Paper

Human Development 2002;45:141–160

Human Development

Always Under Construction

Dynamic Variations in Adult Cognitive Microdevelopment

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Key Words
Cognitive development · Dynamics · Expertise · Learning · Scaffolding · Variation

Abstract

People's activities vary dynamically from moment to moment, and analysis of level of skill complexity in successive activities provides a tool to portray and analyze variation as skills are learned. Systematic examination of these variations is crucial for illuminating the dynamic nature of learning and development – the ways that people construct activities under the influence of multiple factors interacting in complex ways, in context, over time. A study of adults learning to use a computer program illustrates three important patterns in the dynamic variation of adult cognitive microdevelopment: (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.

People's activities vary widely in content and complexity, not only across long-term developmental epochs but also from moment to moment. Analysis of the pervasive variability in people's activities potentially provides new data for analyzing processes of change in learning and development. Traditional static concepts such as stage and intelligence have proven inadequate for dealing with the important, far-reaching

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variability that researchers are uncovering in people's actions and thoughts. Even during adulthood, which is traditionally considered a period of stability, 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.

Researchers on adult cognitive development have described a number of important kinds of variability in longitudinal studies, including variation by age, cohort, and generation, as well as individual variation [Baltes & Mayer, 1999; Howe, 1999; Schaie, 1996; Sinnott, 1998; Smith & Pourchot, 1998; Tennant, 1997]. Most research has focused on variation in long-term changes, which we call *macrodevelopment.* A challenge that has been barely touched is the issue of variation in short-term changes, called *microdevelopment.* A recent surge of research on microdevelopment (also termed microgenesis) has demonstrated the pervasiveness of variability in activity structures, mostly in children [Branco & Valsiner, 1997; Fischer & Bidell, 1998; Granott & Parziale, in press; Kuhn, Gracia-Mila, Zohar, & Anderson, 1995; Siegler, 1994]. Systematic research on microdevelopmental variation in adults is especially sparse, and useful concepts for explaining its dynamics are even rarer.

A set of powerful new tools and concepts are available to facilitate research on cognitive variability through the application of nonlinear dynamics to development and learning. In the last decade a growing number of cognitive and developmental scientists have recognized the potential of nonlinear dynamics for creating a new kind of analysis of complex patterns of learning and development [Bogartz, 1994; Case & Okamoto, 1996; Fischer & Bidell, 1998; Port & van Gelder, 1995; Thelen & Smith, 1998; van der Maas & Molenar, 1992; van Geert, 1991, 1998]. Creation of these tools requires determination of major types and sources of variability in activities followed by careful analysis and explicit modeling of processes of growth. A first step is recognizing that widely used concepts such as ability, developmental stage or level, and developmental sequence need to be treated as variable characteristics rather than static entities. Then dynamic systems tools can be applied to examining how dynamic cognitive systems produce variations in activity, ability, level, and sequence.

Our approach begins with a framework that integrates nonlinear dynamics with developmental construction to provide a set of concepts and methods to describe and explain variability in the organization and growth of human activities in context – dynamic skill theory [Fischer, 1980b; Fischer & Bidell, 1998; Fischer & Granott, 1995]. Within this framework, cognitive development in both childhood and adulthood is analyzed as a dynamic system in which a person's activities in context vary and grow from the mutual influence of multiple, specified factors interacting over time. That is, in the dynamic system of cognitive development: (a) multiple factors of differing importance contribute to cognitive growth; (b) these factors constantly interact with each other in complex ways, directly and indirectly; (c) the interactions take place in multiple contexts, from immediate to historic-cultural, and (d) these interactions in context unfold over multiple time scales, from microscopic to macroscopic. These four key aspects of a dynamic system – multiple factors, complex interactions, multilevel contexts, and multilevel time scales – work together to generate changes that are complex, emergent, and self-organized. Developmental variability in activity, including stability as its special case, is the direct manifestation and production of the underlying dynamic system. Consequently variation in activity is an important resource for revealing fundamental dynamic mechanisms through analysis of patterns in the variability.

We argue that the complex dynamic variations that occur in adult cognitive microdevelopment reveal active construction, organization, and generalization. After examining concepts of variation, we use one learning situation to illuminate and illustrate how microdevelopmental variability shows three basic kinds of dynamic patterns that begin to capture dynamic construction: range between attractors, shifting pathways, and asynchrony for individuals across tasks and domains.

Conceptualization of Dynamic Variation

The term *variation* has several different meanings, including the three found in the following sources: standard dictionary, statistical textbook, and dynamic skill analysis. Analyzing these three meanings will help clarify how we use the concept of dynamic variation.

The *Oxford Dictionary* [Pollard, 1994] defines variation as 'the extent to which something varies'. The basic literal meaning of variation has to do with difference from the majority or norm. In daily life as well as the behavioral sciences, the phrase 'individual difference' is often used as a synonym for variation in normal performance between types of people.

Variation is a fundamental concept in statistics, where it generally refers to the spread of scores in a distribution [Kotz & Johnson, 1982]. The most commonly used measures of variation are the variance (the sum of squared deviations around the mean) and the standard deviation (the square root of the variance), which are widely used as a basic unit in conventional statistical analysis, such as analysis of variance and regression. These variation measures derive from a fixed reference system, the mean, since they are based in difference from the mean. They are used to estimate linear relationships among variations from this fixed norm, including random variance, unexplained or error variance, and explained variance. A large part of variation is treated as measurement error and random variation.

In contrast to the above conventional meanings of variation as differences from a fixed reference system of either the majority or the mean, the dynamic skill approach considers variation as a direct manifestation of dynamic processes, which is called *dynamic variation.* It assumes that human development is a complex dynamic process rather than a simple static, linear system and that variation and growth reflect this process instead of resulting from measurement error or random noise. Variation in an evolving dynamic process is analogous to diverse waves in a running stream. On the surface, these waves appear disordered, complicated, and even random; but in nature they are the inherent feature, true indicator, and direct product of the dynamics of a complex system involving water flow and wind. Understanding such a dynamic system requires systematic investigation of dynamic variation.

Two lines of developmental research are related to the concept of dynamic variation. First, cognitive development, one of the most dynamic phenomena of the human mind, has been predominantly analyzed in terms of static stages produced by a static system. Cognitive developmental stages, levels, and sequences as well as many other developmental concepts have been treated as mostly static entities that represent and explain static abilities. In the past two decades, a new line of developmental researchers pioneering dynamic systems theory [such as Fischer & Bidell, 1998; Thelen & Smith, 1998; van der Maas & Molenaar, 1992; van Geert, 1994, 1998] have been actively advocating to change this widely spread misrepresentation of human cognitive development in static terms.

Second, individual difference, a classic topic in developmental science, has been misleadingly analyzed in terms of typologies defined by deviations from developmental norms instead of as variable patterns of individual adaptation and development. This trend has been recently challenged by a new line of research on developmental variation [such as Miller & Coyle, 1999; Nesselroade, 1991; Siegler 1994], in which several dynamic developmental variations in individual performances have been identified as pervasive and important.

In our framework, dynamic variation integrates dynamic systems and developmental variation, using patterns of variation to begin to capture the dynamics of phenomena of development. Because multiple factors interact from moment to moment in specific contexts, observed variations are overt manifestations of covert dynamic processes, even those that have been treated as apparently static outcomes, such as ability and skill. From dynamic patterns of activity, we hypothesize and investigate complex dynamic processes of growth and variation.

Dynamic variation in activity has the following characteristics. First, it is pervasive rather than abnormal or exceptional. The complexity of activity varies widely and systematically from moment to moment within and across contexts. Each individual shows such variation, which is in addition to the wide between-group variations that occur across ages, tasks, social groups, and cultures. Most research has focused on between-group variations and neglected consideration of variation within a person [Fischer et al., 1993; Thelen & Smith, 1998; Valsiner, 1991; van Geert, 1994]. Viewed from a dynamic perspective, stability is a special case of variation in which a dynamic system seeks an equilibrium state or approaches an attractor [Fogel, 1993; Thelen & Smith, 1998; van der Maas & Molenaar, 1992; van Geert, 1998]. In other words, stability reflects order within the extensive variations in a changing dynamic system rather than a relatively fixed characteristic, as assumed by concepts of both individual difference and fixed norm or mean.

Second, dynamic variation is authentic change rather than measurement error, random noise, or illusion. It is a manifestation of underlying developmental dynamics, such as coordination of skills, emotional regulation, task differentiation, contextual support, feedback from the task and from human partners, systemic limits, and iterative change [Branco & Valsiner, 1997; Fischer, 1980a, 1980b; Fischer & Granott, 1995; Fogel, 1993; Fogel & Lyra, 1997; Granott, Fischer, & Parziale, in press; Lewis & Douglas, 1998; Siegler, 1994; van Geert, 1991, 1998]. Compared with conventional static concepts that are fixed, abstract, and product-based, dynamic variation is emergent, self-organizing, evolving, concrete, complicated, and process-based – and thus difficult to understand from a static perspective. For developmental researchers to use new concepts and methods to represent, describe, analyze, and eventually understand dynamic variation is a challenging task.

Third, dynamic variation is important rather than marginal or negligible. Researchers should not ignore, downplay, or explain away dynamic variation as 'error' or 'noise'. It should be treated as the primary index of dynamic processes and the best means to discover and explain dynamic patterns of growth, including special cases of stability such as normative age changes [Fischer & Bullock; 1981; Fischer & Bidell, 1998; Fischer & Granott, 1995]. Direct and systematic examination of pervasive and complex variations can reveal dynamic patterns, and eventually underlying dynamic mechanisms. Dynamic variation should be the starting point, primary data, and central phenomenon of dynamic inquiry, not a derivative to be explained far down the line by static concepts and not a problem of error to be avoided or removed.

In short, although developmental variations are vast and complex, they are the inherent materialization of dynamic systems. Systematic analysis of developmental variations in context thus provides the fundamental base for finding the underlying dynamic order in what people do, say, think, and feel.

Microdevelopmental Analysis of Dynamic Variation

Microdevelopmental analysis is an established method for examining short-term psychological change (for example, online progressions, evolving events, and real-time transitions) through intensive observation and analysis of specific activities of individual people in a particular situation [Branco & Valsiner, 1997; Fischer & Granott, 1995; Flavell & Draguns, 1957; Granott, 1993; Granott et al., in press; Karmiloff-Smith, 1979; Kuhn et al., 1995; Siegler, 1996; Vygotsky, 1935/1978; Werner, 1956]. Thus, as a direct means for analyzing short-term change [Siegler & Crowley, 1991], it is an ideal method for describing dynamic variations, uncovering dynamic patterns, and setting a stage for modeling dynamic mechanisms. In this paper, on the basis of an empirical study of adults learning to use a computer program [Yan, 1998], we illustrate how to use skill methods to analyze microdevelopment in order to identify patterns in the dynamic variations in adult performance in a learning situation.

In the study, six graduate students, averaging approximately 30 years of age, were randomly selected from a group of 33 volunteers in an introductory statistics course in a graduate school. Based both on students' self reports and questionnaires examining their general computer experience, two students (Susan and Tom) had computer experience at the beginning level, two (Cathy and Jack) at the intermediate level, and two (Lily and Mark) at the advanced level. None of them had previous experience in using the computer program, Statistical Analysis System (SAS), a widely used program for statistical analysis.

After the class was taught how to use SAS, each student spent one hour using the program to complete a simple statistical project. A teaching assistant (the first author) was present throughout the session and answered the student's questions in a one-on-one tutorial context. The teaching assistant carefully controlled his help, responding only to questions the student asked and not providing extra intervention or instruction. The task required that each student complete a fairly rigorous procedure, like most computational tasks using computer programs. Students had to create a data file and a statistical analysis file, and then to combine these two files into one batch file to submit to the network system for processing. In short, the specific task served as a window for observing and analyzing individual microdevelopment of learning SAS in a social interactive context. This design is similar to Fox's [1993] pioneering study of naturally occurring human tutorial dialogue, which showed how the tutor-student interactive process is embedded in the students' cognitive process. Tutor and student interact in a way that is cognitively beneficial to the student, and the cognitive processes are partially determined by the interaction between tutor and student.

The standard dynamic-skill-theory scale for complexity was used to measure students' performances in using SAS. The scale assesses the complexity of cognitive struc-

Table 1. Eight skill levels for assessing cognitive complexity in the microdevelopmental scale

Level	Skill category
1	Single sensorimotor actions
2	Sensorimotor mappings
3	Sensorimotor systems
4	Single representations
5	Representational mappings
6	Representational systems
7	Single abstractions
8	Abstract mappings

ture of students' performance, and it has been validated through extensive research from several laboratories with several methods for specifying levels of skill complexity [Commons, Trudeau, Stein, Richards, & Krause, 1998; Dawson, in press; Fischer, 1980b; Fischer & Bidell, 1998; Fischer & Granott, 1995; Kitchener, Lynch, Fischer, & Wood, 1993]. A metaphor for the complexity scale is the combination of points to make lines, lines to make planes, and so forth in geometric space, with each new kind of geometric entity representing a developmental level of complexity.

Students' performance in the study was ordered on a scale of eight hierarchical complexity levels (Cohen's Kappa = 0.94, indicating good interrater agreement), as shown in table 1. For instance, if a learner typed 'EDIT' and showed that he or she understood EDIT as a command for opening and editing a file, the cognitive complexity of this performance was coded at the level of single representations (EDIT represents opening a file) and assigned a score of 4. If a learner typed 'EDIT PROJECT1.SAS' and knew not only the meaning of EDIT and PROJECT1.SAS but also the logical relationship between EDIT as a command and PROJECT1.SAS as a file name, then the cognitive complexity of this performance was greater than the previous one and was coded at the level of representational mappings (relating the representations of EDIT and the specific file) and assigned a score of 5. If a learner typed 'EDIT PROJECT1.COM' right after typing 'EDIT PROJECT1.SAS' and knew the logical sequence between these two SAS statements, then the cognitive complexity of this performance was even higher and was coded at the level of representational systems (relating the two relations specified by the typed commands) and assigned a score of 6.

Graphs of the complexity of performance over time demonstrate a microdevelopmental pathway for each of the six students, as seen in figure 1. Skill level is plotted on the Y axis as a function of sequential steps of performance on the X axis during the one-hour SAS tutorial session. Each performance step represents a distinct activity by a student, and raters agreed nearly perfectly in dividing the sequence of interactions into activities.

There are a variety of ways to record and describe a dynamic process. Each of them is merely an approximate representation of some attributes of the real process – one record of each individual's moment-to-moment cognitive footprints. In figure 1 each microdevelopmental pathway is a discrete two-dimensional graphic representation of an evolving continuous process for a single person working on a specific cognitive task in a tutorial context. Such microdevelopmental pathways can be used to analyze dynamic variations in cognitive activities.

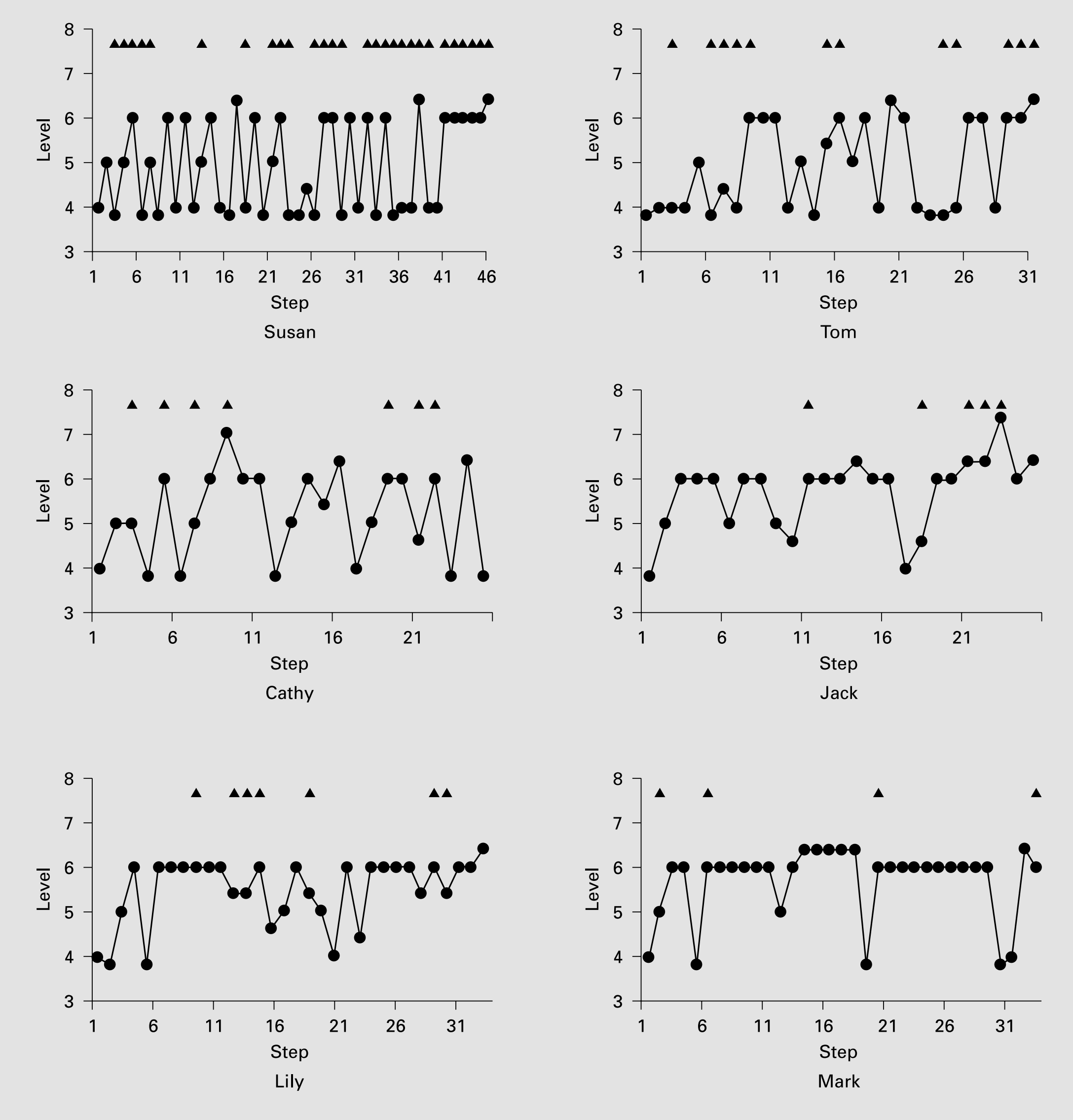

Fig. 1. Microdevelopmental trajectories of six students. Note: Susan and Tom were beginning computer users, Cathy and Jack intermediate-level computer users, and Lily and Mark advanced computer users. The trajectories were obtained by applying the microdevelopmental scale in table 1 to each student's performance sequence during a one-hour session. The triangles indicate where help was provided by the teaching fellow.

Table 2. Means and SD of skill levels for six students

Student	Mean	SD
Susan	5.00	1.02
Tom	4.92	0.99
Cathy	5.19	0.99
Jack	5.73	0.83
Lily	5.47	0.75
Mark	5.68	0.81

Table 2 shows the different means and standard deviations in skill level for the six students for each pathway. Comparing the average skill levels in table 2 with the microdevelopmental pathways in figure 1 demonstrates how impoverished the standard statistical descriptors are for the microdevelopmental pathways of each individual. In a sense, microdevelopmental pathways are like fine documentary movies recording each individual's learning history, whereas the mean and standard deviation are like a few blurred snapshots sketching group members' silhouettes. The richness of microdevelopmental pathways provides important information for research on dynamic variations in microdevelopment.

Patterns in Dynamic Variations

The six students' microdevelopmental pathways in figure 1 show large variations in level of complexity, number of steps to complete the project, and overall shape over time, to name just a few of the features. Besides these interindividual differences, there are also substantial intraindividual variations, with the complexity of each individual's performance changing from moment to moment. These pathways appear to be irregular, and they might seem counter-intuitive based on static expectations about the nature of learning. They illustrate the naturally high variability that occurs in learning and problem solving, where smooth growth occurs only under special, limited circumstances [Estes, 1955; Fischer & Granott, 1995; van Geert, 1991]. Dynamic skill analysis requires that we accept the variability of performance and search for meaningful patterns in microdevelopmental pathways.

The study illustrates three important patterns in microdevelopmental pathways, each reflecting important dynamic growth processes: range of variation in level, kind of pathway shown, and asynchrony due to task and domain. We will use the microdevelopmental pathways to illustrate these patterns and explain how they relate to hypotheses about dynamic construction processes in adult cognitive development.

Microdevelopmental Range between Upper and Lower Attractors

When people learn tasks and solve problems, they produce activities that differ widely in level of complexity, varying from moment to moment within a range that does not show simple upward progression [Fischer, 1980a; Fischer & Granott, 1995; Granott, 1993]. The extent of this variation in performance from lowest to highest level is what we call the microdevelopmental range, as illustrated by the graphs in figure 1. No trajectory moves along a straight line, but instead each one fluctuates up and down within a range that reflects constraints.

In figure 1, Susan's performances fluctuated widely and frequently within the range. Susan was a beginning computer user, with only minimal prior experience, and she frequently performed at a low level (Level 4 single representations or below), not sustaining more complex activities until the end of the session. Most of her activites that reached higher levels were supported by scaffolding from the teaching assistant, as with her movement to a Level 5 mapping at Step 2 and a Level 6 system at Step 5. Scaffolding is shown by the small triangles at the top of each graph. After each scaffolded activity, she quickly dropped down again to Level 4 or below. Although Susan's performance levels varied substantially throughout the hour-long SAS session, her performance levels showed certain constraints: At the bottom of her microdevelopmental range, she performed with complex sensorimotor systems (for example, Level 3.8 at Step 8), never going far below the level of single representations (Level 4). At the top, she performed with complex representational systems (such as Level 6.4 at Step 17).

Similar to Susan, the other five students' pathways also showed an overall pattern of wavelike fluctuation within a range. All six pathways demonstrated multi-level nonlinear variations rather than linear growth or constant performance, even when the student had extensive computer knowledge. Their microdevelopmental ranges varied roughly from Level 3 sensorimotor systems (such as Mark's Level 3.8 performance at Step 5) to Level 7 single abstractions (such as Jack's Level 7.4 performance at step 23).

Why do the microdevelopmental pathways obtained in the study show a robust wave-like pattern rather than a straight line or even a linear progressive trend? Why does this wave-like pattern have certain boundaries or constraints instead of varying more widely in the developmental scale, which potentially extends down at least to Level 1 single actions (table 1) and up to Level 10 principles [Fischer, Hand, and Russell, 1984]?

This robust pattern of microdevelopment demonstrates a characteristic common in dynamic systems – the existence of attractors, relatively stable states, constraints, or limits toward which performance is pulled or attracted in dynamic systems [Fischer & Bidell, 1998; Kelso, 1995; Thelen & Smith, 1998; van Geert, 1991]. In the face of the many factors for which people constantly vary, adjust, and reorganize their activities, each student's pathway revealed two point attractors, an upper one at Level 6 and a lower one at Level 4, as shown in figure 1. From Susan's many-wave pathway to Cathy's and Mark's few waves, these two levels were shared upper and lower attractors in the microdevelopmental range (a characteristic that is missed completely by analyses of mean performance).

The wave-like variations within the dynamic range reflected students' evolving knowledge and skills, the changing affordances and demands of the task, the periodic scaffolding from the teaching assistant, and various other factors. These variations were constrained by the upper attractor of Level 6, which was the complexity of performance required to use the SAS computer program effectively to proceed through the task sequence. At the same time, all the students possessed basic typing skills, which would seem to account for the lower attractor of Level 4, which is required to type a word or symbol into the computer.

The tutor-tutee interaction frequently provided scaffoldings that were targeted to each student's specific performance at the moment and that resulted in a dynamic co-

construction between tutor and tutee. The scaffolding pulled a student's activity temporarily toward the upper attractor, but to maintain that high performance, students had to sustain the complex activity on their own beyond the moment of scaffolding. Less expert students had difficulty sustaining stable performance at the upper attractor without scaffolding. Consequently the task, the skills of students, and the tutor-tutee interaction worked together to produce the emergent microdevelopmental range with two point attractors.

Similar phenomena of microdevelopmental range have been observed in other studies [Baker-Sennett, Matusov, & Rogoff, 1992; Brown & Reeve, 1987; Fischer & Granott, 1995; Granott, 1993; Parziale, 1997; Siegler, 1996; van Geert, 1998]. The various studies used different tasks (for example, understanding how a small robot works, or building a bridge with marshmallows and toothpicks), different interactive contexts (a student working alone, a student with a teacher, two students working together as a pair), and different groups of students (from grade school students to graduate students and experienced teachers). In all studies, each student's cognitive microdevelopment varied extensively within a range over a short time period, as in figure 1.

Related patterns of variation in level have been observed in macrodevelopmental studies across an even wider range of ages and tasks, especially showing developmental range as a function of contextual support for high-level skill [Bullock & Ziegler, 1994; Fischer, Rotenberg, Bullock, & Raya, 1993; Fischer & Bidell, 1998; van Geert, 1998]. In macrodevelopment, the developmental range moves between the upper bound of optimal level (the limit on performance within a high support context) and that of functional level (the limit within a low support context). The robustness of these multi-level dynamic variations across tasks, contexts, and age groups belies assumptions of stable, static performance and suggests that micro- and macrodevelopmental ranges reflect fundamental mechanisms of learning and development.

Microdevelopmental Pathways from Novices to Experts

Another important general pattern illustrated by the pathways is variability as a function of expertise. When people learn a task, their pathway proceeds with its own sequence that differs from others in its shape, including number of steps, level of complexity, sequence of performances, and time to complete the task, to name just a few characteristics. Despite the rigorously constrained procedure required by the computational task in the study, each pathway in figure 1 is distinctive, with each student manifesting his or her own unique unfolding course of activity.

Evidence of Change from Novice to Expert. A powerful factor affecting the shapes of pathways that students show is their degree of knowledge about a domain, varying from novice to expert. In the study, pathways of the least experienced students, Susan and Tom, oscillated with the highest frequency between the two attractors. The students with intermediate experience, Cathy and Jack, evidenced oscillations with more relaxed waves and less frequent drops to the lower attractor, suggesting transition toward new knowledge. For the most expert students, Lily and Mark, the pathways started with a few fluctuations and then showed some long series stabilized at the upper attractor.

Susan's and Mark's pathways mark the extremes of the variation from novice to expert, and their dramatic differences suggest distinct underlying cognitive processes.

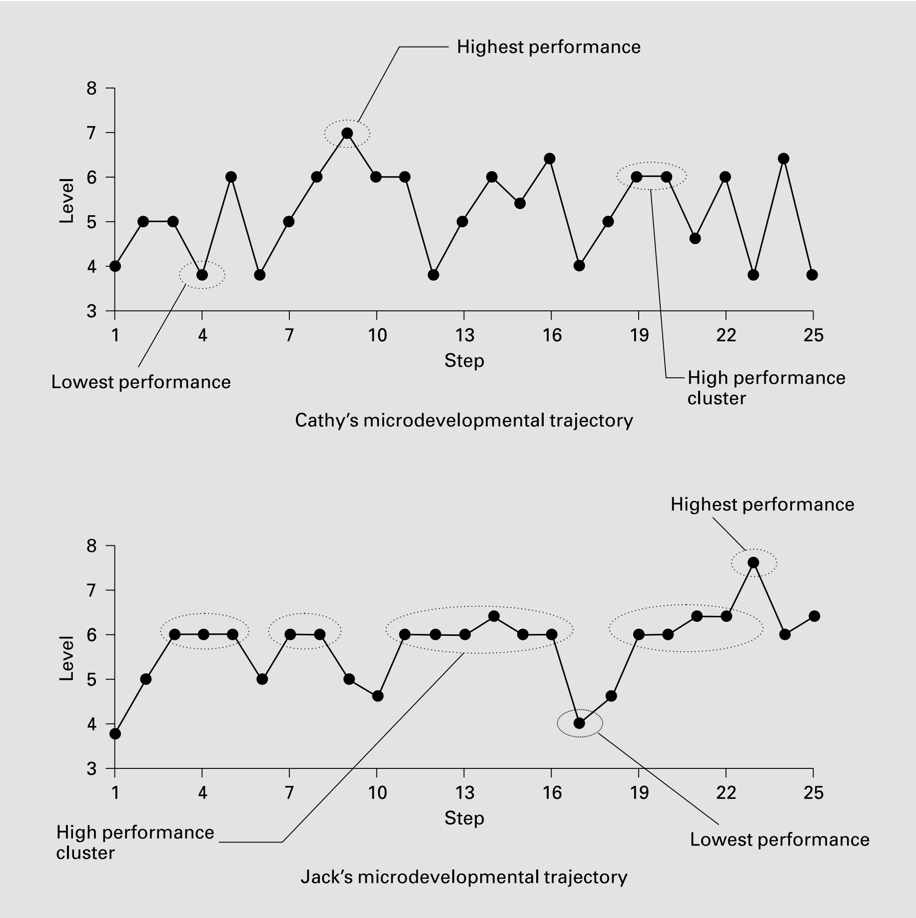

Fig. 2. Comparing the microdevelopmental pathways of two intermediate-level computer users, Cathy and Jack.

As a beginning computer user, Susan had more than 15 wave-like fluctuations, the highest number among the six students. On the other extreme, Mark, a highly expert computer user, had a total of only five fluctuations, the lowest among the students. Corresponding closely to their computer knowledge levels, the number of fluctuations decreased gradually from Susan to Tom, Cathy, Jack, Lily, and Mark.

The pathways of the two intermediate-level learners, Cathy and Jack, illustrate further how microdevelopmental graphs can facilitate analysis of dynamic growth processes (fig. 2). Although the two pathways show similar wave-like overall profiles and even have the same number of steps for completing the task, careful examination reveals distinctive patterns, which suggest differences in the growth of expertise.

Cathy's and Jack's pathways suggest that Jack progressed further toward expert consolidation of his knowledge in the task. Cathy's pathway had only a few clusters of consecutive performance at one high level, such as the two Level 6 activities at steps 20 and 21. Frequent ups and downs dominated her pathway. In contrast, Jack's pathway showed more clusters of consecutive high performance at the upper attractor, such as the long string of Level 6 activities between steps 11 and 16. As a result, his pathway suggests a trend toward skill consolidation, and it begins to look like those of the expert students, Lilly and Mark.

Cathy and Jack also showed differences in the specific skills they constructed. For example, Cathy showed her highest performance at Step 9, when she came to understand the special technical meaning of the symbol *semicolon* in SAS language and showed understanding of a single abstraction (Level 7). Different from the semicolon used in written English, the semicolon in SAS is a unique command for executing a programming command. In order to understand the abstract meaning of the semicolon in SAS, she had to understand a characteristic of the command syntax in SAS, which required generalizing across specific commands. Her achievement is analogous to the way a 13-year-old can use the term *verb* to indicate generalization of the common function of various words, such as *eat, walk, run, play,* and *speak* [Fischer et al., 1984].

Jack's pathway peaked almost at the end of the session. With support from the teaching assistant, Jack learned to differentiate the dollar sign (the system prompt for receiving a system command) from the semicolon (the unique symbol for executing a SAS command), thus showing a high-level abstract understanding (Level 7.6).

Growth Processes. Why did the six microdevelopmental pathways vary systematically as a function of expertise in using computer programs? More generally, why did each person proceed through such a distinctive pathway, even when the task limited performance in major ways and even when students had similar computer experience like Cathy and Jack?

To address the first question, we suggest a general characteristic for movement from novice to expert in microdevelopment. When novices begin to learn a new computer program, they need a large-scale reorganization of their skills, which requires repeated, long-term activities to build. During the early part of the construction process, novices show numerous, rapid fluctuations within a developmental range between upper and lower attractors, trying to build an appropriate skill but having difficulty sustaining it. They often need scaffolding from others to construct an appropriately complex skill, even for a moment.

As people gradually reorganize skills to adapt to a broader range of situations, their activities begin to show transient stability, with less extreme, slower fluctuations – gradual, short-term building toward a higher level, which we call scalloping [Fischer & Bidell, 1998; Fischer & Granott, 1995]. Examples of scalloping include steps 6 through 12 for Cathy and steps 17 through 24 for Jack in figures 1 and 2. After the gradual construction of expert skills, people can move more quickly to high-level performance and sustain that performance for longer periods, often without scaffolding from others. In this way, learners' pathways show gradual construction of more stable skills, demonstrating how learning and development involve not simple linear growth but complex dynamic construction and re-construction.

With regard to the second question (the diversity of microdevelopmental pathways) expertise is only one of many factors that contribute to dynamic construction and emergent reorganization during learning. Performance of the task involved not only learning history but also cognitive style, cultural background, emotional state, scaffolding, and even uncontrolled differences in social interaction and task requirements, to name only a few relevant factors. Even with the strong constraint imposed by the procedure in the task, students had different problems to overcome, different emotional reactions to the materials, different levels of understanding on various issues, and different strategies to learn with help from the teaching assistant. They each created their own unique microdevelopmental pathway to achieve the same computational goal. It is a mistake for researchers to treat skill as uniform and stable, ignoring variations among performances and small steps in learning. Examining sequential variation in microdevelopmental pathways, researchers can uncover and analyze meaningful dynamic mechanisms of skill acquisition and cognitive microdevelopment.

From a dynamic systems perspective, a microdevelopmental trajectory is a pathway taken by a dynamic system through a state space over time. For the complex dynamic process of learning a computer program, the state space is very large, even though the procedure to complete the computational task is relatively fixed. Different microdevelopmental pathways show different learning dynamics within this large state space. At the same time, specific factors produce general patterns in learning dynamics, such as the shift from rapid fluctuation between upper and lower attractors in novices to short-term building of stable performance (scalloping) at the upper attractor in intermediate learners to relatively long stretches of stable performance at the upper attractor in experts.

Similar variations in pathways have been found in other microdevelopmental studies [for example, Fischer & Bidell, 1998; Fischer & Granott, 1995; Granott & Parziale, in press; Ruhland & van Geert, 1998; van Geert, 1998]. For instance, Granott [1993, in press] discovered recurring progression-regression sequences (scalloping) in microdevelopment when two adult learners worked together to make sense of a toy robot. In one dyad from Granott's study, the whole session consisted of four long progression-regression sequences – four scallops. In each scallop, the two collaborating students started with a very low level of performance and then gradually built up a relatively high-level performance. However, when they encountered a new feature of the robot or the situation, such as a changed wire or a question from someone about their activity, their performance collapsed back abruptly to a low level, and then they began to rebuild their knowledge again.

Microdevelopmental Asynchrony and Task-Specific Attractors

In the third pattern of dynamic variation, skill level varies widely in different tasks and domains, including those that are logically equivalent, such as two different computer tasks that accomplish the same operation and result (for example, calculating an arithmetic mean). We call this cross-task variation *microdevelopmental asynchrony* because people show disparate skill levels, not synchronous ones – contrary to predictions from conceptions of stable stage or ability. Even beyond the variations of range and pathway that we have described, asynchrony occurs in people's performances across tasks and domains. One of the most salient, even surprising kinds of asynchrony involves the low skill levels that expert adults often show in performing a task.

The student named Mark provides a good example of this asynchrony. Mark had advanced knowledge of computers, graduating from one of the best computer science programs in the United States and working for several years as a professional programmer for one of the largest computer companies. With his educational training and professional experience as well as formal instruction in the course, one might expect that Mark would have immediately displayed high stability in level of performance in the assigned task of making a computer perform a basic statistical procedure in SAS. However, Mark's observed microdevelopmental pathway in figure 1 did not support this reasonable expectation.

As shown in figure 1, Mark's programming sequence broke down four times during the session. On four occasions, he did not understand something required by the task and produced a skill at the lower attractor. These breakdowns were scattered from the beginning through the middle to the end of the session. Mark's low-level performances included using an inappropriate key to delete a letter, not knowing how to deal with a system signal after submitting the command file, not knowing the correct command to read the log file, and adding an extra space between two file names for printing two files in a single statement. Consonant with his expertise, Mark did show relatively high-level performance on most steps in the session, yet his knowledge of the required task was still under construction. A gap existed between his professional skills on many computational tasks and his current knowledge about the specific task he was required to complete in the study. Because of his expertise, he could learn quickly to fill the gap, fixing errors and building better understandings, but he still had to adapt to the new task and learn its specific requirements.

In addition to the four breakdowns, the level of Mark's performance is surprising in another way. Given his age and his demonstrated skills in classes and on the job, he is clearly capable of high-level abstractions in many domains, including the highest level in table 1 as well as even higher levels involving more complex relations among abstractions [Fischer & Bidell, 1998; Fischer et al., 1984; Fischer & Yan, 2002] (Levels 9 and 10 are not shown in table 1 because no activity in the study demonstrated these levels of complexity). However, Mark's most complex performance in the session involved only representational systems (Level 6 to 6.4 in figure 1), not even single abstractions (Level 7). A number of other students showed abstract skills at Level 7, including Cathy and Jack (fig. 2). In the SAS task Mark used skills at levels far below his best capability.

All six students showed similarly low levels of performance with the task, well below the highest levels that they likely were capable of in other situations. The skill levels shown or required in various intellectually demanding tasks in school and on the job (such as conducting research projects, writing theses, dealing with conflicting evidence and arguments, and writing codes with C programming language) were frequently much higher, involving complex abstract relations at Levels 8, 9, and 10 [see Dawson, in press; Fischer, Yan, & Stewart, in press; Kitchener & King, 1994]. Yet in the computer task their highest levels did not go beyond Level 6 representational systems for four students and Level 7 single abstractions for two. Combining across all activities, students' average skill levels varied from 4.92 (near representational mappings) to 5.73 (moving toward representational systems), as shown in table 2.

Why did these intelligent graduate students show such a low level of performance for a new task (near the upper attractor of their microdevelopmental range), and why did they frequently regress to very low levels near the lower attractor at Level 4 single representations? How do we explain this microdevelopmental asynchrony in the dynamic construction of learning the SAS task, and in similar findings from other studies [Fischer & Bidell, 1998; Fischer & Granott, 1995; Granott, 1993, in press; Parziale, 1997, in press; Roberts, 1981; van Geert, 1998].

Factors that are commonly invoked to explain variations in developmental level include previous experience with computers and the difficulty of generalizing skills across tasks. With regard to previous experience, some Macintosh users had difficulty with linear command sequences in SAS, apparently because they had not experienced such sequences on their Macintosh computers. Also, many students had no experience with using a computer program in a fully networked system (as opposed to a stand-alone personal computer), and this limitation affected their performance negatively, apparently because they did not understand the coordination of the system on the personal computer with the system on the central computer in the network [Yan, 2000]. In general, transforming knowledge to generalize it from one task to another is not automatic but requires much effort and energy to orchestrate new and old knowledge dynamically in a new task [Dunbar, in press; Fischer & Farrar, 1987; Fischer & Yan, 2002; Perkins & Salomon, 1989]. Even the most skilled experts cannot skip the essential process of dynamic reorganization with a new task.

Most important for explaining microdevelopmental asynchrony, however, is an essential point about tasks: Most tasks have an ideal level for performance, a task level, which is usually below the highest level that a person can do [Commons et al., 1998; Fischer, 1980b; Fischer & Granott, 1995; Fleishman, 1975; Granott, Fischer, & Parziale, in press; Welford, 1968]. For a given task, success requires performance at a specific level of complexity, although one can read most of the cognitive development literature without ever seeing mention of this fact. Most tasks and activities do not require the highest skill levels for successful performance, and high levels of abstraction can even be inappropriate and distracting [Fischer et al., 1984; Hand, 1981; Piaget, 1972; Roberts, 1981].

The task in this study seems to require a level of representational systems (Level 6 in table 1), nothing more. Understanding new components may sometimes be facilitated through abstractions, as illustrated by Cathy's and Jack's insights about the meaning of semi-colon and dollar-sign symbols in the computer program. For the most part, however, the task does not require high-level skills, and thinking about it with complex abstractions can even interfere with required performance. Each task has a characteristic skill at a particular complexity level that is optimal for success, with virtually all activities below that level involving inadequate performance or error. (Performing at the complexity level does not guarantee success, of course, because an activity can be incorrectly complex.) Correct performance has a typical level that is often below the capacities of the person. By analogy, an Olympic high jump champion trying to score a basket in basketball needs to jump to the basket, not jump as high as he or she possibly can.

Microdevelopmental asynchrony expands even more when differences in task, content, and context increase. Assessments of relatively similar contexts and tasks do not show all the variations in people's activities; more diverse situations are required. For example, the adults in Granott's [1993] study were faced with understanding Lego robots at a time when these toys were first being developed. Consequently none of the adult learners had ever experienced the toys, nor had they built robots on their own. The robot task was highly novel for them, and each adult began his or her activities with the robots at extremely low skill levels – primitive sensorimotor actions similar to those of young infants (Levels 1 and 2 in table 1) that were far below those shown in the current study.

The evidence of microdevelopmental asynchrony indicates that adult learners do not routinely work at abstract levels in most tasks at most times. Across tasks and domains, asynchrony in level is the rule rather than the exception [Fischer, 1980b]. Adults meet various cognitive challenges in their lives, and they have to work hard to generalize their abstract reasoning across tasks and domains. When they construct a higher level of understanding in one task or domain, they should not expect to easily and immediately produce a similar level of understanding in another task or domain. This kind of generalization takes time and effort.

Conclusion: Analyzing Dynamic Growth Processes

Dynamic variations in learning and problem solving are not only pervasive and complex, but also researchable and understandable. With a focus on variation, researchers can detect and analyze meaningful patterns that provide insights into the dynamics of growth in learning, problem solving, and cognitive development. We have described three dynamic patterns that have important implications for the nature of growth: Microdevelopment takes place within a multiple-level range rather than along a single growth line, with upper and lower attractors specifying the range. Microdevelopment unfolds in a variety of individual sequences from which types of developmental pathways for novice and expert emerge. Complexity levels of activity show extensive asynchrony, varying with demands of task and domain as well as individual capacities.

All three patterns reveal different aspects of dynamics. Range involves local but pervasive dynamics that limit performance in specific contexts. Pathway concerns dynamics in sequencing and organizing and is at the heart of illuminating skill construction and understanding over time. Asynchrony has to do with the larger-scale dynamics of tasks, domains, and capacities.

The processes behind asynchrony illustrate how traditional explanations and arguments can be brought together and transformed through dynamic analysis: Conventionally, the three main competing explanations of asynchrony have been cognitive transfer or generalization, horizontal *décalage*, and competence vs. performance. Cognitive transfer indicates that components of knowledge and skill learned in task A are adapted for use in task B through transferring or generalizing them [Mayer and Wittrock, 1996]. Horizontal décalage begins with an assumption of general synchrony across domains and explains asynchrony in terms of objects' resistance to people's activities [Piaget, 1983]. Competence/performance models contrast basic competences behind activities with lower-level performances that arise through processes intervening between competence and activity, often interfering with full realization of competence [Chomsky, 1965; Flavell & Wohlwill, 1969; Overton & Newman, 1982]. A fourth relevant explanation is social support such as scaffolding, which produces higher-level performance when support is provided [Fischer et al., 1993; Rogoff, 1990; Vygotsky, 1935/1968].

The explanation in terms of the dynamics of skill asynchrony brings these four explanations together through a framework that combines skill analysis, interaction analysis, growth models, and dynamic systems concepts such as attractor. The framework explains when synchrony and asynchrony occur for multiple factors working together dynamically [Fischer & Bullock, 1981; Fischer & Bidell, 1998]. Individual tasks are characterized by a task level, an upper attractor toward which activitites move even when people are capable of much more complex, developmentally advanced levels, as well as by a lower attractor toward which people's activitites fall back. Construction of an appropriately complex skill can be momentarily supported by scaffolding from a teacher, parent, or other expert, but to sustain it on their own, people need to be able to construct and sustain it without scaffolding. Transfer and generalization come from repeated reconstruction of higher-level skills, as demonstrated by the scallops in microdevelopmental pathway [Fischer et al., in press; Granott et al., in press]. In this way people gradually construct generalized competences, as illustrated by the movement from novice to expert in figure 1. The result is gradual reduction of décalage within a domain as well as long-term development of general capacities.

The variation-centered dynamic approach fundamentally reshapes traditional views of learning and development, showing that human cognition is a constantly varying system and not a fixed entity, even in adults. Stability in cognition and skill should be treated as a special case of variability rather than the other way around. Individual activities arise from dynamic constructions among multiple factors in context over time, and variations in microdevelopment are a direct manifestation of the underlying processes of learning and development. Systematic examination of dynamic variations is crucial for making progress in understanding development and learning. Instead of focusing on IQ, stage, grade-point-average, and other variable-centered static constructs, analysis needs to shift to variation-centered dynamic concepts such as range, pathway, asynchrony, and scaffolding, and to the dynamic phenomena represented by these concepts. How do these four phenomena vary over time, task, domain, person, and culture?

Systematic analysis of dynamic variations has positive, practical implications for learning and development in adulthood. Because of the rapid pace of change in modern society (shifts in the job market, development of new knowledge, rapid technological advances) adults need to be able to dynamically reorganize their own activities periodically throughout their long lives. Concepts of range, pathway, asynchrony, and scaffolding can help adult learners to adapt more effectively, understanding, for example, that mistakes in learning a new task can be used to start healthy new directions in a dynamic process of learning desirable new skills – instead of being treated as symptoms of low intelligence, disability, or cognitive aging. Indeed, research on learning shows that adults can learn with great effectiveness, even better than children, so long as they let themselves act like little children to learn new low-level skills. Adults need to move beyond embarrassment and expose themselves to situations that facilitate building the low-level skills that are required for new competences [Fischer & Bidell, 1998; Fischer et al., in press; Marshall, 2000; Snow & Hoefnagel-Hohle, 1978].

Describing and analyzing dynamic variations in activities is a challenging task. Examining microdevelopmental variations for a dynamic skill perspective is a promising enterprise for meeting this task. Cognitive skills constantly undergo dynamic reorganization in adults as well as children, and human cognitive development is always dynamic and always under construction, from the beginning of life to the end.

Author's Note

The authors thank Marc Schwartz, David Stevens, and Jeffrey Stewart for productive discussions that helped formulate arguments presented in this paper and Thomas Bidell, Nira Granott, and James Parziale for helping lay the groundwork for this research. The research was supported by grants from Frederick P. Rose and Sandra P. Rose, the Harvard Graduate School of Education, and the Spencer Foundation.

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