The Science of the Individual

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ABSTRACT— Our goal is to establish a science of the individual, grounded in dynamic systems, and focused on the analysis of individual variability. Our argument is that individuals behave, learn, and develop in distinctive ways, showing patterns of variability that are not captured by models based on statistical averages. As such, any meaningful attempt to develop a science of the individual necessarily begins with an account of the individual variability that is pervasive in all aspects of behavior, and at all levels of analysis. Using examples from fields as diverse as education and medicine, we show how starting with individual variability, not statistical averages, helped researchers discover two sources of ordered variability—pathways and contexts—that have implications for theory, research, and practice in multiple disciplines. We conclude by discussing three broad challenges—data, models, and the nature of science—that must be addressed to ensure that the science of the individual reaches its full potential.

In all disciplines that seek to understand individuals two points are accepted as fact. First, the object of interest is the individual, not the statistical average (Bergman & Vargha, 2013; Levsky & Singer, 2003; Murray, 1938). No matter how elegant the theory, how sophisticated the methods, or how precise the estimates, progress is measured by insights about individuals. Second, human individuals are remarkably variable: Regardless of age and across all cultures, a person changes dramatically over time, and even moment-to-moment as a function of context (Fischer & Bidell, 2006; van Geert & van Dijk, 2002; Mischel, 1973). Importantly, this kind of individual variability is not limited to behavior: It is pervasive at every level of analysis, from minds (Siegler, 2007), to brains (Mazziotta et al., 2009), to genomes (Chen et al., 2012), and to cells (Dawson, 1986). In each case, individual variability is the rule, not the exception.

The importance of individuals and the fact of variability present a challenge for most traditional models, regardless of discipline, because the models focus almost exclusively on stability in the population and ignore individual variability (Anastasi, 1937; Chomsky, 1957; Fodor, 1983). By analyzing statistical averages, not individuals, these models provide descriptions about global regularities in everything from cancer (Fearon & Vogelstein, 1990) to cognition (Piaget & Inhelder, 1966). However, we argue that the value of such models ultimately depends on whether they apply to individuals; after all, a science of the group is a poor substitute for a true science of the individual. Traditional models often assume that insights about the population automatically apply to all individuals (Molenaar, 2013). This assumption is simple, it is understandable, and it is necessary to justify the use of averages to understand individuals. However, it is also wrong!

Over the past two decades, a substantial body of evidence has accumulated showing the difficulty of inferring anything about individuals from insights about a population. For example, Molenaar (2004) has argued that such an inference is only possible under strict conditions (called ergodic assumptions) that are almost never met for individuals. In addition, mounting evidence indicates that more often than not, population insights represent at best a small subset of individuals (Borkenau & Ostendorf, 1998). At worst, they are statistical artifacts that represent nobody (Estes, 1956; von Eye, 2009)! As evidence about the importance of individual variability has become overwhelming, and the failure of traditional approaches ever more obvious, disciplines interested in individuals have been thrust into the same explanatory crisis, which we call the Crisis of Variability. The one thing that is known for certain is that the average is not good enough if the goal is to understand individuals: We must explain patterns of individual variability.

In recent years a number of scholars have emphasized the centrality of the individual, and have sought to explain both variability and stability in individuals (e.g., Fischer & Bidell, 2006; van Geert & van Dijk, 2002; Molenaar, 2013; Thelen & Smith, 2007). As a result of their work (and others), a science centered on individual variability has emerged as an important perspective in many fields, including cell biology, cancer, neuroscience, and psychology (e.g., Blau & Liakopoulou, 2013; Garrett & Samanez-Larkin, 2013; Nesselroade, Gerstorf, Hardy, & Ram, 2007; Ståhlberg, Kubista, & Åman, 2011). Indeed, the influence of this work is so widespread that we cannot do justice to it in one article. Here we emphasize that, despite differences in theory and method,

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a common assumption underpins this work: In contrast to traditional models, explaining individual variability is essential to understanding individuals. While still in its infancy, this research is already producing groundbreaking insights.

Take, for example, a recent study on personal genomics (Chen et al., 2012). Here, researchers studied one individual using intensive genomics testing on multiple occasions over 14 months. By focusing on individual variability over time and integrating multiple sources of "-omics" data simultaneously (genomics, transcriptomics, proteomics, metabolomics), researchers were able to identify a cluster of temporally correlated measures that organized into biologically plausible pathways. One of the discoveries turned out to have practical value: After a viral infection, scientists found abnormalities in the insulin-regulating pathway of the individual subject. This in turn led to a diagnosis of diabetes that, happily, resolved in response to diet and exercise. Importantly, these discoveries would have been invisible to researchers who relied on population averages to understand individuals.

Why now?

A century ago Stern (1900) recognized the importance of individual variability, although his call was mostly ignored (Lamiell & Laux, 2010). Why is it only now that research is starting to move toward analyzing individual patterns of variability? We see at least two reasons for this shift. The first is access to data. Modeling individuals requires massive amounts of data that a decade ago would have been difficult and expensive to collect (King & King, 2011). In the personal genomics study, for example, scientists amassed 3 billion data-points on a single person! Data are becoming easier to collect, share, and analyze across disciplines and levels of analysis, with so-called big data empowering researchers in many domains to turn their attention to the individual.

The second reason is the invention of a framework that can sustain a science of the individual. Since the mid-twentieth century several relevant disciplines have (quietly) undergone a dramatic shift, moving from traditional static perspectives—based on statistical averages and assuming linear change—to a dynamic perspective that analyzes individual variability in growth processes and moment-to-moment activity.

The heart of this new approach is dynamic systems theory—a flexible set of concepts and nonlinear mathematical models uniquely suited to analysis of complex phenomena in fields as diverse as physics, meteorology, biology, and psychology (to name a few). A full treatment of dynamic systems is beyond the scope of this article (see Abraham & Shaw, 1992; van Geert, 1998; Thelen & Smith, 2006). Here we limit our discussion to two dynamic systems concepts—individual-in-context and variability-as-information—that are relevant to the science of the individual. We address how researchers have used these concepts to create new insights, overturn misconceptions, and resolve long-standing arguments about the nature and nurture of individuals.

Dynamic systems

A dynamic systems perspective requires that all behavior be analyzed in the context where it occurs. Behavior is not something that a person "has"—instead, it emerges from interactions between the individual and his or her contexts. Performance in sports illustrates this principle. Even the relatively simple act of throwing a baseball is not a fixed action. Indeed no two pitches are ever the same. Context matters! In the moment, a pitcher throws differently depending on multiple factors working together: temperature, crowd noise, lighting, fatigue, a runner on base, and even the catcher's skill (to name a few). Understanding a pitcher's performance, including its variability, depends on analyzing how these factors function in the immediate context, including the characteristics of the person throwing the ball, of course. These kinds of dynamic processes shape all activities, not just throwing a baseball (Rose & Fischer, 2009).

Because the dynamic systems approach assumes that behavior is actively organized and context-dependent, variability is expected as a natural outcome. In contrast to most traditional models, which assume individuals have relatively stable behavior, the dynamic systems approach starts by assuming individuals vary, and seeks to identify stable patterns within that variability (van Geert, 2000). This assumption represents a fundamental difference from other approaches, and it has important conceptual and methodological consequences for the future of the science of the individual. If variability is systematically ignored, individuals become synonymous with statistical averages, and researchers lose the ability to account for the very processes that underpin the phenomena they seek to explain. Individual variability is the essence of adaptive behavior, whether we are talking about a person or a cell.

STABILITY FROM VARIABILITY

Dynamic systems concepts have influenced the way scientists think about individuals in many disciplines. However, changing concepts is only the first step. For the concepts to be useful, scholars must be able to analyze patterns of individual variability, not just pay homage to them. Fortunately, dynamic systems theory offers powerful methods to detect and model these naturally occurring patterns. Here we focus on two kinds of ordered variability that are particularly instructive for building a science of the individual: pathways and context. The goal is to show how the tools of dynamic systems can predict and explain patterns of individual variability, going beyond traditional average-based statistical models.

Multiple Pathways

Historically, in disciplines that study individuals, development has been viewed as a linear progression through a universal sequence, where the start and endpoint are determined (Gottlieb, Wahlstein, & Lickliter, 1998). The dynamic systems perspective offers a stark contrast, in which variability in the sequence is natural, and multiple pathways to the same outcome are expected. Of course, the notion of variability in developmental processes is not new (Dewey, 1963; Fischer & Bidell, 2006; Vygotsky, 1978). What is new is that research grounded in dynamic systems has shown how a focus on variability in pathways leads to the discovery of new kinds of order in developmental processes. This insight has implications for research and practice, especially where normative approaches have not been effective. Research on single-word reading illustrates this principle nicely.

Without a doubt, the act of reading is a complex process with multiple components that come together to influence success (LaBerge & Samuels, 1974). In one study, Knight and Fischer (1992) applied concepts and tools from dynamic systems to analyze pathways for reading single English words in 1st-, 2nd-, and 3rd-grade students. Classic models assume that skillful single-word reading depends on the early integration of sound analysis with visual-graphic skills (Torgesen, Wagner, & Rashotte, 1994; Wolf, 2007). This prototypical model, shown in Figure 1, begins with word definition (a child must know the word before he/she can use it). To start, sound analysis (assessed by rhyming words) and visual-graphic skills (assessed by letter identification or spelling) are independent. An early step in reading is learning to integrate sight and sound on the way to proficiency with single words.

For many children in the study the results supported the average-based model. Not only did it explain the pathway of a majority of children but also was consistently associated with good reading skills. However, many students did not follow this pathway. Were these students simply delayed compared with their peers? Using dynamic methods capable of detecting patterns in individual variability, Knight and Fischer discovered that many of the children were in fact not delayed—they were progressing along two alternative pathways (Figures 2 and 3), both notable for their lack of integration. For pathway B (Figure 2), letter definition led development, but reading and rhyming remained independent. Interestingly, while this pathway characterized many struggling readers, some students following this path had strong reading skills. In contrast, pathway C (Figure 3) was marked by a three-strand progression where reading, letter identification, and rhyming were independent of one another.

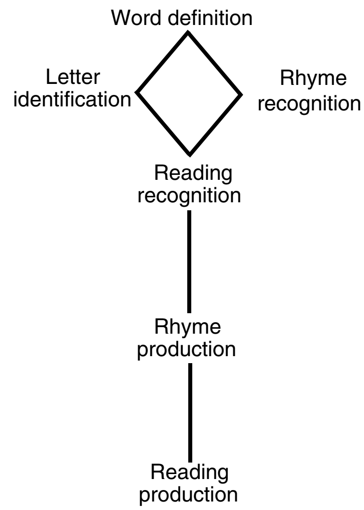

Fig. 1. Pathway A: normative pathway for reading single words.

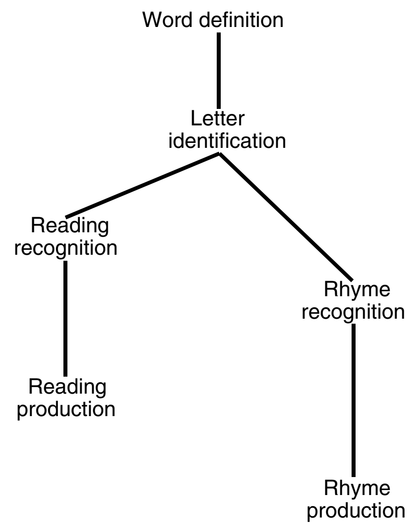

Fig. 2. Pathway B: independence of reading and rhyming.

This path characterized most children with profound reading problems. Remarkably, in this study all 120 students showed one of the three pathways—there were no ambiguous cases!

Multiple pathways are not limited to behavior or learning; indeed, they are evident in all disciplines and at all levels of analysis. For example, consider research on colorectal cancer—one of the most common and lethal cancers in the world. For decades, the dominant average-based model assumed that the cancer unfolded along one pathway, consisting of a linear sequence of morphological steps, each triggered by specific genetic mutations (Fearon & Vogelstein, 1990). However, accumulating evidence over the past decade has shown that the cancer is influenced by multiple genetic and epigenetic factors, and that it is far more variable than the dominant model suggested (Pancione, Remo, & Colantuoni,

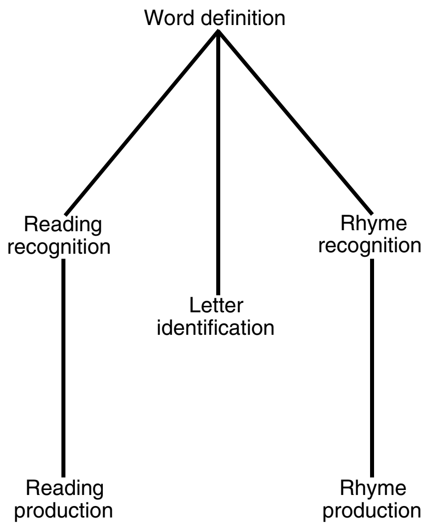

Fig. 3. Pathway C: independence of reading, letter identification, and rhyming.

2012). It quickly became clear that advancing understanding of colorectal cancer depends fundamentally on developing models that can account for the pervasive variability that is its hallmark (Issa, 2008).

Explaining this variability requires a dynamic perspective, emphasizing the interactions among multiple factors across levels and over time (Grizzi & Chiriva-Internati, 2006; Qu et al., 2007). For example, Cheng and colleagues (2008) performed a deep analysis of the molecular profiles of 161 colorectal cancers. They found evidence of not a single progression, but three distinct pathways, each with different molecular mechanisms. Although further research may change the story, the discovery of multiple pathways has moved the field beyond the single-pathway model, and toward analysis of the dynamic patterns of colorectal cancer. It has also catalyzed nuanced molecular-level classification of colorectal tumors, which has shown promise for improving early identification and prediction of treatment response (Al-Sohaily, Biankin, Leong, Kohonen-Corish, & Warusavitarne, 2012).

The detection of multiple pathways in reading and cancer provide powerful examples of the individual variability inherent in development. It also speaks against the assumption, built into many diagnostics and standardized assessments, that individuals develop the same way, along the same linear path. On the contrary, variability pervades individual development. Normative statistical analysis often makes individuals appear similar in assessment results. For example, in the study of reading pathways, statistical tests led to the erroneous conclusion that there was one pathway—the predicted, normative one integrating sight and sound. Similarly, in the research on pathways for colorectal cancer there was an "average" pathway, but it turned out to characterize a small number of individuals. In both examples the existence of multiple pathways was not detected initially because the alternatives were invisible to statistical techniques that rely on averages to characterize individual development. This misconception has profound consequences: For reading, ignoring multiple pathways leads to misdiagnosis of delay in reading. For colorectal cancer, the error can be a matter of life or death.

Person-in-Context

People routinely show systematic patterns of variability, not just over time (pathways), but in moment-to-moment behavior. Activity emerges from interactions of individuals with context, and systematically different patterns emerge for different individuals. Traditional models usually assume that behavior is stable, and therefore they ignore the influence of context, focusing instead on averages to reveal "true" behavior (or ability or knowledge) (Gottlieb et al., 1998). In contrast, the dynamic systems perspective assumes that context matters, and seeks to identify patterns within the person–context interaction. Because variability is analyzed and not ignored, scientists can identify factors that systematically affect individual behavior (Rose & Rouhani, 2012). In other words, they can find order in the variability.

Take, for example, the "stepping reflex", which is the pattern of leg movements (steps) an infant makes when held upright, standing on his or her feet. Present at birth, this reflex seems to disappear after a couple of months, only to reappear around the time of walking—something that puzzled researchers for decades. Classic explanations for this phenomenon were based on neurology: Brain areas matured and suppressed the newborn reflex, according to experts (Conel, 1960).

Thelen (1986) radically changed this interpretation by using dynamic systems analysis to offer a different explanation, which considered infants' bodies and contexts in new ways. The traditional explanation had treated these contexts as irrelevant. As it turned out, the stepping reflex disappeared not because of brain changes but because of changes in leg weight: Babies' legs showed an increase in mass that made it impossible for them to lift their legs when standing in an upright position. Thelen tested infants who had "lost" the reflex by placing them in a tub of water, where the buoyancy reduced the effective weight of their legs. Now, held upright, infants' reflex returned: They stepped just like younger infants. By manipulating the nonobvious variable of leg mass, Thelen controlled the emergence and suppression of a reflex previously thought to be under strict neurological control. The powerful influence of person-in-context helped Thelen to discover the underlying dynamics of infant motor development.

The centrality of context extends down to the cellular level as well. Here, context (called the "microenvironment") is known to play a fundamental role in the growth and function of healthy and cancer-related cells (Burness & Sipkins, 2010, p. 107; Clausson, Grundberg, Weibrecht, Nilsson, & Söderberg, 2012; Coghlin & Murray, 2010; Polyak & Kalluri, 2010). In addition, modern genetic research has shown the importance of "epigenetic factors" arising from gene–context interactions. Consider again the case of colorectal cancer: The dominant model had assumed that progression was driven by only a few specific genetic mutations (Fearon & Vogelstein, 1990). But current research suggests something different: Not only do epigenetic factors matter, but it appears that epigenetic changes far outnumber genetic changes in colorectal cancer (Pancione et al., 2012). Perhaps most important, these insights are leading to novel approaches to treatment that are likely to yield tremendous benefits for individuals with colorectal cancer.

A final example showing the importance of understanding patterns of variability across context comes from a landmark study of children's social behavior (Shoda, Mischel, & Wright, 1994). In this study, researchers collected intensive observational data (for example, 169 hours of video per individual) for 84 children over the course of a 6-week residential summer camp program. Traditional models based on averages assume personality is a stable "trait" that is best understood by focusing on rank-order scores across dimensions (such as extraversion). In contrast, critics argue that "personality" is not stable, and that the dominant influence on a person's behavior is the context. Arguments of this kind had gone in circles in a decades-long debate, and progress had been decidedly limited.

Fortunately, the debate has been resolved by Shoda and colleagues who, by using a dynamic approach that highlights individual variability, were able to reconcile the arguments and move the field forward. Two findings from their study are relevant to this article. First, as critics argued, children's behavior was variable across context. Moreover, different contextualized patterns led to the same rank-order score. For example, of two children with the same aggregate aggression score, one child was aggressive with peers, but not with the teachers; whereas the other was aggressive with teachers, not peers. Second, and most important, while children's behavior varied across context, there was stability in the way it varied (e.g., the child who was aggressive with teachers, but not peers was likely to maintain the same pattern over time). Taken together, the findings reveal something important about personality: It is stable as static models suggested, but not in the way they assumed. Likewise, behavior is variable as critics suggested, but it is not random, as they assumed. Instead, individual behavior varies systematically across contexts. In other words, there is stability in the individual variability.

The detection of ordered variability across contexts has obvious implications for both research and practice. For children's social behavior, it reconciles a long-standing (and largely unproductive) debate about personality involving traits versus situations. Individuals respond differently to distinct contexts! For cancer research, the effects of context are even greater, and the implications for practice are profound. Realization of the pervasiveness of effects of cell context and genome context has led to a flurry of insights about early diagnostics and has greatly improved classification criteria for colorectal cancer. With traditional mean-based analyses, these patterns were impossible to detect because the search was for main effects in isolation. Context plays a fundamental role in both colorectal cancer and social behavior.

These findings and insights point the way to a new kind of analysis, a new kind of science, in which the focus is on individual patterns of behavior. Research *starts with* a focus on individual variations across contexts, and it builds from there to the creation of generalizable models of growth and learning. The main task for scientists is to build tools for analyzing patterns of growth and learning of individual people. In other words, research starts with characterizing how individuals grow and learn, how people differ across contexts, and how growth is shaped by the patterns and pathways through which we grow.

LOOKING FORWARD

A science based in dynamic systems and centered on individual patterns of variability provides an opportunity to analyze everything from how people act to how cells behave, while at the same time using methods that keep the complexity of the patterns intact. This approach makes it possible to move beyond static explanations of behavior, where oversimplification is the rule. However, there is much work to be done to ensure that the science of the individual reaches its full potential. Here we conclude by emphasizing three challenges that must be addressed to create effective and scalable research that is focused on individual variability rather than statistical averages: issues of data, the importance of models, and the nature of science.

The Role of Data

One reason it is possible to have a science of the individual now is the new capacity based on technological innovation to collect and analyze massive amounts of data on individuals (Frankel & Reid, 2008). However, sheer quantity is not enough: Quality matters (Rose & Fischer, 2011). For example, to identify patterns of individual variability across contexts, researchers need reliable data on individuals that sample more than one context on multiple occasions. Similarly, an important issue for modeling individual pathways is not only quantity and quality of data but also the intervals for data collection (van Geert & van Dijk, 2002). What intervals will be useful? Which ones will produce data that lead to reliable findings?

Sophisticated research about the individual is now possible, but it is not inevitable. What is required is that intelligent choices be made about digital data—from the ways that it is formatted, stored, and analyzed. As researchers we must have a clear sense of how to collect optimal data. We need to engage with technology experts to understand what is possible to collect, and what the trade-offs will be. Most important we must ensure appropriate standards that not only meet the needs of science but also (most importantly) protect the rights of the individuals we aim to understand.

The Power of Models

Dynamic concepts have influenced the way scientists think about the individual across disciplines. What we need now are more tools for building realistic models of individual behavior, learning, and development. Realizing the full power and potential of the dynamic systems approach to the science of the individual requires building mathematical models that go beyond conjecture to make concepts testable and falsifiable (Abraham & Shaw, 1992; van Geert, 1998; van der Maas & Molenaar, 1993). Although the field is young, there are a number of such models available (e.g., logistic growth, predator–prey, cusp catastrophe), and we need to provide ways for scholars to apply them in research.

Of course, these models are just the beginning. The future of the science of the individual depends on making a firm commitment to developing dynamic tools that capture how individuals grow, learn, and develop. We need imaginative work to replace the static models used by and taught to scientists around the world today.

The Nature of Science

Like all sciences, the science of the individual seeks insights that apply to both the general and the particular. In this article, we have focused on the limitations of traditional “aggregate-then-analyze” approaches, in which dogmatic belief in universals has led to neglect of the particular. At the same time, we must avoid overcorrection: Wholesale rejection of even the possibility of universals does not (and never will) serve the needs of science. The reality (or not) of universals is an empirical question, not an assumption. Answering this question may be accomplished best by pursuing an “analyze-then-aggregate” approach, in which the starting point is patterns of individual variability. Then data can be aggregated to ask how individuals vary rather than focusing on population means. In recent years there have been advances in these methodologies (Nesselroade et al., 2007), and we believe such work represents a core part of the methodological backbone for the science of the individual.

CONCLUSION

Human behavior is remarkably variable. It changes systematically over time, and it fluctuates moment-to-moment depending on the immediate context. If this kind of individual variability is ignored or marginalized, it acts as noise disguising the dynamic nature of individual behavior and growth, and it will often mislead researchers. In contrast, starting with a focus on individual variability, rather than statistical averages, leads to new, elegant explanations for the richness of behavior, including models and methods for analyzing variability over time and across contexts. These concepts and tools help more closely align theory, research, and practice, and give us the best opportunity to develop usable knowledge about the complex and variable ways that individuals behave, learn, and grow.

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