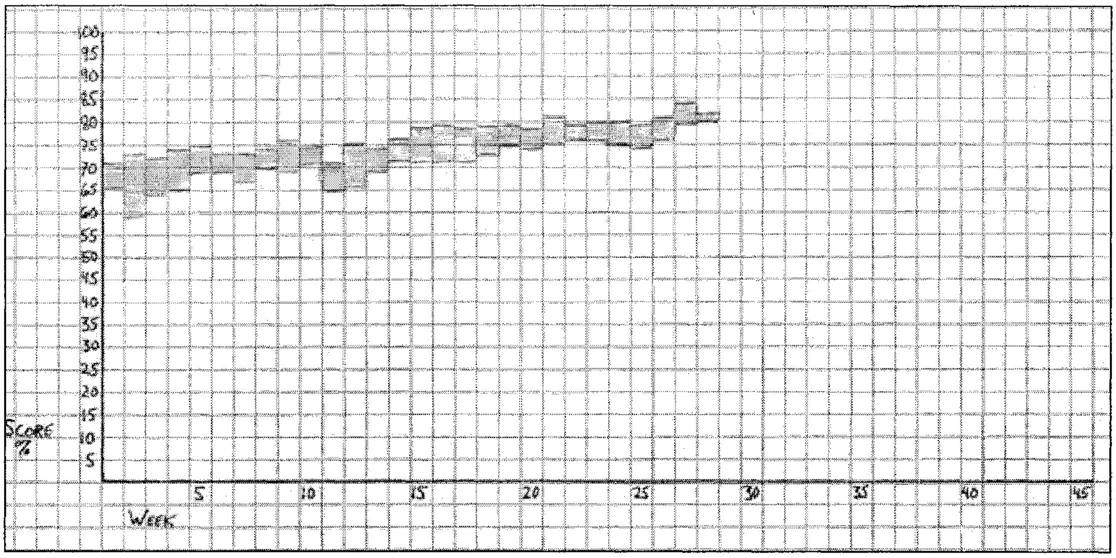

Figure 4.4 Score Graph for Case #107

This client's stay in residential treatment lasted 28 weeks and led to a negative discharge. He gained 14 points over a period of 25 weeks. He displayed a low amount of variation, with only 29% of his weeks showing significant variance. This client's lower attractor seemed to be around 65, while his upper attractor approximated 80. This difference of 15 points represents the average Zone of Proximal Development for this sample group.

This case does not fit the predicted pattern of a treatment failure. The client's steady upward progress on scores and end-of-stay stability look like the exemplar of a successfully subtle bifurcation. I can only assume that the client was either taken into custody (arrested) for actions that are not reflected in his scores, or that he ran away right before his anticipated graduation. His scores and progress do not match this outcome. It is also quite possible that this client was behaviorally skilled enough to manage a subtle upward bifurcation without genuinely changing in fundamental ways; in this sense, he may exactly fit the pattern of a subtle bifurcation that does not reach a sufficiently high attractor.

Case #123

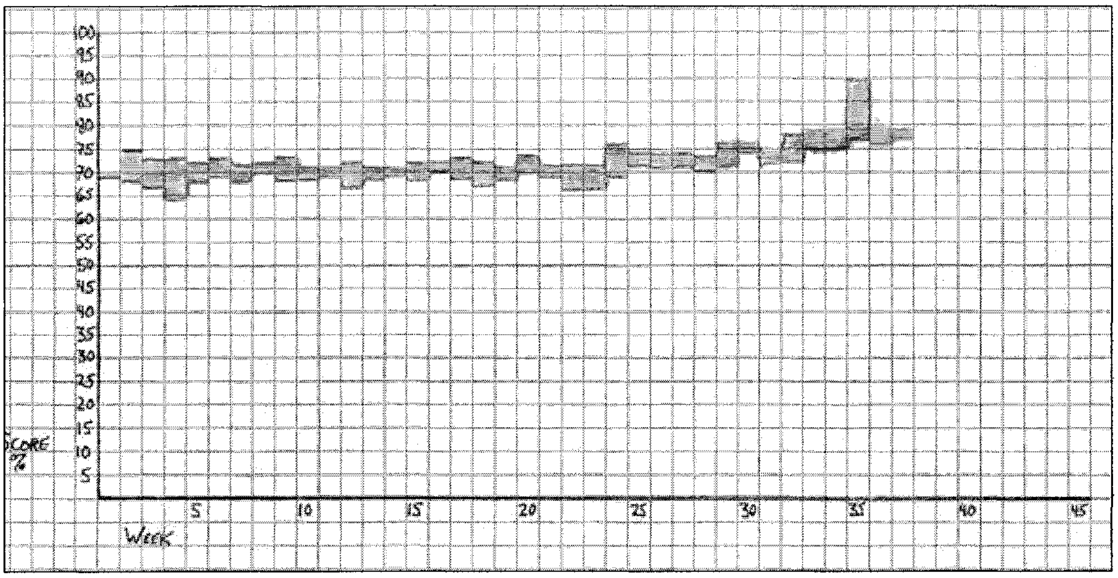

Figure 4.5 Score Graph for Case #123

This client remained in residential treatment for 37 weeks and received a positive discharge. He took 31 weeks to gain 9 points, with only 8% of his weeks showing significant variance (the least of any sampled cases). His lower attractor seemed to hover around 67, while his upper attractor approximated 77. This difference of 10 points demonstrates a below-average Zone of Proximal Development for this sample group.

This case displayed very few weeks of high variance. Instead, the client displayed minimal variance and slow, steady progress, exemplifying the hypothesized pattern for subtle change.

This case started with high, stable scores and very slowly arced upward. the client's week of highest variance occurred at week 35, when his scores drove upward, ranging from 77 to 89. This "exuberant" variance probably indicates playful experimentation in a healthy direction (e.g., showing off), rather than the typical chaotic variance associated with learning and development.

Case #131

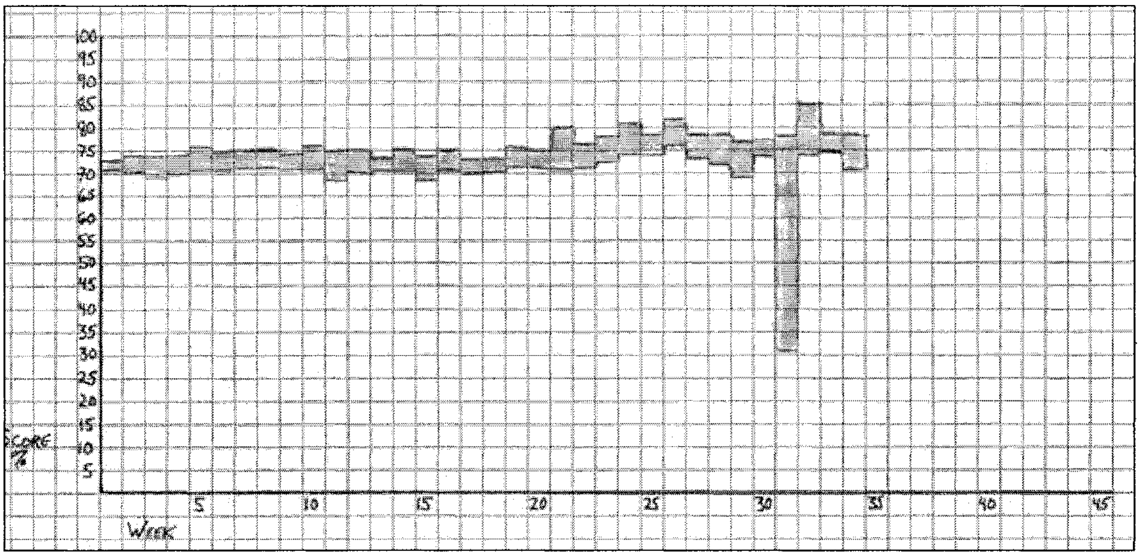

Figure 4.6 Score Graph for Case #131

This client remained in residential treatment for 34 weeks and received a positive discharge. This client generally showed little variance and smooth, steady progress, except for an anomalous week (week 31) soon before his discharge. This uncharacteristic week, which may have been the result of a conflict with a peer or family member, skews his numbers; without it, he is an exemplar of "slow and steady" change. Excluding this regression, he took 11 weeks (from week 15 to week 26) to gain 8 points, with 24% of his weeks showing significant variance.

This client's lower attractor is around 70, while his upper attractor approximated 80. This difference of 10 points represents a below-average Zone of Proximal Development for the sample group. This case displayed very few weeks of high variance followed by weeks of improved scores, fitting the hypothesized pattern for subtle change.

Abrupt

Case #8

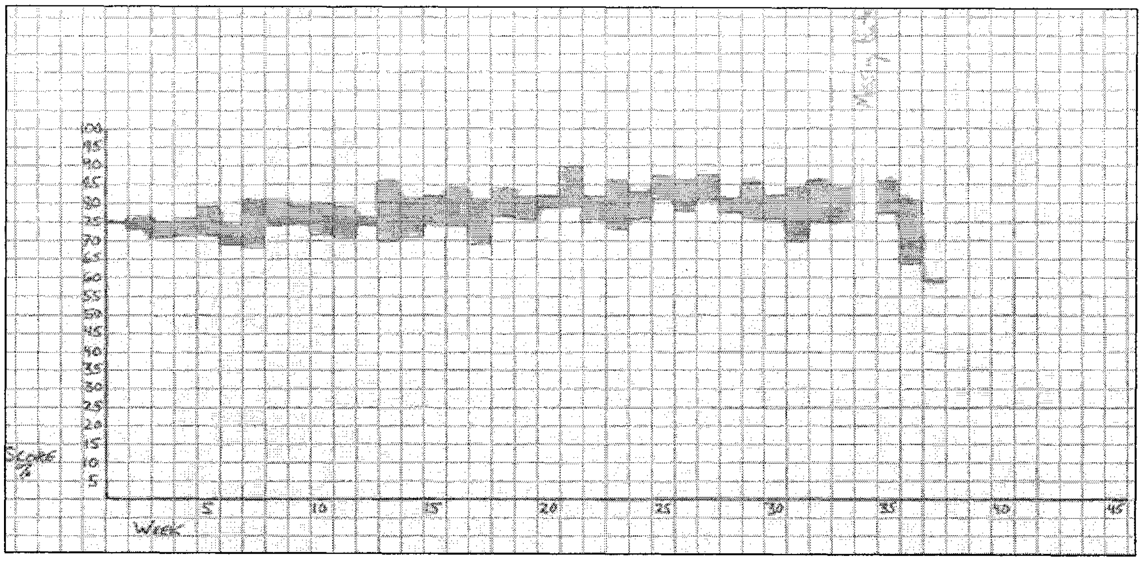

Figure 4.7 Score Graph for Case #8

This client's stay in residential treatment lasted 37 weeks and led to a positive discharge. Over 19 weeks (from week 6 to week 25), he gained 12 points from his lowest to his highest average weekly score. He displayed a chaotic amount of variation, with 71% of his weeks showing significant variance. He probably received word of his impending discharge at the end of week 35 because his scores dramatically dropped and varied wildly. This client's lower attractor seemed to range around 70, while his upper attractor approximated 85. This difference of 15 points represents the average Zone of Proximal Development for this sample group.

This case adequately fits the predicted pattern of a highly abrupt bifurcation leading to a successful change. This client proved capable of tolerating high (>15 points) variance, but he did not achieve consistent, low-variance weeks.

Case #10

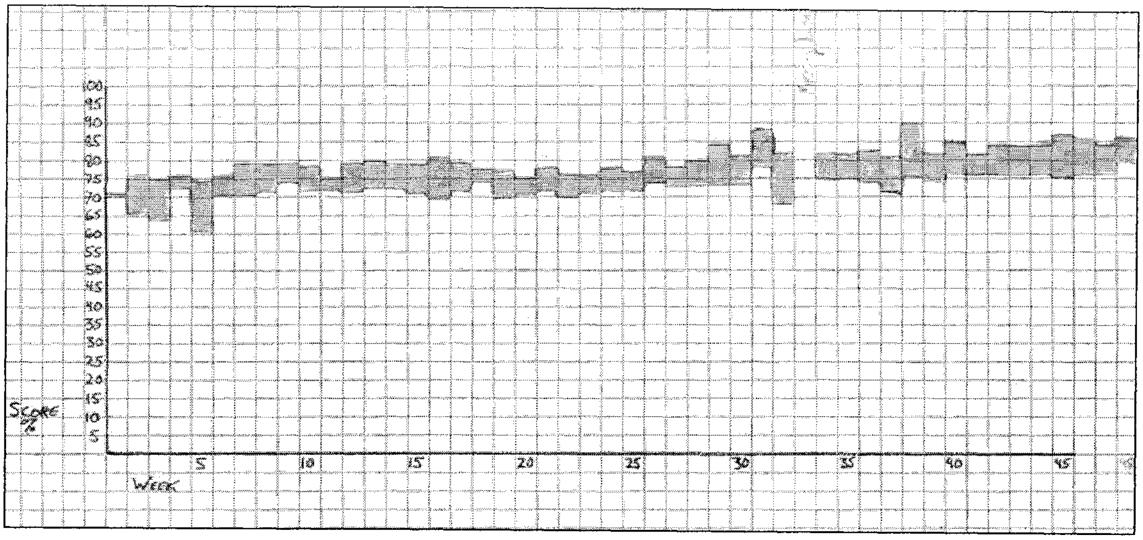

Figure 4.8 Score Graph for Case #10

This client remained in residential treatment for 48 weeks and received a positive discharge. His path resembled that of case #8, except that this client remained in treatment long enough to achieve a stable level of behaviors. He took 43 weeks to gain 13 points in his average weekly score, with 74% of his weeks showing significant variance. His last week was stable and high scoring. This client's lower attractor seemed to hover around 70, while his upper attractor approximated 80. This difference of 10 points represents a below-average Zone of Proximal Development for this sample group. This case displayed weeks of high variance followed by weeks of improved scores, which fits the hypothesized pattern for abrupt change.

Case #31

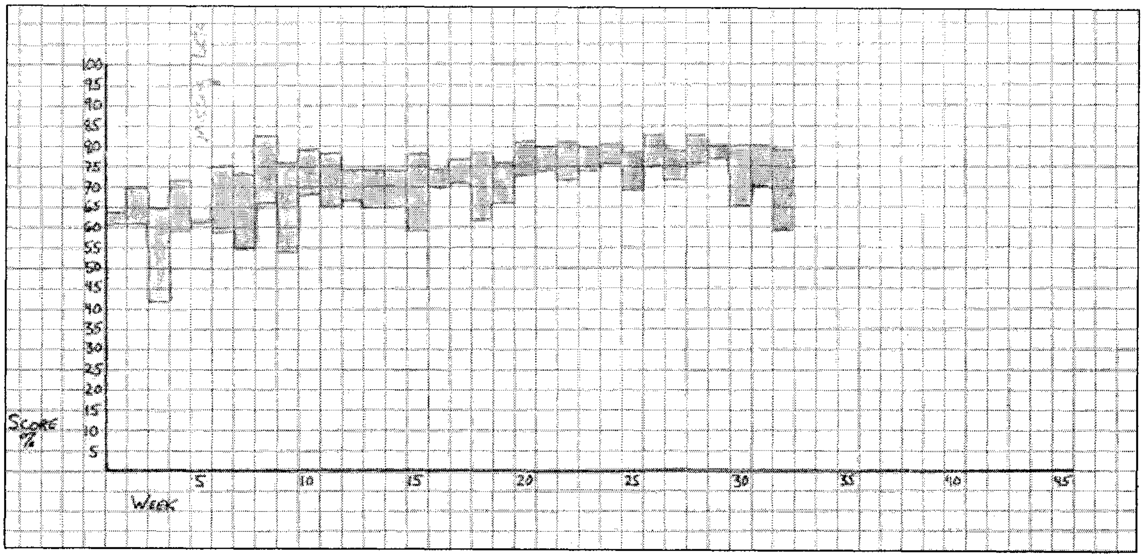

Figure 4.9 Score Graph for Case #31

This client remained in residential treatment for 32 weeks and received a positive discharge. He took 23 weeks (from week 3 to week 26) to gain 23 points in his average weekly scores, with 71% of his weeks showing significant variance. His progress fits the model of a abrupt bifurcation quite well. This client's lower attractor seemed to hover around 60, while his upper attractor cycled around 80. This difference of 20 points represents an above-average Zone of Proximal Development for this sample group.

This case displayed weeks of very high variance followed by weeks of improved scores and lower variance, fitting the hypothesized pattern for abrupt change. Like case #8, he regressed at the very end of his stay. He probably received word of his impending discharge after week 29, his highest scoring and least variable week. Again, this example fits the pattern of a client who does not stay long enough (perhaps due to financial or political pressures) to stabilize at an improved level of functioning.

Case #42

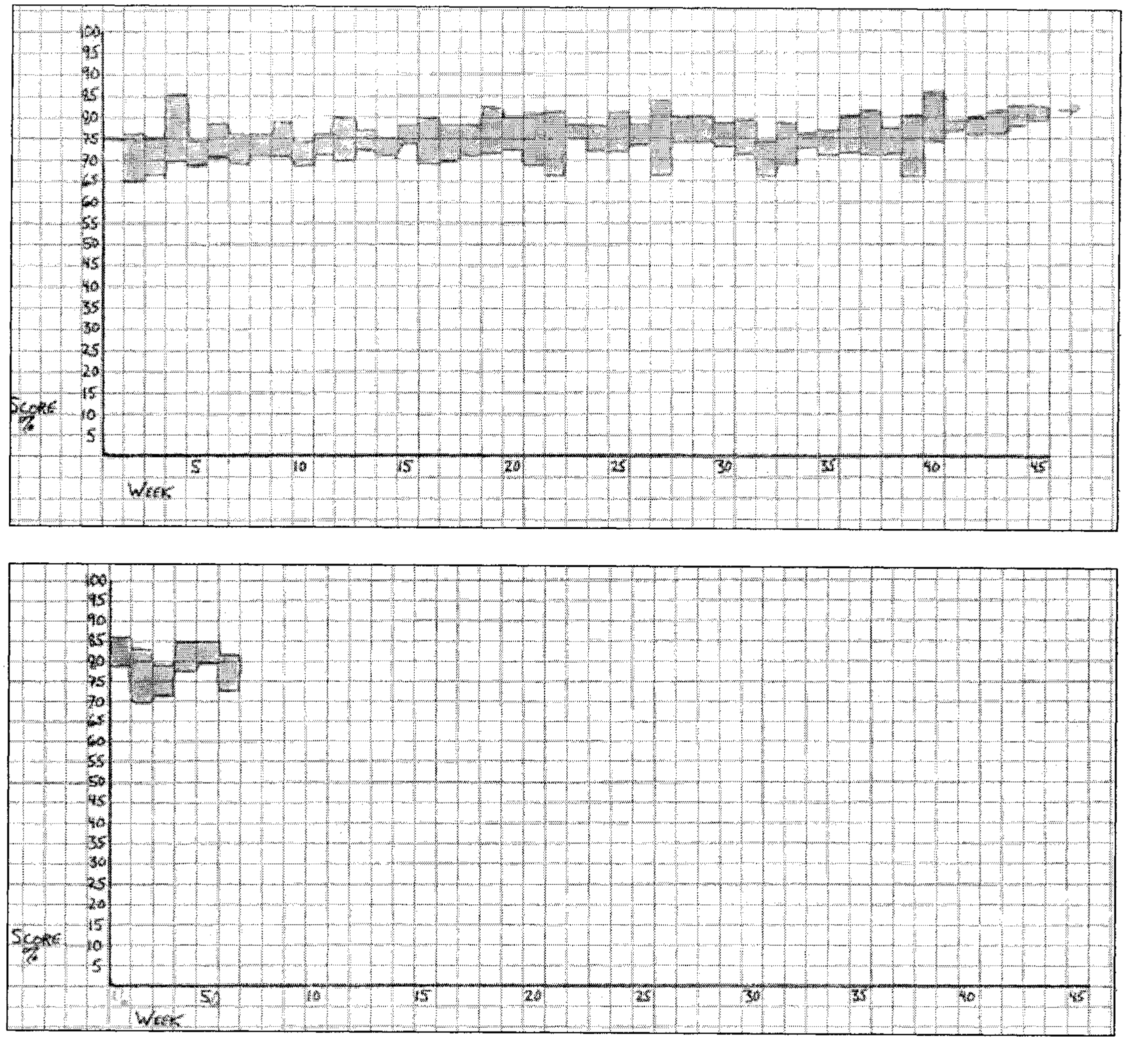

Figure 4.10 Score Graph for Case #42

This client remained in residential treatment for 51 weeks and received a positive discharge. He took 44 weeks to gain 13 points in his average weekly scores, with 58% of his weeks showing significant variance. He probably received word of his impending discharge after week 46 because he showed some regression and high variance in the following weeks. He seems to have experienced some additional chaos, but then to have regained his stability at the end. This client's lower attractor seemed to be 70, while his upper attractor approximated 85. This difference of 15 points reflects the average Zone of Proximal Development for this sample group. This case displayed weeks of high variance followed by weeks of improved scores, fitting the hypothesized pattern for abrupt change.

Case #49

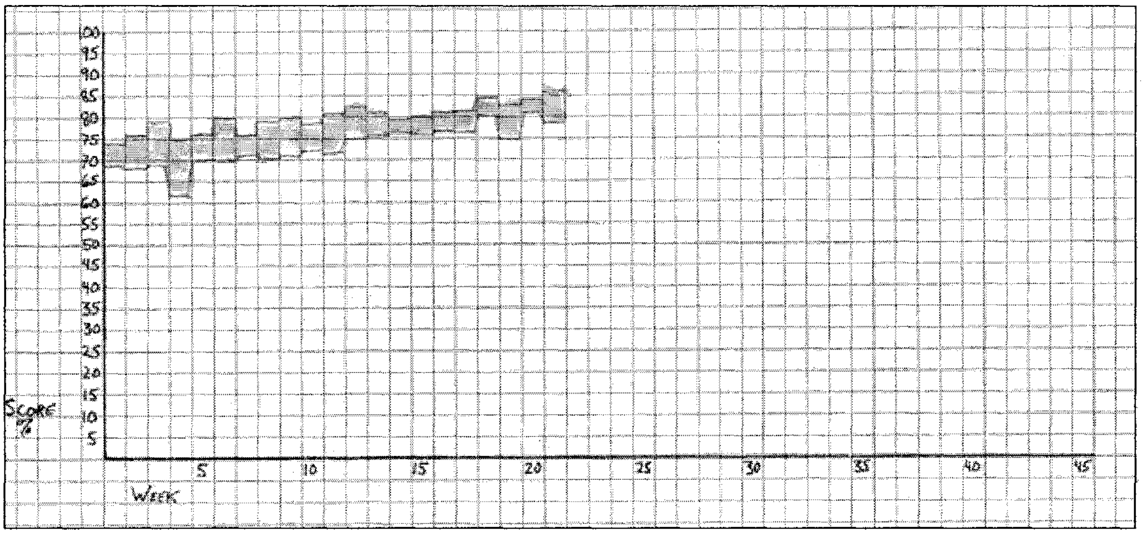

Figure 4.11 Score Graph for Case #49

This client remained in residential treatment for 21 weeks and received a positive discharge. He took 20 weeks to gain 11 points in his average weekly scores, with 52% of his weeks showing significant variance. His highest variability and lowest scores occurred at the beginning of his stay, followed by continual improvement. This client's lower attractor seemed to be around 70, while his upper attractor approximated 83. This difference of 13 points represents a slightly below-average Zone of Proximal Development for this sample group. This case displayed weeks of higher variance followed by weeks of improved scores, fitting the hypothesized pattern for abrupt change.

Case #50

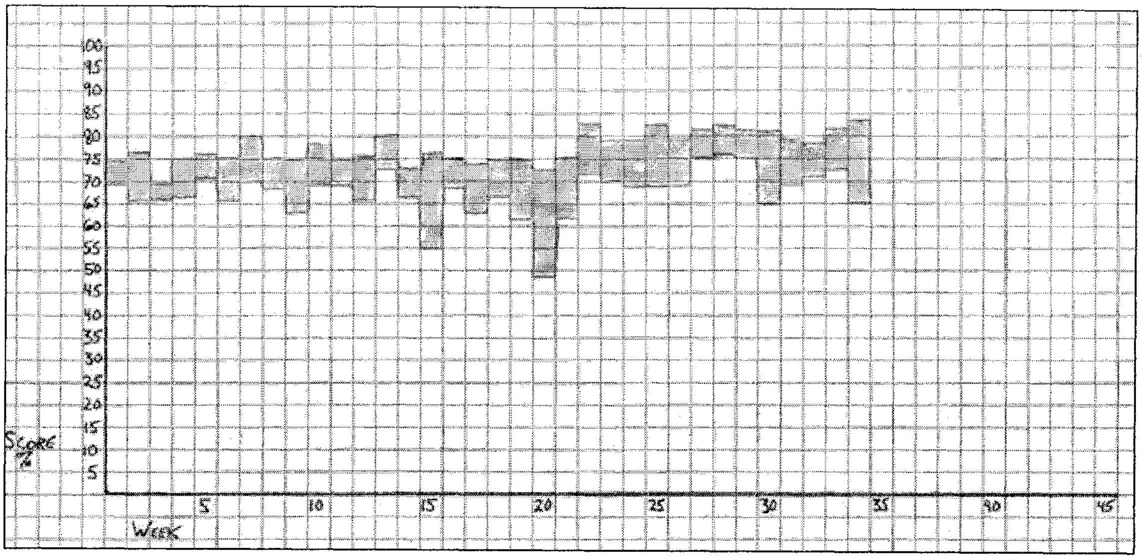

Figure 4.12 Score Graph for Case #50

This client remained in residential treatment for 34 weeks and received a positive discharge. He took only 8 weeks (from week 20 to week 28) to gain 17 points in his average weekly scores, with 88% of his weeks showing significant variance. His pattern approximately fits that of the "saxophone curve," with maximum variance and poorest performance occurring midway through his stay. This high-variance and low -scoring period was followed by rapid gains.

This client's lower attractor seemed to hover around 63, while his upper attractor approximated 80. This difference of 17 points reflects a slightly above-average Zone of Proximal Development for this sample group. This case displayed numerous weeks of high variance and regression immediately followed by weeks of improved scores, fitting the hypothesized pattern for highly abrupt successful change.

Case #61

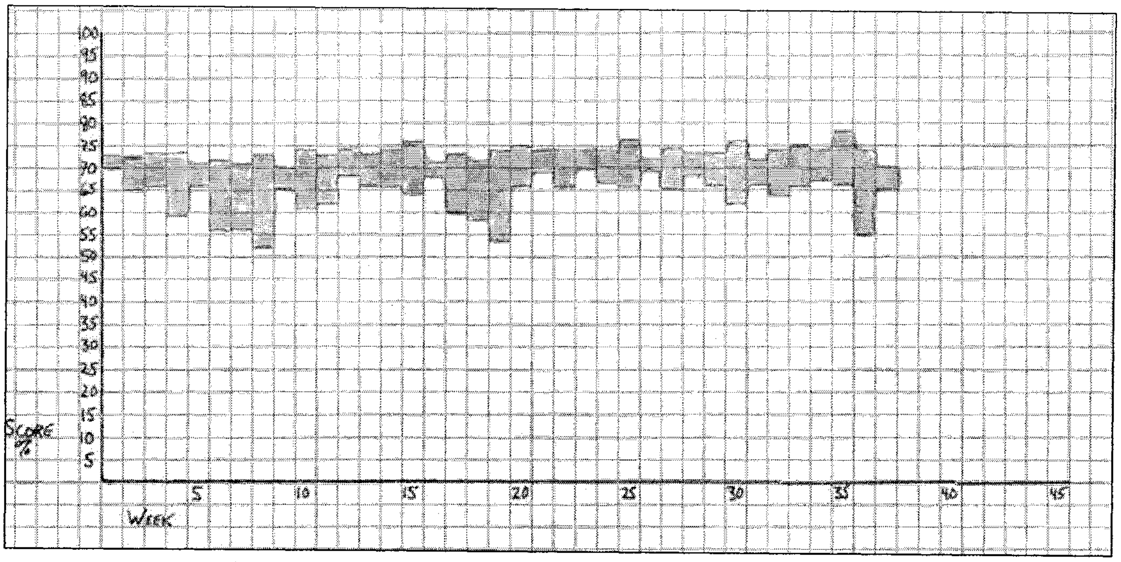

Figure 4.13 Score Graph for Case #61

This client remained in residential treatment for 37 weeks and received a positive discharge. He took only 4 weeks to gain 9 points on his weekly average scores (his lowest average occurred at week 19), with 70% of his weeks showing significant variance. This client's lower attractor seemed to hover around 55, while his upper attractor approximated 74. This difference of 19 points reflects an above-average Zone of Proximal Development for this sample group.

This client's modest improvement approximates a flatter version of the "saxophone curve" model, albeit with a higher initial average score and a lower final average score. Like several other cases with positive discharges, he regressed at the end, probably after being notified of his imminent release.

This case displayed weeks of high variance followed by weeks of improved scores, somewhat fitting the hypothesized pattern for abrupt change. This case appears to have been a "close call"—the client could easily have been negatively discharged, but he managed to squeak by, receiving a positive discharge before reaching an appropriate stage of treatment to merit release. This result is unusual and may have been the result of financial or political pressures.

Case #62

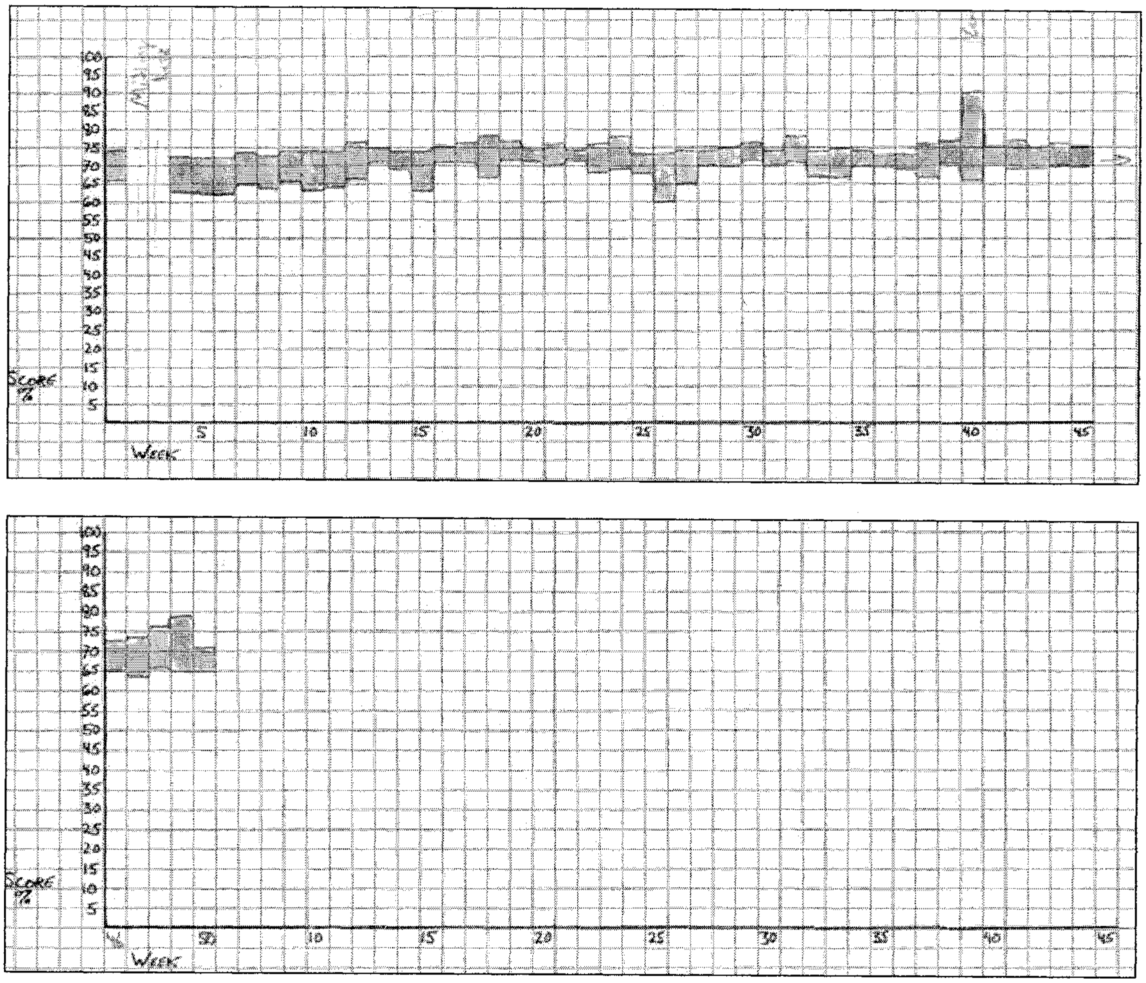

Figure 4.14 Score Graph for Case #62

This client remained in residential treatment for 50 weeks and received a positive discharge. He took 39 weeks to gain only 7 points in his average weekly scores, with 54% of his weeks showing significant variance. This case exemplifies the healthily abrupt bifurcation pattern. This client's lower attractor seemed to hover around 63, while his upper attractor approximated 77. This difference of 14 points fits with a roughly average Zone of Proximal Development for this sample group. This case displayed weeks of high variance followed by weeks of improved scores, fitting the hypothesized pattern for successful abrupt change.

Case #64

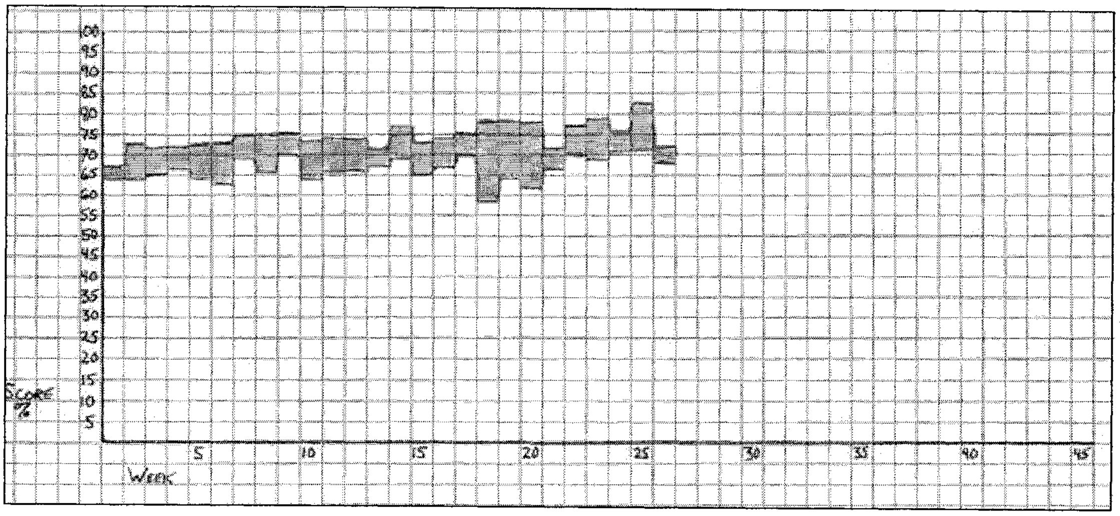

Figure 4.15 Score Graph for Case #64

This client remained in residential treatment for 26 weeks and received a positive discharge. He gained 11 points over a period of 24 weeks, with 69% of his weeks showing significant variance. His scores showed steady improvement, with a drop during the final week, probably due to anxiety about his impending discharge. This client's lower attractor seemed to hover around 63, while his upper attractor approximated 77. This difference of 14 points reflects a roughly average Zone of Proximal Development for this sample group.

This case displayed weeks of higher variance followed by weeks of improved scores, exactly fitting the hypothesized pattern for abrupt change; note the highly variant weeks from 18 through 20, followed by rapid progress and decreased variance.

Case #65

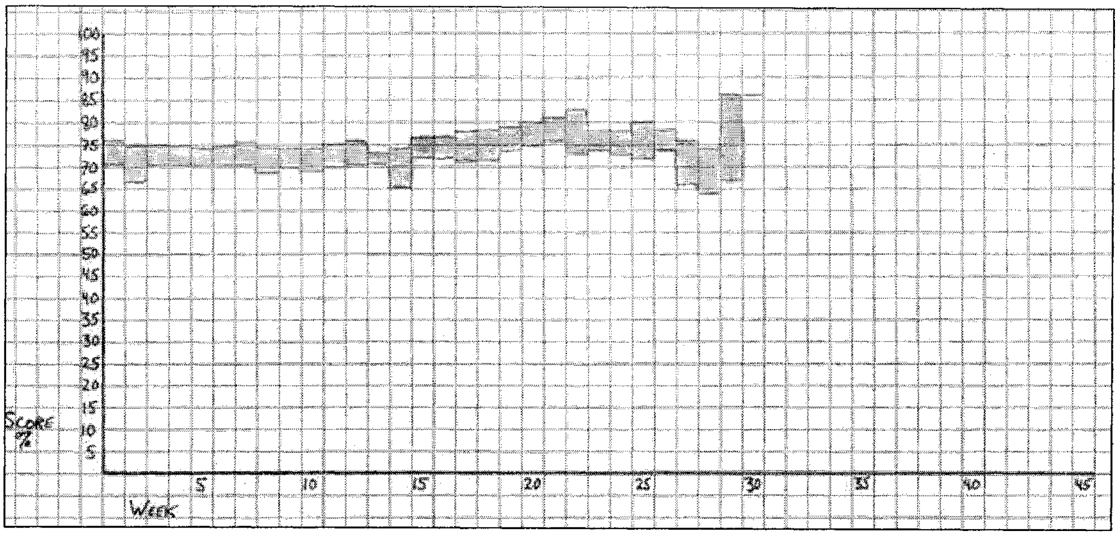

Figure 4.16 Score Graph for Case #65

This client remained in residential treatment for 30 weeks and received a positive discharge. He took 8 weeks to gain 7 points, with only 31% of his weeks showing significant variance. This client's lower attractor seemed to hover around 70, while his upper attractor approximated 80. This difference of 10 points demonstrates a below-average Zone of Proximal Development for this sample group.

This case displayed below average variance, fitting the hypothesized pattern for either minimally abrupt or subtle change. His scores dropped and his variance increased at the end of his stay. This pattern might indicate that the client did not spend enough time in treatment to complete the process, and that he was beginning a period of more abrupt change. It is also possible that some other factor, such as fears about his post-treatment living situation, might have created this variability and regression. His final week showed the highest variance, although he left with high scores (86%).

Case #72

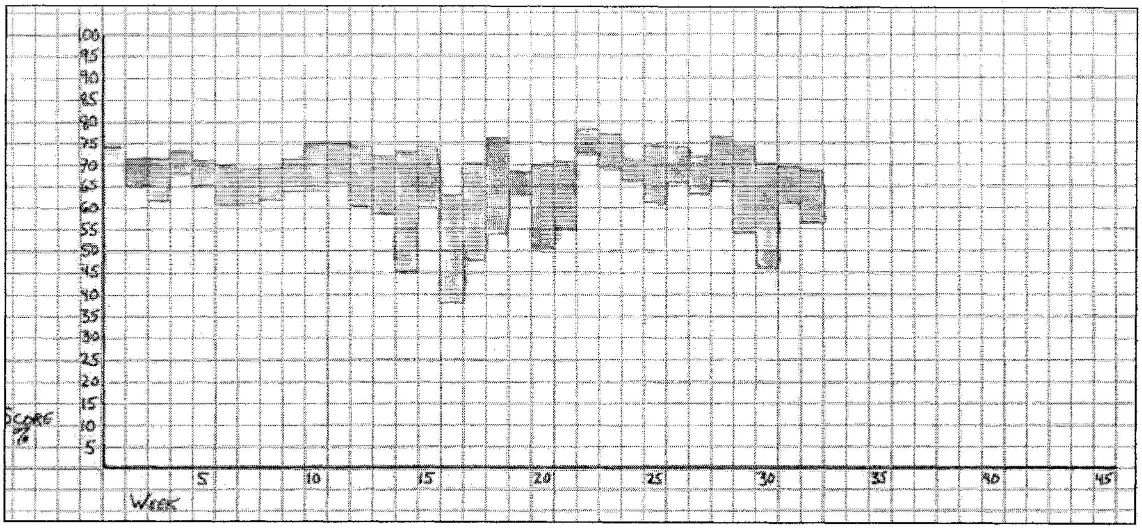

Figure 4.17 Score Graph for Case #72

This client remained in residential treatment for 32 weeks and received a positive discharge. He gained 21 points on his average score over 6 weeks (from week 16 to week 22), with 84% of his weeks showing significant variance. His ending scores and variance were no better than those at the beginning. It is curious that he received a positive discharge, but he might have made adequate changes, in the opinions of program staff and other stakeholders.

This client's lower attractor seemed to cycle around 55, while his upper attractor approximated 75. This difference of 20 points represents an above-average Zone of Proximal Development for this sample group. This case displayed weeks of very high variance (up to 27 points) followed by weeks of improved scores, fitting the hypothesized pattern for abrupt change.

Case #77

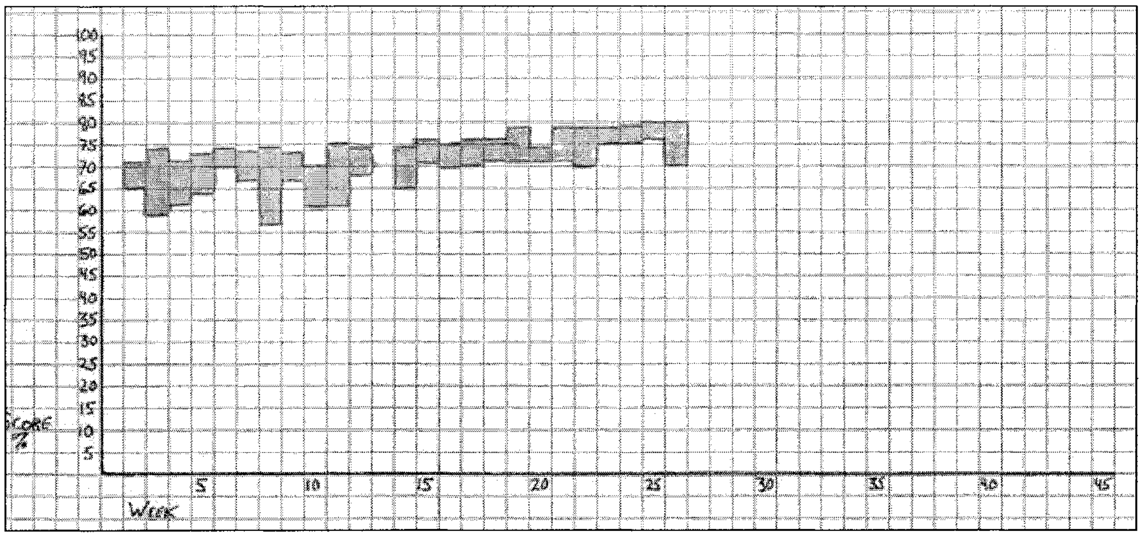

Figure 4.18 Score Graph for Case #77

This client remained in residential treatment for 26 weeks and received a positive discharge. He gained 11 points on his average weekly scores over 15 weeks, with 48% of his weeks showing significant variance. These numbers all approximate the means for this sample group. This client's lower attractor approximates 62, while his upper attractor cycles around 78. This difference of 16 points reflects a roughly average Zone of Proximal Development for this sample group.

This case displayed weeks of high variance followed by weeks of improved scores and reduced variance, which exactly fits the hypothesized pattern for abrupt change; this subject exemplifies the abrupt bifurcation pattern.

Case #111

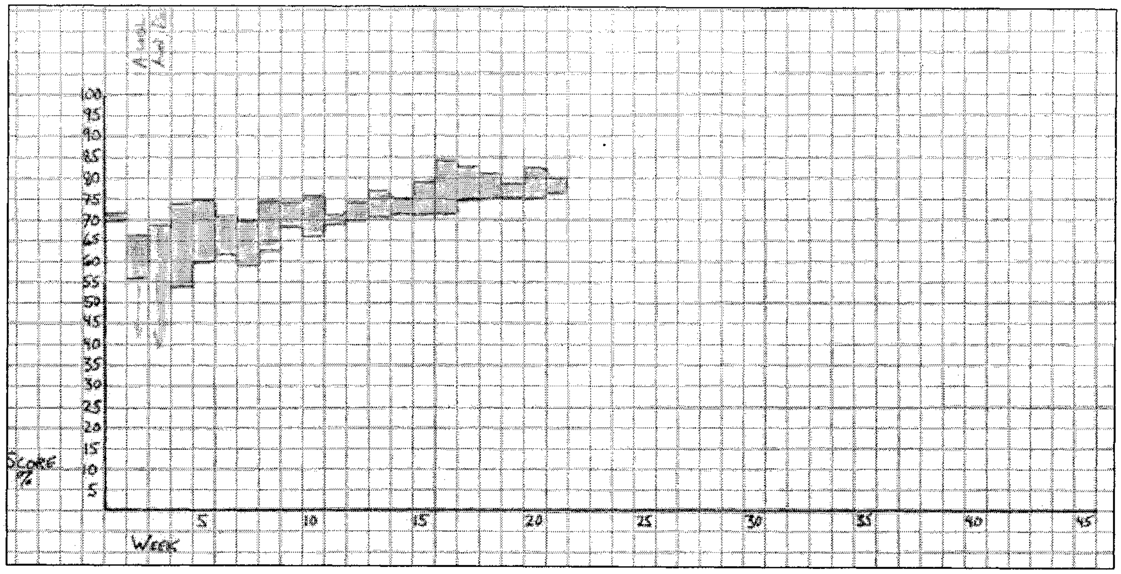

Figure 4.19 Score Graph for Case #111

This client remained in residential treatment for 21 weeks and received a positive discharge. He gained 16 points over 19 weeks, with 57% of his weeks showing significant variance. His lower attractor looks like a 60, while his upper attractor approximates 82. This difference of 22 points reflects an above-average Zone of Proximal Development for this sample group.

This client showed the classic pattern of early struggles, including an AWOL in his second week. Following his early period of high variance and lower scores, he made rapid progress. This case displayed weeks of high variance followed by weeks of improved scores, exactly fitting the hypothesized pattern for abrupt change.

Case #113

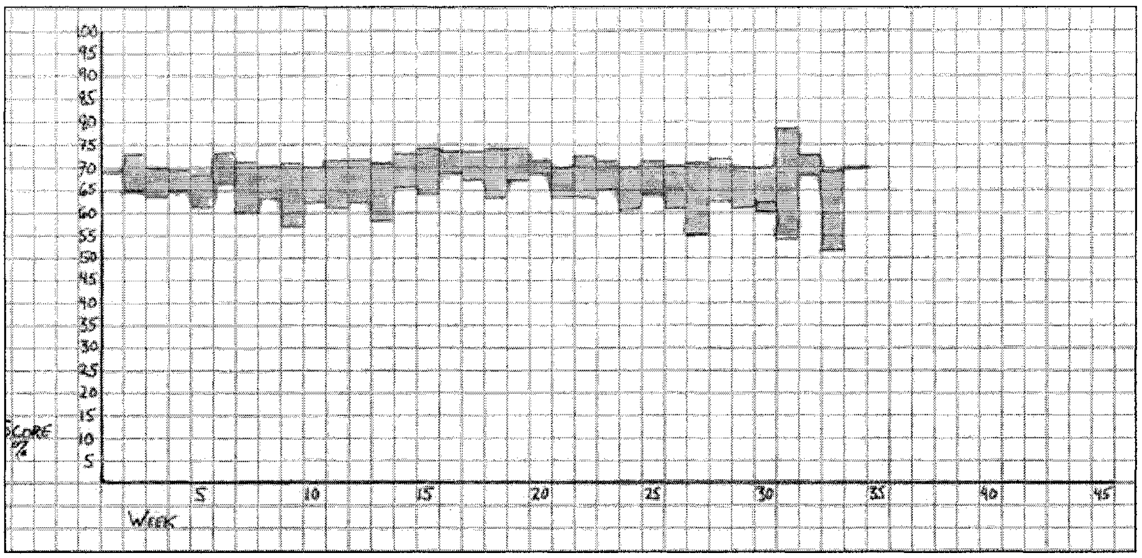

Figure 4.20 Score Graph for Case #113

This client remained in residential treatment for 34 weeks and received a positive discharge. He gained 6 points from his lowest to his highest average weekly score over a period of 7 weeks (week 9 to week 16) , with 81% of his weeks showing significant variance. He displayed a lengthy regression following his peak. Because his progress was adequate to earn a positive discharge, I did not count this regression period as an overall loss of point average.

This client's lower attractor seemed to cycle around 62, while his upper attractor approximated 73. This difference of 11 points reflects a below-average Zone of Proximal Development for this sample group. This case displayed weeks of high variance followed by weeks of improved scores, as well as some weeks that decline, fitting the hypothesized pattern for abrupt change. The client showed healthily chaotic progress until week 19, and regression after that. His end-of-stay regression did not affect his discharge. This might be an example of a case in which enough early progress was shown to initiate a positive discharge, but the case lacked an acceptable placement to be discharged to; under these conditions, clients often lose interest and motivation, and regress.

Case #127

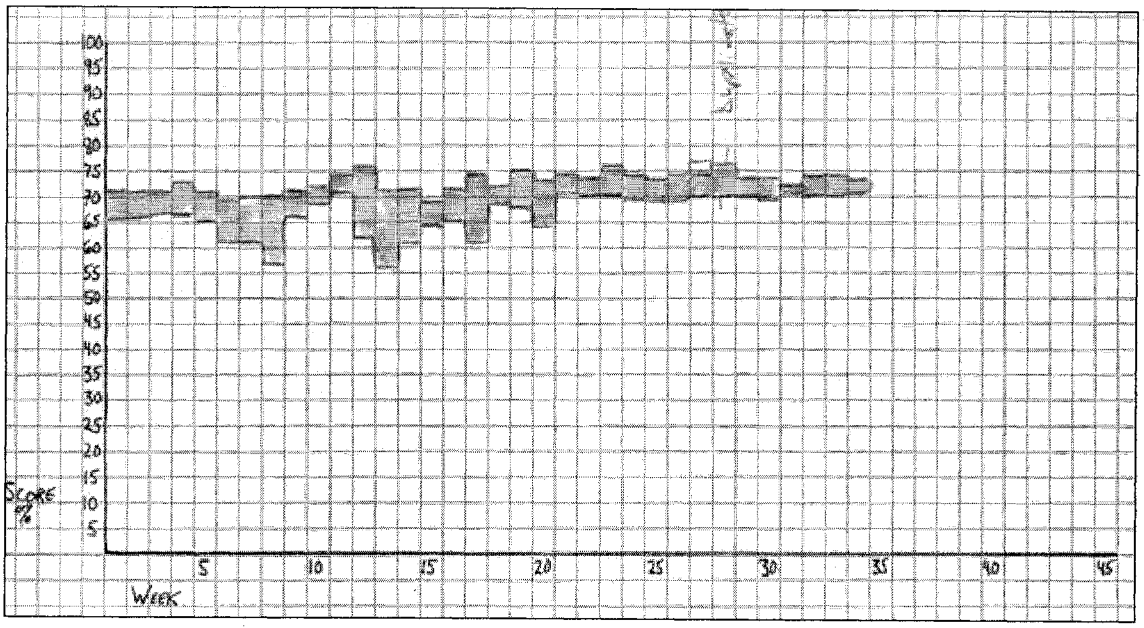

Figure 4.21 Score Graph for Case #127

This client remained in residential treatment for 33 weeks and received a positive discharge. He took 21 weeks to gain 8 points, with 38% of his weeks showing significant variance. His lower attractor cycles around 62, while his upper attractor approximates 75. This difference of 13 points represents a slightly below-average Zone of Proximal Development for this sample group.

This case displayed some weeks of high variance followed by weeks of improved scores, fitting the hypothesized pattern for abrupt change. The weeks with significant variance occurred early in his stay, with almost no variance after week 20.

Case #128

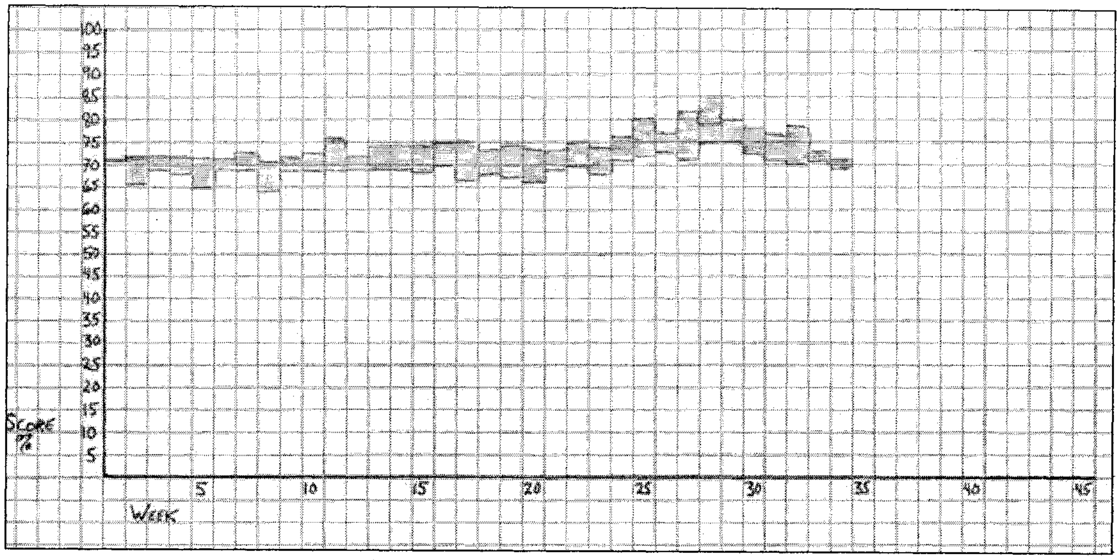

Figure 4.22 Score Graph for Case #128

This client remained in residential treatment for 34 weeks and received a positive discharge. He gained 7 points, taking 21 weeks (from week 8 to week 29) to do so, with only 30% of his weeks showing significant variance. His lower attractor hovered around 65, while his upper attractor approximated 80. This difference of 15 points depicts the average Zone of Proximal Development for this sample group.

This case displayed only a few weeks of high variance followed by weeks of improved scores, fitting the hypothesized pattern for minimally abrupt change. The client's peak scores occurred 6 weeks before his discharge, demonstrating some regression at the end. His largest gains and highest scores followed his weeks of maximum variance, thus supporting the hypothesis. This may be a case in which the client was not pushed hard enough to produce healthier levels of variance throughout his stay, and he would have benefited from more challenges.

Implosive

Case #13

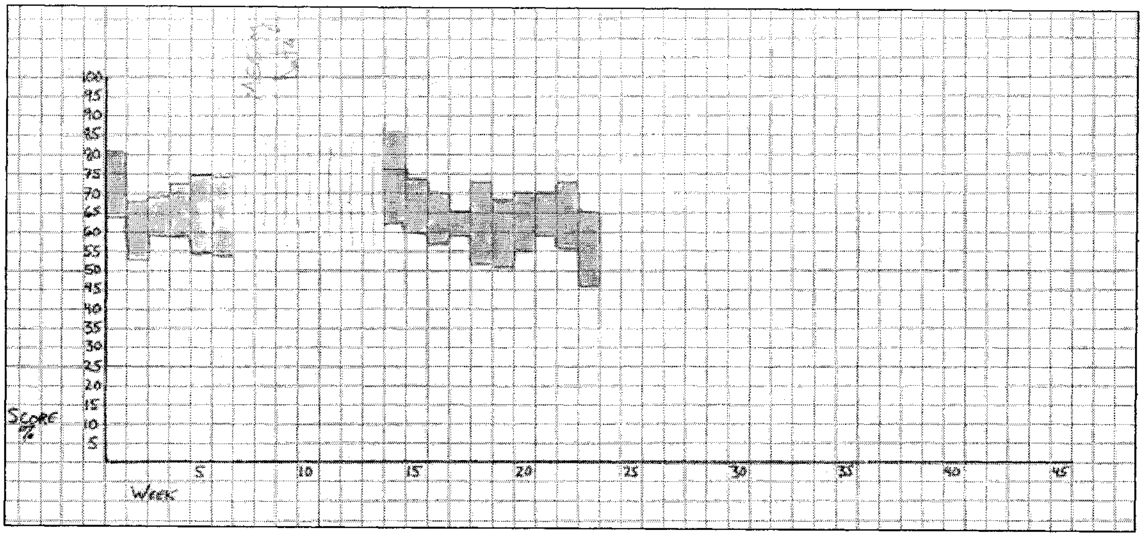

Figure 4.23 Score Graph for Case #13

This client's stay in residential treatment lasted 23 weeks and led to a negative discharge. He lost 18 points from his highest average weekly score (week 1) to his lowest average weekly score (week 23), a period of 22 weeks. He displayed an implosive amount of variation, with 100% of his weeks showing significant variance. Unfortunately, this case was missing 7 weeks of data; I retained it for this study because the existing data still provided a clear example of this type of outcome.

This client's lower attractor seemed to be around 55, while his upper attractor approximated 70. This difference of 15 points reflects the average Zone of Proximal Development for this sample group.

This case exactly fits the predicted pattern of an eventually implosive bifurcation leading to an unsuccessful change attempt.

Case #48

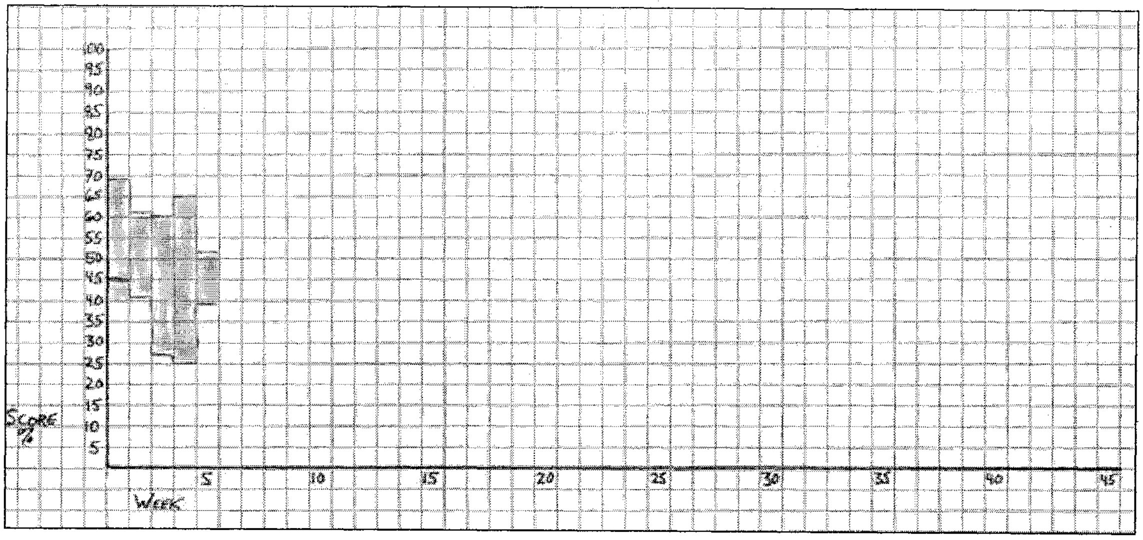

Figure 4.24 Score Graph for Case #48

This client's stay in residential treatment lasted only 5 weeks and led to a negative discharge. He lost 10 points from his highest to his lowest average weekly scores, over a period of only 4 weeks (week 1 to week 4). He displayed an immediately implosive amount of variation, with 100% of his weeks showing significant variance.

This client's lower attractor, while never stable, might have been between 25 and 30; his upper attractor approximated 60. This difference of at least 30 points reflects a significantly large Zone of Proximal Development for this sample group. Cases with such a short treatment stay are difficult to evaluate for Zone of Proximal Development; for example, this client never reached a clear, stable attractor. This case fits the predicted pattern of an immediately implosive bifurcation illustrating an unsuccessful change attempt.

Case #57

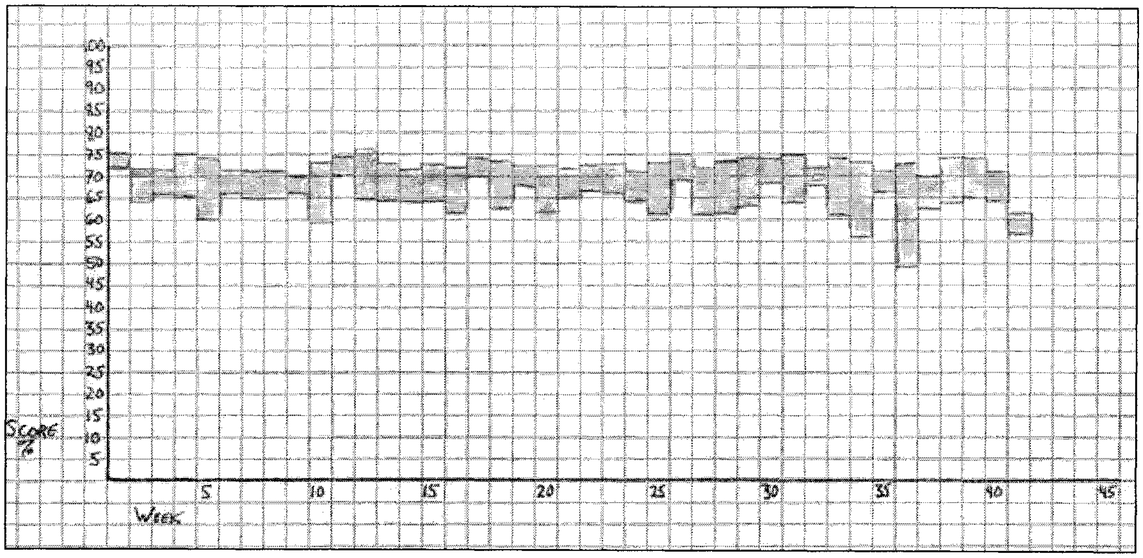

Figure 4.25 Score Graph for Case #57

This client's stay in residential treatment lasted 41 weeks and led to a negative discharge. He took 30 weeks (week 11 to 1eek 41) to lose 9 points between his highest and lowest average weekly scores (week 41). He displayed a moderately high amount of score fluctuation, with 68% of his weeks showing significant variance. Until the 30-week mark, this client showed the potential for positive change; something happened, and his average scores dropped while his variance increased.

This client's lower attractor seemed to hover around 60, while his upper attractor approximated 75. This difference of 15 points reflects the average Zone of Proximal Development for the sample group. This case initially fit the predicted pattern of an abrupt bifurcation; it devolved into an eventually implosive bifurcation, illustrating an unsuccessful change attempt.

Case #59

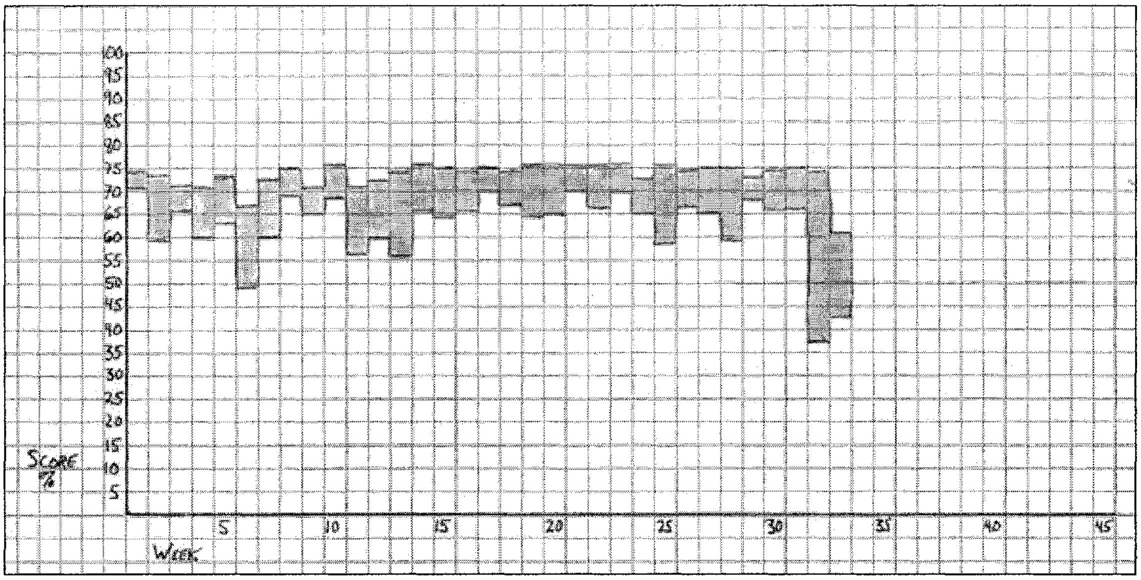

Figure 4.26 Score Graph for Case #59

This client's stay in residential treatment lasted 33 weeks and led to a negative discharge. He took 12 weeks (week 21 to week 33) to lose 22 points from his highest to his lowest average weekly scores. He displayed a moderately high amount of variation, with 71% of his weeks showing significant variance. True to theory, his best weeks were preceded by highly variable periods. Until week 17, his pattern could have resulted in a successful abrupt change; at that point, however, upward progress ceased.

This client's lower attractor seemed to be 60, while his upper attractor approximated 75. This difference of 15 points represents the average Zone of Proximal Development for the sample group. This case fits the predicted pattern of an eventually implosive bifurcation illustrating an unsuccessful change attempt.

Case #70

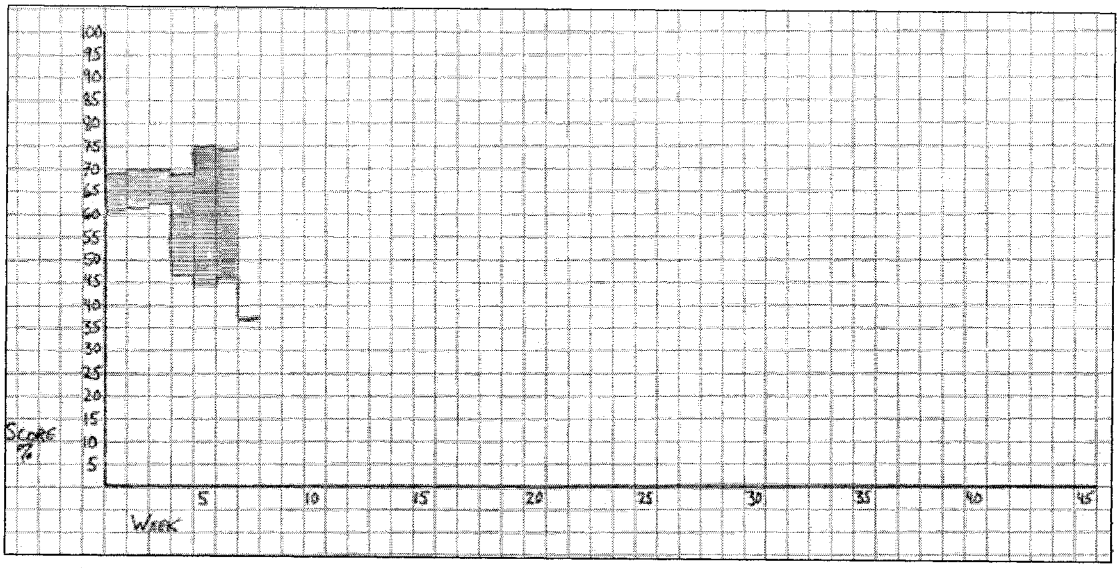

Figure 4.27 Score Graph for Case #70

This client's stay in residential treatment lasted only 7 weeks and led to a negative discharge. He took 4 weeks (from week 3 to week 7) to lose 30 points from his highest to his lowest average weekly score. He displayed an implosive amount of variation, with 100% of his weeks showing significant variance. This client ran away ("went AWOL") at the beginning of his seventh week, following a day with a 37% average score. Clearly, weeks with as much as a 41-point score variation were too much for this client to handle.

This client's lower attractor seemed to be around 45, while his upper attractor approximated 73. This is a difference of 28 points, a significantly large Zone of Proximal Development for this sample group.

This case exactly fits the predicted pattern of an immediately implosive bifurcation, illustrating an unsuccessful change attempt. The system (client) was unable to sustain his initial efforts, went into extreme oscillation, and imploded.

Case #97

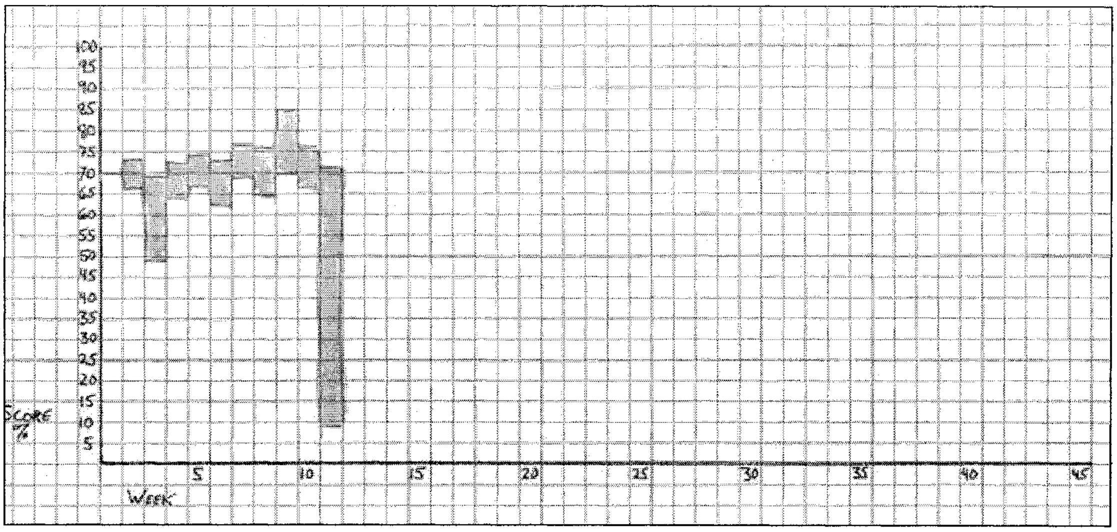

Figure 4.28 Score Graph for Case #97

This client's stay in residential treatment lasted only 11 weeks and led to a negative discharge. He lost 25 points from his highest to his lowest average weekly score, and he took only 2 weeks (week 9 to week 11) to do so. He displayed an implosive amount of variation, with 100% of his weeks showing significant variance. Interestingly, up till week 9, he showed steady progress, seemingly able to tolerate this high variance, and he reached high score levels. Something averse may have happened at week 10 that led to his dramatic final week's 62-point variance and AWOL exit from treatment. This scenario might also mean that his initial progress was too much of a strain; he might have benefited from encouragement to slow down.

This client's lower attractor seemed to cycle around 55, while his upper attractor approximated 75. This difference of 20 points represents a large Zone of Proximal Development for this sample group.

This case fits the predicted pattern of an implosive bifurcation, illustrating an unsuccessful change attempt. It is interesting to ponder whether some upsetting external event, on par with the death of a family member, changed a potentially successful abrupt pattern into an implosion.

Cases fitting two or more patterns

Case #71

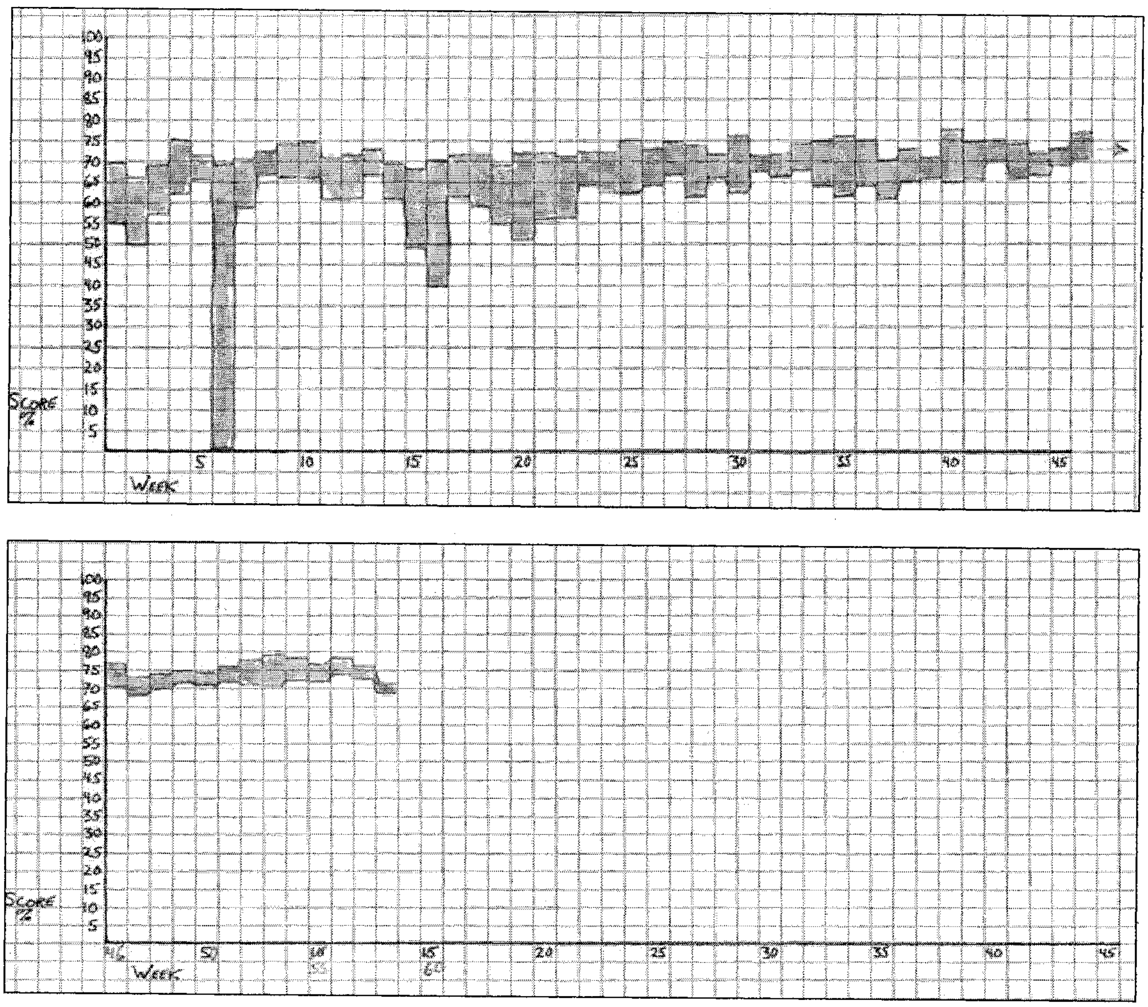

Figure 4.29 Score Graph for Case #71

This client's stay in residential treatment lasted 58 weeks and led to a negative discharge. He gained 27 points on his average weekly score over 50 weeks (from week 6 to week 56). He displayed an above-average amount of variation, with 60% of his weeks showing significant variance. His lower attractor seemed to hover around 60, while his upper attractor approximated 75. This difference of 15 points represents the average Zone of Proximal Development for this sample group.

This case does not really fit the predicted pattern of any one bifurcation; it shows periods of high variance and upward progress, fitting the abrupt change pattern, and other periods that look implosive. At the end of his long stay, there was very little variance, with the pattern becoming smooth. His overall gain in points and his lengthy stay indicate that some negative event (such as a fight, or a theft) might account for his discharge status; otherwise, the case looks like a positive treatment outcome. This is an interesting and probably anomalous case that highlights the complexity of human change.

Case #87

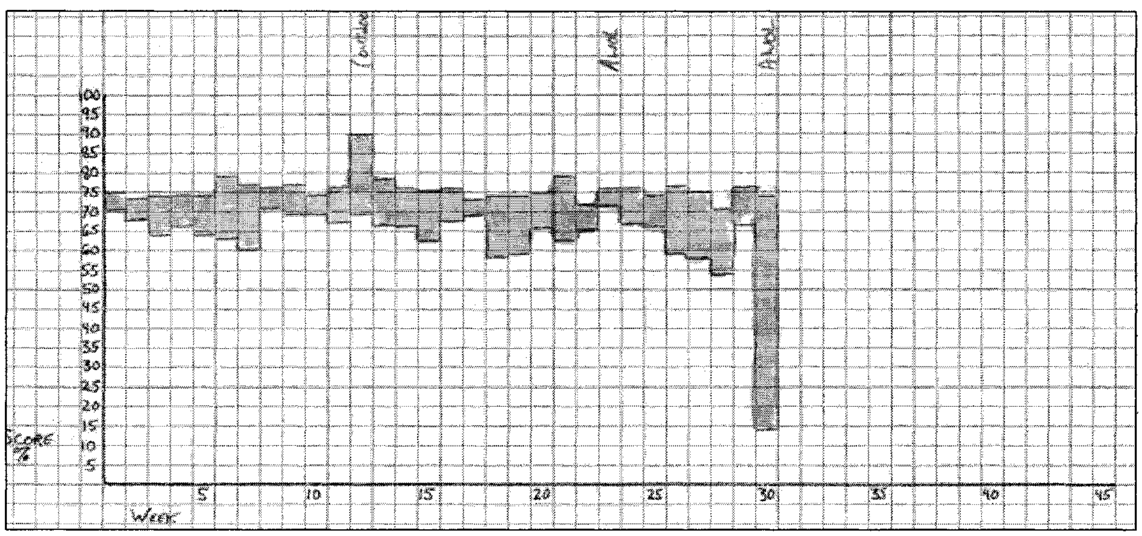

Figure 4.30 Score Graph for Case #87

This client's stay in residential treatment lasted 30 weeks and led to a negative discharge. He lost 14 points from his highest to his lowest on his average weekly score over a period of 18 weeks (week 12 to week 30). He displayed a high amount of variation, with 80% of his weeks showing significant variance. This client's lower attractor seemed to hover around 60, while his upper attractor approximated 76. This difference of 16 points represents a roughly average Zone of Proximal Development for this sample group.

This client showed some successful progress early in his stay, with only moderate amounts of variance; he went AWOL once during week 23, and then oscillated out of control after that. His final week's scores ranged from 14 to 74, a 60-point variance, before he ran away for a final time.

This case fits two predicted patterns: Initially, the client showed a healthy amount of abrupt change, but he then shifted to an implosive bifurcation pattern.

Case #98

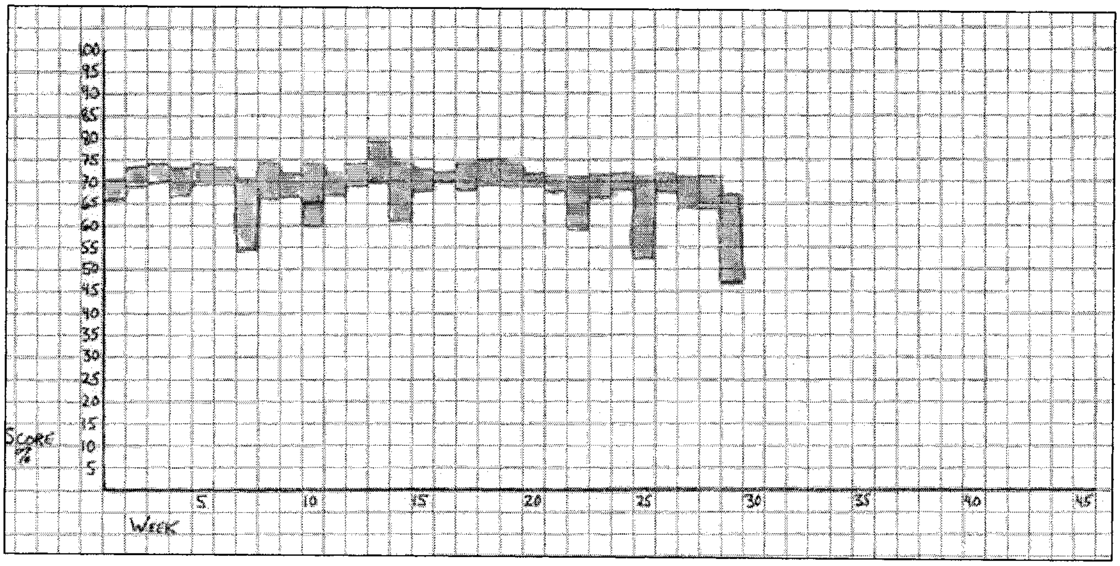

Figure 4.31 Score Graph for Case #98

This client's stay in residential treatment lasted 29 weeks and led to a negative discharge. He took 16 weeks (from week 13 to week 29) to lose 17 points from his highest (week 13) to his lowest average weekly score. He displayed a below-average amount of variation, with 34% of his weeks showing significant variance. Until week 20, he showed healthily chaotic variance and upward score progress; after that, his scores dropped. His final week showed 20 points of variance, with a low score of 52.

This client's lower attractor seemed to hover around 65, while his upper attractor approximated 75. This difference of 10 points fits with a below-average Zone of Proximal Development for this sample group. This case initially fit the abrupt change pattern, but then it became implosive, with dropping scores and increased variance.

Case #114

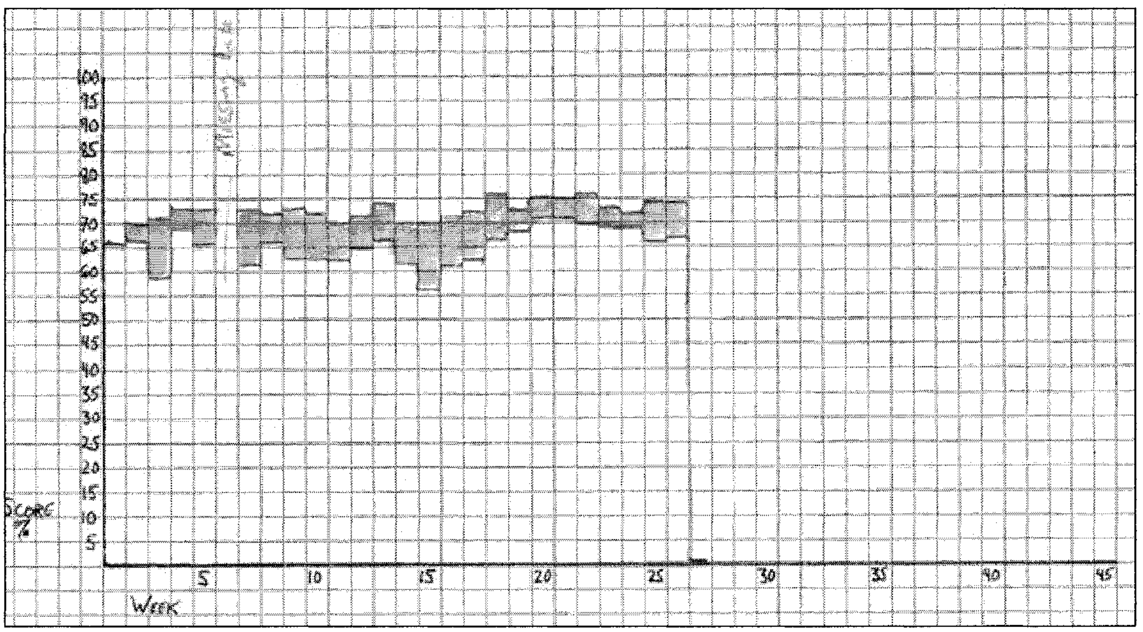

Figure 4.32 Score Graph for Case #114

This client's stay in residential treatment lasted 27 weeks and led to a negative discharge. He lost 1 point from his highest to his lowest average weekly score over a period of 6 weeks (week 21 to week 27). He displayed a moderate amount of variation, with 63% of his weeks showing significant variance. The data for week 6 is missing. This client's lower attractor seemed to hover around 62, while his upper attractor approximated 74. This difference of 12 points represents a below-average Zone of Proximal Development for the sample group.

This case does not fit the predicted pattern of an eventually implosive bifurcation because of its moderate amount of variance. This client showed healthily abrupt progress until week 22, after which he regressed, going AWOL in his final week. It is possible that this case could have resulted in a positive outcome, but that some external event inspired the client to run away. It is also quite possible that his progress was too rapid, and that he could not sustain the amount of variance and progress he was initially making. Because of these unknown factors, and his sudden AWOL, this case cannot be considered a good fit with any bifurcation type.

In sum, 27 (87%) of these 31 sample cases clearly fit into one of the hypothesized bifurcation patterns. Another 3 cases show attributes of two patterns, without a clear overall type. One case (#71) makes very little sense at all; the client appeared to fit all three bifurcation patterns at various stages of his stay, smoothing out at the end, but he was discharged negatively and must thus be considered a poor fit for the hypothesized patterns. Case #114 exactly fit the predicted pattern for healthy abrupt change until he suddenly ran away; this scenario supports truisms about the unpredictability of human behavior. Case #107 absolutely does not fit the predicted pattern of a treatment failure. His steady upward progress in scores and end-of-stay stability look like the exemplar of a successfully subtle bifurcation. It is also quite possible that this client was behaviorally skilled enough to manage a subtle upward bifurcation without genuinely changing in fundamental ways. In this sense, he might exactly fit the pattern of a subtle bifurcation (and first-order change) that does not reach a sufficiently high attractor. Without any additional information (which would violate the conditions of this study), this case must be considered a poor fit for the hypotheses.

Table 4.1 summarizes the results of this case-by-case analysis. The table lists the cases by their identification numbers and indicates which bifurcation pattern(s) they appear to match (research question 2). It also lists the treatment outcomes of these cases, and whether the cases fit the hypothesized predictions for variance preceding progress (research question 3).

Table 4.1 Case-by-Case Analysis of Bifurcation Type

Case #:	Subtle	Abrupt	Implosive	Outcome	Prediction "Fit"
8		✓		pos	✓
10		✓		pos	✓
13			✓	neg	✓
31		✓		pos	✓
42		✓		pos	✓
48			✓	neg	✓
49		✓		pos	✓
50		✓		pos	✓
57			✓	neg	✓
59			✓	neg	✓
61		✓		pos	✓
62		✓		pos	✓
64		✓		pos	✓
65		✓		pos	✓
70			✓	neg	✓
71	✓ ?	✓ ?	✓ ?	neg	?
72		✓		pos	✓
76	✓			neg	✓
77		✓		pos	✓
87		✓ ?	✓	neg	✓ ?
91	✓			pos	✓
97			✓	neg	✓
98		✓ ?	✓	neg	✓ ?
107	✓ ?			neg	✓ ?
111		✓		pos	✓
113		✓		pos	✓
114		✓ ?	✓ ?	neg	✓ ?
123	✓			pos	✓
127		✓		pos	✓
128		✓		pos	✓
131	✓			pos	✓

Note that all of the cases with positive outcomes clearly fit into either the subtle or abrupt bifurcation types. Four of the negative outcome cases (#87, #98, #107, and #114) seem to fit into two bifurcation categories, while case #71 shows elements of all three.

Research Question 4

The fourth research question was whether, for this sample group of subjects, a causal, predictive relationship exists between the subjects' percentage of weeks with significant variance and the subjects' positive or negative discharges from the treatment program. Given the almost infinite variability and unpredictability of human behavior, the resultant 90% fit with the hypothesized bifurcation types was encouraging.

For this analysis, I derived and used the following independent and dependent variables to examine the data. Using a calculator, I analyzed the 31 cases and recorded their values for each variable (see fig. 4.3 and Appendix B).

The independent variable "amount of progress" is named variable A. Variable A is the change in weekly score average from lowest to highest. For 9 cases, this number was negative because their scores generally trended downward and they were negatively discharged. These changes in weekly average scores ranged from -25 to +27. For variable A, the mean of the positive numbers was 11.74. For fuzzy-set assignment, membership criteria were 0 = none (no or negative progress); .17 = negligible gain; .33 = moderate gain; .5 = average gain (to be determined from an analysis of all cases used); .67 = above average gain; .83 = very large gain; and 1.0 = complete, or extreme, gain.

The independent variable "percentage of weeks with significant variance" that the case displays is labeled as variable B. Variable B is measured by the percentage of weeks in each subject's stay during which they displayed above-average (more than 6%) score variance. An analysis of the entire sample indicated that, of the cases that did not show 100% extreme variance, 51.6% of their weeks had score ranges of more than six points. Those cases in which all the weeks of their stay displayed extreme variance were excluded from this calculation of average variance because their inclusion would seriously skew the results upwards. Before I gathered these sample data, I analyzed a convenience sample of 15 cases and found that they displayed a 5.5% mean variance during a one-week period. This result fits with the long-term observations of the staff members at the treatment center, who regard weekly variance of less than 5 or 6 points as stable. This similarity in numbers also supports my assertion that the scoring system is quite stable over time, and thus useful for this type of study. Therefore, weekly score ranges greater than six points were rated as displaying significant variance. This variable showed a range from 8% to 100%. For fuzzy-set assignment, membership criteria were 0 = no variance; .17 = minimal variance; .33 = some, but still below average variance; .5 = average variance; .67 = above average variance; .83 = a very large amount of variance; and 1.0 = total variance.

The independent variable "time," the weeks taken to move from the case's low average to high average weekly scores, is identified as variable C. Nine of the cases' numbers were negative, since their highest average occurred before their lowest average and resulted in a negative discharge. Many cases with positive outcomes show some regression before discharge. This pattern is commonly referred to by the clients as "short-timers' disease" and is perhaps analogous to collegiate springtime "senioritis." Therefore, these positive-outcome cases simply include the weeks taken to achieve sufficient upward progress and exclude any end-of-stay regression. For example, case #128 was given a positive discharge following 29 weeks of consistent progress. His last 5 weeks show some regression, possibly due to anxiety over his next placement. It would be unfair and inaccurate, however, to rate this case as having an overall negative score trend; thus, I did not include his brief regression in the calculation for this variable. Variable C showed a range from -35 to +50; the mean of the positive numbers was 22. For variable C's fuzzy-set assignment criteria, see table 4.2.

For each of the independent variables, I then assigned fuzzy-set membership values (see Appendix B). I initially used absolute raw values for variables A and C, reasoning that the amount of change, rather than the direction of that change, was all that mattered for my purposes. This choice created elliptical, conflicting values, and so I changed the values to reflect direction instead.

I placed the mean positive raw score in the middle (.5) of the fuzzy range, and the rest of the scores were arrayed roughly equally around this point.

Table 4.2 Fuzzy-Set Values for the Independent Variables

Fuzzy Value	**A: Gain in Weekly Averages**	**B: % Weeks with Variance**	**C: # of Weeks from Low to High Average**
1.0	25 +	90 +	45 +
.83	20 – 24	75 – 89	36 – 44
.67	15 – 19	60 – 74	27 – 35
.50	10 – 14	45 – 59	18 – 26
.33	5 – 9	30 – 44	9 – 17
.17	0 – 4	15 – 29	0 – 8
0	Negative	0 – 14	Negative

I then assigned each independent variable for each case its appropriate fuzzy value based on this table. Ragin (2000) asserts that

> … the specific translation of ordinal ranks to fuzzy membership scores depends on the fit between the *content* of the ordinal categories and the researcher's *conceptual understanding* of the fuzzy set. This point underscores the principle that fuzzy sets must be carefully calibrated with respect to the sets they reference (p. 157).

Fuzzy-set scores are not assigned based on ratio scales, but rather on degrees of membership. For variable A, any negative number merits assignment of a fuzzy value 0, since the case is "entirely not in" the set of cases displaying a "gain in weekly average scores." For variable C, any case that did not show upward progress is "entirely not in" the set of cases displaying "weeks from low average score to high average score."

Next, I assigned fuzzy values to the dependent variable in the algorithm A + B + C = D. The dependent variable (D), "Bifurcation Type," describes the case's degree of membership in Prigogine & Stenger's (1984) typology of bifurcations. I could have broken this variable down into three separate fuzzy variables, with each describing the case's degrees of membership in subtle, abrupt, and implosive bifurcations, but doing so seemed unduly cumbersome. Therefore, I assessed each case's overall amount of variance and the outcome of the change effort. By definition, smooth/subtle bifurcations can lead to either successful changes or inadequate changes. Abrupt change is, by definition, successful; however, if it is too variant for the system to handle, it becomes implosive. In Watzlawick et al.'s (1974) terms, subtle change is first order, adequate for some situations, and insufficiently adaptive for others. Abrupt change is analogous to second-order change. Watzlawick et al. (1974) did not include a term to describe implosive change efforts that spiral out of control, leading to failure. I believe that this distinction is an important elaboration contributed by Chaos Theory.

Because the Q-sorts and case-by-case analyses indicated that several cases seemed to fit in between two of the three (subtle, abrupt, and implosive) bifurcation types, I used a seven-value fuzzy set for this dependent/outcome variable D. I assigned each case a fuzzy value based on the hierarchy detailed in table 4.3.

Table 4.3 Fuzzy Set Descriptors for the Dependent Variable *D*

Fuzzy Value	**Bifurcation Description**
1.0	Rapidly implosive (less than 12 weeks); negative discharge
.83	Eventually implosive; negative discharge
.67	Highly abrupt; positive discharge
.5	Abrupt; positive discharge
.33	Minimally abrupt; positive discharge
.17	Subtle, some gain and/or loss; positive or negative discharge
0	Subtle, no positive change; negative discharge

It is important to note that this scale features unsuccessful discharges at both ends of the continuum. A failure to make adaptive changes is a treatment/learning/developmental failure, regardless of whether the system shows no variance or too much. In terms of applications, the type of failure is important; it provides direction to curriculum and intervention improvement.

Analysis

After creating Excel spreadsheets for these above data, I used the Fuzzy-Set/Qualitative Comparative Analysis 1.1 (fsQCA) software program (Ragin, Drass, & Davey, 2003) to analyze this sample group of cases, searching for necessary and sufficient causes for these treatment discharge outcomes. A *necessary cause* is a condition that must be present to produce a particular outcome; a *sufficient cause* is a condition that can, by itself, produce a particular outcome. This Boolean logic-based analysis allows researchers to assess combinations of causal conditions. The fsQCA software program allows the user to evaluate combinations of fuzzy variables with both probabilistic and veristic analyses. In simple terms, this statistical analysis, rather than comparing two real groups, compares an observed group with a theorized group that exemplifies hypothetical conditions. Because the veristic analysis is more appropriate for smaller *n* studies, I chose the probabilistic approach. I used a *p* value of .05, the standard for social science, and a test proportion of .80 ("almost always sufficient"), the most rigorous standard. Because this research potentially affects vulnerable children, it seemed most ethical to use the highest reasonable benchmark for statistical analysis.

The fsQCA software also allows for a "fuzzy adjustment" factor. Because social science data are generally imprecise, and because the fuzzy-set membership is a construct by which the researcher makes decisions to assign each case's variables a fuzzy value, the opportunity for error is large. "Furthermore, it is likely that measurement in the middle range of most fuzzy sets will be more imprecise than it is at either extreme" (Ragin, 2000, p.224). The fuzzy values of 0 and 1 contain cases with more extreme, obvious scores; the middle fuzzy values rely more on fine-grained choices and are more likely to be imprecise. In the present study, 31 cases with 4 variables each created 124 fuzzy values. If only a few of these values are off base, that fact will eliminate the finding of necessary and sufficient causes. Therefore, I used the recommended fuzzy adjustment of one level (.17). Any larger adjustment risks an overly generous analysis.

Analysis of Entire Sample

I first analyzed all 31 of the cases, using the algorithm A+B+C=D. The analysis indicated that at the .80 (almost always) level, with a $p < .05$ and a fuzzy adjustment of .17, there was one necessary condition, variable B ($p < .001$). There was one combination, a*B*C, that passed the test as both necessary and sufficient to cause D (the small letter 'a' indicates the absence of cause 'A').

For the entire sample group ($n = 31$), the value of variable B (percentage of weeks displaying higher than average variance) was greater than or equal to the value of the outcome variable D in all 31 cases ($p < .05$). Thus, the amount of variation is a necessary condition to cause the treatment outcome.

Furthermore, the combination of variable B with variable C (number of weeks from lowest to highest average weekly scores) is both necessary and sufficient to cause the outcome D. This combination is causal in combination with the negation of variable A ($1 - A$), amount of score change; in logic terms, $a + B + C$ is a sufficient combination ($p < .05$) to cause the bifurcation type. In other words, the amount of score change does not cause the type of bifurcation. This result fits with the idea that individuals are diverse in their ability and motivation to change. One person may find a small change to be overwhelming (an implosive bifurcation), while another may make a large change quite easily (a subtle bifurcation).

Analysis of Cases with Positive Outcomes

I then separated the cases into two groups by their discharge types. I discovered that the cases that led to positive outcomes (success in treatment) shared more commonalities, while the cases with negative outcomes shared fewer.

As for the entire sample group, the positive group ($n = 19$) showed that variable B (percentage of weeks with variance) was a necessary condition for a positive treatment outcome.

Furthermore, the combination of variable B with variable C (number of weeks from lowest to highest average weekly scores) is both necessary and sufficient to cause a positive outcome. This combination is causal with any value of variable A; in algebraic terms, both a + B + C and A + B + C are sufficient combinations ($p < .05$). In other words, the amount of score change does not cause the type of bifurcation. This result fits with the idea that individuals are diverse in their ability and motivation to change. In summary, the complex causal combination of an acceptable amount of progress coupled with a moderate amount of variation over a sufficiently long time is both necessary and sufficient to produce a positive discharge from treatment.

Analysis of Cases with Negative Outcomes

For the 12 sample cases with negative treatment outcomes, the same statistical analysis showed no necessary or sufficient causes. Thus, at the 80% ("almost always") benchmark level, the cases with a negative outcome did not display any necessary or sufficient causes. However, at the 65% ("usually sufficient") level, the cases with negative outcomes did display the same necessary and sufficient causal relationships as the cases with positive outcomes. It is safe to state that, in this sample, the cases with negative outcomes showed less of an overall cohesive causal relationship between variance and outcome than the cases with positive outcomes. It is important to note that there were fewer negative cases than positive (12 vs. 19), and that random sampling chance could explain this difference. However, the Q-sorts also support the idea that the cases with negative outcomes show a wider range of patterns than the cases with positive outcomes.

In summary, this data analysis indicates that there is a strong causal, predictive relationship between the amount of variance a case displays, the case's bifurcation pattern, and the case's discharge status. This probabilistic analysis indicates that for all cases, as well as for cases displaying successful stays in treatment, the percentage of a client's weeks during which he displayed above-average variability almost always (>.80) has a necessary causal relationship with his outcome type. In addition, the complex causal combination of variability and the length of time it took to show acceptable progress is almost always sufficient to predict the outcome type, regardless of other variables. This causal combination is true for cases that start at any score level (initial condition); what matters seems to be the amount of variance displayed and the length of time the individual takes to develop his final level of behavioral competence.

Additional DST Predictions

Dynamic Systems Theory predicts that for a gradual progression between attractors that are close together, there should be less variance than for cases in which there is a faster change between attractors that are farther apart. In algebraic terms, we can ask "Is any combination of causes A (amount of score gain) and B (percentage of weeks with significant variance) necessary or sufficient to predict C (length of time for the gain to occur)?

The data analysis showed that, for the 19 cases with positive outcomes, larger amounts of score gain (A) coupled with lower amounts of variance (b) are almost always (.80) sufficient to require longer times to move from lower to higher states (C). This analysis supports the prediction from Dynamic Systems Theory that rapid gain almost always requires more variance, while slow gain almost always requires less.

The other prediction of Dynamic Systems Theory is that sudden progress should be accompanied by more variance than gradual progress. In other words, for positive progress, cases with lower values of C (length of time for the gain to occur) accompanying higher values of A (amount of score gain) should cause higher values of B (percentage of weeks with significant variance).

This data analysis shows that the combination of variables A and C is neither necessary nor sufficient to cause variable B at the .80 (almost always) level. However, this combination is both necessary and sufficient at the .65 (usually) level. In addition, A (score gain) is usually a necessary condition for the outcome B (percentage of weeks with significant variance). This information supports the idea that larger amounts of progress will usually require more time, and will usually produce more variance. Thus, for cases leading to positive discharges, the prediction from Dynamic Systems Theory that sudden progress (as measured here by variable C, time required to move from lowest average week to highest average week) should be accompanied by more variance than gradual progress usually holds true.

Emergent Question: Zone of Proximal Development and Fuzzy-Set Evaluation

Upon examining the numbers describing each case's Zone of Proximal Development during the case-by-case analysis, I decided that this variable was worthy of further analysis. This additional analysis was not part of my original plan, but it emerged as an interesting subject for exploration. This variable (E) is different from variable B, percentage of weeks with variance; the Zone of Proximal Development is independent from variance, and only describes the approximate distance between lower and upper attractors. I assigned fuzzy values to these Zone of Proximal Development numbers based on this rubric (the mean, median, and modal raw value for Zone of Proximal Development in the sample group was 15):

Table 4.4 Fuzzy Set Assignment for Zone of Proximal Development (ZPD)

Fuzzy Value for ZPD		Raw Values
1.0	Extremely large ZPD	22 – 30
.83	Very large ZPD	20 – 22
.67	Above-average ZPD	17 – 19
.50	Average-sized ZPD	14 – 16
.33	Below-average ZPD	12 – 13
.17	Very small ZPD	10 – 11
0	Extremely small ZPD	0 – 9

I then included this variable E, size of Zone of Proximal Development, as ZPDFUZZ in the fs/QCA software (Ragin et al., 2003) and evaluated it in all combinations with the other variables for necessity and sufficiency in causing the outcome variable D, bifurcation type. Interestingly, this new variable size of Zone of Proximal Development was sufficient in combination with the necessary variable B (percentage of weeks with significant variance) to cause the outcome variable D at the .80 (almost always) level.

In summary, the repeated finding that variable B "percentage of weeks with significant variance" is a necessary condition for the outcome serves primarily to validate the bifurcation construct. Because the amount of variation is this closely related to, and is causal for, the outcome type of bifurcation, the construct seems valid in this randomly sampled group ($n = 31$).

The inclusion of an estimated Zone of Proximal Development (variable E), ascertained from a strictly visual analysis of each case's graph, added a strongly causal attribute; the combination of variables B and E was both necessary and sufficient to cause the outcome D in all cases. This variable E was, somewhat surprisingly, more powerful than the mathematically derived variable A (points gained/lost).

Summary

In conclusion, the four research questions are answered in the following ways. In answer to research question 1, patterns of behavioral change are evident when the scores are drawn on a bar graph. Sometimes a single case shows multiple patterns during different phases of learning; however, most of these sample cases displayed one predominant pattern. The Q-sorters were able to quickly create groups based on a visual scan of the cases' attributes.

In answer to the second research question, the patterns almost always suggested at least one of three general types of bifurcations (subtle, abrupt, or implosive). Some cases display two or all three of these bifurcation types during successive phases. In addition, some cases do not fit neatly into one of these three types; some fall in between, and their group membership is not clear unless some mathematical criteria (i.e., cut-off points) are decided upon. Given these criteria, most of the sample cases showed strong similarities to the hypothesized typology; data analysis indicates that the amount of variance, amount of change, and time taken to make this change all fit with the predictions of Dynamic Systems Theory.

There appears to be a relationship between fluctuating scores (weekly averages displaying variance above 6%) and periods of adaptive change, which answers research question 3. Cases leading to positive discharges displayed two overall bifurcation patterns: subtle ("slow and steady") and abrupt ("ups and downs"). Those cases fitting within the subtle bifurcation pattern did not typically show much variance, although when they did display brief periods of increased fluctuations, those periods were often followed by upward progress. For those cases fitting the abrupt change pattern, there was a strong relationship between fluctuation and progress. This relationship is not absolute or particularly predictable (as befits the observations of Chaos Theory), but it certainly seems to exist.

In response to the fourth research question, there is a relationship between type of bifurcation and the subjects' successful completion of the treatment program. As shown by the fsQCA data analysis, variable B (percentage of weeks with significant variance) is a necessary cause of these sample cases' discharge statuses, particularly for those who were successful. Furthermore, the combination of variable B with variable C (number of weeks from lowest to highest average weekly scores) is both necessary and sufficient to cause the outcome D. This was true for the entire sample group and for the cases with positive outcomes; the cases with negative outcomes did not display this same causal combination at the .80 (almost always) level of probabilistic analysis, but did at the .65 (usually) level. For this sample group, the cases with positive outcomes showed more causal similarity than did the cases with negative outcomes.

In answer to the emergent question about the predictive power of an estimated Zone of Proximal Development, the complex combination of percentage of weeks displaying significant variance and size of the Zone of Proximal Development is both necessary and sufficient to cause the type of outcome. This is a significant (and unexpected) finding, and its potential applications and some suggestions for further study will be discussed in the next chapter.

Finally, in answer to the predictions derived from DST, I found support for the prediction that rapid gain almost always requires more variance, while slow gain almost always requires less. In addition, this data analysis supports the idea that larger amounts of progress will usually require more time, and they will usually produce more variance. For cases leading to positive discharges, the prediction from DST that sudden progress should be accompanied by more variance than gradual progress usually holds true.

CHAPTER 5: DISCUSSION

How do humans learn, change, and develop? This broad question has driven research in the disciplines of education, human development, and psychology for the past century. European and American education systems have predominantly relied on pre- and post-intervention testing to guide curriculum design. Learning and development theories have generally been derived from cross-sectional, static observations; these studies provide snapshots of change products, without illuminating the process (Granott & Parziale, Eds., 2002). A research approach named the *microgenetic method* (Siegler & Crowley, 1991; Grannot & Parziale, Eds., 2002), which examines change while it is occurring, can offer useful data about the change process. A newer interdisciplinary, metatheoretical framework called *Dynamic Systems Theory* (DST) (Thelen & Smith, 1994, 1998, 2003; Lewis, 2002; van Geert, 1991, 1994, 1998) has suggested a solution to the theory problem. DST posits:

1. Forms and patterns create one another via self-organizing processes; structure emerges, and, thus, must neither be the result of preordained internal (genetic, organismic) instructions, nor be produced strictly by external (environmental, mechanistic) pressures.
2. Self-organizing systems tend to become more complex. They do so to increase their adaptive success. More sophisticated systems generally have more tools and options available to handle environmental pressures.

3. Systems reorganize via discontinuous, abrupt changes that are characterized by instability and high variability. These phase transitions (bifurcations) are unpredictable and nonlinear.
4. Self-organizing systems are, paradoxically, highly sensitive and highly stable. They are able to exist at the edge of chaos, thus maintaining an extreme sensitivity to environmental information. They are prone to simultaneously maintain stability (homeostasis) and strive to assimilate feedback into their existing structures (Lewis, 2002, p. 39).

Microdevelopmental research studies report that periods of high variability are typical precursors to gains in learning and development; Dynamic Systems Theory explains this phenomenon as a normal, and indeed necessary, part of the change process. The guiding research problem for this study was whether the observed behavioral fluctuations among these adolescent participants are consistent with the features predicted by DST. To address this problem, I developed four research questions. First, when scores are drawn on a bar graph, are any patterns evident? Second, if there are any evident patterns to the data, do these patterns fit with the three general types of bifurcations: subtle, abrupt, and implosive? Third, for the individual cases in the sample, is there evidence that periods of increased variance precede upward progress? Finally, for the sample group of subjects, is there a causal, predictive relationship between the amounts of variance each case displays, their bifurcation patterns, and their positive or negative discharges from the treatment program?

Discussion of Research Questions

Research Question 1

Patterns of behavior were evident when the scores were drawn on a bar graph. Sometimes a single case showed multiple patterns during different phases of learning. The Q-sort results indicated that there were noticeable differences among cases, and that there were distinctive, describable patterns to these data. Although the sorters picked different characteristics to group on, their classifications demonstrated that there were indeed clear groups. They quickly defined these groups, and the assignment of individual cases to group membership was usually easy.

Research Question 2

The score patterns usually suggested at least one bifurcation type. Chaos Theory (Prigogine & Stengers, 1984) describes three general types of bifurcations: subtle, abrupt, and implosive. In a subtle bifurcation, the system makes minimal adaptations without displaying dramatic fluctuations. In an abrupt bifurcation, the system displays noticeable, unpredictable fluctuations and reorganizes at a more adaptive, higher level of complexity. In an implosive bifurcation, the system does not successfully make the leap to a more adaptive level of complexity; it instead implodes (or explodes), perhaps surviving by reorganizing at a lower level of complexity. Some of these cases displayed two or all three of these bifurcation types during successive phases. In addition, some cases did not fit neatly into one of these three types; some fell in between, and their group membership was not clear unless some mathematical criteria (i.e., cut-off points) were decided upon. Given these criteria, most of the sample cases showed strong similarities to the hypothesized typology; data analysis indicated that the amount of variance, amount of change, and time taken to make this change all supported the predictions of Dynamic Systems Theory.

Research Question 3

There appeared to be a relationship between fluctuating scores (weekly averages displaying variance above 6%) and periods of adaptive change. Cases that led to positive discharges displayed two overall bifurcation patterns: subtle ("slow and steady") and abrupt ("ups and downs"). Those cases that fit within the subtle bifurcation pattern did not typically show much variance, although when they did display brief periods of increased fluctuations, upward progress often followed these periods. For those cases fitting the abrupt change pattern, there was a strong relationship between fluctuation and progress. This relationship is not absolute or particularly predictable (as befits the observations of Chaos Theory), but it certainly seems to exist. Lewis (2000) asserts that "Systems reorganize via discontinuous, abrupt changes, characterized by instability and high variability. These phase transitions (bifurcations) are unpredictable and nonlinear" (2000, p. 39). My findings suggest that this statement should be changed to say, "Systems *often* reorganize via discontinuous, abrupt changes, characterized by instability and high variability. They can also reorganize incrementally, via subtle changes." Some phase transitions are indeed quite subtle and create successful change without instability or high variability. This behavior might be analogous to Watzlawick et al.'s (1974) first-order change, although it may actually be just as profound and enduring as second-order change. If the zone of proximal development is small enough, and the time allotted is long enough, the system may make the change via a subtle bifurcation. This is probably a sensible strategy, as it exposes the system to less chaos. These data show that incremental changes can be just as valid, adaptive, and profound as abrupt changes.

Often, systems do change in an abrupt, chaotic manner. This type of phase transition looks (and probably feels) sudden, unpredictable, and discontinuous. These abrupt transitions are characterized by instability. They typically feature periods of heightened variability that leads to successful reorganization at higher levels of adaptive complexity. If the zone of proximal development is large enough (but not too large), and the time allotted is brief enough (but not too brief), the system can make the change via an abrupt bifurcation.

Often, however, systems fail to make adaptive changes. This failure occurs because the system is unwilling and/or unable to change, and thus does not create adequately increased complexity. From a Piagetian perspective, the system assimilates new information up to a certain point, but it does not accommodate the process by changing. This pattern seems, from my data analysis, to characterize a subtle bifurcation that may fail to adequately increase the system's structural complexity. The other way for a system to fail to make necessary changes is by an implosive bifurcation. This type of failure is characterized by too much variability; the system fluctuates out of control. If the distance between lower and higher attractors is too large for the system to navigate, there is a risk of implosion. The system cannot accommodate the flood of information.

This information is no surprise to educators. We regularly watch students "flame out" when their reach exceeds their grasp. Many teachers learn, the hard way, that too-high expectations can cause frustrated learners to shut down. Unfortunately, our responses often come too late; we adjust the curriculum for the next semester.

In their article "Nonlinear Phenomena in Learning Processes," Stadler, Vetter, Haynes and Kruse (in Pribram & King, 1996) assert that the theory of self-organization in the learning of complex systems can be examined by three empirical hypotheses focused on variability:

1. When measured over a sufficiently long time, with nearly constant learning effort and linear increase of task difficulty, learning processes will show characteristic nonlinearities in performance *(phase transitions).*
2. The stability of some parameters of the performance will break down at the end of each phase of stagnation *(critical fluctuations).* In contradiction to naïve expectation, one hypothesis should be that at the end of the highly optimized performance, the rate of errors increases.
3. Again in contradiction to naïve expectation, the learner will also show a significant increase in sensitivity to disturbances at the end of this phase of optimized performance *(critical slowing down)* (p. 159).

The first prediction is not well addressed by the present study. It would be very difficult to control the complex challenges of residential treatment so as to provide a linear increase in task difficulties. Instead, long-term learning/change efforts usually involve high initial difficulty and varying learning challenges. Some days are difficult, some are fairly easy. Still, there is evidence of phase transitions in these data. Most of the sampled subjects, regardless of outcome, did show increased amounts of variance preceding any improved, stabilized states.

Stadler et al.'s second prediction finds some support here, although it is difficult to define "optimized performance." Indeed,

> ...each person functions at diverse levels depending on demands of the task, domain, background, scaffolding, and capacity and thus shows asynchrony in level, not simple consistency. Tasks and situations attract specific skill levels that are often below people's highest capacities (Yan & Fischer, 2002).

It is very difficult to know whether learners are performing at their peak ability; they usually perform at a level that is merely "good enough." Still, many of the subjects did display not only increased variance but also drops in average scores (critical fluctuations) before they attained higher stable states. For example, cases 50 and 72 clearly displayed this phenomenon. Stadler et al.'s third prediction finds some interesting support in these data. Nearing the end of a successful treatment program, many of the subjects displayed sudden regressions. Cases 8 and 113, for example, clearly displayed this predicted phenomenon, which could be interpreted as "critical slowing down" due to an increased sensitivity to disturbances. Experience indicates that when learners are nearing the end of a successful course, they often become more fragile, sensitive to criticism, and perfectionistic. This behavior can lead to lowered performance levels.

In sum, Stadler et al.'s (1996) predictions receive some support from these data. However, their hypotheses would be better tested by a more controlled, quantified, microdevelopmental study.

Research Question 4

There was a relationship between type of bifurcation and the subjects' successful completion of the treatment program. As shown by the fsQCA data analysis, variable B (percentage of weeks with significant variance) is a necessary cause of the discharge status of these sample cases, particularly for those who were successful. Furthermore, the complex causal combination of the percentage of weeks with significant variance and time required to progress was almost always necessary and sufficient to predict the type of bifurcation and discharge status. In his description of DST, Lewis (2002) asserts:

> Self-organizing systems are, paradoxically, highly sensitive and highly stable. They are able to exist at the edge of chaos, thus maintaining an extreme sensitivity to environmental information. They are simultaneously prone to maintain stability (homeostasis), and strive to assimilate feedback into their existing structures" (p. 39).

This statement is well supported by my data. I was surprised to see just how powerfully the sample subjects fought to maintain homeostasis, despite powerful incentives to change. These subjects received a barrage of feedback, yet many managed either to ignore it or to assimilate it into their current cognitive structures without significantly altering their behaviors. This pattern fits with my experience. I used to tell clients, "If it were easy to change, we would just send you a postcard with the instructions; you wouldn't have to spend 10 months in residential treatment."

Two typical failure patterns support this idea. For subtle bifurcations leading to failed change efforts, the system (person) might be able to assimilate information without accommodating (changing) his or her schemata. Despite the consequences, many humans filter feedback into their existing maladaptive cognitive structures, rejecting any information that requires profound change. This principle is illustrated by the fact that prisons are packed with repeat offenders. For implosive bifurcations, the system is overwhelmed by feedback. The client cannot assimilate the new flood of information and is unable to accommodate it quickly enough to maintain a secure-enough level of homeostasis. He retreats to older, maladaptive behaviors, triggering even stronger feedback. The system fluctuates beyond its tolerable boundaries and implodes. Both of these failure patterns reflect the assertion that "self-organizing systems are, paradoxically, highly sensitive and highly stable" (Lewis, 2002, p. 39).

Supplemental Analyses

Upon examining the numbers that describe each case's apparent Zone of Proximal Development during the case-by-case analysis, I decided that this variable was worthy of further analysis. Doing this was not part of my original plan, but the subject emerged as interesting for exploration. Analysis showed that the causal combination of percentage of weeks with significant variance and estimated Zone of Proximal Development was both necessary and sufficient to predict the type of outcome. This is a significant finding, and a discussion of its implications will follow.

In addition, I proposed to explore whether these data supported two predictions derived from DST. According to DST, these data should show that, for a progression between attractors that are close together, there should be less variance than for cases in which the change is from attractors that are farther apart. Furthermore, sudden progress should be accompanied by more variance than gradual change. I found support for both these predictions. Clients that made greater progress usually required more time and usually displayed more variance. Rapid gain was almost always accompanied by more variance, while slow gain almost always displayed less variance.

In summary, this study generally supports the predictions of nonlinear Dynamic Systems Theory. The subjects who progressed to positive discharges (who, in a sense, succeeded) did appear to do so by learning adaptive behaviors via an increase in complexity. They did not lose the ability to behave maladaptively, as shown by their frequent retreats to their lower score attractors; instead, they added to their repertoires. Quick progress was almost always preceded by increased variability. Smooth progress required more time. Very large amounts of variability were indeed dangerous and often caused implosion. These findings are consistent with the Chaos Theory-derived predictions of DST; however, this study suggests that DST needs to further explore failures to change and develop.

In the literature review, I suggested that if the predictions of Dynamic Systems/Chaos Theory were supported by these data, then the fractal relationship between microdevelopment and macrodevelopment should be apparent. The data indicate that this prediction was at least partially true. There are two parts to this issue. For cases in which learning/change/development successfully occurred, this prediction was accurate. The microdevelopmental patterns observed by Thelen and Bates (2003), Yan and Fischer (2002), and Stadler et al. (1996) seemed to be repeated at the macrodevelopmental scale in my data. This was especially true for the 42% of the sample cases that fit into an abrupt bifurcation pattern. Even those cases that displayed a more subtle bifurcation pattern showed some periods of heightened variability and regression. For cases that led to unsuccessful change efforts, the above DST prediction received less support.

Learning/change/development efforts fail for many reasons, and they follow many patterns. A person might appear to be following a healthily subtle or abrupt change pattern, and then suddenly implode. This implosion might be to the result of a characteristic of open systems; Lewis (2002) called it "an extreme sensitivity to environmental information" (p. 39). Open systems are not machines, and their behaviors remain highly volatile. This difference between successful adaptation and failure may reflect a fundamental truth: The road to developmental success is narrow, while opportunities for failure are infinite. As Leo Tolstoy wrote, "Happy families are all alike; every unhappy family is unhappy in its own way" (*Anna Karenina*, chapter 1, first line).

This study adds a useful piece to the education, counseling, and learning and development knowledge base by testing some of the predictions of nonlinear Dynamic Systems Theory. The data set provides a rare example of microdevelopmental measurements (dense, multiple daily scores) spread out over a macrodevelopmental (many months) period. This study provides support for some of the predictions of DST, and it suggests a few modifications.

There were some surprises from these data. First, the subjects' change patterns were more complex than I had anticipated, especially with regard to multiple bifurcation patterns. Second, fewer successful subjects displayed the "saxophone curve" pattern than I had expected. This discrepancy is probably an example of an illusory correlation; when I was practicing therapy with these clients, I noticed and remembered cases that fit my expectations, disregarding the majority that did not. This is one reason that scientific studies are necessary: Experiential and anecdotal evidence is prone to human bias. Third, the patterns of successful subjects were more similar than those who failed. This observation seems to support some traditional ideas about straight and narrow paths, much to this researcher's surprise.

Limitations

This study could be improved in several ways. First, a more rigorous and focused application of theoretical constructs to these data would have helped to clarify the results, since fuzzy-set membership assignment is a qualitative process that relies on the researcher's skilled use of theory. Second, the use of more advanced graphing software would have made analysis easier, more communicable, and more precise. Third, the fuzzy-set descriptions and assignments are probably under-theorized and, perhaps, too fine-grained. Three- or five-level fuzzy sets would likely have been easier, clearer, and perhaps more fair. My attempt to be as exact as possible may have been unwise. Fourth, the case-by-case analysis would have yielded richer data had I known more details about the individual cases; however, to maximize the confidentiality of a vulnerable population I did not seek additional, possibly identifying, information. Ethics took precedence over information.

Implications

A recent study (Gershkoff-Stowe & Thelen, 2004) addresses the relationship between regression ("U-shaped behavior") and infant development:

> When the component changes are slow and the context is stable, then the softly assembled behavior may appear stable. Conversely, when the components themselves are in rapid flux, there may be changes in the relative contributions to the ensemble and thus, the behavior itself may be fragile and transient. By this logic, U-shaped behavior is the result of these continually changing configurations that may give the appearance of regressions, but are actually windows on these processes of continual reorganization in systems undergoing relatively rapid change (p. 17).

This suggests that what appears to be regression to a lower level of organization may actually be an essential part of the reorganization process when a system is undergoing abrupt change. This premise is a persuasive argument for the function of variance, but it seems to insist that there is no such thing as true failure. Practitioners in education and psychotherapy attest to the contrary; this apparent denial of true regression might be a weakness in the application of a theory based on human motor development (DST) to other disciplines, or it might simply require an expansion of the theory.

One of the tantalizing suggestions of DST is that although the future behaviors of open systems are unpredictable, patterns do emerge, and these patterns are often stable. In the case of human learning/change/development, the emergence of patterns may provide useful tools. For example, imagine that one is suddenly tasked with raising a child. In the absence of prior observations, history, and data, one could not predict the best ways to teach, nurture, and relate to her. The data are completely chaotic. After a few days, patterns begin to emerge; the child likes animals, avoids bedtime, and loathes spinach. The observant caretaker can begin to craft reinforcements and anticipate challenges. Soon, the child's zones of proximal development for various tasks will become apparent and can be used to create curricula. As fresh information pours in, the caretaker adapts his guidance efforts to the child's capacities. Prediction becomes possible.

For educators, this study has several implications. Formative assessments could provide useful indices of individual and group Zones of Proximal Development for specific classes. Learners could be challenged according to this information, with the potential of producing maximum results in an allotted time. Fluctuations could be anticipated and valued as evidence of progress rather than inadequacy. In addition, educational failure rates could be decreased by continual monitoring of those variances beyond the student's typical Zone of Proximal Development. At the first sign of excessive fluctuation, the learner could be offered a break. Expectations could be temporarily lowered and support increased. When the system (student) stabilizes, challenges could then be carefully increased until variance was at a healthy level. This process would require attention and effort, but it could dramatically decrease the number of students who are "left behind."

For counselors and therapists, this study suggests that humans involved in change efforts are likely to display some predictable patterns. Attention to these patterns might improve treatment planning and pacing. Excessive cognitive, emotional, and/or behavioral fluctuations indicate a risk of implosion; the counselor or therapist might be wise to "lighten things up" by spending a few weeks consolidating gains, praising the client's progress, and pursuing stability at the current level of functioning.

Clinical interventions might have their greatest impact if they are targeted at these "sensitive periods." Also, interventions might *induce* a phase transition, which may be one compelling way to characterize treatment progress

> .... for example, treatment progress, operationalized as a destabilization of the system, may be tested by examining the observed amplitude of oppositional outbursts. Evidence for a clinically induced phase transition might include an increase in the standard deviations of the amplitude of outbursts and a decrease in *within-subject* correlations between, for instance, different contexts and the occurrence of oppositional behavior (Granic & Hollenstein, 2003, p. 648).

For change agents in organizations, this study also has some potentially useful implications. When second-order (Watzlawick et al., 1973) or double-loop (Argyris, 1995) change is required within a limited timeframe, healthy amounts of fluctuation must be induced; otherwise, the system is more likely to retreat to its comfortable (but inadequate) initial form. Leaders charged with organizational change must attend to measures of fluctuation (such as employee turnover) and judge the limits of healthy variability. The organization can be evaluated in much the same way an individual is, with its Zone of Proximal Development and tolerance for variance. Constant assessment and appropriate adjustments could improve the chances of a successful organizational change effort.

Recommendations

1. My next step will be to examine these data at a different level. I will use similar fuzzy-set variables to study the subjects' performance on a specific activity. For example, how do the score patterns for the second hour of the school day look? How do variations from the norm affect the rest of the client's day? I hypothesize that people might display considerable performance fluctuation on a particular task, but they will compensate on other daily tasks to maintain overall homeostasis. This inclination allows the system a higher degree of abrupt change for one learning task, while it maintains enough overall stability to resist implosion.
2. Future studies should replicate this one, using similar data from different populations. This kind of data is available for younger children, adolescent girls, adults in certain treatment programs, and the developmentally challenged. If DST is as useful as it seems here, then similar behavior patterns should be observed in other data sets.
3. Developmental Systems Theory has some potentially useful applications for educational and therapeutic assessment. This study finds support for the idea that a learner's effective ZPD can be quickly (albeit roughly) assessed, and that a curriculum could then be adapted to best fit the individual's needs. Students or clients could be tested early in the change process. Such testing could be accomplished via simple observations of their behavior, or by

presenting them with simple and then challenging tasks, and measuring the score difference. The amount of variance a subject displays and the distance between higher and lower attractors might provide invaluable information. Throughout a change process, the expectations could be adjusted to provide enough of a challenge to create healthy abrupt change and thus speed up the process while avoiding implosion. This application will require considerable research and refinement before it can be widely used, but the benefits could be enormous.

4. This study applied fuzzy-set analysis to data that fails the standards for typical statistical analysis. Much of the educational and social science data that is typically subjected to parametric statistical analysis is inappropriate for such manipulation. For example, the Likert scales typically used in surveys and self-reports are actually fuzzy-set constructs, and they would benefit from fuzzy-logic analysis. The use of fuzzy sets for the analysis of educational and social science data deserves further exploration.

> Fuzzy sets are one proposed method for managing vagueness. They can be used to help make analyses, perhaps ironically, less fuzzy because vagueness is managed formally. Like all other efforts at formalization, whatever else they may buy us, they can help lay bare assumptions and force researchers to be explicit about what exactly they mean (Verkuilen, 2005, p.464).

I plan to examine a large data set of Likert-scale survey responses using parametric, nonparametric, and fuzzy-set analyses; this comparison might provide some answers regarding the utility and appropriateness of different analytic approaches.

Conclusion

For the participants in this study, the change process usually displayed the patterns predicted by Dynamic Systems Theory. DST was first specifically used as an explanation for infant motor development (Thelen, Kelso, & Fogel, 1987; Thelen & Ulrich, 1991). DST was then applied to language development (van Geert, 1991, 1995) and the learning of specific, time-limited tasks (Yan, 2000; Yan & Fischer, 2002). Researchers and theorists (Thelen & Bates, 2003; Thelen & Smith, 1993, 1994, 2003; Thelen, 2005; Lewis, 2002a, 2004; van Geert, 1991, 1994, 1998) have suggested that DST might be a powerful metatheory that explains most (or all) fundamental change processes in nature. During the past two years (2003 through 2005) alone, books have been published that apply DST to organizational leadership, economics, evolution, artificial intelligence (AI), transportation planning, emotion, brain function, identity formation, cellular biology, parent-child relationships, creativity, archeology, and psychotherapeutic technique! Clearly, DST has informed and stimulated disciplines that use systems approaches. The results of this study suggest that Dynamic Systems Theory offers both a useful explanatory lens and some exciting practical applications for students of human development, education, and psychology. The development models created by Vygotsky and Piaget provide useful explanations of these change mechanisms and create a common language for explaining learning and development processes; in addition, their models seem compatible with recent nonlinear dynamic-systems perspectives. This historical continuity is reassuring and suggests that DST indeed offers a potential interdisciplinary metatheory to explain development, growth, learning, and change.

REFERENCES

Adami, C., Ofria, C. & Collier, T. C. (2003). Evolution of biological complexity. *Procedings of the National Acadamy of Sciences of the United States of America, 97(9),* 4463–4468.

Argyris, C. (1999). *On organizational learning* (2nd Ed.). Malden, MA: Blackwell.

Ashby, W.R. (1960). *Design for a brain: The origin of adaptive behavior.* New York: Wiley & Sons.

Ashby, W.R. (1966). *An introduction to cybernetics.* New York: J. Wiley.

Barab, S., Cherkes-Julkowski, M., Swenson, R., Garrett, S., Shaw, R., & Young, M. (1999). Principles of self-organization: Learning as participation in autocatakinetic systems. *The Journal of the Learning Sciences, 8 (3 & 4),* 349-390.

Barton, S. (1994). Chaos, self-organization, and psychology. *American Psychologist, 49,* 5-14.

Bateson, G., Jackson, D., Haley, J., & Weakland, J. (1956). Toward a theory of schizophrenia. *Behavioral Science, 1(4),* 251-264.

Bateson, G. (1972). *Steps to an ecology of mind.* San Francisco: Chandler.

Bateson, G. (1979). *Mind and nature: A necessary unity.* New York: Dutton.

Bateson, G. (1991). *A sacred unity: Further steps to an ecology of mind.* New York: Harper Collins.

Bijou, S. & Baer, D. (1961). *Child development.* Englewood Cliffs, N.J.: Prentice-Hall.

Bronfenbrenner, U. (1979). *The ecology of human development: Experiments by nature and design.* Cambridge, MA: Harvard University Press.

Butz, M. (1997). *Chaos and complexity: Implications for psychological theory and practice.* Bristol, PA: Taylor & Francis.

Butz, M., Chamberlain, L., & McCown, W. (1997b). *Strange attractors: Chaos, complexity, and the art of family therapy.* New York: Wiley.

Crannell, C.W. (1942). The choice point behavior of rats in a multiple path elimination problem. *The Journal of Psychology, 13,* 201-222.

Erikson, E. (1950). *Childhood and society.* New York: Norton.

Feyerabend, P. (1993). *Against method.* London, New York: Verso.

Fischer, K. & Granott, N. (1995). Beyond one-dimensional change: Parallel, concurrent, socially distributed processes in learning and development. *Human Development, 38,* 302-314.

Fisher, K. & Yan, Z. (2002). Darwin's construction of the theory of evolution: Microdevelopment of explanations of variation and change in species. In N. Granott & J. Parziale (Eds.) *Microdevelopment: Transition processes in development and learning* (pp. 294-318). Cambridge: Cambridge University Press.

Flavell, J. (1963). *The developmental psychology of Jean Piaget.* Princeton, N.J.: Van Nostrand.

Fogel, A. (1993). Origins of the self in early infancy: Is perception sufficient? *Psychological Inquiry, 3(2),* 115-117.

Fogel, A. & Thelen, E. (1987). The development of early expressive and communicative action: Re-interpreting the evidence from a dynamic systems perspective. *Developmental Psychology, 23,* pp. 747-761.

Ford, D. & Lerner, R. (1992). *Developmental systems theory: an integrative approach.* Newbury Park, CA: Sage Publications.

Foucault, M. (1965). *Madness and civilization: A history of insanity in the age of reason.* New York: Random House.

Foucault, M. (1970). *The order of things: An archeology of the human sciences.* NewYork: Pantheon.

Foucault, M. (1978). *The history of sexuality.* New York: Vintage Books.

Gershkoff-Stowe, L. & Thelen, E. (2004). U-shaped changes in behavior: A dynamic systems perspective. *Journal of Cognition and Development, 5(1),* 11-36.

Gibson, E (1969). *Principles of Perceptual Learning and Development.* New York; Appleton-Century-Crofts.

Gilgen, A. (1995). Prefatory Comments. In F. Abraham & A. Gilgen (Eds.). *Chaos theory in psychology.* Westport, CT: Praeger.

Gleick, J. (1987). *Chaos: Making a new science.* New York: Viking.

Gliner, J. & Morgan, G. (2000). *Research methods in applied settings: An integrated approach to design and analysis.* Mahwah, New Jersey: Lawrence Erlbaum.

Goerner, S. (1994). *Chaos and the evolving ecological universe.* Luxembourg: Gordon and Breach.

Goldin-Meadow, S. & Alibali, M. W. (2002). Looking at the hands through time: A microgenetic perspective on learning and instruction. In N. Granott & J. Parziale (Eds.) *Microdevelopment: Transition processes in development and learning* (pp. 80-105). Cambridge: Cambridge University Press.

Gottlieb, A. (2000). Philosophy's martyr: Socrates. In Raphael, F. & Monk, R. (Eds.). *The great philosophers.* New York: Routledge.

Gottlieb, G. (1992). *Individual development and evolution: The genesis of novel behavior.* New York, Oxford: Oxford University Press.

Granic, I. & Hollenstein, T. (2003). Dynamic systems methods for models of developmental psychopathology. *Development & Psychopathology, 15(3),* 641-670.

Granott, N. (2002). How microdevelopment creates macrodevelopment: Reiterated sequences, backward transitions, and the Zone of Current Development. In N. Granott & J. Parziale (Eds.) *Microdevelopment: Transition processes in development and learning* (pp. 213-242). Cambridge: Cambridge University Press.

Granott, N. & Parziale, J. (Eds.). (2002). *Microdevelopment: Transition processes in development and learning.* Cambridge, UK: Cambridge University Press.

Haley, J. (1959). The family of the schizophrenic: A model system. *American Journal of Nervous and mental Disorders, 129,* 357-374.

Harris, A. (2005). *Gender as soft assembly.* Hillsdale, NJ: The Analytic Press.

Hunt, M. (1993). *The story of psychology.* New York: Doubleday.

Jaffe, C. M. (2000). Organizing adolescents(ce): A dynamic systems perspective on adolescence and adolescent psychotherapy. *Adolescent Psychiatry, 25,* 17-43.

Kuhn, D. (1995). Microgenetic study of change: What has it taught us? *Psychological Science, 6(3),* 133-139.

Kuhn, T. (1970). *The structure of scientific revolutions.* Chicago: University of Chicago Press.

Lask, B. (1987). Cybernetico-epistobabble, the emperor's new clothes and other sacred cows. *Journal of Family Therapy, 9,* 207-215.

Lerner, R. M. (1991). Changing organism-context relations as the basic process of development. *Developmental Psychology 27(1),* 27-32.

Lerner, R. M., Lerner, J. V., Stefanis, I. D. & Apfel, A. (2001). Understanding developmental systems in adolescence: Implications for methodological strategies, data analytic approaches, and training. *Journal of Adolescent Research, 16(1),* 9-27.

Lerner, R. M. (2002). *Concepts and theories of human development.* Mahwah, N.J.: L. Erlbaum Associates.

Lerner, R. M. & Castellino, I. R. (2002). Contemporary developmental systems theory and adolescence: Developmental systems and applied developmental science. *Journal of Adolescent Health, 31(6S),* 122-135.

Lewin, K. (1943). Psychology and the process of group living. *The Journal of Social Psychology, SPSSI Bulletin, 17,* 113-131.

Lewin, K. (1951). *Field theory in social science: Selected theoretical papers.* D. Cartwright (Ed.). New York: Harper & Row.

Lewis, M. D. & Granic, I. (Eds.). (2000a). *Motion, development, and self-organization: Dynamic systems approaches to emotional development.* New York : Cambridge University Press.

Lewis, M. D. (2004). Trouble ahead: Predicting antisocial trajectories with dynamic systems concepts and models. *Journal of Abnormal Child Psychology, 32(6),* pp.665-671.

Lewis, M. D. (2002a). The promise of dynamic systems approaches for an integrated account of human development. *Child Development, 71(1),* 36-44.

Lewis, M. D. (2002b). Interacting time scales in personality (and cognitive) development: Intentions, emotions, and emergent forms. In N. Granott & J. Parziale (Eds.) *Microdevelopment: Transition processes in development and learning* (pp. 183-212). Cambridge: Cambridge University Press.

Minuchin, S. (1974). *Families and family therapy.* Cambridge, MA: Harvard University Press.

Moore, C. F., Dixon, J. A. & Haines, B. A. (1991). Components of understanding in proportional reasoning: A fuzzy set representation of developmental progressions. *Child Development, 62(3),* 441-459.

Muenziger, K.F. (1938). Vicarious trial and error at a point of choice: 1. A general survey of its relation to learning efficiency. *The Journal of Genetic Psychology, 53,* 75-86.

Muenziger, K.F. (1956). On the origin and early use of the term vicarious trial and error (VTE). *Psychological Bulletin, 53,* 493-494.

Oxford English Dictionary On-Line (2000). http://dictionary.oed.com. Retrieved February 18, 2004. Oxford: Oxford University Press.

Pepper, S. C. (1942). *World hypotheses: A study in evidence.* Berkeley, CA: University of California Press.

Piaget, J. (1951). *The child's conception of the world.* New York: Humanities Press.

Piaget, J. (1977). *The Essential Piaget.* (H.E. Gruber & J.J. Vonèche, Eds.). NY: Basic Books.

Prigogine, I. & Stengers, I. (1984) *Order out of chaos: Man's new dialogue with nature.* Toronto ; New York: Bantam Books.

Prochaska, J. O. & DiClemente, C. C. (1992). *Stages of change in the modification of problem behaviors.* Newbury Park, CA: Sage.

Ragin, C. (1987). *The comparative method: Moving beyond qualitative and quantitative research strategies.* Berkeley and LA: University of California Books.

Ragin, C. (2000). *Fuzzy-set social science.* Chicago: University of Chicago Press.

Ragin, C. & Giesel, H. (2002). *Software guide.* Based on: fs/QCA 0.963 © Copyright 1999-2000, Kriss A. Drass.

Ragin, C., Drass, K, & Davey, S (2003). Fuzzy-Set/Qualitative Comparative Analysis 1.1. Tucson, Arizona: Department of Sociology, University of Arizona.

Sacks, O. (1985). *The man who mistook his wife for a hat.* New York: Summit Books.

Sawada, D. & Caley, M. (1985). Dissipative structures: New metaphors for becoming in education. *Educational Researcher, 14,* 13-19.

Selvini Palazzoli, M., Boscolo, L., Cecchin, G. & Prata, G. (1978). *Paradox and counterparadox.* New York: Jason Aaronson.

Siegler, R. S. & Crowley, K. (1991). The microgenetic method: A direct means for studying cognitive development. *American Psychologist, 46(6),* 606-620.

Skinner, B. F. (1938). *The behavior of organisms; an experimental analysis.* New York: Appleton-Century-Crofts.

Skinner, B. F. (1974). *About behaviorism.* New York: Knopf.

Stadler, M., Vetter, G., Haynes, J., & Kruse, P. (1996). Nonlinear phenomena in learning processes. In K. Pribram & J. King (Eds.), *Learning as self-organization* (pp. 157-169). Mahwah, NJ: Erlbaum.

Steenbeek, H. & van Geert, P. (2002). Variations on dynamic variations. *Human Development, 45,* 167-173.

Thelen, E. (2005). Dynamic systems theory and the complexity of change. *Psychoanalytic Dialogues, 15(2),* 255-274.

Thelen, E. & Bates, E. (2003). Connectionism and dynamic systems: Are they really different? *Developmental Science, 6(4),* 378-391.

Thelen, E. & Smith, L. B. (2003). Development as a dynamic system. *Trends in Cognitive Sciences, 7(8),* 343-349.

Thelen, E. & Smith, L. B. (1998). Dynamic systems theories. In W. Damon (Ed.), *handbook of child psychology: Vol. 1. Theoretical models of human development* (5th ed.). New York: Wiley.

Thelen, E. & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action.* Cambridge, MA: MIT/Bradford.

Thelen, E. & Smith, L. B. (Eds.). (1993). *A dynamic systems approach to development: Applications.* Cambridge, MA: MIT/Bradford.

Thelen, E. & Ulrich, B. D. (1991). Hidden Skills: A dynamic systems analysis of treadmill stepping during the first year. *Monographs of the Society for Research in Child Development, 56(1).*

Thelen, E., Kelso, J.A.S., & Fogel, A. (1987). Self-organizing systems and infant motor development. *Developmental Review*, 7, pp. 39-65.

Thom, R. (1975). *Structural stability and morphogenesis.* New York: Benjamin.

Tolman, E. (1932) *Purposive behavior in animals and men.* New York: The Century Co.

Tolstoy, L. (1870) *Anna Karénina.* Grand Rapids, Mich.: Christian Classics Ethereal Library. Boulder, CO: NetLibrary.

van Geert, P. (2002). Developmental dynamics, intentional action, and fuzzy sets. In N. Granott & J. Parziale (Eds.) *Microdevelopment: Transition processes in development and learning* (pp. 319-343). Cambridge: Cambridge University Press.

van Geert, P.(1998). We almost had a great future behind us: The contribution of non-linear dynamics to developmental-science-in-the-making. *Developmental Science, 1(1),* 143-159.

van Geert, P. (1995). Growth dynamics in development. In R. F. Port & T. van Gelder (Eds.) *Mind as motion: Explorations in the dynamics of cognition.* Cambridge, MA: Bradford/MIT Press.

van Geert, P. (1994a). *Dynamic systems of development: Change between complexity and chaos.* Hempstead: Prentice Hall.

van Geert, P.(1994b). Vygotskian dynamics of development. *Human Development, 37,* 346-369.

van Geert, P. (1993). A dynamic systems model of cognitive growth: Competition and support under limited resource conditions. In E. Thelen & L. B. Smith (Eds.) *A dynamic systems approach to development: Applications.* Cambridge, MA: MIT/Bradford.

van Geert, P. (1991). A dynamic systems model of cognitive and language growth. *Psychological Review, 98,* 3-53.

Verkuilen, J. (2005). Assigning membership in a fuzzy set analysis. *Sociological Methods & Research, 33(4),* 462-496.

Von Bertalanffy, L. (1968). *General systems theory: Foundations, development, applications.* New York: George Braziller.

Vygotsky, L.S. (1978). *Mind in society.* (Cole, M., John-Steiner, V., Scribner, S., and Souberman, E., Eds. /Trans.). Cambridge, MA: Harvard University Press.

Watzlawick, P., Weakland, J. H., & Fisch, R. (1974). *Change: Principles of problem formation and problem resolution.* New York: Norton.

Wiener, N. (1948). *Cybernetics; Or, control and communication in the animal and the machine.* New York: Wiley.

Yan, Z. & Fischer, K. (2002). Always under construction: Dynamic variation in adult cognitive microdevelopment. *Human Development, 45,* 141-160.

Yan, Z. (2000). Dynamic analysis of microdevelopment in learning a computer program. Dissertation, Harvard University. Retrieved November 12, 2003. ProQuest Dissertations and Theses.

Zadeh, L. A. (1994). Soft computing and fuzzy logic. *IEEE Software, November 1994,* 48-56.

Zadeh, L. A. (1965) Fuzzy sets. *Information and Control, 8,* pp. 338-353.

APPENDIX A: SCORESHEET

This is a sample sheet used by the treatment center to record clients' behavior scores. This sheet contains the data for one client during one week of his stay in residential treatment. The left column details the activities for which the client was scored. For example, "First Period" is the first period of the school day, from 8:15 to 9:20 am, Monday through Friday. Like most activity periods, this one has a possible maximum of 10 points. An average performance earns the client 7 of the 10 possible points; above average behaviors can earn 8, 9, or 10 points, while unacceptable actions cost the client points.

Since different days have different activities, the possible number of points varies. Therefore, daily points are totaled and then divided by the possible points for the day, giving a percentage score. These daily scores are used to derive the client's weekly average. In this example, the client's scores ranged from 65% to 71%, with a weekly average of 69%. Weekly averages are used by the treatment center staff to determine progress and privileges.

In this example, the client was not participating in any normal activities between breakfast and personal time on Wednesday, December 25, most likely due to the holiday. Because of this, he was not scored for the majority of the day. This is recorded as "NS" (no score). If the client is not scored for at least 40% of the day, the treatment center records a "No Score" for the entire day so as not to unfairly skew the client's averages.

21

Level I/II 7 Level III 7.5 Level IV 8

CLIENT:	#57	M 12/23	T 12/24	W 12/25	R 12/26	F 12/27	SAT 12/28	
1) Overnight Score	10 Points	7	7	7	7	7	7	7
2) Breakfast & Chore-	10 Points	-3 4	7	7	7	7.5	-1 6	7
3) Showers	10 Points	-1 6	7	NS	-1 6	7.5	7	7
4) First Period- 8:15- 9:20	10 Points	8 +1	7	NS	NS	7		
5) Second Period- 9:25- 10:20	10 Points	7	7		NS	7		
6) Third Period- 10:25- 11:20	10 Points	7	7		7	+.5 7.5		
7) Fourth Period/ D&A- 11:25- 12:15	10 Points	8	7		7	+1 8		
8) Fifth Period	10 Points	4				7		
9) Community Service Activity	20 Points						-3 11	
10) Personal Time / Free Time	10 Points						7	+1 8
11) Education Group	10 Points						-2 5	7
12) Lunch / Chores	10 Points	7	+1 8		7	7	7	NS
13) Daily Group- 1:05- 2:00	10 Points		7		+.5 -.5 7			
14) Staff Choice	10 Points						NS	7
15) Room Time 3:00 - 3:30	10 Points						7	7
16) Recreation	10 Points	7	7		7	7.5 +.5	7	7
17) Evening Group 4:00- 5:00	10 Points	7	7		7	7		
18) Dinner/ Chores	10 Points	7	7		+.5 7.5	7	7	+1 8
19) Free time /House Issues	10 Points	-1.5 5.5	7		7	7		
20) Personal Time	10 Points	7	sick bed -1 6		7	7		
21) Goals / Thinking Errors Group	10 Points							7
22) D & A Stepwork	10 Points						+1 8	
23) Meeting	10 Points	7	7		7	7		NS
24) Personal Time / Majors	10 Points	NS	7	7	7	7	7	NS
25) Movie / Team Building Activity	10 Points						7	
26) Hygiene	10 Points	7	7	7	7	7	7	7
27) Completion of TX	10 Points	7	NS	NS	6.5	5	NS	NS
* Overall Points Added/Deducted		-2			+1			
TOTAL POINTS:		105/~~180~~ 170	119/~~180~~ 170	/170	112/~~180~~ 160	1[illegible]/180	100/~~170~~ 150	79/~~150~~ 110
TOTAL %:		65	70	NS	70	71	67	72

APPENDIX B: DATA

Raw scores for each sample case

Case #	A: Δ avg.	B: % weeks w/ variance	C: # weeks
8.	12	71	19
10.	13	74	43
13.	-18	100	-22
31.	23	71	23
42.	13	58	44
48.	-10	100	-4
49.	11	52	20
50.	17	88	8
57.	-9	68	-35
59.	-22	71	-12
61.	9	70	4
62.	7	54	39
64.	11	69	24
65.	7	31	8
70.	17	100	-1
71.	27	60	50
72.	21	84	6
76.	6	26	-1
77.	11	48	15
87.	-14	80	-18
91.	14	13	26
97.	-25	100	-2
98.	-17	34	-16
107.	14	29	25
111.	16	57	19
113.	6	81	7
114.	-1	63	-6
123.	9	8	31
127.	8	38	21
128.	7	30	21
131.	8	24	11

Raw scores and corresponding fuzzy set values

Case #	A: Change	A: Fuzzy	B: Var.	B: Fuzzy	C: weeks	C:Fuzzy	D:BiFuzz	Outcome
8	12	0.5	71	0.67	19	0.5	0.67	pos
10	13	0.5	74	0.67	43	0.83	0.67	pos
13	-18	0	100	1	-22	0	0.83	neg
31	23	0.83	71	0.67	23	0.5	0.5	pos
42	13	0.5	58	0.5	44	0.83	0.5	pos
48	-10	0	100	1	-4	0	1	neg
49	11	0.5	52	0.5	20	0.5	0.5	pos
50	17	0.67	88	0.83	8	0.17	0.67	pos
57	-9	0	68	0.67	-30	0	0.83	neg
59	-22	0	71	0.67	-12	0	0.83	neg
61	9	0.33	70	0.67	4	0.17	0.5	pos
62	7	0.33	54	0.5	39	0.83	0.5	pos
64	11	0.5	69	0.67	24	0.5	0.5	pos
65	7	0.33	31	0.33	8	0.17	0.33	pos
70	-30	0	100	1	-1	0	1	neg
71	27	1	60	0.67	50	1	0.83	neg
72	21	0.83	84	0.83	6	0.17	0.67	pos
76	-6	0	26	0.17	-1	0	0	neg
77	11	0.5	48	0.5	15	0.33	0.5	pos
87	-14	0	80	0.83	-18	0	0.83	neg
91	14	0.5	13	0	26	0.5	0.17	pos
97	-25	0	100	1	-2	0	1	neg
98	-17	0	34	0.33	-16	0	0.17	neg
107	14	0.5	29	0.17	25	0.5	0.17	neg
111	16	0.67	57	0.5	19	0.5	0.5	pos
113	6	0.33	81	0.83	7	0.17	0.67	pos
114	-1	0	63	0.67	-6	0	0.83	neg
123	9	0.33	8	0	31	0.67	0.17	pos
127	8	0.33	38	0.33	21	0.5	0.33	pos
128	7	0.33	30	0.33	21	0.5	0.33	pos
131	8	0.33	24	0.17	11	0.33	0.17	pos
Mean	5.516129	0.375484	59.74194	0.570323	11.19355	0.328065	0.553871	
Median	9	0.33	63	0.67	11	0.33	0.5	
Mode	11	0.33	100	0.67	19	0	0.5	

APPENDIX C: SOFTWARE OUTPUT

FSqca software output for all cases, A + B + C = D:

```
**********************
* FUZZY-SET ANALYSIS *
**********************

File:  C:/Diss7All.csv
Model: D = A + B + C

Cases Read:      31
     Valid:      31  100.0%
   Missing:       0    0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 30 ( 96.8% of Total)
Method: Probabilistic
Test Proportion:  0.80
             *p < 0.05
Fuzzy Adjustment: 0.17

            N Cause    Observed   Binomial
Variable  >= Outcome  Proportion         p
=========================================
a                       25        0.83     0.428
A                       21        0.70
b                       16        0.53
B                       30        1.00     0.001*
c                       26        0.87     0.255
C                       18        0.60
==================================================

1 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion:  0.80
              p < 0.05
Fuzzy Adjustment: 0.17

The Following Causal Expressions Pass the Test for Sufficiency but
ARE NOT Included in the Solution because they are Redundant or
because they are Absorbed by other Terms:

a*B
   Tested N:      28   Proportion Sufficient: 1.000   Binomial p: 0.002
A*B
   Tested N:      21   Proportion Sufficient: 1.000   Binomial p: 0.009
B*c
   Tested N:      28   Proportion Sufficient: 1.000   Binomial p: 0.002
```

```
B*C
   Tested N:      19   Proportion Sufficient: 1.000   Binomial p: 0.014
a*B*c
   Tested N:      28   Proportion Sufficient: 1.000   Binomial p: 0.002
A*B*c
   Tested N:      20   Proportion Sufficient: 1.000   Binomial p: 0.012
a*B*C
   Tested N:      18   Proportion Sufficient: 1.000   Binomial p: 0.018
A*B*C
   Tested N:      19   Proportion Sufficient: 1.000   Binomial p: 0.014

*** FUZZY-SET SOLUTION ***

*** Sufficient combinations satisfying necessary conditions:

B
   (Simplifying Assumptions)
   a*B*C
      Maximum membership score: 0.50


*** Sufficient combinations NOT satisfying necessary conditions:

Coverage Measure:   0.856
```

This is the output for the 19 cases with positive outcomes, A + B + C = D:

```
**********************
* FUZZY-SET ANALYSIS *
```

```
*********************

Diss7Pos.csv
Model: D = A + B + C

Cases Read:       19
     Valid:       19  100.0%
   Missing:        0    0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 19 (100.0% of Total)
Method: Probabilistic
Test Proportion:  0.80
             *p < 0.05
Fuzzy Adjustment: 0.17

            N Cause    Observed   Binomial
Variable  >= Outcome  Proportion          p
==========================================
a                       16         0.84     0.455
A                       18         0.95     0.083
b                       14         0.74
B                       19         1.00     0.014*
c                       16         0.84     0.455
C                       15         0.79
=================================================

1 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion:  0.80
              p < 0.05
Fuzzy Adjustment: 0.17

The Following Causal Expressions Pass the Test for Sufficiency but
ARE NOT Included in the Solution because they are Redundant or
because they are Absorbed by other Terms

a*B
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
A*B
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
B*c
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
B*C
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
a*B*c
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
A*B*c
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
a*B*C
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
A*B*C
   Tested N:      17   Proportion Sufficient: 1.000   Binomial p: 0.023
```

```
*** FUZZY-SET SOLUTION ***

*** Sufficient combinations satisfying necessary conditions:

B
   (Simplifying Assumptions)
   a*B*C
      Maximum membership score: 0.50
   A*B*C
      Maximum membership score: 0.50

*** Sufficient combinations NOT satisfying necessary conditions:


Coverage Measure:   0.850
```

Output for negative outcome cases A + B + C = D at .80 (almost always):

****
* FUZZY-SET ANALYSIS *
****

File: Diss6Neg.csv
Model: D = A + B + C

Cases Read: 12
Valid: 12 100.0%
Missing: 0 0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 11 (91.7% of Total)
Method: Probabilistic
Test Proportion: 0.80
*p < 0.05
Fuzzy Adjustment: 0.17

Variable	N Cause >= Outcome	Observed Proportion	Binomial p
a	9	0.82	0.617
A	3	0.27	
b	2	0.18	
B	11	1.00	0.086
c	10	0.91	0.322
C	3	0.27	

0 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion: 0.80
p < 0.05
Fuzzy Adjustment: 0.17

No Sufficient Causes Found

Output for negative outcome cases A + B + C = D at .65 (usually):

****
* FUZZY-SET ANALYSIS *
****

File: Diss6Neg.csv
Model: D = A + B + C

Cases Read: 12
Valid: 12 100.0%
Missing: 0 0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 11 (91.7% of Total)
Method: Probabilistic
Test Proportion: 0.65
*p < 0.05
Fuzzy Adjustment: 0.17

Variable	N Cause >= Outcome	Observed Proportion	Binomial p
a	9	0.82	0.200
A	3	0.27	
b	2	0.18	
B	11	1.00	0.009*
c	10	0.91	0.061
C	3	0.27	

1 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion: 0.65
p < 0.05
Fuzzy Adjustment: 0.17

The Following Causal Expressions Pass the Test for Sufficiency but ARE NOT Included in the Solution because they are Redundant or because they are Absorbed by other Terms

a*B
Tested N: 11 Proportion Sufficient: 1.000 Binomial p: 0.009
B*c
Tested N: 11 Proportion Sufficient: 1.000 Binomial p: 0.009
a*B*c

Tested N: 11 Proportion Sufficient: 1.000 Binomial p: 0.009

*** FUZZY-SET SOLUTION ***

*** Sufficient combinations satisfying necessary conditions:

B
(Simplifying Assumptions)
a*B*C
Maximum membership score: 0.17

*** Sufficient combinations NOT satisfying necessary conditions:

Coverage Measure: 0.863

Output for positive outcomes for A+B=C (1st DS prediction):

```
**********************
* FUZZY-SET ANALYSIS *
**********************
```

```
File:  Diss7Pos.csv
Model: C = A + B

Cases Read:      19
     Valid:      19  100.0%
   Missing:       0    0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 19 (100.0% of Total)
Method: Probabilistic
Test Proportion:  0.80
             *p < 0.05
Fuzzy Adjustment: 0.17

            N Cause    Observed   Binomial
Variable  >= Outcome  Proportion         p
==========================================
a                      16         0.84      0.455
A                      15         0.79
b                      16         0.84      0.455
B                      15         0.79
===============================================

0 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion:  0.80
              p < 0.05
Fuzzy Adjustment: 0.17

All of the Causal Expressions that Pass the Test for Sufficiency
Are Included in the Solution

*** FUZZY-SET SOLUTION ***

A*b
   (Simplifying Assumptions)
   A*b
      Maximum membership score: 0.50

Coverage Measure:   0.641
```

Output for all cases for A + C = B (2nd DS prediction):

```
**********************
* FUZZY-SET ANALYSIS *
**********************
 Diss7All.csv
```

```
Model: B = A + C
 Cases Read:      31
     Valid:      31  100.0%
   Missing:       0    0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 29 ( 93.5% of Total)
Method: Probabilistic
Test Proportion:  0.80
             *p < 0.05
Fuzzy Adjustment: 0.17

            N Cause    Observed   Binomial
Variable  >= Outcome  Proportion         p
==========================================
a                      24         0.83     0.463
A                      18         0.62
c                      25         0.86     0.284
C                      16         0.55
===============================================

0 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion:  0.80
              p < 0.05
Fuzzy Adjustment: 0.17
No Sufficient Causes Found
 The Following Causal Expressions Pass the Test for Sufficiency
for at Least Half of the Cases Tested

a
   Tested N:      30   Proportion Sufficient: 0.600
A
   Tested N:      23   Proportion Sufficient: 0.826
c
   Tested N:      30   Proportion Sufficient: 0.667
C
   Tested N:      21   Proportion Sufficient: 0.714
a*c
   Tested N:      30   Proportion Sufficient: 0.667
A*c
   Tested N:      22   Proportion Sufficient: 0.864  !
a*C
   Tested N:      20   Proportion Sufficient: 0.850
A*C
   Tested N:      21   Proportion Sufficient: 0.810
```

Output for all cases for B+E=D (zone of proximal development with amount of variance) at .80:

```
**********************
* FUZZY-SET ANALYSIS *
**********************
```

```
File:  Diss7All.csv
Model: D = B + ZPDFUZZ

Cases Read:      31
     Valid:      31  100.0%
   Missing:       0    0.0%

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 30 ( 96.8% of Total)
Method: Probabilistic
Test Proportion:  0.80
             *p < 0.05
Fuzzy Adjustment: 0.17

            N Cause    Observed   Binomial
Variable  >= Outcome  Proportion         p
==========================================
b                      16        0.53
B                      30        1.00      0.001*
zpdfuzz                18        0.60
ZPDFUZZ                22        0.73
===============================================

1 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion:  0.80
              p < 0.05
Fuzzy Adjustment: 0.17

*** FUZZY-SET SOLUTION ***

*** Sufficient combinations satisfying necessary conditions:

B

*** Sufficient combinations NOT satisfying necessary conditions:

b*ZPDFUZZ

Coverage Measure:   0.838
```

Output for all cases for B + E = D at .65:

```
**********************
* FUZZY-SET ANALYSIS *
**********************
```

File: C:/Documents and Settings/Kurt.DELLL800R/My Documents/Dissertation/Diss7All.csv
Model: D = B + ZPDFUZZ

```
Cases Read:      31
     Valid:      31  100.0%
   Missing:       0    0.0%
```

*** NECESSARY CAUSE ANALYSIS ***

Number of Cases Tested (Outcome > 0): 30 (96.8% of Total)
Method: Probabilistic
Test Proportion: 0.65
*p < 0.05
Fuzzy Adjustment: 0.17

Variable	N Cause >= Outcome	Observed Proportion	Binomial p
b	16	0.53	
B	30	1.00	0.000*
zpdfuzz	18	0.60	
ZPDFUZZ	22	0.73	0.225

1 Necessary Cause(s) Included in the Analysis

*** SUFFICIENT CAUSE ANALYSIS ***

Method: Probabilistic
Test Proportion: 0.65
p < 0.05
Fuzzy Adjustment: 0.17

*** FUZZY-SET SOLUTION ***

*** Sufficient combinations satisfying necessary conditions:

B
+
B*ZPDFUZZ

*** Sufficient combinations NOT satisfying necessary conditions:

Coverage Measure: 0.799